Automation and Disappearing Routine Occupations in Japan *

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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 evidence that automation reduces 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.

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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 has 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. Dekle (2020) shows that industries that introduce more robots did not decrease labor demand. 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 Adachi et al. (2022) is the first to use application-weighted robot price as an instrumental variable and 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]

[2]See Appendix E for a detailed discussion of the relation to Adachi et al. (2022).

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.[3]

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.[4]

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 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

Table 1 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. This rough classification is inevitable due to the data constraint, and we cannot use ONET data to classify it more systematically. Table C.1 in the Appendix C shows that our rough classification of routine occupation actually exhibits the highest routine task score in 2012, where the detailed occupation categories are available so that we are able to compute task score based on O-NET data. In 1997, ESS data used JSCO revised in 1986. In 1982, ESS

[3]See Table A.1 in Appendix A for the coverage by survey year.

[4]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 but mainly go to school.

data followed JSCO revised in 1979 at the category level we are using.[5] We exclude workers in agricultural and fishing industries from our analysis.

Table 1: 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.

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-

[5] To be precise, ESS data used 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.

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 from 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 compiled by Adachi et al. (2022). JARA data is the primary source of Japan's robot data, first used by Dekle (2020), then used by other papers including Adachi et al. (2022). This 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.[6] 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.

Robot 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.[7] We use data complied by Adachi et al. (2022). JIP data contains labor inputs, capital stocks, exports, imports, and outputs by industry from 1982 to 2012. JIP data is also consolidated into the above 13 industries.

[6]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 B presents the shipment of robots by industry and application. Table C presents the shipment of robots by robots' structure and applications.

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

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.[8] 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.[9]

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

where $\Delta R_{i,t,t+15} = R_{i,t+15} - R_{i,t}$ is a change in the number of robots in industry i from year t to $t+15$ from the JARA data where $R_{i,t}$ is the number of robots in industry i in year t, $L_{i,t}$ is a number of workers in industry i in year t from the JIP data, $\Delta Y_{i,t,t+15}$ is a change in a real output in industry i from the JIP data, $Y_{i,t}$ is a real output in industry i from the JIP data. The second term controls the industry-specific demand shock. In Table D.3, we report our estimates using the un-adjusted penetration of robots as in Adachi et al. (2022) 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 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 share of high-school-educated workers, the share of college-educated workers, the share of female workers, the share of workers aged below 35, the share of workers aged above 50, and the share of manufacturing sector employment. All the variables are in log units.[10] Finally, to separate the effects of automation from the effects of other capital investments

[8] 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) impute these with one (zero after taking the log) in 2017, but this introduces undesirable bias across industries with different stock values before 2017.

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

[10] We also check if our results hold when we control contemporaneous demographic changes across commuting zones. We include log changes in the share of high-school-educated workers, the share of college-educated workers, the share of female workers, the share of workers aged below 35, and the share of workers aged above 50. Our results are unchanged. To be compatible with Adachi et al. (2022), we exclude demographic changes from the covariates of the specification we report in the paper.

or international trade, we control technology exposure covariates, which 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:

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

where $\Delta x_{i,t,t+15}$ is a change in technology or trade values in real. It includes changes in IT capital stock, innovation capital stock, competitive assets, offshoring values, and total imports in industry i from year t to $t+15$. $L_{i,t}$ is the number of workers in industry i in year t. All of these industry-level variables $\Delta x_{i,t,t+15}$ are from Adachi et al. (2022).[11]

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.[12] [13] 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.[14] [15]

[11]We do not impute values with one in 2017 as in Adachi et al. (2022) because we do not use the data in 2017.

[12]Adachi et al. (2022) was the first to use the application-weighted robot price as an instrument variable. What is new in this paper is the usage of the export price rather than the domestic price, which is less affected by domestic demand shocks.

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

[14]The actual, not predicted, value is as follows:

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

where $\omega_{i,a,1982}$ is the share of robot quantities of application a in industry i, and $\Delta \ln p^R_{a,i,t,t+15}$ is the 15-year changes in price of robots of application a shipped to industry i. Directly using this price, not the predicted one, introduces omitted variable biases from unobserved demand shock.

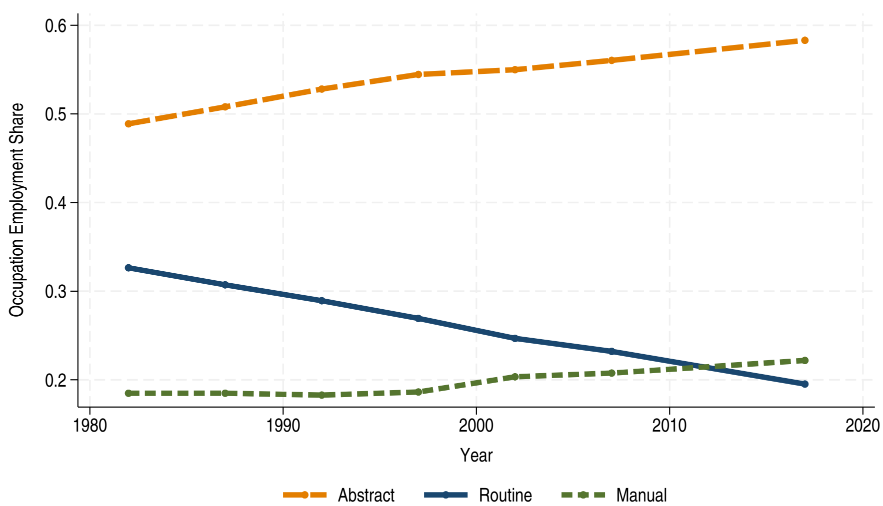
[15]We admit that our current instrumental variable is not perfect but also think that it is the best of the available options. As Adachi et al. (2022) notes, using robot stock in foreign countries as an IV is impossible for the period before 1995 when the IFR data became available. As noted in Figure 2, robot penetration was rapid before 1995 in Japan, so it is impossible to use the IFR data as in Acemoglu and Restrepo (2020). The same is true for Graetz and Michaels (2018). which rely on the data for multiple countries in the IFR data. Thus, it is inevitable to use information on robots produced in Japan to study the effects of automation in Japan during the periods when robot penetration is rapid.

4 Summary Statistics

4.1 Macro Trends

To start the analysis, we first show the time trend of employment share by occupation group in Japan. Figure 1 shows the employment share by the occupation group 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.[16][17]

Figure 1: Employment Share by Occupation Group in Japan



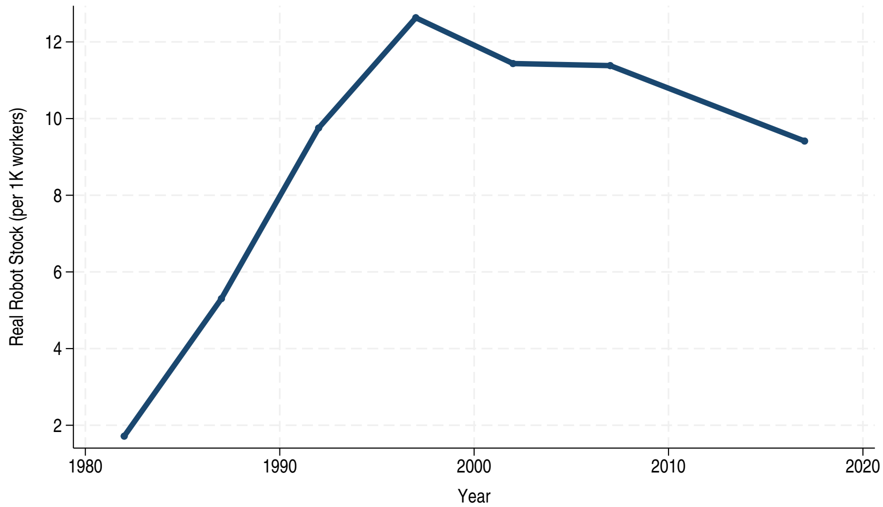
Notes: The figure shows the employment share by occupation group in Japan. Data is from ESS.

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.

[16] 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 with interpreting the pattern in Figure 1 is that the composition effects can solely drive it. Figure C.4a in Appendix C negates this concern by showing that the shift from routine to abstract occupations is common across genders.

[17] Figure C.1 in Appendix C shows the time-series of routine occupation shares by commuting zones' APR measures. It shows that commuting zones with larger robot exposures experienced more rapid decreases in routine occupation shares.

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 by the degree of robot penetration. The samples are 200 CZs for two 15-year periods (1982-1997 and 1997-2012). This table shows the summary statistics, mean, and standard deviation for each variable. Samples of CZs are split into two groups based on the adjusted penetration of robots (APR). High robot CZs are the commuting zones with APR larger than the median, and low robot CZs are the ones with APR smaller than or equal to the median. [18] The last two columns show the difference between the two groups of commuting zones and the t statistics.

APR is the running variable defined in the previous subsection, and the mean is 0.45 for high robot CZs and -0.19 for low robot CZs. The difference is 0.63 percentage points, with t-statistics of 3.12.

The employment rate is defined as the share of the employed population to the total population aged between 25 and 64. Both CZs have employment rates of 78% to 79%, and the difference of 1 percentage point (after rounding) is not economically sizable. The differences in occupational shares are also not sizable. Both CZs have 46-47% of abstract, 33% of routine, and 20-21% of manual occupation shares.

The growth in employment rate is smaller in high robot CZs with 0.90 percentage points relative to low robot CZs with 0.76 percentage points, but the difference is not significant. High robot CZs experience statistically larger increases in abstract occupation shares (4.45 percentage points

[18] Figures C.5 and C.6 in Appendix C show the adjusted penetration of robots by commuting zone in a map of Japan.

v.s. 3.64 percentage points) and larger decreases in routine occupation shares (-8.86 percentage points v.s. -7.69 percentage points).[19]

There are no huge differences in local demographics. The share of high-school-educated workers is 64 to 65%, the share of college-educated workers is around 10%, the share of female workers is around 42%, the share of workers aged below 35 is 31%, and the share of workers aged above 50 is around 32%.

Table 2: Summary Statistics by Robot Penetration

	High Robot CZ (100)		Low Robot CZ (100)		High - Low Robot	
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	t Stat.
Robot Penetration						
Adjusted Penetration of Robots	0.45	1.92	-0.19	2.13	0.63	3.12
Initial Labor Market Variables						
Employment Rate	0.78	0.05	0.79	0.05	-0.01	-1.24
Abstract Occupation Share	0.47	0.07	0.46	0.06	0.00	0.59
Routine Occupation Share	0.33	0.08	0.33	0.07	0.01	0.95
Manual Occupation Share	0.20	0.04	0.21	0.04	-0.01	-2.43
Changes in Labor Market Variables						
Changes in Employment Rate	0.90	3.01	0.76	3.34	0.15	0.46
Changes in Abstract Occupation Share	4.45	4.58	3.64	5.59	0.82	1.60
Changes in Routine Occupation Share	-8.86	4.44	-7.69	5.94	-1.18	-2.24
Changes in Manual Occupation Share	4.41	5.32	4.05	5.85	0.36	0.64
Initial Local Demographic Variables						
Share of High-School-Educated Workers	0.65	0.14	0.64	0.13	0.01	0.96
Share of College-Educated Workers	0.11	0.06	0.09	0.05	0.02	3.94
Share of Female Workers	0.42	0.03	0.42	0.03	-0.01	-2.07
Share of Workers Aged Below 35	0.31	0.06	0.31	0.06	-0.00	-0.07
Share of Workers Aged Above 50	0.32	0.07	0.32	0.06	-0.00	-0.59

Notes: Samples are 200 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the summary statistics, mean, and standard deviation for each variable. Samples of CZs are split into two groups based on the adjusted penetration of robots (APR). High robot CZs are the commuting zones with APR larger than the median, and low robot CZs are the ones with APR smaller than or equal to the median. APR is 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 occupational employment share is the share of employment in each occupation relative to total employment for the workers aged between 25 and 64. The occupation categories are defined in the main text. All the summary statistics are unweighted.

Table 3 shows the summary statistics for the main variables we use for the analysis by the subperiod (1982-1997 and 1997-2012). The samples are 200 CZs for two 15-year periods (1982-1997 and 1997-2012). This table shows the summary statistics, mean, and standard deviation for each variable.

APR of 1.84 is larger for the first period while it is negative at -1.58 in the latter period, which is consistent with the macro time series presented in Figure 2.

Employment rate increased from 77% to 79%. The abstract occupation share increased from 44% to 49% while the routine occupation share decreased from 36% to 31%. The manual occupation share stays constant at around 20%.

[19]Figures C.2 and C.3 in Appendix C show the bivariate relationships between the changes in routine occupation share and the robot penetration across commuting zones.

Growth in the employment rate is larger in the first half by 2.03 percentage points (1.84 percentage points v.s. -0.18 percentage points). Declines in routine occupation share are larger in the latter half.[20] The change in manual occupation share is larger in the latter half.

Local demographic characteristics have changed over time. The share of high-school-educated workers increased from 55% to 73%, and the one of the college-educated population increased from 8% to 13%. The share of female workers increased slightly, the share of workers aged below 35 decreased by 6 percentage points, and the share of workers above 50 increased by 6 percentage points.

Table 3: Summary Statistics by Sample Period

	1982-1997		1997-2012		1st - 2nd Half	
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	t Stat.
Robot Penetration						
Adjusted Penetration of Robots	1.84	1.06	-1.58	1.21	3.42	30.11
Initial Labor Market Variables						
Employment Rate	0.77	0.05	0.79	0.04	-0.02	-4.01
Abstract Occupation Share	0.44	0.06	0.49	0.06	-0.04	-7.23
Routine Occupation Share	0.36	0.07	0.31	0.06	0.05	7.45
Manual Occupation Share	0.20	0.05	0.21	0.04	-0.01	-1.39
Changes in Labor Market Variables						
Changes in Employment Rate	1.84	3.07	-0.18	2.96	2.03	6.72
Changes in Abstract Occupation Share	4.47	5.14	3.62	5.08	0.85	1.66
Changes in Routine Occupation Share	-5.09	4.24	-11.46	4.16	6.38	15.19
Changes in Manual Occupation Share	0.62	4.33	7.84	4.21	-7.22	-16.92
Initial Local Demographic Variables						
Share of High-School-Educated Workers	0.55	0.11	0.73	0.09	-0.18	-17.68
Share of College-Educated Workers	0.08	0.04	0.13	0.06	-0.05	-9.51
Share of Female Workers	0.42	0.04	0.43	0.03	-0.01	-2.79
Share of Workers Aged Below 35	0.34	0.05	0.28	0.05	0.06	11.44
Share of Workers Aged Above 50	0.29	0.06	0.35	0.05	-0.06	-9.83

Notes: Samples are 200 CZs $\times$ two 15-year periods (1982-1997 and 1997-2012). This table shows the summary statistics, mean, and standard deviation for each variable. Samples of CZs are split into two groups based on the adjusted penetration of robots (APR). High robot CZs are the commuting zones with APR larger than the median, and low robot CZs are the ones with APR smaller than or equal to the median. APR is 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 occupational employment share is the share of employment in each occupation relative to total employment for the workers aged between 25 and 64. The occupation categories are defined in the main text. All the summary statistics are unweighted.

[20]This looks inconsistent with the hypothesis that automation, which grew faster in the first half, led to declines in routine occupation shares at the macro level. However, it is important to note that one should avoid jumping onto any causal interpretation just by looking at macro time-series trends. In fact, in the following analysis, we use cross-sectional variations within each period and show that automation leads to decreases in routine occupation shares. Moreover, bilateral correlation within each period shows that the decline in routine occupation share correlates with automation in the first half and not in the second half as presented in Figure C.2 and C.3 in Appendix C, respectively.

5 Effects of Automation on Labor Demand across Local Labor Markets

5.1 First Stage

Table 4 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. The regression includes covariates that control initial commuting zone characteristics and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

The first stage is strong. If the price of exporting robots increases, robot penetration decreases, and the F-statistics is 745.12.

Table 4: First Stage using Price of Exporting Robots as IV

	(1)
Price of Exporting Robots	-53.00
	(4.37)
Observations	400
Initial CZ Covariates	✓
Tech 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 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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 5 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.[21] Column (1) uses changes in employment rate relative to population as an outcome. Columns (2),

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

(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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.[22]

Column (1) shows that the effect on the total employment rate is not statistically significant. Contrary to the findings in Acemoglu and Restrepo (2020) for the US, we do not find evidence that robots lead to decreases in the total employment rate.[23] 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.[24] The estimate in Column (4) is statistically insignificant, which implies that automation did not increase manual occupation shares.

[22]We use the EHW standard errors as the baseline and do not report shift-share standard errors from Adao et al. (2019) in the main text. In most of the applications in Adao et al. (2019), the shift-share standard errors are larger and more conservative when rejecting the null hypothesis. However, in this case, the EHW standard errors are more conservative. See Kikuchi et al. (2023) for the version where both confidence intervals are reported.

[23]In fact, Table D.1 in Appendix D 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.

[24]In Table D.7 in Appendix D, we separate abstract occupations into two subgroups: management, professionals, and technical occupations and clerk and sales occupations. It shows that the action is at the transition from routine occupations to clerk and sales occupations.

Table 5: 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	0.18	1.01	-1.15	0.13
	(0.21)	(0.32)	(0.25)	(0.27)
Observations	400	400	400	400
Initial CZ Covariates	✓	✓	✓	✓
Tech 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. 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

Mechanism: Manufacturing to Service To study the mechanism behind the finding in Table 5, 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 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 6 shows the results.

The declines in routine share within each sector are clear from Columns (2) and (4). This is mostly offset by the expansion of non-routine occupation in the service sector as indicated in Column (3), not the rise in non-routine occupation employment within manufacturing sectors as the insignificant estimate in Column (1) implies.

Table 6: 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	0.16	-0.60	1.00	-0.56
	(0.20)	(0.22)	(0.33)	(0.17)
Observations	396	396	396	396
Initial CZ Covariates	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓

Notes: Samples are 198 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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.

5.3.1 Why We Use Number of Establishments and a Proxy

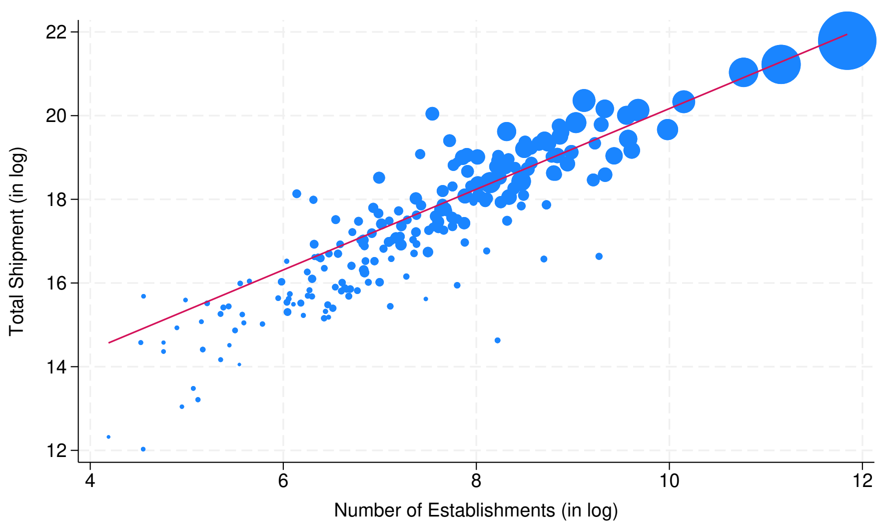
We need to use the number of establishments for the entire sectors because that is the only available variable for sectoral activities at the unit of pairs of commuting zones and sectors for the sample periods.

First, we confirm that the number of establishments is a good proxy for sectoral activities. We show a correlation between the number of establishments and shipments for the manufacturing sector, where we have both variables across commuting zones.

Figure 3 shows a scatter plot for a bi-variate correlation between the number of establishments in the manufacturing sector and total shipment in the manufacturing sector in 1982 across commuting zones in Japan. Each dot represents a commuting zone, and the size corresponds to the population in 1982 in each commuting zone. The line is a linear fitted line, weighted by the population in 1982.

Both measures have a high correlation of 0.89, and the estimate of the coefficient of the bivariate regression is 0.95 with a standard error of 0.02. Therefore, we think it is appropriate to use the number of establishments as a proxy for sectoral activities for sectors without sales or shipment data available at the commuting zone level.

Figure 3: Number of Establishments and Total Shipment in Manufacturing Sector



Notes: The figure shows a scatter plot for a bi-variate correlation between the number of establishments in the manufacturing sector and total shipment in the manufacturing sector in 1982 across commuting zones in Japan. Each dot is a commuting zone, and the size corresponds to the population in 1982 in each commuting zone. The line is a linear fitted line, weighted by the population in 1982. The estimate is 0.95 with a standard error of 0.02. Data for the number of establishments is from the Establishment and Enterprise Census. Data for the total shipment is from the Census of Manufacturers.

5.3.2 Effects of Automation on Number of Establishments by Sector

Table 7 shows the result for the relationship between the number of establishments by sector and automation. 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 as shown in Column (1) and the share of the manufacturing sector as shown in Column (3). 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 7 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 7: Effects of Automation on Changes in the Number of Establishments

	Log Changes		Changes in
	Manufacturing	Service	Manufacturing Share
Adjusted Penetration of Robots	26.35	-0.77	2.76
	(4.98)	(1.06)	(0.62)
Observations	400	400	400
Initial CZ Covariates	✓	✓	✓
Initial CZ Covariates	✓	✓	✓
Tech Change Covariates	✓	✓	✓
Period FEs	✓	✓	✓

Notes: Samples are 200 CZs × 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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 group.

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 8 shows the results.[25] Columns (1)-(3) show the results for occupation for male workers, and Columns (4)-(6) show the ones for female workers. The positive estimates in Columns (1) and (4) show that abstract occupation shares increase for both male and female workers. The negative estimates in Columns (2) and (5) show that routine occupation shares decrease for both male and female workers though the estimate for female workers is not statistically significant at the 5% level. Estimates in Columns (3) and (6) are not statistically significant from zero. In sum, the shift from routine to abstract occupation is significant for both types of workers.

[25] The sample size decreased from 400 to 394 because some commuting zones did not have one of the occupations in either male or female workers.

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

	Dep. Var.: Changes in Employment Rate					
	Male Workers			Female Workers		
	Abstract	Routine	Manual	Abstract	Routine	Manual
	(1)	(2)	(3)	(4)	(5)	(6)
Adjusted Penetration of Robots	1.28	-1.64	0.36	0.67	-0.48	-0.19
	(0.41)	(0.32)	(0.33)	(0.32)	(0.38)	(0.38)
Observations	394	394	394	394	394	394
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓

Notes: Samples are 197 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

Changes in Occupation Share by Worker Age Group Next, we study the effect on occupation employment share by worker age group. Table 9 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 the decline in the routine occupation share are significant for both age groups while the estimates for middle and old-aged workers are insignificant for the increase in the abstract occupation share. This suggests that the adjustment of labor markets occurs particularly 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 group. Table 10 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.

None of the estimates for college-educated workers is significant while the ones for non-college-educated workers are significant for the increase in abstract and the decrease in routine occupations. This means that 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.

Table 9: 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	1.77	-1.58	-0.19	0.36	-0.74	0.38
	(0.47)	(0.45)	(0.37)	(0.37)	(0.32)	(0.37)
Observations	396	396	396	396	396	396
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech Change Covariates	✓	✓	✓	✓	✓	✓
Period FEs	✓	✓	✓	✓	✓	✓

Notes: Samples are 198 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

Table 10: 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	0.34	-0.24	-0.10	1.21	-1.31	0.10
	(0.54)	(0.40)	(0.33)	(0.26)	(0.27)	(0.25)
Observations	304	304	304	304	304	304
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech 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 occupations 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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.[26] One can use data on wages from the Basic Survey on Wage Structure (BSWS) from the Ministry of Health, Labour and Welfare as in Kambayashi et al. (2008) or Kawaguchi and Mori (2016) with a different specification rather than commuting zone level analysis.[27] Second, it would be fruitful to examine the effect on skill distribution, namely educational upgrading.[28]

[26] Table D.6 in Appendix D shows the estimates based on the interval imputation method to estimate conditional means and variances. We do not find evidence that automation affects earnings, days worked, or daily wages.

[27] BSWS's sampling frame does not allow to do commuting zone level analysis.

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

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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

B Theoretical Rationale for Adjusted Penetration of Robots

B.1 Measuring Robot Penetration

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.2 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.3 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

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

■

B.4 A Theoretical Framework that is Consistent with Main Empirical Results

The key empirical finding is that automation decreases the routine occupation share and increases the abstract occupation share. In particular, the paper shows that there is an increase in sales and clerk occupations.

One clarification is that we do neither aim to construct a general model to guide which regressions to run nor claim that this is the only theoretical model that can rationalize our findings. Rather, we aim to theoretically clarify the *sufficient* conditions for our findings to be consistent with the theory.

Theoretical Framework We extend the previous task framework with multiple occupations. Consider the following production function at an industry level.

$$Y = \alpha^{-\alpha}(1-\alpha)^{\alpha-1}\left(\left[\min_{s\in[0,1]} x(s)\right]^{\frac{\sigma-1}{\sigma}} + (L^A)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}\cdot\alpha}\left(L^M\right)^{1-\alpha} \quad (1)$$

where Y is the output, $x(s)$ is the quantity of task s, L^A is abstract labor (sales, clerks, admins, professionals), and L^M is manual labor (security workers, service workers). $\alpha^{-\alpha}(1-\alpha)^{\alpha-1}$ is a convenient normalization.

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

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

If $s < \theta$, both robot capital $M(s)$ and routine labor $L^R(s)$ 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. We also assume free mobility of labor across occupations so that the wages are equalized at W.

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

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

Characterization Since automation is always profitable, all the tasks, that can be technologically automated, will be automated, and the equilibrium quantity of each task will be

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

For simplicity, assume $\gamma_M = \gamma_L = 1$.

Solving for factor demand for each factor, we have

$$\begin{aligned}
RM &= \theta \cdot \frac{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}}{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}+1} \cdot \alpha Y \\
WL^R &= (1-\theta)\frac{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}}{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}+1} \cdot \alpha Y \\
WL^A &= \frac{1}{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}+1}\alpha Y \\
WL^M &= (1-\alpha)Y
\end{aligned}$$

Comparative Statics We consider an increase in θ and see how relative labor demand responds.

Consider a relative demand for manual labor to abstract labor.

$$\frac{L^M}{L^A} = \left(\left(\frac{\theta R + (1-\theta)W}{W}\right)^{1-\sigma} + 1\right) \cdot \frac{1-\alpha}{\alpha}.$$

Taking the derivative with respect to θ,

$$\frac{\partial\left(\frac{L^M}{L^A}\right)}{\partial\theta} = (1-\sigma) \cdot \frac{1-\alpha}{\alpha} \cdot W^{\sigma-1} \cdot \underbrace{(R-W)^{-\sigma}}_{<0}$$

where $R < W$

What we find in the data is that automation increases abstract occupations more than manual occupations,

$$\frac{\partial\left(\frac{L^M}{L^A}\right)}{\partial\theta} < 0.$$

Therefore, the necessary and sufficient condition is that the production task done by robots and routine labor and the abstract task done by abstract labor are complements,

$$\sigma < 1.$$

In fact, this condition is consistent with the prediction of relative labor demand for routine labor to others. Focusing on the ratio of routine labor to manual labor,

$$\frac{\partial\left(\frac{L^R}{L^M}\right)}{\partial\theta} = (1-\theta)\frac{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}}{\left(\frac{\theta R+(1-\theta)W}{W}\right)^{1-\sigma}+1}\cdot\frac{\alpha}{1-\alpha}.$$

If $\sigma < 1$, the share of routine occupations decreases, which is our main empirical finding.

$$\frac{\partial\left(\frac{L^R}{L^M}\right)}{\partial\theta} < 0.$$

C More Facts

C.1 Occupation Classification and Task Score

We are aware that our occupation classification is rough. However, the occupation categories in ESS are not detailed enough to do this and are not consistent over time. For example, in 1982, ESS only had 11 occupation categories as documented in Table 1. “Manufacturing process, machine operation workers” is one occupation category in 1982, and we can not split it into more detailed categories. Thus, we decided to keep our rough categories, which are as detailed as possible in this context, as they are.

To validate that our categories are consistent with the concept of routine-ness, which we want to analyze, we examine the correlation between task score and occupation categories for 2012. In particular, we examine if our three occupation categories capture the heterogeneity in routine task intensity at the task level.

We use JobTag data available on the webpage of the Ministry of Health, Labour and Welfare of Japan and compute task score for routine-ness for each detailed 167 occupation classifications available in the ESS data in 2012. Following Komatsu and Mugiyama (2021), we first use the following three scores: “work according to the speed of equipment” in the Work Content measure, “repetitive work” in the Work Content measure, and “control machines and process of machine manufacture” in the Generalized Work Activities measure.[29] As in Komatsu and Mugiyama (2021), we normalize these three scores so that the mean is zero with a standard deviation of one across 167 occupation classifications in 2012. We then sum up these three scores into one-dimensional scores and normalize them again.

Table C.1 shows the routine task score by occupation category, abstract, routine, and manual. It shows the number of detailed occupations, mean, standard deviation, minimum, and maximum of the score by group. 42 out of 167 occupation categories are in the routine occupation group and its average routine task score is 0.79 with a standard deviation of 0.44. The average scores for abstract and manual occupations are negative. It is reassuring that our group of routine occupations is distinctive in the routine task intensity.

Table C.1: Routine Task Score by Occupation Group

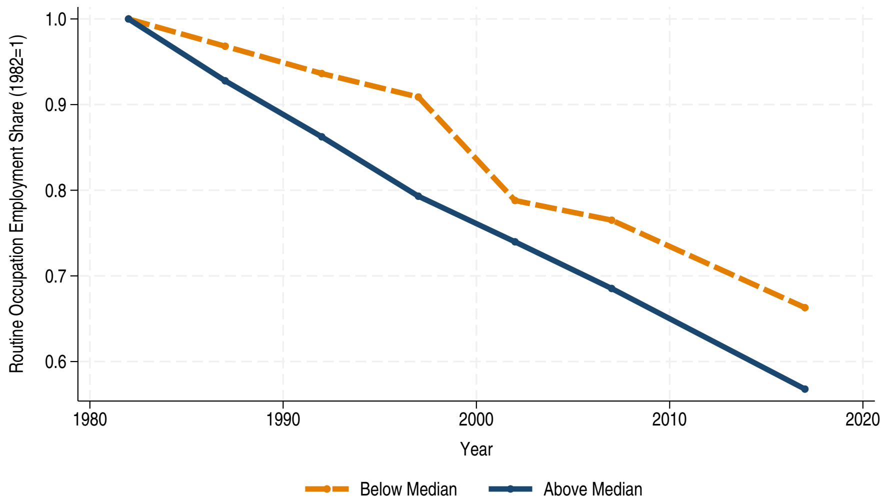
Occupation Categories	Num. of Occupations	Mean	Std. Dev.
Abstract	79	-0.25	0.59
Routine	42	0.79	0.44
Manual	46	-0.10	0.66

Notes: The table shows the summary statistics for the routine task score by occupation group. Detailed occupation categories in the ESS data in 2012 are grouped into abstract, routine, and manual occupations according to the crosswalk provided in the main text. The number of occupations is the count of the detailed occupation categories in each group. The mean and standard deviations are the weighted statistics on the routine task score computed following Komatsu and Mugiyama (2021).

[29] We use Version 4.00.01. available at https://shigoto.mhlw.go.jp/User/download.

C.2 Occupation Share by Robot Penetration

Figure C.1: Routine Occupation Share by Robot Penetration



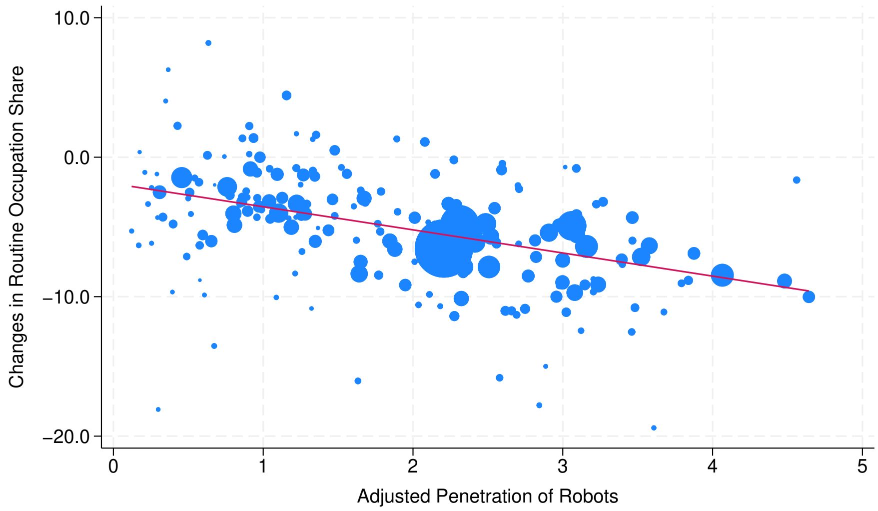
Notes: The figure shows the employment share of routine occupation by subgroup of commuting zones. The share in 1982 in each group is normalized to be one. The blue solid line shows the share of routine occupation for commuting zones with the adjusted penetration of robots above the median. The orange dashed line shows the share of routine occupation for commuting zones with the adjusted penetration of robots below and equal to the median. The adjusted penetration of robots in each commuting zone is the average of the value within each commuting zone over two time periods in the analysis (1982-1997 and 1997-2012). Data is from ESS.

We also include graphs showing a correlation between the penetration of robots and changes in the share of routine occupation in the two sample periods. Figure C.2 shows the relationship between the changes in routine occupation share and the adjusted penetration of robots across commuting zones in the periods from 1982 to 1997. Each dot is a commuting zone, and the size corresponds to the population in 1982 in each commuting zone. The line is a linear fitted line, weighted by the population in 1982. It shows a negative correlation, which means that commuting zones with a larger adjusted penetration of robots also experienced larger declines in the routine occupation share from 1982 to 1997.

Figure C.3 repeats the analysis for the period from 1997 to 2012. We do not see a negative correlation in this period.

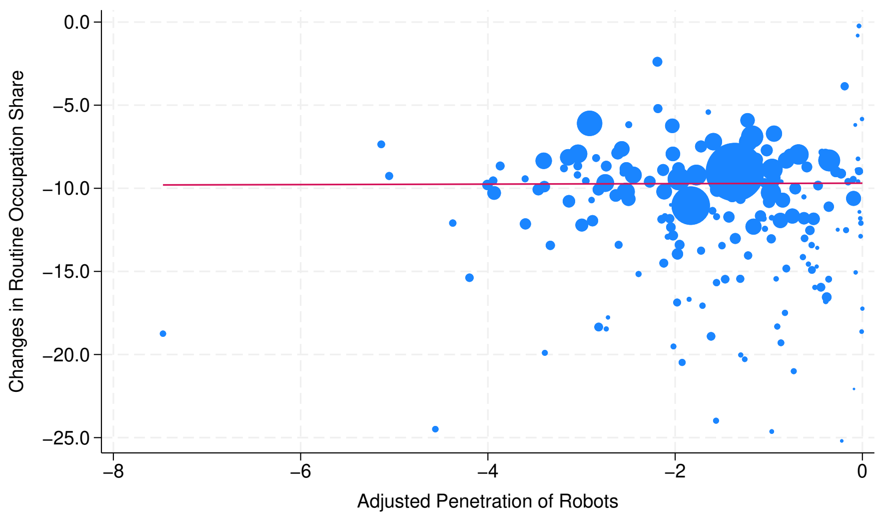
It is important to note that these bivariate relationships should not be taken as definitive evidence to draw any conclusions for the causal relationships between automation and changes in occupation share because of many contemporaneous covariates that affect both variables and endogeneity, which we address including covariates and using IVs.

Figure C.2: Changes in Routine Occupation Share and Robot Penetration: 1982-1997



Notes: The figure shows a scatter plot for a bi-variate correlation between the changes in routine occupation share and the adjusted penetration of robots across commuting zones in the periods from 1982 to 1997. Each dot is a commuting zone, and the size corresponds to the population in 1982 in each commuting zone. The line is a linear fitted line, weighted by the population in 1982. Data is from ESS.

Figure C.3: Changes in Routine Occupation Share and Robot Penetration: 1997-2012



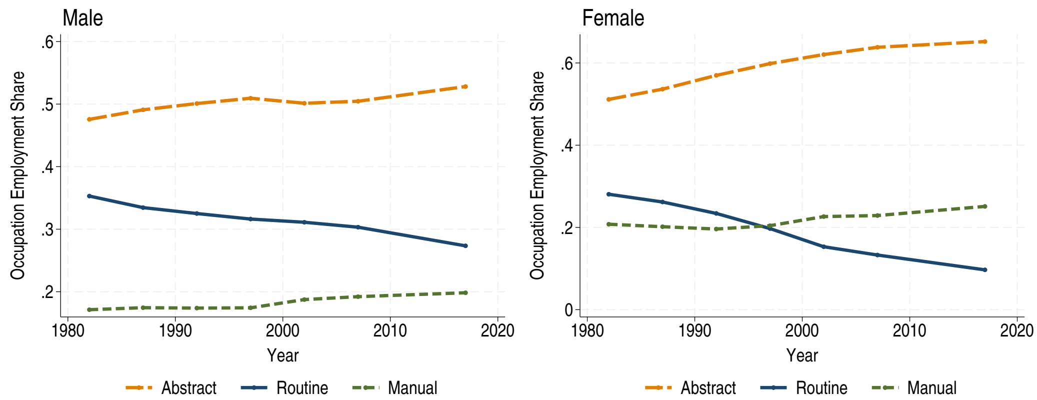
Notes: The figure shows a scatter plot for a bi-variate correlation between the changes in routine occupation share and the adjusted penetration of robots across commuting zones in the periods from 1997 to 2012. Each dot is a commuting zone, and the size corresponds to the population in 1997 in each commuting zone. The line is a linear fitted line, weighted by the population in 1997. Data is from ESS.

C.3 Occupation Share by Demographic Group

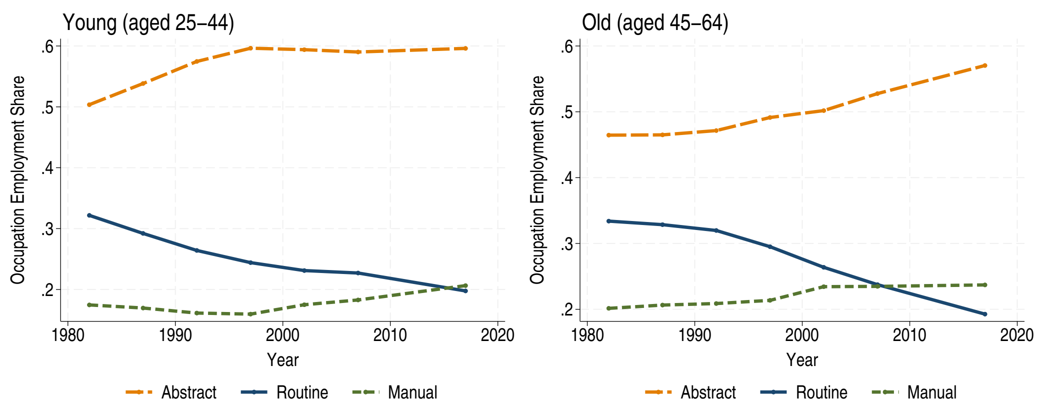
Figure C.4 shows the occupation share over time for each gender. It shows that the shift from routine to abstract occupations is common across gender and age groups, but the shift only appears for non-college-educated workers, not for college-educated workers.

Figure C.4: Employment Share by Occupation Group in Japan: By Demographic Group

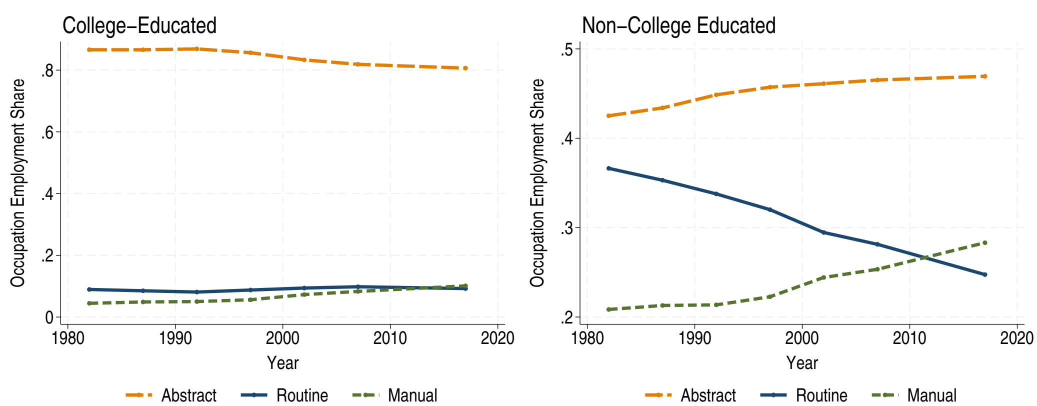
(a) Gender



(b) Age



(c) Education



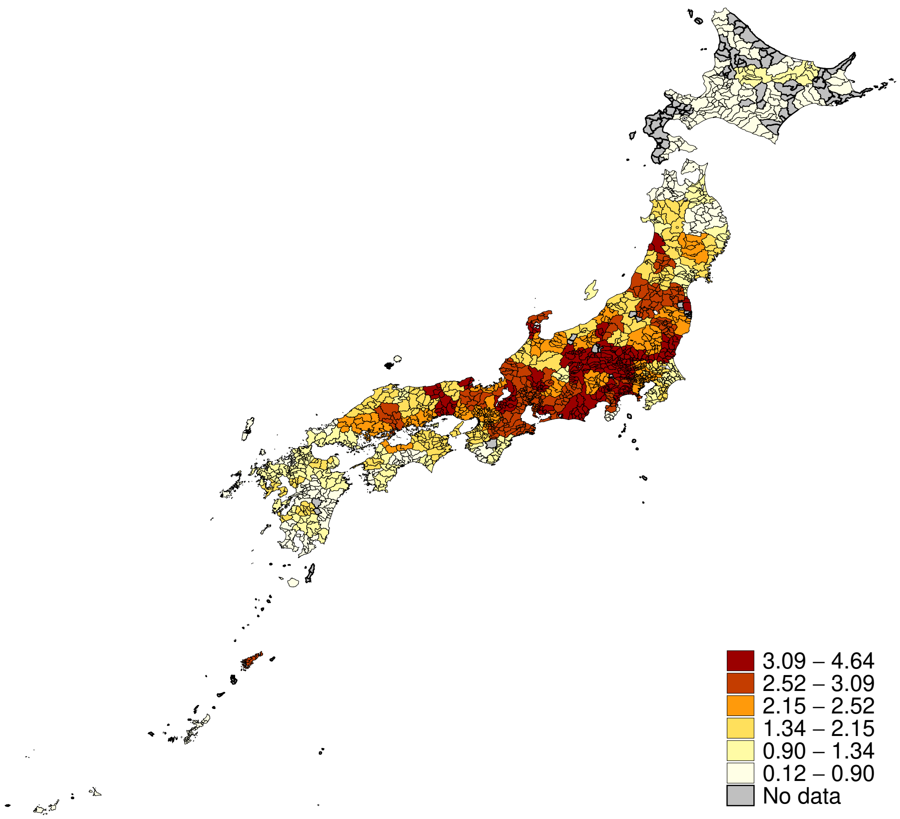
Notes: The figure shows the employment share by occupation group in Japan. Data is from ESS.

C.4 APR by Commuting Zone

Figure C.5 and C.6 show the adjusted penetration of robots (APR) across commuting zones in Japan for 1982-1997 and the one for 1997-2012, respectively. Gray areas have no data on APR because they lack at least one of the 13 sectors' employment in the ESS data so we cannot compute APR.

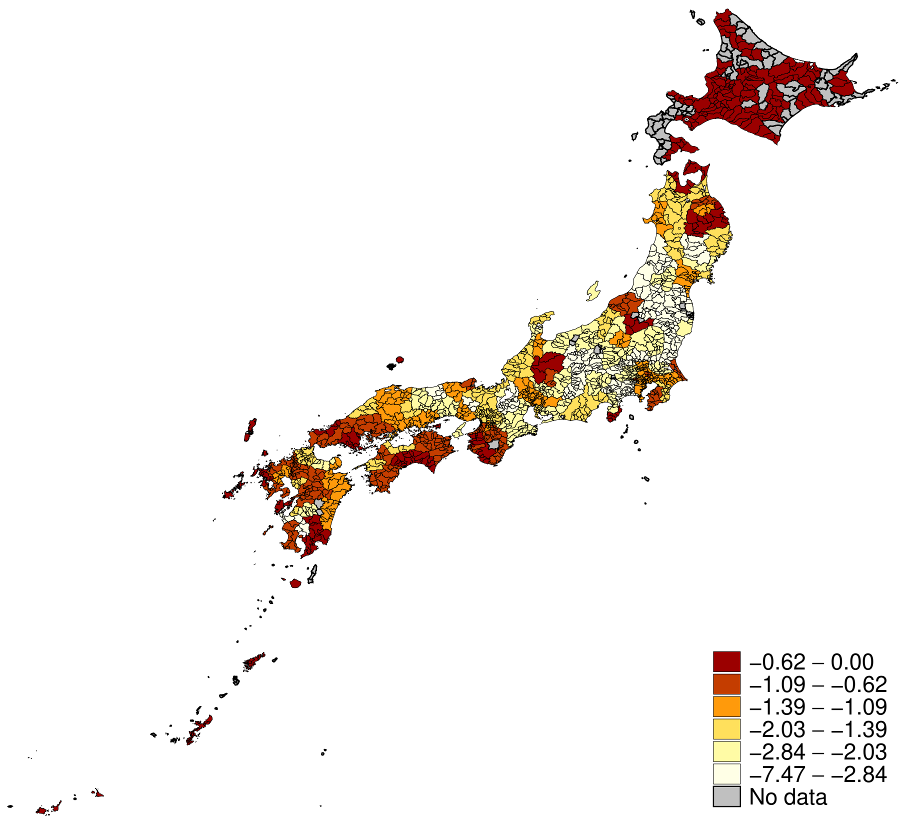
Focusing on the first half (1982-1997) when robot penetration is more apparent, APR is higher in regions in the eastern half or Kinki-region while it is low in Hokkaido and Kyushu-region.

Figure C.5: Robot Penetration across Regions: 1982-1997



Notes: The figure shows the adjusted penetration of robots across commuting zones in Japan for 1982-1997. See the main text for the definition of the adjusted penetration of robots. Data is from ESS.

Figure C.6: Robot Penetration across Regions: 1997-2012



Notes: The figure shows the adjusted penetration of robots across commuting zones in Japan for 1997-2012. See the main text for the definition of the adjusted penetration of robots. 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, and 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.

None of the estimates is significant, which means that automation did not change the employment rate across demographic groups in Japan, which is consistent with the finding in Adachi et al. (2022).

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	-0.01	0.33	0.16	0.22	0.42	0.08
	(0.25)	(0.36)	(0.36)	(0.24)	(0.37)	(0.24)
Observations	342	342	342	342	342	342
Initial CZ Covariates	✓	✓	✓	✓	✓	✓
Tech 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 the population for different demographic groups across commuting zones in Japan. We use IV regressions. Column (1) uses males, Column (2) uses females, and 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. All columns include covariates that control initial commuting zone characteristics and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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 5 in the main text. The estimate (-0.76) for the decline in routine occupation share shown in Column (3) of Table D.2 is smaller than the one of Table 5 (-1.15). 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	-0.02	0.65	-0.76	0.11
	(0.16)	(0.28)	(0.22)	(0.26)
Observations	400	400	400	400
Initial CZ Covariates	✓	✓	✓	✓
Tech 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. We use OLS regressions. 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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.

Here, we run the same regressions, but using $PR_{c,t,t+15}$ instead of $APR_{c,t,t+15}$ as the running variable. We confirm that our results are robust even if we use the un-adjusted measure in Table D.3 as in Adachi et al. (2022).

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	0.24	1.34	-1.52	0.18
	(0.28)	(0.44)	(0.35)	(0.36)
Observations	400	400	400	400
Initial CZ Covariates	✓	✓	✓	✓
Tech 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. 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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. The effect on log shipment in the manufacturing sector in Column (1) is statistically significant, which means that automation expands the manufacturing sector relatively. We do not observe a decline in retail and wholesale sales in Column (2), which implies that the robot adoption did not steal sales from other industries. The ratio is not statistically significant at 5% in Column (3).

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

	Dep. Var. Log Changes in Sales		
	Manufacturing	Retail & Wholesale	Manufacturing Share
	(1)	(2)	(3)
Adjusted Penetration of Robots	12.14	2.91	9.22
	(3.84)	(3.34)	(5.12)
Observations	400	400	400
Initial CZ Covariates	✓	✓	✓
Tech 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

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. The estimate in Column (1) is statistically significant, which means that automation did not increase the share of non-regular workers.[30] Estimates on employment and population changes are not statistically significant.

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	0.65	3.56	3.05
	(0.31)	(1.95)	(1.82)
Observations	400	400	400
Initial CZ Covariates	✓	✓	✓
Tech 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 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 and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

[30]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.

D.6 Effects on Earnings, Days Worked, and Daily Wages

Table D.6 shows the relationship between automation and earnings, days worked, and daily wages. The ESS data only records them in rough bins. We follow Canavire-Bacarreza et al. (2023) to estimate the mean and the variable of the log earnings and log days worked using the interval regression using the bin intervals as the thresholds. We use age, age squared, gender, and college-education dummies to estimate them for each individual for each year separately. We then use the mean of ten repetitions in the simulation.

Column (1) uses log changes in annual earnings, Column (2) uses log changes in days worked, and Column (3) uses log changes in daily wages, computed by dividing annual earnings by days worked in a year. None of the estimates is statistically significant. This implies that automation did not affect earnings or days worked.

Table D.6: Effects of Automation on Earnings, Days Worked, and Daily Wages

	Dep. Var. Log Changes in		
	Annual Earnings	Days Worked	Daily Wages
	(1)	(2)	(3)
Adjusted Penetration of Robots	1.52	-0.12	1.63
	(0.81)	(0.22)	(0.76)
Observations	400	400	400
Initial CZ Covariates	✓	✓	✓
Tech 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 annual earnings, Column (2) uses log changes in days worked, and Column (3) uses log changes in daily wages, computed by dividing annual earnings by days worked in a year. All columns include covariates that control initial commuting zone characteristics and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

D.7 Unpacking the Increases in Abstract Occupation

Table D.7 shows the relationship between automation and employment outcomes across commuting zones in Japan using the same specification in the main text. Column (1) uses the change in the share of workers working in management, professional, and technical occupations as the outcome. Column (2) uses the changes in the share of workers working in clerk or sales occupations as the outcome. Column (3) uses the changes in routine occupation share and Column (4) uses the ones in manual occupation share as the outcomes.

The result suggests that labor demand shifts from routine occupations to low-skill abstract occupations. We note that we do not track the same individuals over time. Thus, using panel data and tracking the same individuals to study occupational mobility at the micro-level would be an important next step for future research.

Table D.7: Effects of Automation on Changes in Detailed Occupation Share

	Dep. Var.: Changes in Employment Rate			
	Mang, Prof, Tech.	Clerk, Sales	Routine	Manual
	(1)	(2)	(3)	(4)
Adjusted Penetration of Robots	0.46	0.60	-1.18	0.11
	(0.25)	(0.21)	(0.25)	(0.27)
Observations	400	400	400	400
Initial CZ Covariates	✓	✓	✓	✓
Tech 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. Column (1) uses the change in the share of workers working in management, professional, and technical occupations as the outcome. Column (2) uses the changes in the share of workers working in clerk or sales occupations as the outcome. Column (3) uses the changes in routine occupation share and Column (4) uses the ones in manual occupation share as the outcomes. All columns include covariates that control initial commuting zone characteristics and exposure to technological change. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

D.8 Controlling Demographic Changes

The covariates in this paper include the ones in Adachi et al. (2022) to be compatible. The demographic variables include share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50 from ESS. The globalization controls contain log import values from JIP and log offshoring values from BSOBA. The technology controls include log stock value measures for ICT capital, innovation capital, and competition capital from JIP.

However, different commuting zones may face differential trends in demographic changes, such as changes in the share of female workers, young workers, skilled workers, and others. These trends can affect an employment rate and occupational shares and can cause an omitted variable bias.

Thus, we show the version of Table 5 where we control changes in the demographic characteristics across commuting zones, not just the initial values of these. The set of demographic variables we control are the same: share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50.

Table D.8 shows the results. Compared to Table 5, results are qualitatively and quantitatively the same, and none of the estimates is statistically different, which is reassuring.

Table D.8: 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	0.15	0.78	-1.01	0.24
	(0.20)	(0.24)	(0.22)	(0.24)
Observations	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. 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 changes in demographic characteristics. The initial commuting zone characteristics include the share of high-school-educated workers, college-educated workers, female workers, workers aged below 35, workers aged above 50, and workers working in manufacturing sectors. All values are in log units. 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 explained in the main text. The changes in demographic characteristics include changes in the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50. Each observation is weighted by its initial population size. Robust standard errors in parentheses are clustered at the commuting zone level.

E Relation to Adachi et al. (2022)

Our main findings are that automation does not decrease the employment rate, decreases routine occupation share, and increases abstract occupation share. Our result that automation does *not* affect employment rate is consistent with Adachi et al. (2022). However, we do not find supporting evidence for emigration, that is, we do *not* find evidence that automation increases population or employment level while Adachi et al. (2022) claims that automation increases population, and hence employment level. In this section, we briefly discuss where the discrepancy comes from.[31]

Subsection E.1 compares the results in Adachi et al. (2022) to ours in population size, not the employment rate and admits that there is a difference. Subsection E.2 lists the differences in the specifications and estimation methods, which we are aware of. Subsection E.3 presents that several treatments are undocumented in Adachi et al. (2022) or inconsistent with their replication packages. Subsection E.4 tries to replicate the findings in Adachi et al. (2022) and shows that a few of the specifications, which are inconsistent with what they wrote in the paper, can replicate their findings of the positive population effects. It also shows that the specifications, which are consistent with what they wrote in the paper, cannot replicate their findings. Subsection E.5 explores where the differences between the guessed specification of Adachi et al. (2022) and ours come from. Subsection E.6 that our main results survive even if we follow the guessed specification of Adachi et al. (2022).

E.1 Emigration/Total population

Table D.5 in the main text 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. In particular, Column (3) for the population shows an estimate of 3.27 with a standard error of 1.90. This is not statistically significant at a 10 percent level.

It is important to note that our null result on emigration (population level) is different from the findings in Adachi et al. (2022). Column (2) of Table 6 in Adachi et al. (2022) shows an estimate of the coefficient of 1.655 with a standard error of 0.861 for the total population. This is statistically significant at a 10 percent level, not at a 5 percent level. Our estimate is 3.27 with a standard error of 1.90.

Then, one may wonder why there is a difference. While how Adachi et al. (2022) create datasets and variables is not fully documented in several dimensions as we articulate below, we tried to replicate their findings and explore the potential sources for the differences.

E.2 Differences We are Aware of

First, we want to clarify that there are several differences, which we are aware of, between our specification and the one in Adachi et al. (2022).

[31] We thank an anonymous referee for suggesting this exercise.

E.2.1 Imputing 2017 with Zero

This is one of the most fundamental issues in their specifications. It is the imputation in the 2017 data. As noted in our original draft, we dropped 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.

E.2.2 Two-Way Fixed Effects

While Adachi et al. (2022) contain commuting zone fixed effects, we do not. We believe that our specification is cleaner and more transparent. Furthermore, recent development in econometrics raises some concerns about what two-way fixed effects models estimate (De Chaisemartin and d'Haultfoeuille, 2020; Imai and Kim, 2021). Since we are interested in comparing different local labor markets with different robot exposures, we think a model without commuting zone fixed effects is suitable for our purpose. Note that this is also consistent with the literature using the local labor market approach, including Autor et al. (2013) and Acemoglu and Restrepo (2020).

E.2.3 Overlapping Periods:

Adachi et al. (2022) use overlapping periods of 15-year differences, which means that they use the following five 15-year differences as a source of variations: 1982-1997, 1987-2002, 1992-2007, 1997-2012, and 2002-2017. We use only two non-overlapping 15-year differences as follows: 1982-1997 and 1997-2012.

E.2.4 Construction of Robot Exposure Variable:

As articulated in the main text, we follow Acemoglu and Restrepo (2020) to use the adjusted penetration of robots, instead of what Adachi et al. (2022) use. We already showed in Table D.3 that our main result does not change.

E.3 Undocumented Points in Adachi et al. (2022)

After fixing these changes, one may think that it is easy to replicate their findings. Unfortunately, it is not at all. To articulate this difficulty, we clarify that there are at least six major unclear and undocumented points in their treatment of data cleaning and specifications, which can significantly alter their findings.

Adachi et al. (2022) uploaded a part of their code and publicly available data (industry-level data) to run the final regressions.[32] We have checked all of the lines in their code available as well as their accepted manuscript as of October 25, 2022, including the Appendix. Note that they do not post either their cleaning code for ESS data or the CZ-level cleaned data, potentially due to the data disclosure issue. Therefore, the replication code cannot run on any publicly available data.

In particular, below, we will refer to line 133 in "tab_6_7_8_F7.R" where they estimate the model to see the effect of population

[32] See https://github.com/daisukeadachi/aks_robots/blob/main/codes/sub/tab_6_7_8_F7.R

```
m_2sls_pop <- felm(weight_pop_educ__sex__age__log_d15 ~ weight_pop_educ_4_sex__age__log_l15 + weight_pop_educ__sex_2_age__log_l15 + weight_pop_educ__sex__age_1_log_l15 + weight_pop_educ__sex__age_3_log_l15 + weight_pop_educ__sex__age_4_log_l15 + va_soba_d15 + import_total_d15 + asset_IT_d15 + asset_competitive_d15 + asset_innovation_d15 | cluster + year | (quantity_stock_12_log_alpha_level_d15 ~ unitval_t_indagg_stock_12_log_alpha) | 0 | cluster, data = df_reg, weights = df_reg$weight_pop_educ__sex__age__l15)
```

E.3.1 Sample Restrictions

Issue: It is unclear if they restrict their samples to the working-age population or not.

Our Strategy: We do not put any sample restrictions.

E.3.2 Construction of CZ-level Robot Exposure

Issue: In their equation (20) on page 30, they define the CZ-level robot exposure measure as follows:

$$\Delta R_{c,t} = \sum_i l_{c,i,t} \frac{\Delta R_{i,t}}{L_{i,t}} \tag{2}$$

"where $l_{c,i,t} = L_{c,i,t} / \sum_i L_{c,i,t}$ is the share of industry i in the total employment within CZ c in year t, and $\Delta R_{i,t} = R_{i,t} - R_{i,t-15}$ is the change in the robot stock over 15 years."

They report the standard deviation of this variable of 5.25 in their footnote 22 on page 31. However, the standard deviation in our replication is 1.29, which is far different. Since we directly use $\Delta R_{i,t}$ and $L_{i,t}$ from their replication package, the only difference can come from how to construct $l_{c,i,t}$ from the ESS data.

It turns out that it seems that they use the share of industry i in the total employment *within manufacturing sectors*, instead of the entire sector, based on their code. In fact, using a within-manufacturing employment share makes our standard deviation 6.32, which is closer. Thus, it might be a good idea to assume that they do use a within-manufacturing employment share in their code as opposed to what they have written down. Note that this exclusion of non-manufacturing sectors from the construction of the Bartik variables suffers significant issues raised in the recent econometrics literature (Borusyak and Hull, 2023).

Our Strategy: We will try both versions.

E.3.3 Construction of CZ-Level Globalization and Technology Covariates: Formula

Issue: It is unclear how they create their covariates $X_{c,t-15}$ in their equation (19) on page 30. They say "The vector of control variables $X_{c,t-15}$ includes the same control variables used in our industry-level analysis but prorated to each CZ according to its industry composition.".

Based on this explanation, it is fair to assume that this means

$$X_{c,t-15} = \sum_i l_{c,i,t-15} \cdot \frac{X_{i,t-15}}{L_{i,t-15}} \tag{3}$$

where $X_{i,t-15}$ is one of the following variables: log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.

However, in their code, "Globalization Controls" and "Technology Contorls" in their languages seem to be the **15-year differences** of the **level**, not the **lagged** values in **log**, as follows:

```
va_soba_d15 + import_total_d15 + asset_IT_d15 + asset_competitive_d15 + asset_
    innovation_d15
```

This means that they may instead use

$$X_{c,t-15} = \sum_i l_{c,i,t-15} \cdot \frac{\Delta X_{i,t}}{L_{i,t-15}} \tag{4}$$

or

$$X_{c,t-15} = \sum_i l_{c,i,t} \cdot \frac{\Delta X_{i,t}}{L_{i,t}} \tag{5}$$

to be consistent with equation (2). Note that $X_{c,t-15}$ in the LHS of equation (4,5) is not a typo. We follow the notation of Adachi et al. (2022) in equation (19).

Also, it is hard to imagine that they use the initial levels of these variables. Thus, it might be the case that they use changes in log as follows:

$$X_{c,t-15} = \sum_i l_{c,i,t} \cdot \frac{\Delta \ln X_{i,t}}{L_{i,t}} \tag{6}$$

Our Strategy: We will try the specifications using (5): Changes in level and (6): Changes in log.

E.3.4 Construction of CZ-Level Demographic Controls: Variables

Issue: While they say in the text that "The demographic variables include the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50 from ESS", there seems to be only one education-related covariate as follows:

```
weight_pop_educ_4_sex__age__log_l15
```

Also, there are three types of age-related covariates as follows:

```
weight_pop_educ__sex__age_1_log_l15 + weight_pop_educ__sex__age_3_log_l15 + weight
    _pop_educ__sex__age_4_log_l15
```

Our Strategy: Since we do not know what they are, we follow the main text of their paper to include the share of high school graduates workers, 4-year university graduates workers, female workers, workers under age 35, and workers above age 50 from ESS.

E.3.5 Construction of CZ-Level Demographic Controls: Demographic of Workers or Population

Issue: While they write that they use "share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50", it is unclear if they use the share of high school graduates among workers or the one among the population. The same applies to 4-year university graduates. We think it is natural to assume that these are consistently defined as the shares of some groups among workers.

Our Strategy: We will try both versions.

E.3.6 Construction of CZ-Level Demographic Controls: Log or Level

Issue: In the paper, they write that they control the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50. It is fair to assume that they are levels.

However, looking at the code again, all of these demographic variables seem to be logged.

```
weight_pop_educ_4_sex__age__log_l15 + weight_pop_educ__sex_2_age__log_l15 + weight_pop_educ__sex__age_1_log_l15 + weight_pop_educ__sex__age_3_log_l15 + weight_pop_educ__sex__age_4_log_l15
```

Our Strategy: We will try both versions.

E.4 Our Replication Attempts

Just to recap, what we are trying to estimate is the effect of robot penetration on the changes in log population as in their equation (19) on page 30 as follows:

$$\Delta \ln \text{Pop}_{ct} = \beta^{CZ} \Delta R_{ct} + X_{c,t-15}\gamma^{CZ} + \xi_i^{CZ} + \tau_t^{CZ} + u_{it}^{CZ} \tag{7}$$

See the definitions on page 30 in Adachi et al. (2022).

Since there are two options for each of the 4 points, we will have 16 specifications. We report all of the results below. We first show the versions including non-manufacturing sectors to construct the sectoral share used in (2). We then exclude non-manufacturing sectors.

Replication Including Non-Manufacturing Sectors Constructing Robot Exposure: Table E.1 shows the replication including non-manufacturing sectors when constructing robot exposure variables as in (2). All the columns include commuting zone fixed effects and year fixed effects. Columns (1)-(4) of the table use changes in levels of technology and globalization controls (log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.) as covariates following equation (5). Columns (5)-(8) use changes in the log of the technology and globalization controls as covariates following equation (6). Columns (1) and (5) use demographic controls (the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50) in level among the entire population in each commuting zone. Columns (2) and (6) use the ones in level among the workers in each commuting zone. Columns (3) and (7) use the ones in the log among the entire population in each commuting zone. Columns (4) and (8) use the ones in log among workers in each commuting zone. Each observation is weighted by its initial population size. Standard errors are in parenthesis and are based on the Eicker-Huber-White standard error clustered at the commuting zone level.

None of the estimates is statistically significant at 5%, and the magnitudes of the point estimates are far away from what Adachi et al. (2022) report.

Table E.1: Effects of Automation on Changes in Population

	Dep. Var. Log Changes in Population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot Penetration	6.20	5.28	3.52	3.63	5.34	4.64	2.96	3.18
	(3.40)	(2.69)	(2.92)	(2.54)	(3.04)	(2.45)	(2.73)	(2.38)
Observations	1,156	1,151	1,156	1,151	1,156	1,151	1,156	1,151
CZ FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographic Controls								
Level in Population	✓				✓			
Level in Workers		✓				✓		
Log in Population			✓				✓	
Log in Workers				✓				✓
Technology and Globalization Controls								
Changes in Level	✓	✓	✓	✓				
Changes in Log					✓	✓	✓	✓

Notes: Samples are CZs $\times$ five 15-year periods (1982-1997, 1987-2002, 1992-2007, 1997-2012, and 2002-2017). This table shows the relationship between automation and changes in log population across commuting zones in Japan, replicating Column (2) in Table 6 of Adachi et al. (2022). Changes in Robot exposure are defined using the entire sector as the share in the Bartick variable as in (2). All the columns include commuting zone fixed effects and year fixed effects. Columns (1)-(4) of the table use changes in levels of technology and globalization controls (log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.) as covariates following equation (5). Columns (5)-(8) use changes in the log of the technology and globalization controls as covariates following equation (6). Columns (1) and (5) use demographic controls (the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50) in level among the entire population in each commuting zone. Columns (2) and (6) use the ones in level among the workers in each commuting zone. Columns (3) and (7) use the ones in the log among the entire population in each commuting zone. Columns (4) and (8) use the ones in log among workers in each commuting zone. Each observation is weighted by its initial population size. Standard errors are in parenthesis and are based on the Eicker-Huber-White standard error clustered at the commuting zone level.

Replication Excluding Non-Manufacturing Sectors Constructing Robot Exposure: We next use the robot exposure variables, which we construct by excluding non-manufacturing sectors. Table E.2 shows the result. Now, the estimates are statistically significant at 5%. Moreover, the magnitudes of the estimates are close to the ones in Adachi et al. (2022).

We want to stress that we are unsure whether we should cherish this result because this is not what Adachi et al. (2022) wrote in their paper. Removing non-manufacturing sectors when constructing the robot exposure is not a natural way. First, JIP and JARA data have data on capital stocks, imports, and robot stock for non-manufacturing sectors. Thus, it is hard to justify this removal. Second, this removal suffers from the issue documented in Borusyak and Hull (2023) on the share not summing up to one in Bartik variables (shift-share variable).

Table E.2: Effects of Automation on Changes in Population: Excluding Non-Manufacturing Sectors Constructing Robot Exposure

	Dep. Var. Log Changes in Population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot Penetration	3.85	3.72	3.40	3.45	1.83	1.87	1.52	1.65
	(1.33)	(1.20)	(1.23)	(1.16)	(0.82)	(0.71)	(0.74)	(0.68)
Observations	1,086	1,083	1,086	1,083	1,086	1,083	1,086	1,083
CZ FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographic Controls								
Level in Population	✓				✓			
Level in Workers		✓				✓		
Log in Population			✓				✓	
Log in Workers				✓				✓
Technology and Globalization Controls								
Changes in Level	✓	✓	✓	✓				
Changes in Log					✓	✓	✓	✓

Notes: Samples are CZs $\times$ five 15-year periods (1982-1997, 1987-2002, 1992-2007, 1997-2012, and 2002-2017). This table shows the relationship between automation and changes in log population across commuting zones in Japan, replicating Column (2) in Table 6 of Adachi et al. (2022). Changes in Robot exposure are defined using only manufacturing sectors as the share in the Bartick variable as in (2). All the columns include commuting zone fixed effects and year fixed effects. Columns (1)-(4) of the table use changes in levels of technology and globalization controls (log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.) as covariates following equation (5). Columns (5)-(8) use changes in the log of the technology and globalization controls as covariates following equation (6). Columns (1) and (5) use demographic controls (the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50) in level among the entire population in each commuting zone. Columns (2) and (6) use the ones in level among the workers in each commuting zone. Columns (3) and (7) use the ones in the log among the entire population in each commuting zone. Columns (4) and (8) use the ones in log among workers in each commuting zone. Each observation is weighted by its initial population size. Standard errors are in parenthesis and are based on the Eicker-Huber-White standard error clustered at the commuting zone level.

E.5 Exploring the Differences

Now, we try to explore where the differences between their positive population results and our null results come from. We assume and guess that their specification is the one in Column (8) in Table E.2. It is important to repeatedly note that this is inconsistent with what Adachi et al. (2022) wrote in the paper but produces an estimate, which is the closest to the estimates reported in Adachi et al. (2022).

We try to explore the potential reasons for the difference based on the differences in the specifications as listed in Subsection E.2. We estimate the same model but change the specification one by one. To facilitate the comparison, we fix the set of covariates as in Column (8) of Table E.2.

Table E.3 shows the results. Columns (1)-(5) use Robot Penetration as the running variable, which is defined using only manufacturing sectors as the share in the Bartick variable as in (2). Columns (6) and (7) use Adjusted Robot Penetration as the running variable, which is defined as subtracting the output growth rate times robot-to-worker ratio from the robot penetration variable. All the columns include year-fixed effects. All the columns include log changes of technology and globalization controls (log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.) as covariates following equation (5) and demographic controls (the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50) in log changes among workers in each commuting zone. Columns (1), (2), (4), and (6) include commuting zone fixed effects. Columns (2), (6), and (7) drop 2017 from the sample. Columns (4), (5), and (7) use only two non-overlapping 15-year periods (1982-1997 and 1997-2012). As before, each observation is weighted by its initial population size. Standard errors are in parenthesis and are based on the Eicker-Huber-White standard error clustered at the commuting zone level.

Column (1) replicates Column (8) in Table E.2. Column (2) shows still the significant estimate at the 5% level, which implies that dropping 2017 from the sample does not explain the differences. Column (3) drops commuting zone fixed effects, and the estimates are still significant at the 5% level. Column (4) only uses the two non-overlapping periods (1982-1997 and 1997-2012), and the estimates become smaller and insignificant. This implies that using non-overlapping periods or not affects the estimates for the population changes. Keeping commuting zones fixed effects with only two periods is demanding. Thus, Column (5) drops commuting zone fixed effects and uses only the two non-overlapping periods. Then, the estimate becomes 1.13 with a standard error of 0.78, which is still insignificant but similar in size to the ones in Columns (1), (2), and (3). Columns (6) and (7) use the adjusted penetration of robots, which the standard literature and we use, instead of the penetration of robots, which Adachi et al. (2022) use. Column (6) only changes the running variable, keeping commuting zone fixed effects and using overlapping periods. As output data in 2017 is missing in the replication package in Adachi et al. (2022) we have to drop 2017 from the sample by construction. The estimate is still significant (1.90 with a standard error of 0.78), which implies that using different running variables does not explain the differences in the result. This is consistent with what we reported in the main text in D.3 that using an unadjusted robot penetration variable does not alter our main findings. Column (7) uses the adjusted penetration of robots and only keeps the two non-overlapping periods, which is closest to our specification in the main text. The estimate is insignificant (1.56 with a standard error of 1.13). While the magnitudes are off, this is consistent with what we find. [33] From the analysis above, albeit inconclusive, we

[33] Note that the covariates and sample restrictions are still different.

believe that the difference between the findings in Adachi et al. (2022) and ours on the population changes may come from whether using overlapping periods or not and perhaps commuting zone fixed effects, and not from whether using 2017 or different running variables.

Table E.3: Effects of Automation on Changes in Population: Excluding Non-Manufacturing Sectors Constructing Robot Exposure

	Dep. Var. Log Changes in Population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot Penetration	1.65	1.40	1.25	0.16	1.13		
	(0.68)	(0.56)	(0.57)	(0.91)	(0.78)		
Adjusted Robot Penetration						1.90	1.56
						(0.78)	(1.13)
Observations	1,083	867	1,090	434	440	867	440
CZ FE	✓	✓		✓		✓	
Year FE	✓	✓	✓	✓	✓	✓	✓
Drop 2017		✓				✓	✓
No Overlapping Periods				✓	✓		✓

Notes: Samples are CZs $\times$ some of the 15-year periods (1982-1997, 1987-2002, 1992-2007, 1997-2012, and 2002-2017). This table shows the relationship between automation and changes in log population across commuting zones in Japan, replicating Column (2) in Table 6 of Adachi et al. (2022). Columns (1)-(5) use Robot Penetration as the running variable, which is defined using only manufacturing sectors as the share in the Bartick variable as in (2). Columns (6) and (7) use Adjusted Robot Penetration as the running variable, which is defined as subtracting the output growth rate times robot-to-worker ratio from the robot penetration variable. All the columns include year-fixed effects. All the columns include log changes of technology and globalization controls (log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.) as covariates following equation (5) and demographic controls (the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50) in log changes among workers in each commuting zone. Columns (1), (2), (4), and (6) include commuting zone fixed effects. Columns (2), (6), and (7) drop 2017 from the sample. Columns (4), (5), and (7) use only two non-overlapping 15-year periods (1982-1997 and 1997-2012). Each observation is weighted by its initial population size. Standard errors are in parenthesis and are based on the Eicker-Huber-White standard error clustered at the commuting zone level.

E.6 Validating Our Main Results

One may wonder if these differences can challenge and alter our main results—robot penetration decreases routine occupation shares. To study this point, we examine if our main results service when we use the specification of Adachi et al. (2022). In particular, we replace the outcome variable log changes in population with changes in routine occupation share. To facilitate the comparison, again, we fix the sets of covariates and do not try to make them close to our paper. Rather, we tie our hands to the specifications and the set of covariates used in Table E.3.

Table E.4 shows the results. Column (1) shows the estimates with the closest specification in Adachi et al. (2022) including 2017 in the sample. The estimate is not significant at the 5% level. However, dropping 2017 makes the estimate significant at a 1% level even with commuting zone fixed effects and overlapping periods. Column (3) drops commuting zone fixed effects, and the estimate is significant. Column (4) keeps only the two non-overlapping periods keeping commuting zone fixed effects, and the estimate becomes insignificant. As discussed before, having commuting zone fixed effects with only two periods is too demanding. Column (5) drops commuting zone fixed effects. Then the estimates become significant again. Using the adjusted penetration of robots, Columns (6) and (7) show significant estimates.

Therefore, we conclude that our result on the decreasing routine occupation share is robust across a wide range of specifications, including some of the specifications, that we think inappropriate. It is true that our estimate becomes insignificant if we *simultaneously* keep the imputation in 2017, commuting zone fixed effects, which we are not interested in, and non-overlapping periods, which we think are problematic. However, that does not mean that our results are not robust.

Table E.4: Effects of Automation on Changes in Routine Occupation Share: Excluding Non-Manufacturing Sectors Constructing Robot Exposure

	Dep. Var. Log Changes in Routine Occupation Share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot Penetration	-0.22	-0.28	-0.43	-0.30	-0.65		
	(0.13)	(0.10)	(0.13)	(0.20)	(0.19)		
Adjusted Robot Penetration						-0.38	-0.90
						(0.14)	(0.28)
Observations	1,076	860	1,085	428	435	860	435
CZ FE	✓	✓		✓		✓	
Year FE	✓	✓	✓	✓	✓	✓	✓
Drop 2017		✓				✓	✓
No Overlapping Periods				✓	✓		✓

Notes: Samples are CZs $\times$ some of the 15-year periods (1982-1997, 1987-2002, 1992-2007, 1997-2012, and 2002-2017). This table shows the relationship between automation and changes in routine occupation share across commuting zones in Japan. Columns (1)-(5) use Robot Penetration as the running variable, which is defined using only manufacturing sectors as the share in the Bartick variable as in (2). Columns (6) and (7) use Adjusted Robot Penetration as the running variable, which is defined as subtracting the output growth rate times robot-to-worker ratio from the robot penetration variable. All the columns include year-fixed effects. All the columns include log changes of technology and globalization controls (log import values from JIP, log offshoring values from BSOBA, log stock value measures for ICT capital, innovation capital, and competition capital from JIP.) as covariates following equation (5) and demographic controls (the share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50) in log changes among workers in each commuting zone. Columns (1), (2), (4), and (6) include commuting zone fixed effects. Columns (2), (6), and (7) drop 2017 from the sample. Columns (4), (5), and (7) use only two non-overlapping 15-year periods (1982-1997 and 1997-2012). Each observation is weighted by its initial population size. Standard errors are in parenthesis and are based on the Eicker-Huber-White standard error clustered at the commuting zone level.

E.7 Final Responses

In this section, we show that the differences in the results on the increase in population in Adachi et al. (2022) and ours may come from whether using overlapping periods or not and perhaps commuting zone fixed effects.

We also show that regardless of the specifications, our main results of decreasing routine occupation share are robust.