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Robot penetration and task changes[1]

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Abstract

This paper gauges the impacts of robots on task changes, in particular, identifying which tasks increased or decreased as robot penetration was promoted in Japan between 1980 and 2018 by using three unique datasets: the "Production and Shipments of Manipulators and Robots" produced by the Japan Robot Association; the administrative data of the "Basic Survey on Wage Structure" produced by the Ministry of Health, Labour and Welfare; and numerical indicators of occupational characteristics in the Japanese version of O-net by the Japan Institute of Labour Policy and Training. We first construct an index in which tasks have increased or decreased for each industry by using the Japanese version of five-category task scores *a la* Acemoglu and Autor (2011), computed from numerical indicators of occupational characteristics and the Basic Survey on Wage Structure. Then, we clarify how this index has been affected by robot stocks by industry, which is calculated from the Production and Shipments of Manipulators and Robots. The estimation result shows that as robot penetration increases, routine-manual tasks decrease while cognitive tasks relatively increase. A rise in robot penetration leads to a relative increase in employment in occupations requiring more different tasks to the occupations where tasks were lost, indicating that the process of robotization in Japan has caused the *displacement effect*.

Keywords: robot; task; substitute and complement
JEL classification: E24, J24, J62, O33

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1 Introduction

Whether machines will take our jobs away is not a new concern, tracing back, at least, to about 100 years ago. Still, we have not observed a significant decline in the labor share to date. With significant progress in artificial intelligence and machine learning algorithms, the concern has turned into fear, and is becoming increasingly prominent. A study by Frey and Osborne (2017), which identifies the jobs that will disappear in the future, attracted worldwide attention.

Academics tackle this issue from theoretical and empirical angles, reflecting society's anxiety about the future and desire to understand the consequence of robotization. While theoretical studies that discuss the impact of robots on the future labor market, focusing on whether they are alternative or complementary to labor, have been conducted for a relatively long time, empirical analysis has only recently begun to increase. This is because robotization is relatively a recent phenomenon, and the data on robots are only available, at most, for the last two to three decades.

Graetz and Michaels (2018), Bessen et al. (2019), Humlum (2019), Acemoglu and Restrepo (2020), Acemoglu et al. (2020), Adachi et al. (2020a), Aghion et al. (2020), Dekle (2020), de Vries et al. (2020), Fujiwara and Zhu (2020), Adachi (2021), Dauth et al. (2021), Koch et al. (2021) and Mann and Puttmann (2021) estimate the impacts of increase usage of robots on the labor market. Implications from these previous studies are somewhat mixed. For example, regarding the robot's impact on employment, Acemoglu and Restrepo (2020) conclude that increase in robot penetration results in the reduction of employment in the US, while Adachi et al. (2020a) and Dekle (2020) report the opposite result in Japan. Graetz and Michaels (2018) and Fujiwara and Zhu (2020) considering the global data and Dauth et al. (2021) considering the German data present only ambiguous impacts of robots on employment.

This paper also evaluates the impacts of robot penetration on employment. Our focus is on the heterogeneous impacts. Original aspects of our research are twofold. First, we include the 1980s in Japan, when the introduction of robots became very active for the first time in human history. Second, we explicitly consider the task and identify what tasks the introduction of the robot has increased or decreased.

Regarding the first point, we believe that the impact of robots on the labor market can be clarified by using data from 1978, including the early days of the introduction of robots, for Japan, which has been a leading robotics country. We utilize the "Production and Shipments of Manipulators and Robots" published by the Japan Robot Association (hereafter, JARA). Merits in using the JARA data are as follows. First, the sample size is much larger, and provides more detailed information by industry, application, and time. On the cross-sectional dimension, in the 2018 table in the JARA data, 44 industries are covered with 28 major categories and their sub-categories in columns. Rows present 36 applications for 17 major categories with attending sub-categories. On the time-series dimension, while the International Federation of Robotic (hereafter, IFR) data, which is frequently used in the literature, starts from 1993, the JARA data starts from 1978. Third, price information is available. The IFR data only reports quantities, while the JARA data report both quantities and sales. Finally, it is about Japan, which was the largest producer of robots and with the highest robot density and the number of robots installed per worker.[1]

Regarding the second point, Acemoglu and Restrepo (2020) use "the importance of routine jobs in a commuting zone (the fraction of employment in a commuting zone in routine occupations as defined in Autor and Dorn (2013))" as the control variable. Dauth et al. (2021) show that "The negative impact of robots on individual earnings arises mainly for medium-skilled workers in machine-operating occupations, while high-skilled managers gain." However, both Acemoglu and Restrepo (2020) and Dauth et al. (2021) do not consider the differences in tasks explicitly.

The seminal study by Autor et al. (2003) emphasizes the importance of distinguishing tasks: (i) nonroutine-analytical; (ii) nonroutine-interactive; (iii) nonroutine-manual; (iv) routine-cognitive; (v) routine-manual, in understanding the effects of computerization on labor demands. Acemoglu and Autor (2011) further improves the task scores using "O-net," an occupational inquiry database. Now, the five-task scores in Acemoglu and Autor (2011) have established themselves as the standard indices to evaluate the changes in employment characteristics.

There are several attempts to construct the task scores in Japan following Autor et al. (2003) and Acemoglu and Autor (2011). Ikenaga (2009) is the first study in Japan to compute the task score and concludes that shares of routine-manual and routine-cognitive tasks have decreased. The task scores in Ikenaga (2009) are further improved by Ikenaga and Kambayashi (2016). They find similar result to Ikenaga (2009) in that nonroutine tasks have increased, while routine tasks have decreased, and show that the pace of polarization is slower and smaller in Japan compared to other countries. The Japan Institute of Labour Policy and Training (hereafter, JILPT) recently developed the Japanese version of O-net (hereafter J-O-net) and provided numerical indicators of occupational characteristics. A recent study by Komatsu and Mugiyama (2021) calculate the five-task scores in Acemoglu and Autor (2011) by using numerical indicators in J-O-net.

In order to understand the impacts of robot penetration on employment by task, we first construct indices of which tasks have increased or decreased for each industry – We hereafter call these indices the *industry task scores*. Using numerical indicators of occupational characteristics in J-O-net and the administrative data of the Basic Survey on Wage Structure, this study transforms the myriad of occupations' information into a few industry task scores. When aggregating task scores by industries, this study bridges the J-O-net's occupational categories

[1] Japan still maintains the status of robot frontier countries. According to "World Robotics 2020" published by IFR, Japan is the second-largest producer of robots and the third in robot density.

with occupational categories in the administrative data of the Basic Survey on Wage Structure by using the crosswalk file of Komatsu and Mugiyama (2021).

The industry task score is a weighted average of the task score over occupations within the industry. Since five tasks are considered in this paper following Autor et al. (2003), Acemoglu and Autor (2011) and Komatsu and Mugiyama (2021), we have the time series of 5 (tasks) x 12 (industries) = 60 scores from 1978 until 2018. Although more detailed industry classification data is available, we decided to follow Adachi (2021) and consolidate the data into 12 industries.

No single occupation consists of a single task. If one interprets an occupation as consisting of a single task, this may lead to an overestimation of the impact of robots. Therefore, this analysis computes the five-task scores for each occupation and, in aggregate, for each industry and measures how the degree of robot penetration by industry affected these industry task scores. As a result, we can measure the influence of robots on tasks in a very detailed manner.

The occupational and therefore task composition have changed. In major purchasers of industrial robots such as general, electric and transport machineries, routine-manual and nonroutine-manual tasks declined in the 1980s and other tasks increased in exchange. However, in other industries such as nonferrous metals, pulp, paper and printing, and non manufacturing, which were not active purchasers of industrial robots, industry tasks scores were stable during the 1980s.

Then, we regress the industry task scores on robot stocks. This study follows Adachi et al. (2020a) and employs the 2-stage least square method using robot unit prices as instruments to alleviate the endogeneity bias. Also, to alleviate the omitted variable bias, this study adopts several control variables that may affect the composition of occupations within industries: demographics, globalization, and information and communication technology (hereafter, ICT) advancement factors. We also conduct commuting zone level analysis.

We find that the amount of routine-manual task inputs decreases as robot stocks increase, suggesting that the composition of such occupations has declined due to the introduction of robots. In contrast, the amount of analytical, interactive, and cognitive-task inputs increases. If a person's job is lost due to the introduction of a robot, and if a worker moves to another occupation that performs a similar task within the same industry, the industry task scores should not change. However, since they have changed, it can be interpreted as a relative increase in the number of occupations performing different tasks to the occupation where tasks were lost.

Let us now elaborate on the relationship with previous studies. Adachi et al. (2020a), using similar datasets to ours, report an increase in the number of workers after introducing robots. The result of this study point out the importance of the heterogeneous effects on workers. When we look at the breakdown of workers, there are statistically significant changes in the composition of tasks, indicating the displacement effect; "robots directly displace workers from tasks that they were previously performing" as in Acemoglu and Restrepo (2020).

This study is not the first to find such heterogeneous effects among workers.[2] Dauth et al. (2021) point out the substitution between manufacturing and non-manufacturing industries. However, our result indicates that it is not simply a substitution between the manufacturing and non-manufacturing industries. Instead, it is a substitution between routine-manual and nonroutine-analytical or nonroutine-interactive tasks within manufacturing industries.

We also extend our analysis to the commuting zone level analysis. Robotization causes similar compositional changes of tasks to those found in the industry level analysis, even in the regional labor market. Additional insights obtained from the commuting zone level analysis is that robotization does not cause a substitution between routine-manual tasks and routine-cognitive tasks within the same local labor market but shifts of workers across different regions.

The remainder of this paper is structured as follows. After the literature review on the effects of robotization in the labor market, Section 2 explains the data used in this paper and how to construct the industry task scores, the five-task scores by industry. We also show how the task composition has changed in Japan. Section 3 introduces a model to theoretically understand the impacts of robots on tasks in a simple framework. Section 4 presents the estimation strategy and the estimation result. Finally, Section 5 concludes.

1.1 Related literature

Reflecting society's anxiety about the future and desire to understand the consequence of robotization, academics tackle this issue from theoretical and empirical angles. Since the massive robotization is yet to happen and its consequences will become more evident in the future, several discuss possible future scenarios in a hypothetical world replicated by the dynamic general equilibrium model. In such theoretical studies, whether the increasing use of robots reduces labor inputs or not crucially depends on the elasticity of substitution in production technologies. Depending on the size of this elasticity, robots and labor become (Edgeworth) complement or substitute for each other. If they are substitutes (complements), robotization enhanced by improvements in the robot stock augmenting technology, which lead to lower prices of robots, will decrease (increase) labor inputs. Zeira (1998), Benzell et al. (2015), Sachs et al. (2015), Nakamura and Zeira (2018), Caselli and Manning (2019), Berg et al. (2018), Graetz and Michaels (2018), Leduc and Liu (2019) and Acemoglu and Restrepo (2020) explore the consequences stemming from technological progresses in robotics in both short to medium and long-run. Reported results are mixed depending on the model's settings, particularly on the production side, which determines whether robots are substitutes or complements to labor.[3]

[2]The closest to our study are de Vries et al. (2020) and Aghion et al. (2020), which explore the heterogeneous impact of robot adoption by skill level. For details, see Section 1.1.

[3]Guerreiro et al. (2017), Costinot and Werning (2018), and Jaimovich et al. (2021) explore normative aspects of robot penetration, and propose effective policy reactions.

Robotization is a relatively recent phenomenon. The data on robots are only available, at most, for the last two to three decades. Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Dauth et al. (2021) estimate the impacts of increased usage of robots on the labor market. Implications from these previous studies are also somewhat mixed. Graetz and Michaels (2018)evaluate the impacts in Europe with the cross-sectional data on industries and countries, and conclude that robotization increases labor productivity and real wage but causes no significant impact on labor inputs. de Vries et al. (2020) explore the impact of robots on jobs in thirty-seven countries using World Robotics: Industrial Robots by IFR from 2005 to 2015 and conclude that introduction of robots leads to a fall in the share of routine-manual task intensive jobs. Acemoglu and Restrepo (2020) first show that there are three effects of robot adoption on labor: (i) the negative displacement effect – robots replacing humans; (ii) the positive industry productivity effect – robots lowering costs in a particular industry; (iii) the positive general equilibrium effect – robots raising productivity and increasing output and labor demand for the industry introducing the robots. Then, they use the US data by commuting zone to show that more automation leads to fewer labor inputs and the lower real wage through the above three effects. Dauth et al. (2021) focus on detailed Germany labor market data and obtain similar conclusions to Graetz and Michaels (2018) but find no significant impacts on real wage at the macro level. Dauth et al. (2021) find significant heterogeneity in the impacts on real wage among households by income level. These studies use the data from IFR.

The use of administrative data for analysis has been increasing significantly in recent years. Bessen et al. (2019) show that automation increases job separation and decreases wage rate using Dutch micro-data over 2000-2016. Humlum (2019) uses administrative data connecting workers and firms in Denmark and then structurally estimates the dynamic general equilibrium model. He concludes that robot adoption increases the average real wage but reduces the real wage in the manufacturing sector. Acemoglu et al. (2020) use the firm-level data in France and show that firms who adopt robots reduce labor shares but increase value-added, productivity, and employment. Aghion et al. (2020) also use comprehensive micro-data in the French manufacturing sector between 1994 and 2015 and report that automation is positive on employment and wages. Koch et al. (2021) explores the impact of robot adoption using micro-data of Spanish manufacturing firms between 1990 and 2016.[4] They report that robot adoption increases output and productivity and leads to net job creation but does not significantly affect the average wage. Mann and Puttmann (2021) first compute a new measure of automation using patent data between 1976 and 2014. According to their commuting zone level analysis, automation leads to higher employment in local labor markets.

Japan is one of the leading countries in robot production. Several studies utilize the robot adoption data published by JARA. Adachi et al. (2020a) estimate the impacts of robot adoption

[4] Their primary focus is the causal impacts of robots on firms and aims to answer two primary questions: (1) Which firm characteristics prompt firms to adopt robots? (2) What is the impact of robots on adopting firms relative to non-adopting firms?

Table 1: Summary: Aggregate impacts of robots on the labor market

	hours	employment	productivity	wage
Graetz and Michaels (2018)	0	0	+	+
Bessen et al. (2019)	n.a.	-	n.a.	-
Humlum (2019)	n.a.	n.a.	n.a.	+
Acemoglu and Restrepo (2020)	-	-	n.a.	-
Acemoglu et al. (2020)	n.a.	-	+	0
Adachi et al. (2020a)	-	+	n.a.	+
Aghion et al. (2020)	n.a.	+	n.a.	0
Dekle (2020)	n.a.	+	n.a.	n.a.
Fujiwara and Zhu (2020)	0	0	+	0
Adachi (2021)	n.a.	-	n.a.	-
Koch et al. (2021)	n.a.	+	+	0
Dauth et al. (2021)	0	0	+	0
Mann and Puttmann (2021)	n.a.	+	n.a.	0

Note: +, - and 0 denote positive, negative and insignificant impacts, respectively. We report the impacts on macroeconomic variables, but some present average but firm or industry level reactions.

on labor in Japan by industry and commuting zone. A unique aspect of this study is that it uses price information as an instrumental variable. It embodies the information on technology and attempts to eliminate reverse causality, i.e., the impact of the labor market condition on robot adoption. Adachi et al. (2020a) conclude that higher robot penetration results in higher employment and wage in Japan. Dekle (2020) evaluates the three effects in Acemoglu and Restrepo (2020). According to his industry panel estimates, "the displacement effect is insignificant, the productivity effect is sometimes positively significant, and the macroeconomic general equilibrium effect is always highly positively significant." As a result, robots have increased labor demand in Japan. Fujiwara and Zhu (2020) construct the quality-adjusted robot stock using the JARA data and the industrial robot price index in the "Corporate Goods Price Index" of the Bank of Japan. According to their panel estimation by country and industry, industrial robots increase labor productivity and have exerted insignificant effects on hours worked, employment and wage. Adachi (2021) shows a robot shock, an exogenous increase in robot price in Japan, reduces the US occupational wages. This robot shock is estimated using the JARA data.

Table 1 summarizes empirical impacts of robots on labor market variables in aggregate in previous studies. +, - and 0 denote positive, negative, and insignificant impacts, respectively.

Our focus is on the heterogeneous impacts of robot adoption on tasks. Several previous studies also offer the distributional consequences of robot penetration. Humlum (2019) reports that as robots are introduced, wages for production workers decrease, but those for tech workers increase. Acemoglu et al. (2020) and Koch et al. (2021) analyze the impact of robots, distinguishing between the impact on companies that have implemented robots and the impact on their competitors— employment by robot adopting firms increase, but competitors' employment declines. Moll et al. (2021) develop a model where high-skilled workers and owners of the firms are benefited from new technologies. They conclude that automation is responsible for the observed increase in income and wealth inequality.

Acemoglu and Restrepo (2020) use the importance of routine jobs in a commuting zone – the fraction of employment in a commuting zone in routine occupations as defined in Autor and Dorn (2013) – as the control variable. Dauth et al. (2021) conclude that robotization leads to a change in the labor market composition, in particular, pointing out the substitution between manufacturing and non-manufacturing industries. However, the differences in tasks are not explicitly considered in both Acemoglu and Restrepo (2020) and Dauth et al. (2021). In addition, we analyze whether industry differences or task differences are more important in considering the asymmetric impacts of robots.

The most related previous studies are de Vries et al. (2020) and Aghion et al. (2020), which analyze the impacts of robot adoption by task. de Vries et al. (2020) report that a rise in robot adoption decreases the share of routine-manual task intensive jobs. However, there is a one-to-one relationship between occupation and task. The fact that one occupation performs multiple tasks is not taken into account. As a result, as with the criticism to Frey and Osborne (2017), the impact of robots may have been over-estimated. Furthermore, since the data was taken from 2005, the analysis does not include the period when robots rapidly spread, as in our study.

Aghion et al. (2020) analyze the impacts of robot adoption by skilled and unskilled industrial workers and report that the impact of automation is positive on employment, even for unskilled industrial workers. Following Charnoz and Orand (2017), the employment shares for (1) routine jobs, (2) service jobs, and (3) high-skill jobs are calculated by region. The difference between our analysis and theirs is that our task index is rather considered a continuous measure because we measure it by first aggregating the task scores by occupation. Aghion et al. (2020) is considered a discrete measure because they classify the task index by occupation and take the ratio. We think our approach is less susceptible to the criticism mentioned above to Frey and Osborne (2017): by considering the nature of labor in a discrete way for each occupation, the impact of robots on employment is overestimated.

2 Data

This section first explains the robot data and then task scores.

2.1 Robot data

The JARA robot data used in this study has two characteristics: finer granularity and more extended time series. The former provides us with variations in data needed for identification, and the latter enables us to cover the periods of massive robot penetration in the 1980s. Adachi et al. (2020a) and Fujiwara et al. (2021) offer comprehensive and detailed information about the JARA data. Therefore, we only briefly explain the above two characteristics of the JARA data.

One crucial characteristic of the JARA data is its granularity. JARA publishes two types of data. One is publicly shown on the JARA website,[5] and the other is only available as a booklet in Japanese. The latter contains more detailed information by industry and application. When gauging the impacts of robots on different tasks, sharper result can be obtained with more disaggregated data. Therefore, we decide to use the latter, in particular, Table B, which presents sales and the number of robots by industry and application.[6]

In the 2018 table, 44 industries are covered with 28 major categories and their sub-categories in columns. Rows present 36 applications for 17 major categories with attending sub-categories. New robots are invented, and some old robots become obsolete — industries and applications in the table change over time. Also, there are many empty spaces, and each year, around two-thirds of the spaces are empty. Therefore, we follow Adachi et al. (2020a) and consolidate the data into 12 industries and 6 applications. The specific 12 industries consist of "iron and steel," "nonferrous metals," "metal products," "general machinery and equipment," "electrical machinery and equipment," "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."[7] The specific 6 applications consist of "assembling," "dispensing," "handling," "processing," "welding," and "others". Table 2 presents the detailed mapping of sub-categories of applications.

Table 2: Mapping of application classifications in the JARA data

Application classification	Sub-categories
Assembling	General assembling Inserting and mounting Pointing Sealing and gluing Screwing Other assembling
Dispensing	Dispensing Plating
Handling	Material handling Picking and packaging Shipments
Processing	Load and unload Grinding and cutting Deburring Other processing
Welding	Welding (Arc, spot, laser, other) Soldering
Others	Others, education, research and development, clean room

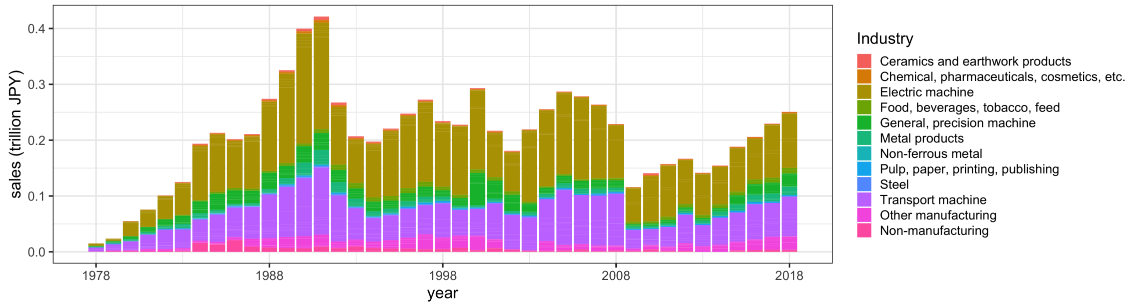
[5] https://www.jara.jp/e/data/index.html

[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 C presents exports of robots by country and applications.

[7] Our classification is the same as that in Adachi et al. (2020a), which use 13 categories of industries. The only difference is the treatment of "general machinery and equipment" and "precision machinery and equipment." Although Adachi et al. (2020a) treat these industries differently, we consider these two a single industry due to the data availability. The precision machinery industry becomes discontinued in the latest Basic Survey on Wage Structure because of the 12th revision of the Japan Standard Industrial Classification.

Figure 1 depicts the trend of robot shipments by industry. Significant heterogeneity in de-

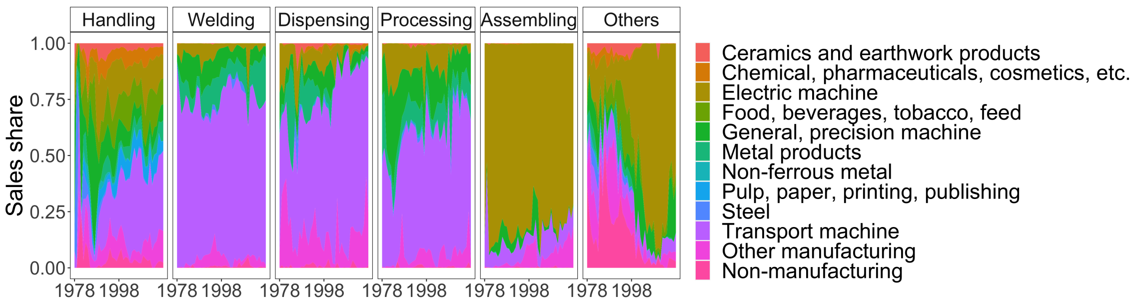
Figure 1: Robot shipments by industry: 1978-2018



mand by industry is observed. The electric and transport-machinery industries are the major demand destinations of robots, accounting for nearly half of the total demand. Some industries are active purchasers of robots while others are not. Notice also that the share of each industry has been stable over time.

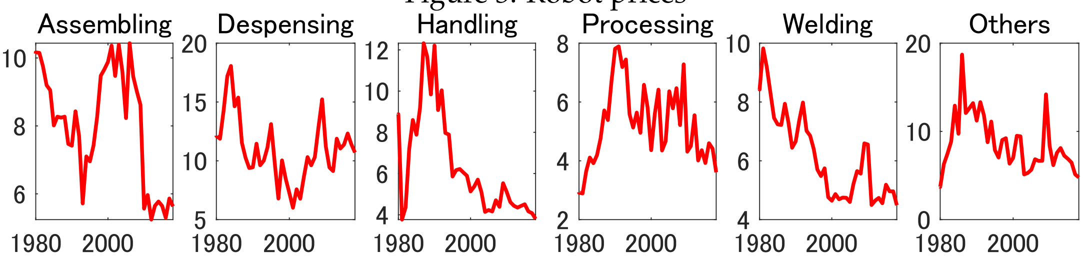
Figure 2 shows the industry share by application. Electric machinery has a high demand for

Figure 2: Industry share by application



assembling robots, while the transportation machinery industry demands welding, dispensing, and processing robots. Figure 3 presents the developments of robot prices by application. Time

Figure 3: Robot prices



paths of robots' prices are different by application. Together with Figure 3, Figure 2 suggests that each industry faces a unique robot price index, hinting that robot prices by industry are suitable instrumental variables to identify the causal effects from robot stocks. Adachi et al. (2020a) indeed employ robot prices by industry as instrumental variables.

The robot price index of industry i, $z_{i,t}$, which is used as an instrument variables, is computed as the composite of prices over application a: $z_{i,t} = \sum_{a \in \mathbb{A}} (z_{a,t})^{\omega_{a,i,t_0}}$, where $z_{a,t}$ is a robot unit price of application a, $\mathbb{A}$ is the set of application robots in the economy, and ω_{a,i,t_0} is a sales weight of application a in industry i at time t_0. The sales weight suffices $\sum_i \omega_{a,i,t_0} = 1$. Then, robot price by application a, $z_{a,t}$, is given by

$$z_{a,t} = \frac{\sum_{i \in \mathbb{I}} sales_{a,i,t}}{\sum_{i \in \mathbb{I}} q_{a,i,t}},$$

where $sales_{a,i,t}$, $q_{a,i,t}$, and $\mathbb{I}$ denote sales and quantities of application a in industry i at time t, and the set of industries in the economy, respectively.

Another critical characteristic of the JARA data is the long time series. The JARA robot data is available after 1978.[8] In contrast, the IRF robot data, which previous studies such as Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) use, is available only after 1993. Industrial robots gradually spread to production sites since 1962, when the first commercial industrial robots were released in the United. States.[9] It seems inappropriate to ignore any developments in the relationship between robots and the labor market before 1993. The long-time series of the JARA data offers an advantage over previous studies. Therefore, we use the Production and Shipments of Manipulators and Robots produced by JARA from 1978 to 2018.[10]

Figure 4 stresses the importance of the long time series of data when examining the effects of robot penetration. Figure 4 presents the historical developments of robot stocks from 1970.[11] Here, the calculation of robot stocks is complicated with finer granularities. Specifically, robot stocks in Figure 4 are the capital stocks aggregated over industries $i \in \mathbb{I} : K_t = \sum_{i \in \mathbb{I}} K_{i,t}$ where $K_{i,t}$ is robot capital stocks in industry i. Industry's capital stocks are the stocks of robots investments, $R_{i,t}$, using the perpetual inventory method: $K_{i,t} = R_{i,t} + (1 - \delta) K_{i,t-1}$, where the depreciation rate δ is set at 10 percent *per annum* following Graetz and Michaels (2018). Robot

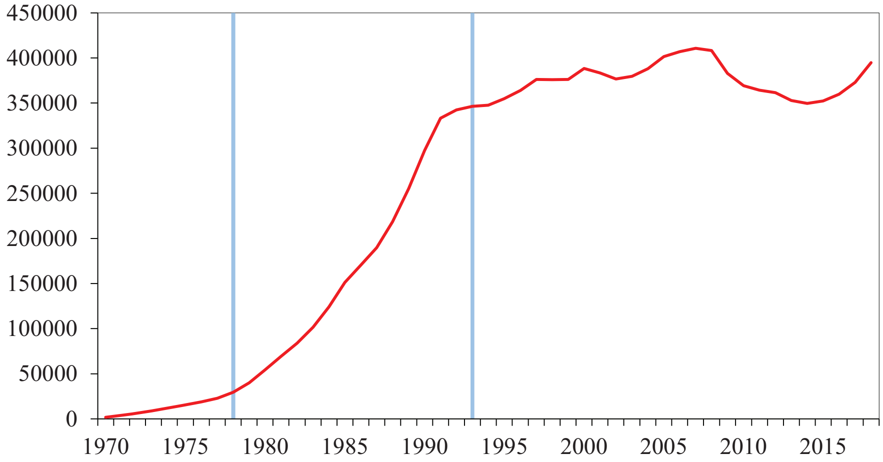
[8] Before 1978, JARA surveyed the state of robot shipments in 1970 and started releasing the statistics on robot shipments in 1974. Notice that the format was different from the current one between 1974 and 1977. In1993, JARA started providing data to IFR.

[9] In 1962, Unimation Inc. released the first commercial industrial robot, "Unimate", in the United. States.

[10] According to the Japanese Industrial Standards (hereafter, JIS), a robot is defined as "a locomotion mechanism that is programmed to operate on two or more axes, has a degree of autonomy, and operates in an environment to perform a desired task. Note 1: A robot includes a control system and an interface to the control system. Note 2: The classification of a robot as an industrial or service robot depends on its intended use." The industrial robot is defined as "A robot that is automatically controlled, reprogrammable, versatile manipulator, programmable in three or more axes, fixed in one place or with mobile functions, and used in industrial automation applications. Note 1: Industrial robots include the following – Manipulators (including actuators) including Control units [including pendants and communication interfaces (hardware and software)]. Note 2: Industrial robots include additional axes by integration." JARA is involved in the creation of JIS standards for robots and industrial robots.

[11] Before 1978, robot shipments in detail are not available. However, JARA provides the aggregate robot shipments of 1970 and 1975 in "Demand and supply trends in robots industry (industrial robots edition)." This study interpolates these shipments data between 1970-1975 and 1975-1978 by the cubic spline, assuming that the robot shipments were for domestic use during the periods.

Figure 4: Robot capital stocks in Japan



Note: Authors's calculation based on JARA, "Production and Shipments of Manipulators and Robots" and JARA, "Trends of Demand and Supply of Robot Industries (Industrial Robot Edition)." Figure presents the domestic robot stocks (the number of robots). Blue bars correspond to 1978 and 1993, respectively.

investment in industry i is the composite over application $a \in \mathbb{A}$:

$$R_{i,t} = \sum_{a \in \mathbb{A}} \left(\frac{sales_{a,i,t}}{z_{a,t}} \right)^{\omega_{a,i,t_0}}, \tag{1}$$

where $sales_{a,i,t}$ is robot sales of application a in industry i at time t.

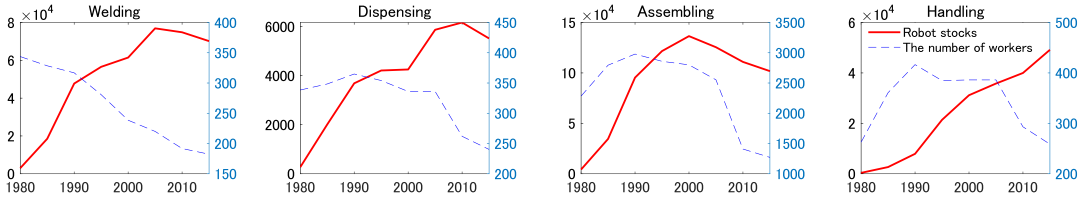
The figure uncovers that robot adoption spread quickly in the 1980s.[12] In fact, JARA (2003) designates 1980 as the initial year of robot dissemination. This JARA data, which includes the period of both robot penetration and afterward, is a valuable source of information to study the effects of robot adoption. It is impossible to ignore the labor market impact of the significant robotization of the 1980s.

Figure 5 depicts robot stocks by application and the number of workers in related occupations. We choose the related occupations based on the occupational titles. Specifically, the selected occupational titles of welding, dispensing, assembling, and handling robots are welder, dispenser, assembler, and packer, respectively. We omit the processing robots and others from the figure because it is hard to find related occupations. This figure shows inverse relations, especially for welding and dispensing robots. The correlation coefficients for these four are negative: -0.893, -0.535, -0.018, and -0.234 from left to right.

The figure appears to be consistent with the displacement story: robots took jobs away from humans (Frey and Osborne, 2017). However, drawing a legitimate implication from this

[12] Kawasaki heavy industry Ltd. released the first domestic industrial robot, "Kawasaki Unimate 2000," in 1969. However, it took time for industrial robots to spread to production sites because early robots had low performance and high maintenance. For example, Kawasaki Unimate 2000 was hydraulic and had a payload of only 12 kg, whereas it weighed 1.6 tons, measured 1.6 x 1.2 x 1.3 meters. In 1980, "Fujikosi" Ltd. succeeded in developing an electric robot that was easy to maintain, and since then, the use of robots has increased.

Figure 5: Robot stocks by application and the number of workers in related occupations



Note: Robot stocks by application are calculated by the perpetual inventory method (the depreciation rate is 10 percent). The number of workers in each occupation is taken from the Population Census. The related occupational titles of welding, dispensing, assembling, and handling robots are welder, dispenser, assembler, and packer, respectively. The scale of the number of workers in related occupations is presented in the right-hand axis.

exercise is difficult because "related occupations" are arbitrary. Further, examining the effects of robotization for each of the hundreds of occupations is not an effective research strategy because it is cumbersome and inevitably involves subjective judgments. Only from the occupation title can we not judge which tasks are required (Arntz et al., 2016). In this regard, Autor et al. (2003) introduce a new perspective, which is tasks instead of occupations, arguing that workers in each occupation perform multiple tasks.

2.2 Task scores

Autor et al. (2003) and Acemoglu and Autor (2011) propose to classify task inputs of workers into five categories: (i) nonroutine-analytical; (ii) nonroutine-interactive; (iii) routine-cognitive; (iv) routine-manual; (v) nonroutine-manual. They assign quantitative scores of these five tasks to each occupation. In particular, Acemoglu and Autor (2011) calculate the five-task scores using numerical indicators of occupational characteristics provided in the job referral database called O-net. JILPT recently developed J-O-net, a comparable job referral database. Komatsu and Mugiyama (2021) calculate the five-task scores for each occupation in Japan using J-O-net.

We calculate the five-task scores following Komatsu and Mugiyama (2021).[13] Table 3, which is the English translation of Table 3 in Komatsu and Mugiyama (2021), summarizes the correspondence of numerical indicators of occupational characteristics and the five-task scores.

If task scores do not differ across occupations, it is not an effective strategy to summarize the number of occupations in a few indicators using task scores. Table 4 reports the correlation coefficients of task scores among occupations.[14] As shown in Komatsu and Mugiyama (2021), nonroutine-analytical and nonroutine-interactive tasks (Tasks 1 and 2) and routine-cognitive tasks (Task 3) are positively correlated with each other. In contrast, they are negatively correlated with routine-manual and nonroutine-manual tasks (Tasks 4 and 5). Occupations that

[13]The JILPT kindly provides us numerical indicators in the "general work activities" category of J-O-net's Occupational Information Database. We use JILPT, "Occupational Information Database: Simplified Numerical Data Download ver. 2.0" for other numerical indicators, which were downloaded in June 2020 from the Occupational Information Provision Site (J-O-NET, https://shigoto.mhlw.go.jp/User/download).

[14]Table 4 is different from Table 5 in Komatsu and Mugiyama (2021) because (i) occupations used in this study are different from the previous study; (ii) they report correlation coefficients weighted by the number of workers.

Table 3: Five-task scores and numerical indicators of occupational characteristics

Five tasks	Autor et al .[2003]	Ikenaga and Kambayashi [2016]	Acemoglu and Autor [2011]	Komatsu and Mugiyama [2021]
Nonroutine Analytical	Math	Math	Analyzing data/ information Thinking creatively Interpreting information for others	Same as on the left
Nonroutine Interactive	Direction, Control, Planning	Persuasion	Establishing and maintaining personal relationships Guiding, directing, motivating subordinates Coaching/developing others	Same as on the left
Routine Cognitive	Set limits, tolerances, or standards	Equipment and control	Importance of repeating the same tasks Importance of being exact or accurate Structured vs unstructured work	Same as on the left
Routine Manual	Finger dexterity	Repairing	Pace determined by speed of equipment Speed time making repetitive motions Controlling machines and processes	Same as on the left
Nonroutine Manual	Eye, hand, foot coordination	Personal assistance service	Spend time using hands to handle, control, feel objects, tools, or controls Operating vehicles, mechanized devices, or equipment Manual dexterity* Spatial orientation*	Same as on the left (excluding *)

Note: English translation of Table 3 in Komatsu and Mugiyama (2021) with some modification. Autor et al. (2003), Ikenaga and Kambayashi (2016), Acemoglu and Autor (2011), and Komatsu and Mugiyama (2021) use the Dictionary of Occupational Titles (DOT), Career Matrix, O-net, and J-O-net, respectively. * represents indicators of the "Abilities" category in the O-net.

Table 4: Correlation matrix of five tasks

	Task 1: Nonroutine analytical	Task 2: Nonroutine interactive	Task 3: Routine cognitive	Task 4: Routine manual	Task 5: Nonroutine manual
Task 1	1.000				
Task 2	0.805	1.000			
Task 3	0.426	0.410	1.000		
Task 4	-0.231	-0.131	0.171	1.000	
Task 5	-0.393	-0.243	-0.141	0.697	1.000

input the first three tasks are distinctively different from those that input the latter two. Since the correlation coefficients lie between -0.4 and 0.8, there are sizable variations in task inputs by occupations. When aggregated, the industry task scores have enough variations for proper empirical analysis as long as the distribution of occupations in each industry is different.

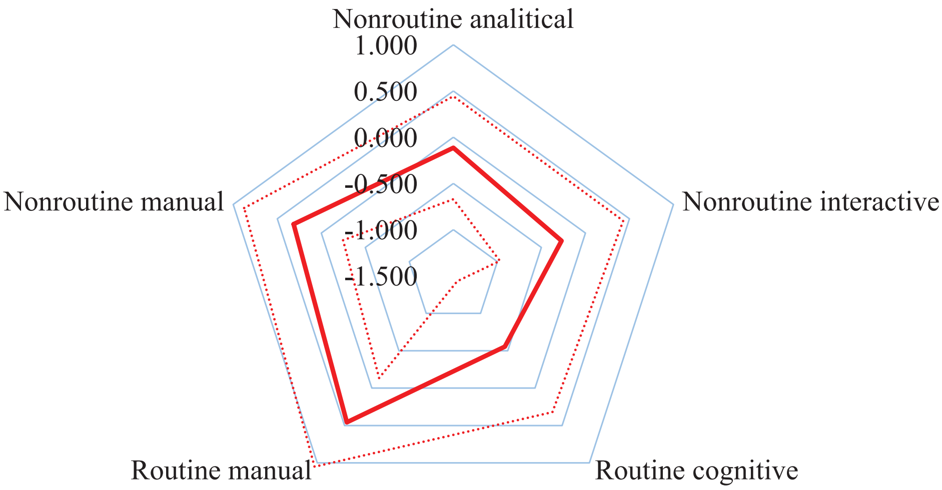
Using the five-task scores and the administrative data of the Basic Survey on Wage Structure, this study transforms the myriad of occupations' information into a few industry task scores. J-O-net's numerical indicators are normalized to have a mean zero and a standard deviation of one when calculating the five-task scores. If a task score uses multiple numerical indicators, we add them to create a composite index and then re-standardize to have a mean of zero and a standard deviation of one.

To clarify the characteristics of the five-task scores, let us focus on the subset of occupations. Specifically, we present the five-task scores of production-related occupations, which are thought to face the direct threat of replacement with increasing usage of robots. Figure 6 depicts the average task scores of 43 production-related occupations. To pick the production-related occupation, we use the occupational titles in Japanese. In particular, occupations with the suffix "kou" in Japanese are considered those engaged in production-related works. Here, we select 43 such occupations as production-related ones.[15] Since task scores are normalized to be zero on average, a positive (negative) score means that a task input of the occupation is higher (lower) than the average. Figure 6 represents the nature of manufacturing. Tasks 4 and 5 (routine-manual and nonroutine-manual) of production-related workers are positive, suggesting that manual-task inputs of these workers are higher than those of the others. In contrast, Tasks 1, 2, and 3 (nonroutine-analytical, nonroutine-interactive, and routine-cognitive) are negative, suggesting that these workers' analytical, interactive, and cognitive task inputs are lower than those of the others.

One might wonder whether all the production-related occupations engage in very similar tasks. However, it is not correct. There are variations in the five-task scores within production-related occupations. Accordingly, one standard deviation of task scores (dotted lines) in Figure

[15] See the note of Figure 6 for specific occupational titles.

Figure 6: Five-task scores of production-related workers



Note: Solid and dotted lines are the average and ±1 standard-deviation bands of task scores. For the details of the task score calculation, see Section 4.1.1. The specific titles of 43 production-related occupations are as follows: steel worker, nonferrous metal refiner, foundry worker, die forger, steel heat treatment worker, rolling and stretching worker, metal inspector, general chemical worker, chemical fiber spinner, glassware worker, ceramics worker, lathe worker, milling machine worker, metal press worker, iron worker, sheet metal worker, electroplater, buffing worker, finisher, welder, machine assembler, machine inspector, machine repairer, heavy electrical equipment assembler, light electrical equipment inspector, automobile assembler, automobile maintenance worker, bread and confectionery manufacturer, light electrical equipment inspector assembly workers, heavy electrical machinery assembly workers, communication equipment assembly workers, semiconductor chip manufacturing workers, printed wiring workers, light electrical machinery inspection workers, automobile assembly workers, automobile maintenance workers, bread and confectionery manufacturing workers, spinning workers, weaving workers, sewing workers, sewing machine operators, lumber workers, wood molding workers, furniture workers, joinery manufacturing workers, paper making workers, paper container workers, process plate-making workers, offset printing workers, and synthetic resin product molding workers.

Table 5: Numerical example: task k score by industry i in year t

Share ($\lambda_{j,i,t}$) matrix from *Wage census*						Task k score vector from *JILPT*			Task k score by industry	
industry\occupation	j_1	j_2	j_3	...			S_j^k			$S_{i,t}^k$
i_1	0.25	0.2	0.05	...		j_1	1.35		i_1	1.2
i_2	0.4	0.1	0.2	...	x	j_2	0.345	=	i_2	0.2
i_3	0.3	0.3	0.3	...		j_3	-1.233		i_3	-0.5
...	...	...	...	...		...	...		...	...

Note: Wage census means the Basic Survey on Wage Structure. Industry i_1 can be replaced with commuting zone c_1.

6 is large. Therefore, it is not appropriate to simplify the analysis by consolidating many occupations into a single "production-related" occupation.

When aggregating task scores by industries, this study bridges the J-O-net's occupational categories with occupational categories in the administrative data of the Basic Survey on Wage Structure by using the crosswalk file of Komatsu and Mugiyama (2021).[16] Suppose more than two occupational categories in the J-O-net correspond to an occupational category in the Basic Survey on Wage Structure. In that case, we take weighted averages by using the weights based on the number of workers in the administrative data of the Basic Survey on Wage Structure in 2005.[17]

The number of occupations is 130 (129 occupations plus one management occupation). Denoting the set of occupations in the economy as $\mathbb{J} = \{1, ..., 130\}$, the task k's score in industry i at time t, $S_{i,t}^k$, is the index given by a weighted average of the score k over occupations $j \in \mathbb{J}$ within the industry:

$$S_{i,t}^k = \sum_{j \in \mathbb{J}} \lambda_{j,i,t} S_j^k, \tag{2}$$

where

$$i \in \{1, ..., 12\}, \quad k \in \{1, ..., 5\}.$$

$\lambda_{j,i,t}$ is a share of occupation j in industry i that suffices $\sum_j \lambda_{j,i,t} = 1$. This share of occupations, which is for regular workers in private firms, is computed using the administrative data of the Basic Survey on Wage Structure. S_j^k is the task k' score of occupation j, which is calculated following Komatsu and Mugiyama (2021). Table 5 illustrates that the industry task score, $S_{i,t}^k$, is computed as the inner product of share ($\lambda_{j,i,t}$) matrix and task score (S_j^k) vector as shown in Since the individual task score is time-invariant, time developments of the industry task score $S_{i,t}^k$ come solely from compositional changes of occupations within industry i. Notice that our industry task score does not capture complete changes of task inputs at both extensive

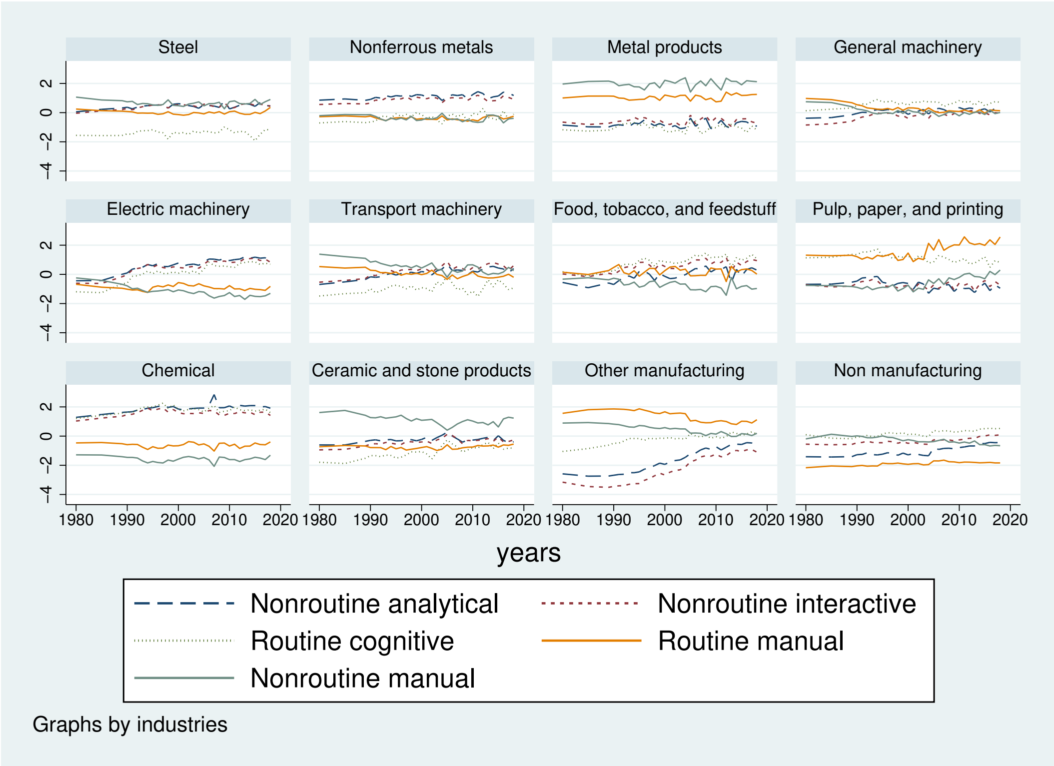
[16] Specifically, we use the crosswalk file corresponding to Japanese standardized occupational category of the year 2005.

[17] Until 1990, the Basic Survey on Wage Structure was produced every five years, but they have been produced annually since then. Accordingly, our sample periods are 1980, 1985, and from 1989 to 2018.

and intensive margins. This study focuses on changes in task scores caused by changes in the number of workers in each occupation.

Figure 7 depicts the time series of the industry task scores . Solid and broken lines represent

Figure 7: Industry task scores



Note: Solid and broken lines are manual-related tasks and the other tasks. Task scores by occupations are aggregated using the shares of occupations within industries as weights. The number of occupations by industry is taken from the administrative data of the Basic Survey of Wage Structure.

developments of manual task inputs and other task inputs, respectively. The figure shows that occupational composition has changed. Expressly, in major purchasers of industrial robots such as general, electric and transport machineries, routine-manual and nonroutine-manual tasks declined in the 1980s and other tasks increased in exchange. However, in other industries such as nonferrous metals, pulp, paper and printing, and non manufacturing, which were not active purchasers of industrial robots, tasks scores were stable during the 1980s.

However, it is too early to make any inferences based on this figure. Robot investments and task inputs are equilibrium objects and likely codetermined. In addition, various factors such as the advancement of ICT, globalization, and demographic changes may affect the labor market in Japan during the sample period. Therefore, it is necessary to make statistical inferences, controlling potential endogeneity and the influence of various factors. In this vein, this study estimates the relationship between robot penetrations and task inputs.

3 Model

We consider a simple model where the introduction of robots induces shifts of tasks. A representative consumer maximize utility U implicitly defined over goods $i \in \mathbb{I}$:

$$\left[\int_0^1 \beta\left(i\right)^{\frac{1}{\sigma}} \left(\frac{C\left(i\right)}{U^{\phi(i)}}\right)^{1-\frac{1}{\sigma}} \mathrm{d}i\right]^{\frac{\sigma}{\sigma-1}} := 1,$$

considering also disutility stemming from labor supply: $v_H\left(H\right)$ and $v_L\left(L\right)$, subject to the budget constraint:

$$\int_0^1 P\left(i\right) C\left(i\right) = W_H H + W_L L + \Pi.$$

C, P, H, L, W, and Π denote consumption, price, task H labor supply, task L labor supply, nominal wage rates, and nominal profits, respectively. β and σ and weight parameter and the elasticity of substitution among heterogeneous consumption goods. As shown in Hanoch (1975), Sato (1975), Matsuyama (2019) and Comin et al. (2021), $\phi\left(i\right)$ defines the Engel effects. We assume that $\phi\left(i\right)$ increases in i, implying that income effects become stronger with higher i. Notice that when $\phi\left(i\right) = 1$, the above collapses to the standard CES demand system.

Each consumer good is produced using the CES technology:

$$Y\left(i\right) = \left\{\alpha\left(i\right)^{\frac{1}{\eta(i)}} \left[\left(\gamma\left(i\right)^{\frac{1}{\varepsilon(i)}} R\left(i\right)^{1-\frac{1}{\varepsilon(i)}} + \left(1-\gamma\left(i\right)\right)^{\frac{1}{\varepsilon(i)}} L\left(i\right)^{1-\frac{1}{\varepsilon(i)}}\right)^{\frac{\varepsilon(i)}{\varepsilon(i)-1}}\right]^{1-\frac{1}{\eta(i)}} + \left(1-\alpha\left(i\right)\right)^{\frac{1}{\eta(i)}} H\left(i\right)^{1-\frac{1}{\eta(i)}}\right\}^{\frac{\eta(i)}{\eta(i)-1}}.$$

$\alpha\left(i\right)$ and $\gamma(i)$ are weight parameters. $\varepsilon\left(i\right)$ and $\eta\left(i\right)$ denote the elasticity of substitution between robots and type L task and that between combined inputs of robots and type L task and type H task, respectively. The key setting is that $\varepsilon\left(i\right)$ decreases in i, implying that robots and type L task becomes more substitutable as with lower i. This pins down whether type L task in each industry i increases or decreases.

$\alpha(i)$ and $\gamma(i)$ increase as i increases. This setting aims to capture the Baumol effects through *robot capital deepening* using the mechanism in Acemoglu and Guerrieri (2008). This together with the Engel effects through $\phi\left(i\right)$ induces labor and production to shift from lower i to higher i goods, as robot penetration increases, in the model.

Robot is simply created only by the type H task: $R = \bar{A} f\left(H_R\right)$,where $\bar{A}$ denotes the technology for robot production. Labor market clearing conditions are given by

$$H = \int_0^1 H\left(i\right) \mathrm{d}i + H_R,$$

$$J = \int_0^1 L\left(i\right) \mathrm{d}i.$$

Goods markets clear as

$$C(i) = Y(i).$$

Since we cannot obtain the analytical solution to the above problem, let us consider the simplified version consisting of only two industries $i = \{1, 2\}$. We set $\sigma = 1, \phi(i) = 1, \eta(i) = 1$, $\varepsilon(1) = \infty$, $\varepsilon(2) = 1$, $v_L(L) = L$ and $v_H(H) = 1/(1+\eta_H)H^{1+\eta_H}$, where $\eta_H > 0$. The disutility function for L task is linear while that for H task is convex, implying that labor adjustments in L task are less costly than in H task.[18] In addition, robots are produced purely exogenously as $\bar{R}$.[19] Under this simplified assumption, the employment ratio in each industry is analytically given by

$$\frac{L_2}{H_2} = \frac{\alpha_2(1-\gamma_2)}{1-\alpha_2}\Gamma^{\frac{1}{1-\alpha_1\beta-\alpha_2(1-\beta)}},$$

$$\frac{L}{H} = \frac{\alpha_1\beta + \alpha_2(1-\beta)}{(1-\alpha_1)\beta + (1-\alpha_2)(1-\beta)}\Gamma^{\frac{1}{1-\alpha_1\beta-\alpha_2(1-\beta)}} - \bar{R},$$

where

$$\Gamma := \left[\alpha_1^{\alpha_1}(1-\alpha_1)^{1-\alpha_1}\beta\right]^{\beta}\left[\alpha_2^{\alpha_2}(1-\alpha_2)^{(1-\alpha_2)}(1-\beta)\right]^{1-\beta}\left[\gamma_2^{\gamma_2}(1-\gamma_2)^{1-\gamma_2}\right]^{\alpha_2(1-\beta)}.$$

Therefore, in industry 2, where the elasticity between task L labor and robots is lower, the size of robot stock does not change the employment ratio. On the other hand, in industry 1, where task L labor and robots are complete substitutes, the share of task L labor decreases as robot adoption increases.

$$\frac{d\frac{L_1}{H_1}}{d\bar{R}} < 0.$$

Whether robots induce the replacement of a particular task to robots depending on the parameters. In the following sections, we empirically evaluate how an increase usage of robots prompts replacements among tasks.

Appendix A shows the relationship between L_1/H_1 and $\bar{R}$ in more general settings.

4 Empirical assessments

This study estimates the effects of robot penetration on task inputs. To this end, we employ two types of panel regression models: an industry-level panel model and a commuting-zone panel model. The industry-level and commuting-zone-level analyses aim to draw national and regional implications, respectively. Methodologically, the commuting-zone-level analysis are

[18] The analytical solution can be also obtained with $v_H(H) = H$ and $v_L(L) = 1/(1+\eta_L)L^{1+\eta_L}$.

[19] It is equivalent to assume that robots are produced without labor and the technology of the robot production is exogenous.

based on the shift-share method *a la* Adao et al. (2019), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (2021).

4.1 Empirical strategy

4.1.1 Econometric model I: industry-level analysis

The first model uses an industry-level panel dataset, and we regress the industry task scores on robot stocks.

$$S_{i,t}^{k} = \alpha_{i}^{k} + \alpha_{t}^{k} + \beta^{k} \ln\left(K_{i,t}\right) + X_{i,t}' \gamma^{k} + \epsilon_{i,t}^{k}, \tag{3}$$

where $X_{i,t}$ and $\epsilon_{i,t}^{k}$ are other control variables, and *i.i.d.* normal residuals. Following Adachi et al. (2020a), to alleviate the omitted variable bias, this study adopts several control variables that may affect the composition of occupations within industries, such as demographics, globalization, and ICT.

Controlling for aging is important. massive population aging in Japan leads to an increase in nonroutine-manual tasks (Ikenaga, 2011). In addition, as in other developed countries, the number of highly educated workers has increased. This increased high-skill labor could also lead to changes in occupational compositions (Autor et al., 2003; Goos and Manning, 2007; Spitz-Oener, 2006). Furthermore, the Equal Employment Opportunity Law enacted in 1985 might affect female participation in labor markets.[20] Considering the above aspects, we employ the ratio of workers under 35, the ratio of workers over 50, the ratio of high school graduates, the ratio of university graduates, and the ratio of females as control variables. We calculate these variables by industry from the administrative data of the Basic Survey on Wage Structure.

Globalization has progressed in the past 40 years. The influx of foreign products and global outsourcing has had significant impacts on domestic manufacturing industries (Felbermayr et al., 2011; Autor et al., 2013; Dauth et al., 2014). We use the openness, the sum of imports and exports, by industry, as a control variable to account for effects from globalization. They are computed by using the Japan Industrial Productivity (hereafter, JIP) database ,[21] a database compliant with KLEMS.[22]

ICT also had a significant impact on the occupational structure, coupled with a shift to high-skilled labor (Autor and Dorn, 2013; Ikenaga and Kambayashi, 2016). To disentangle the effects of ICT advancement, we use ICT stocks by industry, which are again calculated using the JIP database.[23]

[20] Abe (2011) points out that the Equal Employment Opportunity Law's long-term impact on females' employment is small.

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

[22] ICT stocks are calculated in the following manner. First, for the period 1995-2018, we add stocks of information equipment, telecommunications equipment, and computer software in the investment-asset table of JIP2018, which is compiled under the 2008SNA standard. For earlier periods, we use the ITC stocks of the JIP2015, which are compiled under the 1993SNA standard. In connecting these two data, we use the industry correspondence table of JIP2018.

[23] We separately evaluate the impact of ICT on task changes in Appendix C.

One concern about the regression model in equation (3) is the potential endogeneity between robot stocks and labor-related variables used in constructing the industry task scores. To alleviate this endogeneity bias, this study employs the two-stage least square (2SLS) method using robot unit prices, $z_{i,t}$, as instruments.

When the sales weight is time-varying and predicts the labor-related variables on the left-hand side of equation (3), estimated coefficients do not measure the impacts of robots. They also reflect sales-share changes in addition to effects from robotization. To avoid this endogeneity issue and ensure the exogeneity of sales share ω_{a,i,t_0}, we use the sale share at the beginning of the sample periods, that is, the sales share of robots purchased during 1978 to 1980, following Adachi et al. (2020a).

The first stage regression equation is specified as

$$\ln\left(K_{i,t}\right) = \alpha_i^{1st} + \alpha_t^{1st} + \beta^{1st} \ln\left(z_{i,t}\right) + X'_{i,t}\gamma^{1st} + \epsilon_{i,t}^{1st}, \tag{4}$$

where $\epsilon_{i,t}^{1st}$ denotes *i.i.d.* normal residuals.

4.1.2 Econometric model II: commuting-zone-level analysis

The second model uses a commuting-zone-level panel dataset to examine the effects of robotization in local labor markets. The definition of the commuting zone is developed by Adachi et al. (2020b), which apply the methodology of Tolbert and Sizer (1996) to the Japanese data. The specification is similar to that used in the industry-level analysis; we estimate the following equation:

$$S_{c,t}^k = \alpha_c^k + \alpha_t^k + \beta^k \ln\left(K_{c,t}\right) + X'_{c,t}\gamma^k + \epsilon_{c,t}^k, \tag{5}$$

where the subscript c denotes a commuting zone $c \in \mathbb{C}$.

The *commuting-zone task score*, $S_{c,t}^k$, namely task k's score in the commuting zone c, is given by the weighted average of the score k over occupations $j \in \mathbb{J}$:

$$S_{c,t}^k = \sum_{j \in \mathbb{J}} \lambda_{j,c,t} S_j^k, \tag{6}$$

where $\lambda_{j,c,t}$ is a share of occupation j in a commuting-zone c that suffices $\sum_j \lambda_{j,c,t} = 1$. This share is again computed using the administrative data of the Basic Survey on Wage Structure. Since the individual task score is time-invariant, time developments of the commuting-zone task score, $S_{c,t}^k$, come solely from compositional changes of occupations within the commuting zone.

In line with Acemoglu and Restrepo (2020), this study adopts the Bartik-style measurement (Bartik, 1991) of "exposure to robots" using robot stocks and the industry's share in terms of the number of workers within the commuting zone at the initial period of estimation ι_{c,i,t_0}:

$$\ln(K_{c,t}) = \sum_i \iota_{c,i,t_0} \ln(K_{i,t}), \tag{7}$$

where $t_0 = 1980$.

4.2 Empirical result

4.2.1 Industry-level analysis

Table 6 reports the main result of this study. [24] F statistics at the bottom of the table exceed 10,

Table 6: Industrial analysis: main result

	Dependent variables				
Task description	$S^1_{i,t}$ Nonroutine analytical	$S^2_{i,t}$ Nonroutine interactive	$S^3_{i,t}$ Routine cognitive	$S^4_{i,t}$ Routine manual	$S^5_{i,t}$ Nonroutine manual
$\ln(K_{i,t})$	0.619**	0.929***	0.466**	-1.105***	-0.089
	(0.243)	(0.326)	(0.253)	(0.383)	(0.189)
2-way FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Globalization controls	✓	✓	✓	✓	✓
ICT controls	✓	✓	✓	✓	✓
Obs.	382	382	382	382	382
Weak instrument F-stat	12.936	12.936	12.936	12.936	12.936

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{i,t}$ and $K_{i,t}$ are k-th task score and robot stocks in an industry i. The standard errors in the parentheses are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by sales values of robots.

suggesting that weak instruments are not issues in the first-stage IV regression.

First, the amount of routine-manual task inputs decreases as robot stocks increase. As presented in Figure 6, the routine-manual task score is higher in production-related occupations. Therefore, the estimation result in Table 6 implies that production-related occupations have declined due to the introduction of robots. In contrast, nonroutine-analytical, nonroutine-interactive, and nonroutine-cognitive task inputs increase with robot stocks. If a worker moves to another occupation that performs a similar task, resulting industry task scores should not change. Since the industry task scores have changed, it can be interpreted as a relative increase in the number of occupations performing a different task than the occupation where tasks were lost.

Table 7 reports the result of regressing the instrumental variable directly on the industry task scores to check the robustness of the 2SLS estimation. Coefficients are again statistically

[24] Table 6 presents the result estimated with all regression controls. See the Appendix B for the result estimated by adding regression controls in a stepwise manner.

Table 7: Reduced form models

	Dependent variables				
	$S^1_{i,t}$	$S^2_{i,t}$	$S^3_{i,t}$	$S^4_{i,t}$	$S^5_{i,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
$\ln(z_{i,t})$	-0.182***	-0.273***	-0.094**	0.324***	0.026
	(0.060)	(0.073)	(0.068)	(0.079)	(0.056)
2-way FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Globalization controls	✓	✓	✓	✓	✓
ICT controls	✓	✓	✓	✓	✓
Obs.	382	382	382	382	382
R^2	0.916	0.915	0.902	0.687	0.868

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the ordinary least square. $S^k_{i,t}$ and $z_{i,t}$ are k-th task score and robot prices in an industry i. The standard errors in the parenthesis are robust standard errors. All regressions are weighted by sales values of robots in each year.

significant for Tasks 1 to 4. Also, the estimated signs are consistent with the main result in Table 6. Notice that the signs of coefficients are reversed compared to Table 6, because of the inverse relationship between robot prices and robot stocks.

Let us now elaborate on the relationship with previous studies. Adachi et al. (2020a) report an increase in the number of workers after the introduction of robots. At first glance, it may seem like we are getting a contradictory result, but that is not the case. The result of this study points out the importance of the heterogeneous effects on workers. The breakdown of workers presents statistically significant changes in the composition of task inputs, indicating the displacement effect – "robots directly displace workers from tasks that they were previously performing" (Acemoglu and Restrepo, 2020) – at work. This study is not the first to find such heterogeneous impacts. Dauth et al. (2021) conclude that robotization leads to a change in the composition of the labor market.

Dauth et al. (2021) point out the importance of substitution between manufacturing and non-manufacturing industries. Table 8 reports the estimation result after dropping the non-manufacturing industry from the dataset to evaluate whether this substitution is critical for our result. Again, coefficients are positive for Tasks 1 to 3, and it is negative for Task 4, and they are all significant. This invariance in the estimation result suggests that the substitution between manufacturing and non-manufacturing is not the main channel of the heterogeneous impacts from increased robot penetration. The substitution between routine-manual tasks and nonroutine-analytical or nonroutine-interactive tasks must be signed with the increasing usage of robots.

Robustness checks Our main result is based on several assumptions. Here, we conduct several robustness checks. The first is the exogeneity of prices. If there is an endogenous relation-

Table 8: Industrial analysis: manufacturing only

	Dependent variables				
	$S^1_{i,t}$	$S^2_{i,t}$	$S^3_{i,t}$	$S^4_{i,t}$	$S^5_{i,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
$\ln(K_{i,t})$	0.625*	1.026**	0.497	-1.304**	-0.142
	(0.327)	(0.466)	(0.348)	(0.584)	(0.271)
2-way FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Globalization controls	✓	✓	✓	✓	✓
ICT controls	✓	✓	✓	✓	✓
Obs.	352	352	352	352	352
Weak instrument F-stat	8.107	8.107	8.107	8.107	8.107

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{i,t}$ and $K_{i,t}$ are k-th task score and robot stocks in an industry i. Non-manufacturing industries are excluded. The standard errors in the parenthesis are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by sales values of robots.

ship between robot capital stocks and prices, robot prices are not good instrumental variables. Therefore, we conduct regression analyses using an alternative price index. Instead of using robot prices computed from domestic purchases, we use export prices by application as alternative instrumental variables. Note that export prices are not directly affected by domestic robot investments.[25] The estimation result using export prices as instrumental variables is shown in Table 9 (I). Similar results to Table 6 are obtained. Coefficients are significantly positive for Tasks 1 to 3, and it is significantly negative for Task 4.

The next robustness check is about the weight for aggregation used to construct robot stocks and prices. The main analysis employs the sales share purchased from 1978 to 1980 as weight and estimates the model using the data from 1980 and onward. However, if this sales share correlates with outcomes (the industry task scores) through channels other than robot penetration, estimated parameters do not correctly reflect the effects of robot penetration. Therefore, in (II) of Table 9, we re-estimate the model by changing the initial point of the sample period from 1980 to 1985, keeping the weight as it is before. This creates a five-year time lag between the weight and outcomes and, therefore, weakens the potential correlation. The result in (II) of Table 9 still shows that coefficients on Task 1-3 are significantly positive, and that on Task 4 is significantly negative.

An essential variable in this study is, naturally, robot stocks. Table 10 examines the sensitivity of main result to an alternative measure of robot stocks. The first one is stocks constructed using an alternative depreciation rate. We presume that the depreciation rate is 10 percent in the main result, following Graetz and Michaels (2018). As a robustness check, we here examine

[25] Export prices are computed using the export quantities and sales data reported in JARA Production and Shipments of Manipulators and Robots.

Table 9: Industrial analysis: validity checks (I)

Task description	$S^1_{i,t}$ Nonroutine analytical	$S^2_{i,t}$ Nonroutine interactive	$S^3_{i,t}$ Routine cognitive	$S^4_{i,t}$ Routine manual	$S^5_{i,t}$ Nonroutine manual
	Dependent variables				
(I) Price measure: export prices					
$\ln(K_{i,t})$	0.619**	0.929***	0.466*	-1.104***	-0.089
	(0.243)	(0.326)	(0.253)	(0.383)	(0.189)
Obs.	382	382	382	382	382
Weak instrument F-stat	12.936	12.936	12.936	12.936	12.936
(II) Dropping observations in 1980					
$\ln(K_{i,t})$	0.614*	0.848**	0.593*	-1.049**	0.031
	(0.331)	(0.417)	(0.333)	(0.507)	(0.252)
Obs.	370	370	370	370	370
Weak instrument F-stat	8.508	8.508	8.508	8.508	8.508

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. The model includes the individual FE, the time FE, and other control variables (demographic, globalization, ICT). $S^k_{i,t}$ and $K_{i,t}$ are k-th task score and robot stocks in an industry i. The standard errors in the parentheses are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by sales values of robots in each year.

the depreciation of 20 percent, which Nomura and Momose (2008) estimate as to the industrial robots' depreciation rate.[26] (I) in Table 10 presents the estimation result with the capital stocks accumulated based on this depreciation rate. Our main result is robust to this change.

We also examine the alternative measure of robot investments. We use the robot sales deflated by robot prices as robot investments in the main result, and this treatment is consistent with our measure of robot prices. Instead, (II) in Table 10 reports the result based on the capital stocks based only on quantities. Again similar results to Table 6 are obtained. Coefficients are positive and significant for Tasks 1 to 3, and it is negative for Task 4.

Finally, we examine the sensitivity to the initial values of robot stocks. This study presumes that robot stocks are zero before 1978. Although robot stocks before 1980 were small, they were still positive (Figure 4). To check the sensitivity to this assumption, we construct alternative stocks using the 7-year immediate withdrawal method and estimate the model for the sample period after 1985.[27] Since the capital stocks as of 1977 retired in 1985 in the 7-year immediate withdrawal method, the initial value of stocks does not affect the estimated coefficients of this sensitivity check. (III) in Table 10 reports that the main result is robust. Coefficients are significantly positive for Tasks 1 to 3, and it is significantly negative for Task 4.

[26] Adachi et al. (2020a) use a similar value (18 percent) for the sensitivity check.

[27] The x-year immediate withdrawal method calculates the capital stock assuming that the capital remains in operation for x years and depreciates completely after x years. IFR adopts the immediate withdrawal method to calculate the working capital stocks (IFR, 2018).

Table 10: Industrial analysis: robustness checks (II)

	Dependent variables				
	$S^1_{i,t}$	$S^2_{i,t}$	$S^3_{i,t}$	$S^4_{i,t}$	$S^5_{i,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(I) Alternative depreciation rate (20 %)					
$\ln(K_{i,t})$	0.496**	0.744***	0.374*	-0.885***	-0.072
	(0.197)	(0.260)	(0.201)	(0.298)	(0.151)
Obs.	382	382	382	382	382
Weak instrument F-stat	12.013	12.013	12.013	12.013	12.013
(II) Robots measurement: JARA quantities					
$\ln(K_{i,t})$	0.698**	1.047**	0.525	-1.245**	-0.101
	(0.328)	(0.377)	(0.334)	(0.495)	(0.211)
Obs.	382	382	382	382	382
Weak instrument F-stat	10.553	10.553	10.553	10.553	10.553
(III) Immediate withdrawal (life time: 7 years) and the sample period starts from 1985					
$\ln(K_{i,t})$	0.418**	0.577**	0.403*	-0.714**	0.021
	(0.221)	(0.272)	(0.219)	(0.322)	(0.172)
Obs.	370	370	370	370	370
Weak instrument F-stat	7.411	7.411	7.411	7.411	7.411

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. The model includes the individual FE, the time FE, and other control variables (demographic, globalization, ICT). $S^k_{i,t}$ and $K_{i,t}$ are k-th task score and robot stocks in an industry i. The standard errors in the parentheses are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by sales values of robots in each year.

4.2.2 Commuting-zone-level analysis

So far, industry-level analysis suggests that robotization causes changes in the composition of task inputs from routine-manual task toward nonroutine-analytical, nonroutine-interactive, and routine-cognitive tasks. These estimated substitution effects are macroeconomic phenomena because the industry-level analysis implicitly presumes a single unified labor market in the economy. However, in reality, individuals work in local labor markets. The commuting-zone-level analysis in this section explores whether robotization also causes compositional changes of task inputs in the regional labor market.

The estimation result shown in Table 11 is consistent with those obtained in the industry-level analysis. Routine-manual task inputs decline, while nonroutine-analytical and nonroutine-interactive tasks increases.

Table 11: commuting-zone analysis: Bartik measures

	Dependent variables				
	$S^1_{c,t}$	$S^2_{c,t}$	$S^3_{c,t}$	$S^4_{c,t}$	$S^5_{c,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
$\ln(K_{c,t})$	0.271***	0.397***	-0.018	-0.209***	-0.067*
	(0.063)	(0.086)	(0.042)	(0.057)	(0.040)
2-way FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Globalization controls	✓	✓	✓	✓	✓
ICT controls	✓	✓	✓	✓	✓
Obs.	7084	7084	7084	7084	7084
R^2	0.196	0.319	0.142	0.247	0.300

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{c,t}$ and $K_{c,t}$ are k-th task score and robot stocks in a commuting zone c. The standard errors in the parentheses are robust standard errors. All regressions are weighted by sales values of robots.

Some differences are also observed. First, the coefficient on routine-cognitive task inputs becomes smaller and no longer significantly different from zero. This result from the commuting-zone-level analysis implies that robotization does not cause a substitution between routine-manual and routine-cognitive tasks within the same local labor market. Increased use of robots causes shifts of tasks across different regions.

Second, the coefficient of nonroutine-manual task inputs becomes significantly negative, suggesting that robotization substitutes both routine-manual and nonroutine-manual tasks within the regional market. In Table 3, the numerical indicators that make up nonroutine-manual tasks include "Operating vehicles, mechanized devices, or equipment." This estimation result implies that workers who operate equipment and machines moved to other regions. As a result, nonroutine-manual task inputs have decreased at the regional level but have not changed much at the industry level.

Tables 12 and 13 present estimation outputs from several robustness checks in the commuting-zone-level analysis. Table 12 shows that the main result is robust even with IV estimation using

Table 12: commuting-zone analysis: IV regression

	Dependent variables				
	$S^1_{c,t}$	$S^2_{c,t}$	$S^3_{c,t}$	$S^4_{c,t}$	$S^5_{c,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
$\ln(K_{c,t})$	0.241***	0.389***	-0.051	-0.256***	-0.087
	(0.075)	(0.098)	(0.055)	(0.068)	(0.054)
2-way FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Globalization controls	✓	✓	✓	✓	✓
ICT controls	✓	✓	✓	✓	✓
Obs.	7084	7084	7084	7084	7084
Weak instrument F-statistics	1.1e+04	1.1e+04	1.1e+04	1.1e+04	1.1e+04

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{c,t}$ and $K_{c,t}$ are k-th task score and robot stocks in a commuting zone c. The standard errors in the parentheses are robust standard errors. All regressions are weighted by sales values of robots.

Table 13: commuting-zone analysis: dropping 1980

	Dependent variables				
	$S^1_{c,t}$	$S^2_{c,t}$	$S^3_{c,t}$	$S^4_{c,t}$	$S^5_{c,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
$\ln(K_{c,t})$	0.274***	0.401***	-0.018	-0.213***	-0.068*
	(0.064)	(0.087)	(0.043)	(0.057)	(0.041)
2-way FE	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Globalization controls	✓	✓	✓	✓	✓
ICT controls	✓	✓	✓	✓	✓
Obs.	6860	6860	6860	6860	6860
Weak instrument F-stat	0.197	0.320	0.143	0.249	0.310

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{c,t}$ and $K_{c,t}$ are k-th task score and robot stocks in a commuting zone c. The standard errors in the parentheses are robust standard errors. All regressions are weighted by sales values of robots.

robot prices as an instrumental variable.[28] In Table 13, we check the sensitivity of aggregation weights, employment shares within the commuting zone in 1980 in Table 11. Table 13 reports that the result reported in Table 11 is robust even after dropping 1980 out of the sample.

[28]Regional robot prices are averages of industries' robot prices calculated using industries' labor share within each commuting zone as a weight.

5 Conclusion

This study shows that the amount of routine-manual task inputs decreases as robot stocks increase, suggesting that the composition of such occupations has declined due to the introduction of robots. In contrast, the amount of nonroutine-analytical, nonroutine-interactive, and routine-cognitive task inputs relatively increases, suggesting that the displacement effect caused by robotization does not result in replacing occupations with similar tasks but rather in a relative increase in occupations with other types of tasks. For this purpose, we construct the industry task scores by using three unique datasets: the Production and Shipments of Manipulators and Robots, the administrative data of the Basic Survey on Wage Structure and numerical indicators of occupational characteristics from J-O-net.

Focusing on the fact that no single occupation consists of a single task, this analysis computes the five-task scores for each occupation and, in aggregate, for each industry and measured how the degree of robot penetration by industry affected these five-task scores. As a result, we can measure the influence of robots on tasks in a very detailed manner. On the other hand, since the five-task scores are standardized indices, it is difficult to obtain quantitative implications from this study. Therefore, it is impossible to know to what extent workers – how many or what percentage of workers – shifted among industries. These can be easily determined if one interprets an occupation as consisting of a single task, but this may lead to overestimating the impact of robots, as seen in the criticism to Frey and Osborne (2017). Analysis of the quantitative impact of robots on tasks is left for our future study.

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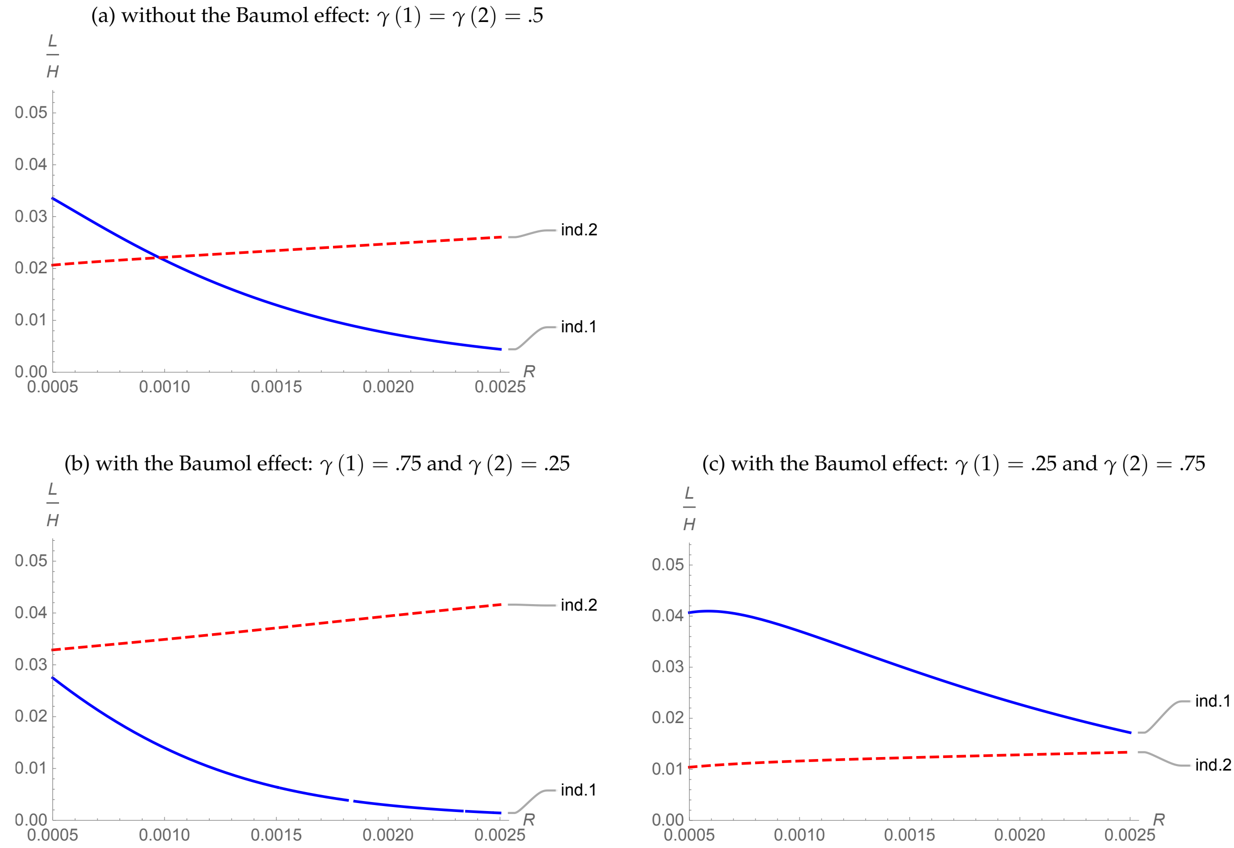
Figure 8: Numerical simulation



Note: parameters are set as follows: $\sigma = 1$; $\eta(1) = 1$; $\eta(2) = 1$; $\varepsilon(1) = 10$; $\varepsilon(2) = 1$; $\beta = .5$; $\phi(1) = 1$; $\phi(2) = 1$; $\alpha(1) = 0.5$; $\alpha(2) = 0.5$; $v_L(L) = L$; $\eta_2 = 1$. In addition, $\gamma(1) = 0.5$ and $\gamma(2) = 0.5$ in (a), $\gamma_1 = 0.75$ and $\gamma_2 = 0.25$ in (b), and $\gamma_1 = 0.25$ and $\gamma_2 = 0.75$ in (c).

Appendix

A Numerical simulation

The panel (a) in Figure 8 displays the case when the parameters in the model presented in Section 3 are set as follows: $\sigma = 1$; $\eta(1) = 1$; $\eta(2) = 1$; $\varepsilon(1) = 10$; $\varepsilon(2) = 1$; $\beta = .5$; $\phi(1) = 1$; $\phi(2) = 1$; $\alpha(1) = .5$; $\alpha(2) = .5$; $v_L(L) = L$; $\eta_H = 1$; $\gamma(1) = .5$; $\gamma(2) = .5$. Contrary to the analytically solvable case in Section 3, robots and labor are not perfect substitutes. As a result, the ratio of L task over H task, L_2/H_2, increases as an increase in robot adoption.

The Baumol effect through the different factor shares by industry is incorporated in panels (b) and (c) in Figure 8. In these cases, only γs are altered such that $\gamma(1) = .75$ and $\gamma(2) = .25$ in (b), while $\gamma(1) = .25$ and $\gamma(2) = .75$ in (c). Factor share of robots is higher in industry 1(2) than in industry 2(1) in the panel (a) ((b)). Acemoglu and Guerrieri (2008) show that the differences in the factor share in the production function shifts the relative prices with the technological progress, which work similarly to the Baumol effect. In the panel (b), the pace of decline L task in industry 1 is larger due to this effect.[29]

Depending on the parameter values, the relationship between L/H and $\bar{R}$ in each sector changes. The relationship between task shifts and robot penetration is explored through estimations examined in Section 4.

B Stepwise regression

This section presents the result estimated by adding regression controls in a stepwise manner.

B.1 Industry-level analysis

Table 14 shows the result of the industry-level analysis. Table 14 (I) shows that the relative

Table 14: Industrial analysis: stepwise regressions

	Dependent variables				
	$S^1_{i,t}$	$S^2_{i,t}$	$S^3_{i,t}$	$S^4_{i,t}$	$S^5_{i,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(I) 2-way FE only					
$\ln(K_{i,t})$	-0.312	0.192	-0.564	-2.511***	0.015
	(0.512)	(0.540)	(0.678)	(0.926)	(0.304)
Obs.	382	382	382	382	382
Weak instrument F-stat	7.572	7.572	7.572	7.572	7.572
(II) 2-way FE + demographic factors					
$\ln(K_{i,t})$	0.728***	1.276***	0.285	-1.665***	-0.048
	(0.276)	(0.437)	(0.259)	(0.577)	(0.224)
Obs.	382	382	382	382	382
Weak instrument F-stat	10.640	10.640	10.640	10.640	10.640
(III) 2-way FE + demographic + global factors					
$\ln(K_{i,t})$	0.593**	0.930***	0.480*	-1.127***	0.003
	(0.263)	(0.357)	(0.279)	(0.426)	(0.235)
Obs.	382	382	382	382	382
Weak instrument F-stat	9.928	9.928	9.928	9.928	9.928
(IV) 2-way FE + demographic + global + ICT factors					
$\ln(K_{i,t})$	0.619**	0.929***	0.466**	-1.105***	-0.089
	(0.243)	(0.326)	(0.253)	(0.383)	(0.189)
Obs.	382	382	382	382	382
Weak instrument F-stat	12.936	12.936	12.936	12.936	12.936

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{i,t}$ and $K_{i,t}$ are k-th task score and robot stocks in an industry i. The standard errors in the parentheses are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by sales values of robots.

decline in routine-manual tasks is so robust that it is statistically significant even without any

[29] Non-homotheticity does not play any significant role in changing the relationship between L/H and $\bar{R}$.

controls. Nonroutine-analytical and nonroutine-interactive tasks become statistically significant when adding demographic factors (Table 14 (II)). When adding the global factor, routine -cognitive tasks become significant (Table 14 (III)) and coefficients approach our preferred specification (Table 14 (IV)).

B.2 Commuting-zone-level analysis

Table 15 is the result of the commuting-zone-level analysis. Table 15 (I) shows that the relative

Table 15: commuting-zone analysis: stepwise regressions

	Dependent variables				
Task description	$S^1_{c,t}$ Nonroutine analytical	$S^2_{c,t}$ Nonroutine interactive	$S^3_{c,t}$ Routine cognitive	$S^4_{c,t}$ Routine manual	$S^5_{c,t}$ Nonroutine manual
(I) 2-way FE only					
$\ln(K_{c,t})$	0.295***	0.427***	-0.040	-0.199	-0.009
	(0.073)	(0.111)	(0.044)	(0.077)	(0.0.041)
Obs.	7084	7084	7084	7084	7084
R^2	0.089	0.193	0.051	0.066	0.065
(II) 2-way FE + demographic factors					
$\ln(K_{i,t})$	0.284***	0.416***	-0.013	-0.226***	-0.071*
	(0.067)	(0.100)	(0.042)	(0.078)	(0.040)
Obs.	7084	7084	7084	7084	7084
R^2	0.189	0.264	0.141	0.126	0.303
(III) 2-way FE + demographic + global factors					
$\ln(K_{i,t})$	0.283***	0.429***	-0.015	-0.250***	-0.071*
	(0.067)	(0.099)	(0.041)	(0.073)	(0.040)
Obs.	7084	7084	7084	7084	7084
R^2	0.189	0.277	0.142	0.176	0.303
(IV) 2-way FE + demographic + global + ICT factors					
$\ln(K_{c,t})$	0.271***	0.397***	-0.018	-0.209***	-0.067*
	(0.063)	(0.086)	(0.042)	(0.057)	(0.040)
Obs.	7084	7084	7084	7084	7084
R^2	0.196	0.319	0.142	0.247	0.300

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2SLS using the robot prices as exogenous instrumental variables. $S^k_{i,t}$ and $K_{i,t}$ are k-th task score and robot stocks in an industry i. The standard errors in the parentheses are robust standard errors. All regressions are weighted by sales values of robots.

increases in nonroutine-analytical and nonroutine-interactive tasks are so robust that they are statistically significant even without any controls. When adding demographic factors, routine-manual and nonroutine-manual tasks become significantly negative as in our preferred specification (Table 14 (II)). Adding the global and ICT factor does not change much, although absolute values of coefficients become slightly smaller (Table 14 (III) and (IV)).

C ICT penetration and task changes

This section provides first the empirical framework and then the result.

C.1 Empirical framework

This appendix presents additional results on the relationships between ICT penetration and task changes. In this analysis, we use the commuting-zone-level data and estimate the following equation.

$$S^k_{c,t} = \underbrace{\alpha^k_c + \alpha^k_t}_{\text{2-way FE}} + \underbrace{\beta^k K^{ICT}_{c,t}}_{\text{ICT's effects}} + \underbrace{\gamma^k X_{c,t}}_{\text{The other effects}} + \epsilon^k_{c,t},$$

where $K^{ICT}_{c,t}$ represents the exposure to ICT in commuting zone c and defined as follows,

$$K^{ICT}_{c,t} = \sum_{i \in \mathbb{I}} \lambda_{i,c,t_0} K^{ICT}_{i,t},$$

where λ_{i,c,t_0} and $K^{ICT}_{i,t}$ are industry i's share of workers in commuting zone c at the initial period t_0 and industry i's ICT capital stocks. As in the main analysis, the exposure to the ITC is Bartik-type measure; the aggregation weight is fixed at the value of the initial period.

The other control variables are the same as in Section 4, although we use robot stocks instead of ICT stocks as a control variable in this analysis.

C.2 Result

Table 16 reports the main estimation result by commuting zones. The result presented in panel (I) shows that the introduction of ICT increased the amount of nonroutine-analytical and nonroutine-interactive tasks. On the other hand, routine-manual and nonroutine-manual tasks decreased upon the introduction of ICT. These results suggest that substitution from manual tasks to nonroutine-analytical and nonroutine-interactive tasks occurred during the sample period.

The above result is consistent with the observed polarization in the labor market (Autor and Dorn, 2013; Ikenaga and Kambayashi, 2016). According to Autor et al. (2003), nonroutine-analytical and nonroutine-interactive tasks require problem-solving, intuition, persuasion, and creativity and are suitable for workers with a higher level of education and analytical capabilities. On the other hand, they also state that manual tasks do not require a higher level of education. Together with the result presented in Table 16, we consider that introduction of ICT has increased the demand for high-skilled workers while it has decreased the demand for middle or low-skilled workers.

One potential concern in panel (I) is the endogeneity. Since the ICT stocks are simultaneously determined with the labor market variables used to construct the task scores on the left-hand side, the result in panel (I) may be distorted by endogeneity. To alleviate the endogeneity

Table 16: ICT adoption and tasks in commuting zone

Task description	*Dependent variables* $S^1_{i,t}$ Nonroutine analytical	$S^2_{i,t}$ Nonroutine interactive	$S^3_{i,t}$ Routine cognitive	$S^4_{i,t}$ Routine manual	$S^5_{i,t}$ Nonroutine manual
(I) OLS					
$\ln(K^{ICT}_{i,t})$	0.117***	0.168***	0.008	-0.103***	-0.044**
	(0.025)	(0.033)	(0.018)	(0.026)	(0.021)
Obs.	7124	7124	7124	7124	7124
R^2	0.184	0.263	0.137	0.200	0.319
(II) 2SLS					
$\ln(K^{ICT}_{i,t})$	0.133***	0.176***	0.004	-0.111***	-0.035
	(0.029)	(0.035)	(0.024)	(0.029)	(0.025)
Obs.	7124	7124	7124	7124	7124
Weak instrument F-stat	1.6e+04	1.6e+04	1.6e+04	1.6e+04	1.6e+04
(III) different sample period (1985-)					
$\ln(K^{ICT}_{i,t})$	0.116***	0.167***	0.006	-0.103***	-0.043**
	(0.026)	(0.034)	(0.018)	(0.026)	(0.021)
Obs.	6900	6900	6900	6900	6900
R^2	0.187	0.266	0.139	0.202	0.328

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The calculation is based on the 2-way FE model with demographic, globalization, and robotization factors. Panel (II) is based on the 2SLS using the ICT prices as an exogenous instrumental variable. $S^k_{c,t}$ and $K^{ICT}_{c,t}$ are k-th task score and ITC stocks in a commuting zone c. The standard errors in the parentheses are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by the ICT stocks.

concern, we use the 2SLS method with ICT prices as an instrumental variable.[30] According to the estimation result in panel (II), the result is in line with the main result in panel (I): the introduction of ICT has increased nonroutine-analytical and nonroutine-interactive tasks, while it has decreased manual tasks. Accordingly, the adoption of ICT has contributed to the polarization of the labor market.

Another concern is related to the aggregation weight used to construct the ICT stocks. Employing the shift-share method, we use the workers' share at the initial period, 1980, as the aggregation weight of ICT capital stocks. However, if the aggregation weight at the initial period predicts subsequent development in the labor markets, factors other than ICT would affect the estimated parameters. Therefore, we leave the aggregate weights as of 1980, shift the starting period for estimation to 1985, and re-estimate the model. The lower panel (III) of Table 16 indicates no significant change in the result even if we weaken the relationship between the aggregate weight and the data used for the estimation by leaving a five-year gap between the two.

In the analysis so far, we estimate the model with all control variables. To check the sensitivity to the choice of control variables, Table 16 reports how the result changes when adding control variables in a stepwise manner. The result shows that the analysis is robust though demographic factors matter for the statistical significance of nonroutine-manual tasks.

[30]This study calculates the ICT price using the JIP statistics as follows. First, we divide the industrial nominal ICT investment by the real ICT investment and then aggregate using industries' worker share within commuting zones at the initial period.

Table 17: ICT adoption and tasks in commuting zone: additional analysis

	Dependent variables				
	$S^1_{i,t}$	$S^2_{i,t}$	$S^3_{i,t}$	$S^4_{i,t}$	$S^5_{i,t}$
Task description	Nonroutine analytical	Nonroutine interactive	Routine cognitive	Routine manual	Nonroutine manual
(I)2-way FE only					
$\ln(K^{ICT}_{i,t})$	0.139***	0.181***	0.013	-0.084***	-0.013
	(0.028)	(0.033)	(0.020)	(0.026)	(0.020)
Obs.	7124	7124	7124	7124	7124
R^2	0.067	0.149	0.025	0.045	0.034
(II) 2-way FE+ demographic					
$\ln(K^{ICT}_{i,t})$	0.126***	0.173***	0.012	-0.098***	-0.037*
	(0.026)	(0.035)	(0.018)	(0.028)	(0.020)
Obs.	7124	7124	7124	7124	7124
R^2	0.179	0.239	0.135	0.147	0.310
(III) 2-way FE+ demographic + globalization					
$\ln(K^{ICT}_{i,t})$	0.124***	0.182***	0.010	-0.115***	-0.043**
	(0.027)	(0.036)	(0.018)	(0.028)	(0.022)
Obs.	7124	7124	7124	7124	7124
R^2	0.180	0.249	0.135	0.180	0.314
(IV) 2-way FE+ demographic + globalization + robotization					
$\ln(K^{ICT}_{i,t})$	0.117***	0.168***	0.008	-0.103***	-0.044**
	(0.025)	(0.033)	(0.018)	(0.026)	(0.021)
Obs.	7124	7124	7124	7124	7124
R^2	0.184	0.263	0.137	0.200	0.319

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. $S^k_{c,t}$ and $K^{ICT}_{c,t}$ are k-th task score and ITC stocks in a commuting zone c. The standard errors in the parentheses are robust standard errors. F-stat is the Cragg-Donald Wald F statistics for the weak identification test. All regressions are weighted by the ICT stocks.