Robots and Employment: Evidence from Japan, 1978-2017*

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Abstract

We study the impacts of industrial robots on employment in Japan, the country with the longest tradition of robot adoption. We employ a novel data set of robot shipments by destination industry and robot application (specified task) in quantity and unit values. These features allow us to use an identification strategy leveraging the heterogeneous application of robots across industries and heterogeneous price changes across applications. For example, the price drop of welding robots relative to assembling robots induced faster adoption of robots in the automobile industry, which intensively uses welding processes, than in the electric machine industry, which intensively uses assembling process. Our industrial-level and commuting zone-level analyses both indicate that the decline of robot prices increased the number of robots as well as employment, suggesting that robots and labor are grossly complementary in the

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production process. We compare our estimates with the ones reported by existing studies and propose a mechanism that explains apparent differences between the results.

Keywords: Automation, Industrial robot, Application of robot, Employment, Factor demand elasticity.

JEL Classification: J23, J24, R23, O33, R11.

1 Introduction

How does automation affect employment? Academic researchers, policymakers, and journalists alike all discuss this topic (Brynjolfsson and McAfee, 2014, Ford, 2015, Frey and Osborne, 2017, OECD, 2019). An example of automation is the use of industrial robots (robots hereafter).[1] This paper analyzes the effect of robot penetration on employment in Japan, relying on a novel identification strategy enabled by a newly digitized data set of robot shipments by destination industry and robot application (task, defined further below) in quantity and sales values.

To estimate the impact of robot penetration on employment, we exploit the variation in robot adoption due to heterogeneous changes in effective robot prices that differ by the characteristics of robot adopters. As our methodological benchmark, Acemoglu and Restrepo (2017) and Dauth et al. (2018) proxied the supply shock of robot to a domestic industry by the robot penetration of the same industry in other developed economies. The presumption is that the industry-level penetration of robots is similar within these economies, because both economies face the same industrial shock to the robot supply, such as innovation in a new robot model that is demanded by both countries. We propose a new identification strategy based on robot applications.

Robot applications are the tasks in the production process that the introduced robots are supposed to do, such as welding and parts assembling. This study substantiates the source of variation of robot adoption across industries by directly appealing to the differences in robot applications in the production process across industries. Exploiting this inter-industry technological variation, we construct a robot price index that each industry faces in each year by averaging the robot price by application, weighted by industry-level application shares of robots. We use this industry-year-level robot price index to estimate the impacts of robot price on robot adoption and employment. Subsequently, we estimate the impact of robot adoption on employment, using the price index as the

[1]Other examples include the use of information and communication technologies (ICT, Autor et al., 2003, among others) and artificial intelligence (e.g., Agrawal et al., 2018). Research on automation in non-industrial contexts is also emerging. Png (2019), for example, finds positive welfare effects on routine cashier workers at supermarkets.

instrumental variable (IV) for robot adoption. The strengths of our methods in comparison to the literature are as follows. First, our method does not require countries of comparison. Second, the regression coefficient reveals gross factor (robot and labor) demand elasticities with respect to robot prices, which are directly interpretable. Furthermore, our method has an additional benefit: The construction of different robot price indices across industries enables us to examine the experience of Japan, which has no comparable foreign counterparts, because robots were adopted in the production process as early as the late 1970s, about 20 years earlier than other developed countries.

We implement our identification strategy employing a new data set featuring a long panel (1978-2017), quantity and sales values, and disaggregation by destination industry and robot applications. Robot applications are the tasks in the production process that the introduced robots are supposed to perform, such as welding and parts assembling. We first demonstrate that various industries use robots in different production processes by showing that the composition of robot applications is substantially different across destination industries. For instance, welding robots and assembling robots consist of 46.3 percent and 7.1 percent of total shipments to the automobile industry, respectively, whereas the values for the electronics industry are 3.0 percent and 76.2 percent, respectively, in the years 1978-82. We next show that the unit price of welding robots fell consistently and substantially between 1978 and 2017, whereas the price drop of other robots was not as striking. Exploiting the heterogeneity of robot application intensity across industries and the different price trends by robot application, we construct the aggregate robot price index by industry that changed differentially across industries. We take this price variation across industries as the source of identification.

We find that robots are complementary to employment at both at the industry and region levels. At the industry level, we show that a 1 percent decrease in robot price increased robot adoption by 1.54 percent. Perhaps more surprisingly, we also find that a 1 percent decrease in robot price increased employment by 0.44 percent. This finding implies that robots and labor are gross complements. Therefore, taken together, our two-stage least squares estimates suggest that a 1 percent robot increase caused by price reduction increased employment by 0.28 percent.

To show the credibility of our identification assumption, we conduct robustness checks by dropping large robot-adopting industries and using different price measures. Robot prices may be directly affected by large adopters. For instance, large adopters, such as the automobile industry, may exert scale effects and reduce the prices of robots they purchase. In this case, prices are endogenous for these adopters. To deal with the concern, we drop these large industries and show that the results are qualitatively the same. To deal with further concerns about using prices as a direct shifter of our IV, we also report the results with alternative IVs based on measures of leave-one-out prices and prices demanded by foreign purchasers. The results are also robust to these considerations.

We move to the commuting-zone (CZ) level analysis to better compare our results with existing estimates in the literature. By constructing shift-share measures of robot exposure, we conduct a two-stage least square estimation resembling the one by Acemoglu and Restrepo (2017) but with our cost-based instrumental variable. Our result indicates that one robot unit per 1,000 workers increased employment by 2.2 percent, corroborating the finding that the robots and labor are gross complements. This contrasts with the finding by Acemoglu and Restrepo (2017), whose corresponding estimate was -1.6 percent. The difference of the results is not surprising, given the difference of the country and the time period covered. Particularly, considering the export-oriented nature of the automobile and electric machine sectors of Japan, robot adoption and its cost-reducing effect have contributed to the expansion of exports and increased the labor demand. This scale effect may well have dominated the substitution effect of robots for labor.

The CZ-level analysis enables us to conduct further analyses regarding spillovers from the manufacturing sector to the non-manufacturing sector, as advocated by Moretti (2010). First, we find that the employment of non-manufacturing sectors neither increased nor decreased upon robot adoption. This fact shows that within-region-across-industry reallocation from service to manufacturing did not happen, suggesting that an across-region reallocation of workers (migration or lack thereof) happened. In other words, in the context of the non-increasing population in Japan, robots might work like a magnet that keeps workers from leaving for other regions. Second, we find that although the total employment increased when robots were adopted, the hours worked per worker decreased. This finding suggests that robots may have worked as work-sharing and time-saving technological changes. In turn, this implies that the hourly-wage effect might be even more positive, which we confirmed in our data.

Relative to the previous literature, for the first time, we propose and implement a robot-cost based identification strategy to estimate the causal effect of robot penetration on labor demand, drawing on newly digitized data covering the long period of 1978-2017 in Japan and the heterogeneous technology of robot use across industries. There is a growing empirical literature studying the impacts of robots on employment (Acemoglu and Restrepo, 2017; Dauth et al., 2018; Graetz and Michaels, 2018; Artuc et al., 2020; Bessen et al., 2019; Koch et al., 2019; Humlum, 2019). The literature is finding mixed evidence from different contexts. Among them, Graetz and Michaels (2018) reported that robot penetration increased labor productivity as well as wages based on an Organisation for Economic Co-operation and Development (OECD) country-industry level analysis. Acemoglu and Restrepo (2017) analyzed US regional labor markets and concluded that robot penetration into a local labor market reduces the employment-to-population ratio and the earnings of all workers regardless of skill levels, implying that all workers lose from robot penetration. In contrast, Dauth et al. (2018) analyzed German regional labor markets to find that the penetration of robots decreased employment in the manufacturing sector but increased employment in the service sector, suggesting the coexistence of losers and winners in local economies. These conflicting empirical results from two major economies, in addition to the theoretical discussion by Berg et al. (2018) and Caselli and Manning (2019) that technological progress should benefit some workers under fairly standard assumptions, warrant further empirical study on other major economies.

The existing literature on the impact of robots on employment does not use robot cost as a robot demand shifter, because robot cost measures are not generally available. For example, the widely used data set compiled by the International Federation of Robotics does not record the sales values at a fine disaggregated level. Thus the unit value per robot is unknown. Graetz and Michaels (2018) is an exception, in that it reports the robot price taken from a survey of a subset of robot producers and shows that the cost reduction was a critical factor behind robot adoption. They did not, however, use the price information in their formal regression analysis.

There is also an emerging literature that uses automation data with firm-level observations to study the margins of adjustment (Bessen et al., 2019, Koch et al., 2019). These papers typically are not aimed at studying a particular machine, but instead, an abstract "automation cost or technology." In contrast, we study the role of a particular well-defined machine, the robot, which makes a quantitative interpretation possible as opposed to a qualitative one.

The use of equipment prices to estimate the elasticity of substitution between production factors is not new.[2] Our paper may be thought of as a contribution to this literature in that it examines a particular type of capital, robots, that is expected to automate the production process and substitute for labor. Recent examples from this literature include Karabarbounis and Neiman (2014), who estimated capital-labor elasticity of substitution using cross-country and time-series variations to study drivers behind recent declines in labor shares in national income. Drawing on their arguments, our finding that robots and labor may be gross complements implies that caution should be taken

[2]See Antras (2004) for a list of papers.

in interpreting that the recent development in robot technology contributes to a decrease in labor shares.

This paper proceeds as follows. Section 2 reviews the necessary background for this paper. This includes the standard shift-share IV-based identification method, cross-country robot adoption trends, and robotics application classifications. Section 3 describes our datasets, with particular emphasis on the critical raw trends of our newly digitized dataset on robot adoption. Section 4 and 5 are the primary analysis sections of this paper, showing two different and complementary empirical strategies of industry-level and commuting-zone-level analyses, and their results. Section 6 discusses the efficiency adjustment over the long-run robot adoption and ensures the robustness of our results when those adjustments are accounted for. Section 7 concludes.

2 Background

As background for our research, we overview a standard identification approach using shift-share instruments, raw trends of robot stock units by country, and the description of robots and robot applications.

By showing cross-country raw trends, we not only convey the significance of our context as the users of robots, but also show why a new identification strategy is needed. Namely, since Japan has a very distinct trajectory in introducing robots for industrial production, it is hard to find similar countries of comparison that would be necessary to construct the shift-share-type instrumental variable prevailing in the literature.

We then move on to describe robots and robot applications. There are two reasons for providing this description. First, it gives readers an understanding of the technological context of our research. Second, by so doing, we introduce a core idea behind our novel identification strategy–an industrial variation in the intensity of different tasks, or applications of robots. Throughout the paper, we use the terms tasks and applications interchangeably.

2.1 Standard Identification Method–Shift-share Instrument

Although we do not employ the standard shift-share identification method in this paper, it is worth mentioning it to highlight the features of our method. When estimating the effect of robots on employment, one confronts a classical identification problem: Observed robot absorption is endogenous to employment. Consider a standard model that attempts to identify the impact of robot adoption in commuting zone (CZ) c in year t on the employment of the industry in the year:

$$\ln(L_{ct}) = \alpha_c + \alpha_t + \beta \ln(R_{ct}) + X'_{ct}\gamma + \varepsilon_{ct}, \tag{1}$$

where L_{ct} is the employment in CZ c in year t, R_{ct} is the stock of robots in CZ c in year t, and X_{ct} is the set of time-varying control variables in CZ c in year t.

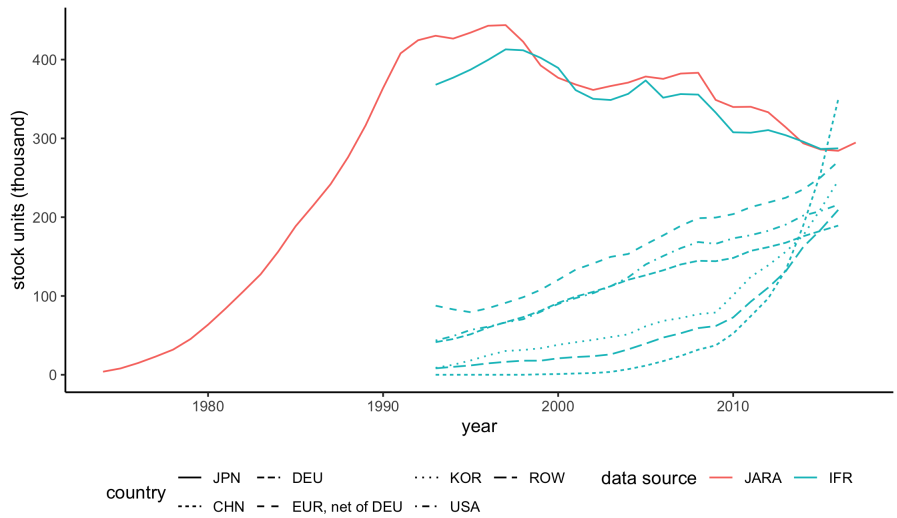
The challenge of estimating this equation is the endogeneity of R_{ct}, as the unobserved product demand shock to the CZ included in ε_{ct} is correlated with R_{ct}. For example, the depreciation of JPY disproportionately increases the product demand in Toyota city, where factories of Toyota Motor Co. are located, which increases both the employment and robot stock of the area. A typical workaround to this problem is to construct a region-level shift-share instrumental variable (IV) Z_{ct}. Formally, the IV is defined as follows:

$$Z_{ct} \equiv \sum_i l_{cit_0} \frac{\Delta R_{it}^{\text{comparison countries}}}{L_{it}}, \tag{2}$$

where c is a region (e.g., commuting zone), t is year, i is industry, l_{cit_0} is base-year (t_0) industrial employment share in (c, t), $R_{it}^{\text{comparison countries}}$ is the operational robot stock in (i, t) of *comparison countries*, and L_{it} is total employment in (i, t). A researcher should use the stock value in comparison countries rather than the country of interest, because the observed robot stocks in the country of interest are subject to endogeneity problem; for example, the increase in the robot stock may be due to a demand boom in (i, t), which raises the industrial labor demand at the same time. In this case, the unobserved error term is positively correlated with the robot stock variable. By using values from comparison countries and assuming that the industrial demands in these countries are uncorrelated, the researcher can take an exogenous source of variation, such as robotics technological growth.

It is not obvious which countries of comparison should be selected. An intuitive method is to take countries that are similar on some measure. Acemoglu and Restrepo (2017), for example, takes Denmark, Finland, France, Italy, and Sweden as comparison countries for the US, based on the similarity of robot absorption trends, while Dauth et al. (2018) takes Spain, France, Italy, the United Kingdom, Finland, Norway, and Sweden for Germany. To see potential comparison countries, the next subsection reviews the trends of robot stock units in several countries. This will demonstrate the difficulty in finding natural comparison countries in our research context.

Figure 1: Trends of Robot Stock Units, by Country



Note: Authors' calculation based on JARA and IFR data. The JARA data show the application-aggregated robot shipment units from Japan to Japan between 1974 and 2017. We supplement the shipment during the 1974-77 period by type-aggregated units. We assume zero units before 1973. To calculate the stock units, we assume eight (8) year immediate withdrawal method to match the stock unit trend of Japan observed in the IFR. The IFR data show stock unit trends for selected countries and aggregated rest of the world (ROW) between 1993 and 2016.

2.2 Trends of Robot Stock Units

To grasp the cross-country trends of robot stock units, we leverage two data sources: the International Federation of Robotics and the Japan Robot Association (JARA). The IFR data are from a country-industry-level panel of operational stock of robots for years 1993 to 2016. This panel has been used intensively in the literature (Graetz and Michaels, 2018, Acemoglu and Restrepo, 2017, among others). The JARA data are based on an establishment-level survey completed by Japanese robot producers, which we will detail in Section 3.1. The JARA provides the statistics to IFR, and thus the Japanese series of the IFR is based on JARA statistics. Remarkably, the dataset is available since 1978. Based on these datasets, we construct the trends of robot stock units for each country in Figure 1.

In the figure, two colors are used to separate the data sources: one for JARA and the other for IFR. Different line types indicate different countries. Note that the solid line represents the trend of Japan, and the trends for Japan overlap well between the IFR and JARA datasets. This is not surprising, because the IFR creates its Japanese series based on JARA data. The two series do not overlap perfectly due to minor adjustments. Several findings stand out from Figure 1. First, Japan experienced a very different trajectory than other countries. There is a rapid increase in the 1980s, and the trend has been stable or even decreased from the 1990s and onward. Second, other large robot purchasers are Germany and other European countries, South Korea, the US, and recently, China. All of these countries increased the stocks rapidly in 1990s and 2000s. Although there are no data available for these countries before 1993, the relative novelty of the robotics technology suggest that the stocks before 1993 would have not been more than those of 1993. Therefore, Japan had a quite unique trend in introduction of robots.

Given that the standard regional shift-share IV (2) leverages the trends of similar comparison countries, how to apply it in our context is not straightforward. To solve the identification problem, we scrutinize robotics technology. In particular, we study the robot applications in the next subsection. The application-level variation turns out to be an additional source of variation that helps the identification in our context and with our dataset.

2.3 Robots and Robot Applications

Given the difficulty of finding countries of comparison, we employ a new identification strategy that is based on industry-level variation in the intensities of robot applications. To understand what this entails, we begin with the definition of an industrial robot (ISO 8373): "an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications." Although well-defined, the definition is fairly broad and thus has different functionalities depending on the particular applications.

In fact, different robot applications are used in different industries with varying intensities. To understand this point better, consider an example task of spot welding (SW) in a certain manufacturing production process. SW combines two or more metal sheets together by applying pressure and heat to the weld area (spot). The task may be conducted in several ways, including using human labor or robots. Furthermore, different industries input the SW task differently. For instance, automobile industry intensively conducts SW, because it has thousands of metal parts that are combined together to make a car body. In contrast, in textile industries such tasks are seldom needed. Therefore, if the automation proceeds in SW task-intensive industries, it is likely that SW-application robots are adopted in such industries.

Another example of a robot application in our paper is surface mounting (SM). SM places surface-mount devices (SMDs) onto a printed circuit board (PCB). Since PCBs are primary inputs to a majority of electric machines, the electric machine industry uses SM robots intensively. Note that robots deployed for SM are different in the type or structure from those used for spot welding (SW). SM requires quick and accurate movement along a horizontal dimension for mounting SMDs. For this purpose, a typical structure of SM robots is called the Selective Compliance Assembly Robot Arm (SCARA), which is well suited to horizontal movements. In contrast, SW requires intensive movements in any directions within three-dimensional spaces. This feature helps welding the body sheets to assemble a complex automobile body shapes without losing an efficiency of production. Therefore, SW robots are typically structured as articulated robots, which are equipped with multiple joints (typically six) that enable smooth movements along any direction.

The difference of mechanical structures by robot applications creates price variation by robot applications. For example, the technological progress of the articulated robot reduced the price of welding robots (including SW robots) relatively faster than that of Assembly robots (including SM robots) in recent decades, as we will see in the data section.

Finally, we discuss the reasons behind robot adoption for such applications. Adoption of robots eventually depends on the productivity of robots relative to human labor, and the relative prices of robots and wages. For example, one of the first robot brands in Japan, the *Kawasaki-Unimate 2000*, was reported to be quite efficient in SW tasks: "The unmanned production line capable of spot welding 320 points per minute took over the work of 10 experienced welders. Including day and night shifts, it saved the labor of 20 people and as a result, the use of such highly versatile robots freed workers from welding, one of Japan's so-called '3K' (kitsui, or 'hard'; kitanai, or 'dirty'; and kiken, or 'dangerous') jobs." (KHI, 2018) The time-saving nature of robots indicates that the hours worked for each worker may decrease more than the headcount of workers when producers adopt robots. We consider this point thoroughly in Section 6. This enhanced productivity of robots relative to human labor and the decrease of the relative price of robots to labor explains robot adaptation.

3 Data

We combine several data sources; two of the most important ones are the robot variables from the Japan Robot Association (JARA) and employment variables from the Employment Status Survey (ESS) from the Japan Statistic Bureau. We also complement these sources with data by Comtrade from the United Nations (UN), the Census of Manufacture, the Survey of Overseas Business

Activities, and the Commodity Distribution Survey from Japan's government surveys. We will detail these below.

3.1 JARA Robot Data

3.1.1 Data Source

Our primary data source for robot purchases is the Appendix tables to *Survey Report on Company Conditions of Manipulators and Robots* (survey tables, henceforth), obtained from *the Japan Robot Association* (JARA, henceforth). The JARA is a non-profit organization of robot-producing member companies. As of October 2019, the number of full member companies is 53, and the associate member companies count 194.[3]

JARA sends an annual questionnaire to member companies and publicizes the survey tables to their member companies.[4] The survey is available starting from 1974, and we focus on the years after 1978 in our main analysis, because the shipment disaggregation by application became available from that year. The long period of coverage enables us to analyze the long-run and potentially time-varying effects of robots on labor markets. Furthermore, the sample period contains the year in which Japan introduced the industrial robots most intensively, as we will see.

The JARA's questionnaire asks for the unit and value of industrial robots that the firm ship by each application, type, structure, and destination industry. We focus on the disaggregation by applications in our main analysis, as we discussed in detail in the previous section. Robot types refer to a robot categorization based on the mechanical way in which robots work. Robot structures refer to a categorization based on the more particular dimensions and directions along which each joint of robots moves. Given the sophistication of robotic technologies, in 2004, the IFR and robot-producing companies agreed that the structure categorization should take over the type categorization. The full lists of the application and type categories are given in Table 1.[5]

We work with 13 industry classifications (12 manufacturing and one "others" aggregates) that are consistent with the other datasets we describe below. The list of industries are: Steel; Non-ferrous metal; Metal products; General machine (includes robot producers); Electric machine;

[3]See `https://www.jara.jp/about/index.html`. (In Japanese. Accessed on October 22, 2019)

[4]In 1996, the questionnaire was sent to 587 establishments and firms. Therefore, one establishment corresponds to one firm. Among them, 445 answered (for a response rate of 76 percent). Among the answering establishments, 231 actually produced robots in the year of the survey. Further details regarding the coverage of data are discussed in Section C.1.

[5]Each application is further discussed in Section A. The structure categorization is discussed in Section C.2.

Table 1: Classifications of Robots

	Classification by Application	Classification by Types
Classification	Handling operations/Machine tending (HO/MT)	Manual manipulator
	Welding and soldering (Welding)	Fixed sequence robot
	Dispensing	Variable sequence robot
	Processing	Playback robot
	Assembling and disassembling (Assembling)	Numerical control robot
	Others	SAL control robot
Available years	1978-2017	1974-2000

Note: Authors' aggregations based on consistently available classifications in JARA data for different years. "SAL control robot" stands for Sensory-, Adaptive-, or Learning-control robot.

Precision machine; Transport machine; Food, beverages, tobacco, feed; Pulp, paper, printing, publishing; Chemical, pharmaceuticals, cosmetics, etc.; Ceramics and earthwork products; Other manufacturing; and Non-manufacturing.

To do the long-run analysis, we construct a time-consistent aggregation of applications, types, and structures. Interestingly, there is no clear pattern of robot sophistication between the different applications while the robot types evolved as the technological frontier of robot-producing industry expanded, as we will see when we discuss the descriptive statistics. Therefore, the application-based classification is relatively stable for each destination industry. This feature provides a justification for our focus on applications. In particular, since we take a weighted average of each category's cost to construct industry-level robot cost measures, it is desirable that the weight is invariant and different across industries. Furthermore, the application-based classification is available for a more extended period, 1978-2017. For these reasons, our primary analysis hinges on the classification by applications.

The dimensions of the summary tables differ by years. The application-destination industry cross tables are available between 1978 and 2017. The details of the availability are discussed in Section C.2.

3.1.2 Raw Trends

We overview some raw aggregate trends of the JARA data to highlight three novelties of our data: the length of the sample period, the availability of the unit value measures, and the availability of data by applications (and types up to 2000). To smooth the year-level volatility, we average observations with five-year bins by taking five-year observations prior to each year (e.g., the observation in 1982 is the simple average of those from 1978 to 1982). Further discussions and descriptive statistics are in Section C.3.

We first describe who buys robots from Japan. Figure 2 shows the industry decomposition of the aggregate sales of robots. The left panel 2a shows the decomposition into export and domestic sales, while the right panel 2b shows the disaggregation of domestic sales into destination industries. From Figure 2a, one can see that the growth of robot adoption within Japan expanded during 1980s, while the trend is stagnant afterward. Then starting around 1990s, the export trend expanded rapidly. This finding corroborates the trend from IFR data shown in Figure 1. Although the structural break before and after 1990 is an interesting phenomenon per se, our focus is on the domestic adoption trend and its industrial variation.

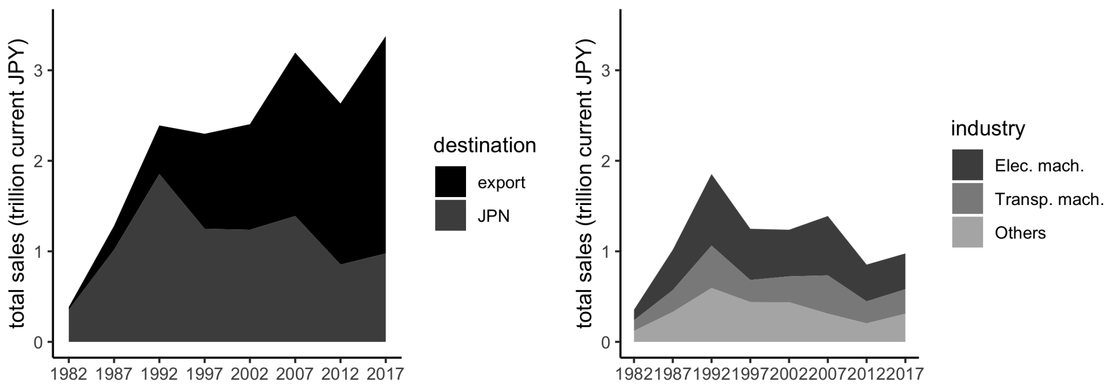
Figure 2b tells us that, within such domestic sales, electric machine and transportation machine (including automobiles) industries are significant purchasers of robots. These two industries represent 68.2 percent of the domestic absorption in 2017. This feature of the data leads our empirical strategy and indicate cautions in the identifications at the same time. Namely, our idea of the empirical strategy is driven by the salient differences in applications between the big buyers. At the same time, since these buyers are large, they might have market powers that affect observed unit values. We argue the first point in the next paragraph and address the concern in detail when discussing the empirical results.

At the same time, we also note that robot adoption was widespread in all manufacturing industries during the 1980s and was not concentrated in particular industries like electric and transportation machines. We confirm this point in a different slice of raw trends in Section C.3.

Next, Figure 3a shows the application-expenditure shares for the large robot purchasers, electric machines, and transportation machinery (including automobiles). We also show the share trend for the other aggregated domestic industries. We highlight two empirical regularities. First, there is significant across-industry variation. The electric machine industry, for example, intensively purchased robots for assembling and disassembling, while the transportation machinery industry bought a significant amount of robots for welding and soldering. In particular, welding robots consisted of 46.3 percent of the total shipments to the transportation machinery industry in years 1978-82, whereas assembling robots consisted of 7.1 percent. In contrast, welding robots consisted of 3.0 percent of the total shipments to the electric machine industry, whereas assembling robots consisted of 76.2 percent during the same period. Second, within-industry patterns of expenditure

Figure 2: Industry Decomposition

(a) Export and Domestic Sales (b) Within Domestic Sales



Note: Authors' calculation based on JARA data. The left panel compares the sales of exports (black) and aggregated domestic industries (dark gray). The right panel shows the decomposition of aggregated domestic industries into three categories: electric machine (Elec. mach.), transportation machine (Transp. mach.), and aggregated other domestic industries (Others).

shares are fairly stable.[6] These points suggest that industries engage in different tasks for which they demand robots. Therefore, the initial composition of applications and the different unit-value evolution afterward had differential effects on robot purchases across industries. We formalize this idea in the following sections.

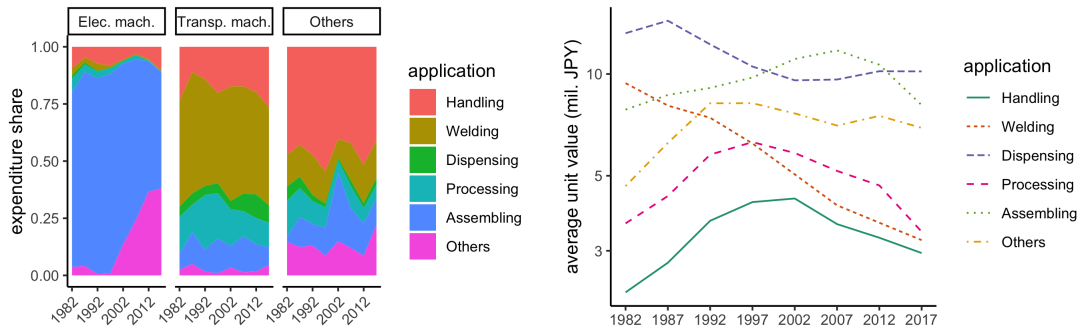
To see how the unit values evolved, Figure 3b shows the trends of the unit values for each application, aggregated across industries. The trends vary across applications. For example, robots for welding and soldering show the stable decline in the unit value for a broad set of industries. This suggests that the production technology for welding-soldering robots grew consistently over the sample period. More importantly, combined with the fact found in Panel (a), the decrease of the unit value of welding-soldering robots was *differentially* enjoyed by the transportation machinery industry, since the industry uses the welding-soldering robot intensively. These observations suggest that the heterogeneous reduction of robot-application price generates differential impacts across industries because of the heterogeneous composition of applications across industries.

The rapid drop of the unit price of welding robot is the key for identification and it is worth

[6]The only exception is the decrease in assembling robots and the increase of other robots shipped for the electric machinery industry. The reason is due to the classification. In the electric machine industry, the assembling process was integrated with the measuring and testing process and thus these robots became classified as other robots.

Figure 3: Application Trends

(a) Expenditure Shares by Industries (b) Unit-Value Trends by Applications



Note: Authors' calculation based on JARA data. The left panel shows the application-expenditure shares for the three industry aggregates: electric machine (Elec. mach.), transportation machine (Transp. mach.), and aggregated other domestic industries (Others). The right panel shows the aggregated unit-value trends for each application. The y-axis is scaled by the natural logarithm. The application list is discussed in the main text and shown in Table 1.

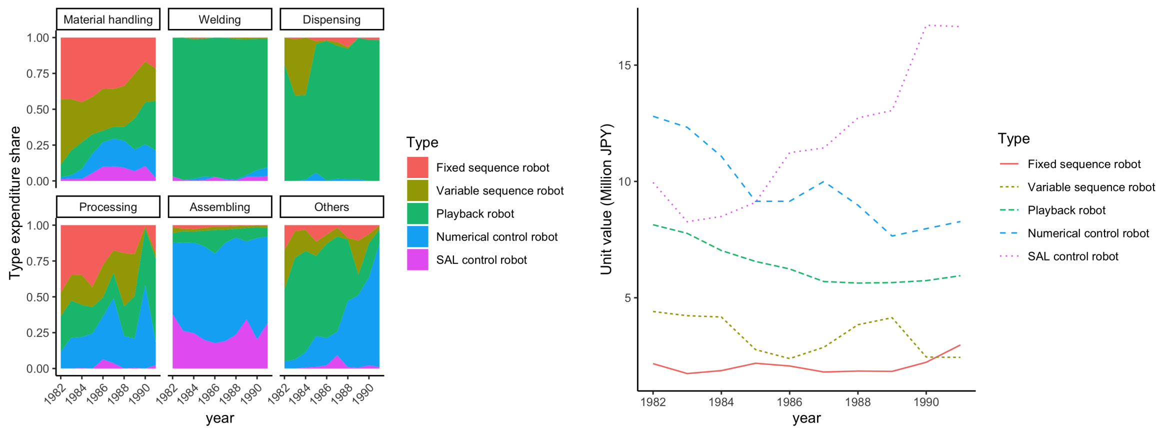
while to document the potential reasons why the welding robots became cheaper. The majority of welding robots is classified as the playback robot, a robot that repeats the same sequence of motions in all its operations, as a robot type. Figure 4a tabulates the relationships between the robot type and the robot application between 1982-1991 and the table shows that almost all of the welding robot consists of the playback robot.[7] Figure 4b shows evolution of the unit price by robot types and we see that the unit price of the playback robot monotonically decreased. This monotonic price decline of the playback robot makes sharp contrast to the price trends of other robot types and reduced the price of welding robots. As a caveat we note that the price trends presented here do not adjust for the quality of robot and the price increase of intelligence robot may well reflect the quality improvement. We will discuss the issues related to quality adjustment in Section 6.

There are technological reasons behind the robot price decline concentrated in the welding robot or the playback robot. We reviewed the articles of Nekkei Telecom data base, a portal website collecting articles whose sources include domestic and international newspapers and magazines, between 1975 and 1985 and found two important technological developments during the period: the adoption of numerical control technology and the substitution of hydraulic actuator by electronic motor actuator (Nikkei, 1982, 1984). These two developments presumably made the welding robot

[7]The type-application cross-tabulation tables are only available between 1982 and 1991. Further details of the JARA dataset is discussed in Appendix C.

Figure 4: Robot Type Trends, 1982-1991

(a) Expenditure Shares by Robot Type (b) Unit-Value Trends by Robot Type



Note: Authors' calculation based on JARA data. The left panel shows the type-expenditure shares for the five robot type aggregates: fixed sequence robot, variable sequence robot, playback robot, numerical control robot, intelligent robot. The right panel shows the aggregated unit-value trends for each robot type.

(or the playback robot) cheaper and gave Japanese manufacturers cost advantage.

In Section C.3, we examine the unit-value trends for each industry to find a relatively small variation across destination industries within an application. This suggests that the robot prices are not solely driven by demand shocks of particular industries, but by the technology for producing robots. Section C.3 further shows detailed descriptive statistics of JARA data and discuss the pre-trend before 1978, the distribution by robot types instead of applications, and some raw correlation between prices and quantities for each application.

3.2 Other Data

For the employment-side variables, we take the Employment Status Survey (ESS) administered by the Ministry of Internal Affairs and Communications (MIC). The ESS has conducted the survey as of October 1979 and in every five years that end with digit 2 or 7 since 1982. It samples roughly one million persons who live in Japan and are age 15 or above, which is roughly one percent of this population in Japan.

We obtain the regional and industrial employment and population variables for each demographic group. In particular, the ESS asks for basic demographic information, such as physical address, age, gender, education attainment, and employment status. For workers, we also obtain the industry classification of the workplace, hours worked, and income. For details of these variables, see Section F.

Our main datasets are made from the JARA and the ESS. We relate robot adoption taken from the JARA to employment and other labor-market variables from the ESS. In addition to these, we supplement the main dataset with the Census of Manufacture (CoM), the Basic Survey on Overseas Business Activities (BSOBA), and the Japan Industrial Database (JIP). These are used mainly to construct control variables. The details are provided in Section 4.3.

The CoM, which is conducted by Japan's Ministry of Economy, Trade and Industry (METI), is an annual survey of manufacturing establishments in Japan. Depending on the year, it takes the universe of establishments. The strength of the dataset is the fine industry coding employed. The ESS surveys the 4-digit Japan Standard Industry Classification (JSIC) for each establishment. Furthermore, the survey asks each respondent for their major products and product codes. Thus, for each establishment, we can observe the intensity of production for each product. This allows us to obtain a fairly accurate measure of employment in robot production. We report some of the results with the employment variable net of such robot-producing workers, as it helps clarify the mechanism. We will come back to this issue when we discuss the regression results. See Section G.1 for details.

The BSOBA, which is also administered by the METI, is an annual survey of the universe of Japanese multinational enterprises (MNEs). For all MNEs, all children and grandchildren subsidiaries must be reported. For each of these headquarters and subsidiaries, information on basic variables, including financial variables from balance sheets, are recorded. This dataset enables us to measure the offshore sales variables for each industry and headquarters location. Since offshoring was a concurrent phenomenon that changed the labor demand in Japan (see, for example, Hummels et al., 2014), we control it with variables constructed from the BSOBA. Section G.2 provides the details.

The JIP, which is administered by Japan's Research Institute of Economy, Trade and Industry (RIETI), releases long-run industrial data for the Japanese economy starting from 1970, assembled from several sources of administrative data (Fukao et al., 2008). The industrial data contain KLEMS variables and variables regarding trade. We use the gross export and import variables to further control the labor-market impacts of offshoring, trade, and technological changes. Detailed discussions about constructing the variables based on the JIP are relegated to Section G.3.

4 Industry-level Analysis

We first analyze the robot impacts at the industry level. By so doing, we discuss the effect with minimal data transformation and explore a proper empirical specification. We then move on to a region-level analysis in the next section, which aims to identify regional implications and provide better comparison to the literature. We find qualitatively similar results between these two approaches.

The similar findings are appealing, given the recent development of econometric theories. For instance, Borusyak et al. (2018) discuss the identification assumptions behind the shift-share instrumental variables (SSIVs) based on exogeneity of the "shift" component and show that the identification variation is at industry level (and time level). Adao et al. (2019) shows that in the presence of cross-regional correlations, the standard SSIV estimators over-reject the null of no effects. Our industrial results indicate that our findings are robust to these concerns, because our findings are robust to the use of industrial variations.

4.1 Robot Aggregation

In this section, we describe the method for constructing the cost indicators for each industry. We will employ the cost indicator as an exogenous shifter of the robot introduction to each industry.

We begin by constructing stock measures of robots. Recall that the JARA data have only the flow shipment variable, whereas we are concerned about the stock of robots and the impact on employment. To construct the robot stock, we follow the immediate withdrawal method, which is also applied by the IFR (IFR, 2018). In particular, we aggregate the robot of a particular application for 12 years to obtain the robotâĂŹs capital stock of the robot. The assumption is that the robot begins to perform the capital service immediately upon purchase and depreciates completely in 12 years. The choice of 12 years is within the range of conventions. We discuss the robustness to other choices of stock measure construction in the robustness section below.

Suppose each industry i produces with labor and robots as primary factors. We assume that the robots are aggregated across applications a and perform service for production in each industry. We then consider the substitutability between labor and robots. Motivated by the observation that the expenditure shares are roughly constant across applications for major industries, such as the electric machine and transportation machine industries (Figure C.3), the robot aggregation is assumed to be Cobb-Douglas:

$$R_{it} = \prod_a (R_{ait})^{\iota_{ai}},$$

where R denotes the quantity of the robots, i indicates industry, t indicates the year, and a indicates the robot application. The aggregation weight ι_{ai} is assumed to be constant over time. Furthermore, given that the variation of trends of unit values are similar across industries within applications (Figure C.4), we assume that the robot market for each application is competitive and sets the same price r_{at} for all buyer industries i. Section H.1 discusses the case without this assumption. Then the price indicator for robots in industry i is given by

$$r_{it} = \prod_a (r_{at})^{\iota_{ai}}.$$

To measure r_{at} in the data, we simply sum the values and quantities across all industries to calculate the average unit value for each application and year. Formally,

$$r_{at} = \frac{\sum_i v^A_{ait}}{\sum_i R_{ait}}, \tag{3}$$

where v^A_{ait} is the sales value of application a to industry i in year t. Furthermore, given the idea that the initial expenditure share is the exogenous source of variation of price changes, we obtain ι_{ai} by the expenditure share on application a for each industry i in year 1982, our earliest year of analysis. Formally, $\iota_{ai} = v^A_{ai,1982} / \sum_a v^A_{ai,1982}$.

4.2 Effect of Robot Adoption on Employment

We consider the following regression specification:

$$\ln(L_{it}) = \alpha_i + \alpha_t + \beta \ln(R_{it}) + X'_{it}\gamma + \varepsilon_{it}, \tag{4}$$

where L_{it} is employment of industry i in year t, R_{it} is the stock of robots in industry i in year t and X_{it} is the vector of control variables explained in Subsection 4.3. Our coefficient of interest is β, the gross elasticity of robot adoption on the employment at industry level. To capture the robot production shock that is not correlated to error term ε_{it}, we instrument $\ln(R_{it})$ with $\ln(r_{it})$, a measure of exogenous change in robot price for each industry in each year. The coefficient of interest does not have a direct structural interpretation, but it makes possible a high-level interpretation of the employment impacts of robots.

The first-stage and reduced-form equations of the two-stage least square (2SLS) estimation of the model (4) are:

$$\ln(R_{it}) = \alpha_i^{FS} + \alpha_t^{FS} + \beta^{FS}\ln(r_{it}) + X_{it}\gamma^{FS} + \varepsilon_{it}^{FS}, \tag{5}$$

$$\ln(L_{it}) = \alpha_i^{RF} + \alpha_t^{RF} + \beta^{RF}\ln(r_{it}) + X_{it}\gamma^{RF} + \varepsilon_{it}^{RF}, \tag{6}$$

respectively, where X_{it}'s are control variables described in Subsection 4.3. If the robot producers' technological innovation drove the cost reduction, then our cost measures and robot purchase in quantity would be correlated negatively; thus β^{FS} is expected to be negative in (5). The reduced form (6), in contrast, expresses the relationship between the robot price and employment, conditional on fixed effects and control variables.

We assume that the variation in r_{it} is exogenous to demand industries. Note that the i-level variation comes from the initial share $\iota_{ai} = s_{ait_0}$ across industries. Our identification assumption is thus that the initial applications shares are uncorrelated with unobserved labor-market factors after conditioning on fixed effects and control variables. In other words, the endogeneity of r_{at} does not give industry i-level variation (Goldsmith-Pinkham et al., 2018), which alleviates the concern about using application prices as shifters of the instrument. We also conduct a robustness check using several price measures that are less endogenous to robot adopters, such as leave-one-out robot prices and export robot prices in the following section.

Interpreting r_{it} as an exogenous price indicator of robots, the first-stage and reduced-form regressions also have an interpretation relevant to the conditional gross own-price elasticity and the conditional gross cross-price elasticity. In this sense, one may view the first-stage (FS) and reduced-form (RF) regressions as giving "low-level" interpretations. Note that standard factor demand theory does not make a particular restriction on these elasticities, because they are a mix of the substitution effect and scale effect (Cahuc et al., 2014).

Note that all the elasticity estimates in equations (4), (5) and (6) are gross concepts. Namely, they contain both the displacement effect, keeping the scale of output constant, and the scale effect, due to the productivity gain made possible by robot adoption. As we show in Section B, the displacement effect is mechanically negative, while the productivity effect is positive if robot adoption improves the overall productivity and the output demand is not perfectly inelastic. Although it would be informative if one could separate the gross estimates into each mechanism, there are few methods for such a purpose to date.[8] For this purpose, we would need to have an exogenous determinant of production scale apart from the exogenous source of robot price variation. For instance, a standard SSIV method by Acemoglu and Restrepo (2017) also estimates the gross effect of robots. The gross effect, however, is still informative for policy makers that are concerned about the total labor market effects of robot adoption. Therefore, we stick to our estimation method and leave addressing this problem as a future work.

4.3 Control Variables

We discuss potential confounders and how we deal with them. First and most importantly, recall that we control for industry-specific time-fixed characteristics and aggregate shocks common across industries. As further possible industry- and time-varying explanations for industrial employment changes, we consider demographics, globalization, and technology, as follows.

First, demographic dynamics change the labor-supply conditions that may correlate with robot adoption incentives for producers and employment at the same time. In particular, in Japan, labor shortages due to aging and low population growth rates have been an acute problem that partly pushes firms to adopt robots (Acemoglu and Restrepo, 2018b). This may bias the 2SLS estimates downward. To alleviate this concern, we control for detailed demographic variables, including education (high-school/4-year university graduate shares), sex ratio (female share), and the age distribution (age under 35/over 50 shares). All of these variables are taken from the ESS.

Second, concurrent globalization alters both the labor demand and robot adoptions. Given the complexity of modern manufacturing production, it is likely that easier access to foreign markets of both outputs and inputs may alter the incentive to adopt new technology and workers (see, for instance, Fort et al., 2018). Depending on the substitutability (e.g., foreign cheap workers replaces the necessity of adopting robots and labor domestically) or complementarity (e.g., high availability of foreign cheap energies enhance the efficiency of robots), the bias may go upward or downward. To alleviate this concern, we control for offshoring, import competitions, and outsourcing. In particular, we take the total import values of each sector from the JIP database. This variable controls for the role of import competition (e.g., Autor et al., 2013) and outsourcing (e.g., Hummels et al., 2014). From the BSOBA data, we take the total gross sales value for each industry. This variable controls the changes in labor demand due to global sourcing (e.g., Antras et al., 2017) or

[8]Dekle (2020) sets up a general equilibrium model and suggests the decomposition of the total effect into the displacement effect, the scale effect, and the general equilibrium income effect.

export platforms (e.g., Arkolakis et al., 2018).

Third and finally, technological changes other than robots, such as increases in ICT adoptions (Autor et al., 2003), may also alter the labor demand and robot adoptions simultaneously. In fact, robots need to be programmed rather than human-operated; as such, robots and ICT adoptions are complementary. Since our interest is the direct impact of robot-based automation on employment, we control for other technological progress. We do so by using intangible capital stock values from the JIP database. In fact, all explanatory variables (i.e., robot, globalization, and technology) are positively correlated. These variables are explained in detail in Section G.3.

4.4 Main Results

With the industry-level aggregate robot service measure and cost indicators, we proceed to the analysis of the effect of robots on employment at the industry level. Several past studies focus on region-level analysis. We conduct a industry-level analysis for two reasons. First, our result is not driven solely by the increased observations by constructing the local-level outcomes by allocating the industry-level variables with fewer observations (Borusyak et al., 2018; Adao et al., 2019). Second, we devote the section to discuss the preferred specifications in several dimensions. We then stick to the preferred specification in the CZ-level analysis. Other specification results can be found in the Appendix.

Table 2 shows the first-stage result of regression (5). Four columns show results with alternative sets of control variables. Column 1 controls only industry and year fixed effects, column 2 adds demographic controls, column 3 globalization, and column 4 technology. The sample size is 104, interacting 13 industries and eight 5-year periods (quinquennially from 1982 to 2017). We report the first-stage IV F-statistics, indicating that those in the specifications from columns 2 to 4 exceed 10, a conventional value for checking weak instruments. In all specifications, we find consistently negative and significant estimates. This result is not surprising, given that the price reductions made by different application compositions drive increases in demand. Our preferred specification is column 4, because it includes all potential confounders discussed in Section 4.3 and has the highest first stage F-statistics among the four specifications. According to column 4, controlling for fixed effects and other factors, a one-percent decline in robot prices drive a 1.54 percent increase in robot adoption.

Table 3 shows the reduced-form result of regression (6). Each of the four columns controls fora different set of control variables, as in Table 2. Again, in all specifications, we find consistently

Table 2: Industry-level, First Stage

	Dependent variable:			
	$\ln(R_{it})$			
	(1)	(2)	(3)	(4)
$\ln(r_{it}^{Z})$	-1.413^{***}	-1.852^{***}	-1.322^{***}	-1.542^{***}
	(0.469)	(0.557)	(0.400)	(0.377)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	9.1	11.047	10.912	16.703
Observations	104	104	104	104
R^2	0.971	0.979	0.984	0.986

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot cost measure and log robot stock measure across industries and years. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

negative and significant estimates, though specification in column 3 shows statistical significance at only the 10 percent level. To clarify, the negative coefficient implies that the fall of the effective robot price induced employment growth, implying that robots and employment are *gross complements*. Our preferred estimate from column 4 indicates that a one percent decrease in robot price *increases* employment by 0.44 percent.

Table 4 shows the 2SLS result of regression (4). Four columns control different sets of control variables. Given the results in Tables 2 and 3, it is not surprising that we find *positive* and significant point estimates in the four specifications. This confirms that robots and employment are gross complementary. Again, our preferred specification (column 4) indicates that a one-percent increase in robot adoption, caused by a drop in the robot prices, *increases* employment by 0.28

Table 3: Industry-level, Reduced Form

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(r_{it}^{Z})$	-0.853^{***}	-0.465^{***}	-0.272^{*}	-0.437^{**}
	(0.130)	(0.144)	(0.151)	(0.171)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	9.1	11.047	10.912	16.703
Observations	104	104	104	104
R^2	0.975	0.984	0.985	0.987

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot cost measure and log employment measure across industries and years. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

percent.

Validating Identification Since the novelty of this paper is the new identification method based on robot prices, we argue that our choice of robot price IV is appropriate. In this section, we discuss two robustness exercises: other price measures and dropping big robot buyers. The first robustness check partly addresses the concern about the endogenous initial industry share of robot applications, as we will discuss.

First, we consider other price measures that do not depend on the own industries' robot prices. Although in the previous section we explained that the source of identification comes from initial application share variations for each industry, our IV does depend on the actual aggregate trends of

Table 4: Industry-level, 2SLS

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(R_{it})$	0.716***	0.251***	0.206*	0.283**
	(0.154)	(0.071)	(0.105)	(0.108)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	9.1	11.047	10.912	16.703
Observations	104	104	104	104
R^2	0.941	0.986	0.988	0.988

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

prices of robots. If the initial application share is endogenous, however, the endogeneity of actual price trends may add bias to our estimates (Goldsmith-Pinkham et al., 2018). To alleviate this concern, we consider the following two alternative price measures. The first measure leaves out the own industry from the calculation of robot prices. Namely, we construct the following robot price:

$$r_{ait}^{LOO} = \frac{\sum_{i' \neq i} v_{ai't}^{A}}{\sum_{i' \neq i} R_{ai't}}. \tag{7}$$

Then we construct the industrial price index based on equation (4.1). This measure is supposed to take the variation that is external to each industry.

Since we have 12 manufacturing industries, however, the leave-one-out price measure may contain feedback bias (dropping one industry in turn affects the price of own industry). To address this further concern, we consider the second measure using export price as follows:

$$r_{ait}^{EXP} = \frac{v_{a,exp,t}^{A}}{R_{a,exp,t}}. \tag{8}$$

Then we aggregate to the industrial price index by equation (4.1). This measure is supposed to take the variation that is further external to each domestic industry, while the concern is that the relevance of IV may be attenuated, because it takes different prices than the actual price each domestic industry faces. We report the results based on these prices in Table 5. Column 1 shows the baseline estimates (thus the same as Table 4, column 4). Columns 2 and 3 are based on leave-one-out prices (7) and export prices (8), respectively. We find that the estimates are robust to these price measures. Therefore, the endogeneity of the actual price measure poses minimal threat to our identification strategy. Furthermore, the robust findings also support our identification idea, the exogenous initial application shares. This is because of the discussion in Goldsmith-Pinkham et al. (2018)–if initial application shares are exogenous, the choice of price measures merely changes the weighting of the Generalized Method of Moments (GMM), affecting the precision of the estimates but not the consistency. This prediction is consistent with our robust findings in Table 5.

Second, we drop large robot buyer industries. The endogeneity of robot prices may be most severe to big robot buyers, such as the transportation industry and electrics, because they may have market power and affect robot prices (recall Figure C.3). If their output demand surges, it may enhance both robot and labor demands. The increase in robot demand decreases prices due to market power. In this case, there is a spurious negative correlation between robot price and labor. While this concern is already addressed by using an arguably exogenous price series in the above analysis, to address this concern in a more direct way, we drop the two large industries, transportation and electrics. The resulting sample is made from smaller industries, whose robot prices are thus less endogenous to robot demand-side shocks. Table 6 shows the 2SLS estimates of these regressions. In column 1, we show the baseline estimate. Columns 2-4 show the dropping of each of the large buyers: Column 2 drops electrics, column 3 drops transportation, and column 4 drops both. We find that the positive results are consistent across columns. The finding suggests that the concern about endogeneity due to market powers of demand industries is minimal.

Table 5: Industry-level, 2SLS, Different Price Measurement

	Dependent variable:		
	$\ln(L_{it})$		
	(1)	(2)	(3)
$\ln(R_{it})$	0.283^{**}	0.303^{***}	0.318^{**}
	(0.108)	(0.101)	(0.139)
Industry FE	✓	✓	✓
Year FE	✓	✓	✓
Demographic Controls	✓	✓	✓
Globalization Controls	✓	✓	✓
Technology Controls	✓	✓	✓
Price Measurement	Industry Aggregate	Leave-one-out	Export
Observations	104	104	104
R^2	0.988	0.987	0.987

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects, demography controls, the logarithm import values from JIP database and logarithm offshoring value added from SOBA, logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Column 1 shows the result with the instrumenal variable of industry-aggregate robot prices (benchmark). Column 2 shows the result with the instrumenal variable of leave-one-out robot prices. Column 3 shows the result with both the instrumenal variable of export robot prices. *p<0.1; **p<0.05; ***p<0.01.

4.5 Heterogeneity

How does our aggregate finding mask heterogeneous impacts to different groups of workers? To see this, we consider our main empirical specification (4) with several subgroups of workers as outcome variables. Table 7 shows the results. In column 1, we show our baseline estimate (the same as Table 4, column 4). We then consider the impacts of robots on the employment of high-school graduates (column 2), four-year university graduates (column 3), female workers (column 4), young workers (less than or equal to 35 years old, column 5), and elder workers (more than or equal to 50 years old, column 6). Perhaps surprisingly, our finding of the positive labor-market implications of robots is robust to all of these subgroups. Moreover, the sizes of the estimated coefficients do not

Table 6: Industry-level, 2SLS, Dropping Major Industries

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(R_{it})$	0.283^{**}	0.283^{**}	0.579^{**}	0.351^{**}
	(0.108)	(0.118)	(0.270)	(0.146)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓
Industries	All	Net Elec.	Net Transp.	Net E&T
Observations	104	96	96	88
R^2	0.988	0.989	0.979	0.988

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects, demography controls, the logarithm import values from JIP database and logarithm offshoring value added from SOBA, logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Column 1 shows the result with the full sample (benchmark). Column 2 and 3 show the results with the electronic machine industry and transportation machine industry dropped, respectively. Column 4 shows the result with both the electronic and transporation machine inustry dropped together. *p<0.1; **p<0.05; ***p<0.01.

differ substantially across demographic groups.

Table 7: Industry-level, 2SLS, Effects on Subgroups

	Dependent variable:					
	$\ln(L_{it})$	$\ln(L_{it}^{HS})$	$\ln(L_{it}^{CG})$	$\ln(L_{it}^{Fem})$	$\ln(L_{it}^{U35})$	$\ln(L_{it}^{O50})$
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(R_{it})$	0.283**	0.279**	0.303**	0.278**	0.328***	0.398***
	(0.108)	(0.107)	(0.117)	(0.115)	(0.114)	(0.125)
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓	✓	✓
Group of Worker	All	High School	4-year Univ.	Female	Age $\leq$ 35	Age $\geq$ 50
Observations	104	104	104	104	104	104
R^2	0.988	0.987	0.989	0.994	0.988	0.986

Notes: Authors' calculation based on JARA, ESS, CoM, SOBA and JIP data. The table presents estimates of the relationship between log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects, demography controls, the logarithm import values from JIP database and logarithm offshoring value added from SOBA, logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Column 1 shows the result with the outcome variable of all workers (benchmark). Column 2 and 3 show the results with the outcome variables of high-school graduates and 4-year university graduates (and more), respectively. Column 4 shows the result with the outcome variable of female workers. Columns 5 and 6 show the results with the outcome variable of workers with age equal or lower than 35, and with age higher than 50, respectively. *p<0.1; **p<0.05; ***p<0.01.

4.6 Further Robustness Checks

We briefly discuss additional robustness checks. In particular, we consider (i) netting out of robot-producing workers, (ii) industry-specific robot prices, and (iii) alternative stock measures. All of these results suggest the validity of our main definitions above.

First, we net out robot-producing workers from employment. Although our primary interest is the robots' gross impact on employment, it may mask a heterogeneity of impacts. As Acemoglu and Restrepo (2018c) clarifies, robot innovation is likely to increase the set of tasks that are input in production. One such example is clearly the robot-producing workers themselves. By measuring the number of such workers, we may gain more insights from our positive estimates found in Section 4.4. Section G.1 discusses in detail how to generate robot-producing worker employment and regression results when robot producers are netted out of the outcome variable.

Second, we consider industry-specific robot prices r_{ait}; in the main specification (3), the robot prices are aggregated and not industry-specific. We also consider industry-specific r_{ait}, calculated by v^A_{ait}/R_{ait}. The use of this variable can be viewed as a robustness check that complements the main specification; the industry-specific prices are likely to reflect the actual prices to each industry. We do not, however, consider it as a main specification. Recall the above discussion regarding the endogeneity concern. The industry-specific-price specification is more vulnerable to this concern, because it varies across industries by definition. In fact, as shown in Section H.1, it is less robust to the inclusion of control variables, suggesting a negative bias due to negative correlations between industry-specific prices and the unobserved component of employment.

Third and finally, we check several measures of robot stocks. Recall that our data come with purchase of robots, which is a flow quantity and monetary values. Robots are durable investment goods, however, and thus the flow values may understate the actual robot stock active in production. To construct the stock variable, our main specifications follow the literature and IFR suggestion and aggregate the 12-year flows of robots, which we call the immediate withdrawal method (IWM). As several authors argue, it is also natural to follow the standard perpetual inventory method (PIM) that is also used in capital formation in National Accounts (Graetz and Michaels, 2018; Artuc et al., 2020). We thus create the robot stock variables based on different-year IWM and PIM with some depreciation rates. When we use alternative measures, we find that the variation in the definition of stock variables has minimal impacts on the regression results. We discuss further details and empirical results in Section E.

Note that the invariance of results with respect to alternative stock measures provides further support for our empirical strategy. The invariance suggests that industry-level robot adoption variation is more significant than time-level variations. Recall that, in our empirical specification, the main identifying variation does not come from the one in application-year prices r_{at}, but instead from that of the initial application shares ι_{ait_0}. Since we take a stand that the latter variable is more exogenous than the former, the invariance to stock measures indicates our method has a minimal concern regarding endogeneity. Section E discusses the detailed construction of variables and regression results.

5 Region-level Analysis

Our industry-level analysis reveals that at the national level, robots and employment are gross complements in our context. In this section, we consider converting the data and regression analysis to the region level. We do so for three purposes: (i) to discuss robots' impacts on subnational and local economies, (ii) to make better comparisons to the literature, and (iii) to delve into spillover effects.

In particular, as the definition of local labor markets, we employ Commuting Zones (CZs) developed by Adachi et al. (2020), who defined CZs following the method employed in, among others, Tolbert and Sizer (1996).[9] CZs made via this method have several strengths. First, they represent the local labor-market delineation better and contain more observations than administrative divisions, such as prefectures. Second and more importantly, they partition the overall national area in a mutually exclusive and exhaustive manner. This point is in contrast to city-level delineations, such as MSAs.[10] This point is especially relevant in our study, because the impacts of robots may not be constrained in urban areas, but also penetrate into rural ones. Rural areas may by overlooked by non-exhaustive regional delineations, such as MSAs.

Based on the industrial robot adoption and price measures and region definitions, we employ the shift-share method to construct a CZ-level robot exposure measure (Acemoglu and Restrepo, 2017):

$$\Delta R_{ct} = \sum_i l_{cit} \frac{\Delta R_{it}}{L_{it}},$$

where c is commuting zones. Following Acemoglu and Restrepo (2017), we call this variable robot

[9]In particular, the hierarchical agglomerative clustering method with average linkages and dissimilarity measures based on bilateral flows of commuters and populations.

[10]A famous regional classification based on city-level density inhabited districts (DIDs) in Japan is proposed and popularized by Kanemoto and Tokuoka (2002).

exposures. To construct CZ-level IVs, we use $t_0 \equiv 1979$ as the base year and similarly generate the shift-share measures but based on price changes:

$$\Delta \ln (r_{ct}) = \sum_i l_{cit_0} \Delta \ln (r_{it}) .$$

With these region-level variables, we then study the following specification:

$$\Delta Y_{ct} = \alpha_c^{CZ} + \alpha_t^{CZ} + \beta^{CZ} \Delta R_{ct} + X_{ct} \gamma^{CZ} + \varepsilon_{ct}^{CZ}, \tag{9}$$

where ΔR_{ct} is instrumented by $\Delta \ln (r_{ct})$. Note that in the region-level specification, we measure changes in robot adoption and prices. We do so for the following two purposes. First, the fixed effect in specification (9) controls the differential growths trends in each location. This is more flexible than just controlling for level differences, and it is preferable when studying regional differences, given that the various regions experience different trends in labor-market characteristics (e.g., Diamond, 2016). Second, it makes the specification more comparable to the ones in the literature, such as Acemoglu and Restrepo (2017). Note that our specification also allows differential trends across CZs, because we access many (in particular, seven time-first differences) time periods.

Table 8 shows the first-stage results. Each column shows the results with a different set of control variables: Column 1 controls only fixed effects, column 2 adds demographic controls, column 3 adds globalization, and column 4 adds technology. The results show a statistically significant and negative correlation between robot price changes and robot exposures, both with and without the covariates. The F test indicates that the use of our price measure passes the test of weak instruments. From now on, we focus on our preferred specification with full controls, the one in column 4.

Table 9 shows the 2SLS results of specification (9).[11] All columns report the preferred specification with the full set of our control variables. The standard deviation of robot exposure measures is 5.25 at the raw level and 2.17 when residualized. For columns 1-6, the outcome variables are log manufacturing employment (column 1), log total employment (column 2, baseline estimate), log total population (column 3), (non-log) employment-to-population ratio (column 4, the main outcome variable of Acemoglu and Restrepo, 2017), log non-manufacturing employment (column 5), and log non-working population (column 6), respectively. First, as our primary interest, column 2 tells us that overall employment increased in CZs that were exposed to robots, confirming the findings in Section 4, even in the first difference-based specification (9) with two-way fixed effects.

[11] Since the reduced-form results are redundant, they are not reported but are available upon request.

Table 8: CZ-level, First Stage

	Dependent variable:			
	ΔR_{ct}			
	(1)	(2)	(3)	(4)
Δr^{Z}_{ct}	-30.074^{***}	-30.928^{***}	-27.330^{***}	-21.179^{***}
	(1.864)	(1.846)	(1.763)	(1.424)
CZ FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-statistics	260.305	280.586	240.268	221.249
Observations	1,466	1,466	1,466	1,466
R^2	0.938	0.941	0.949	0.971

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share logarithm robot prices and shift-share measures of changes in robot stock per thousand workers. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. Column 1 controls the industry and year fixed effects. Column 2 controls the demographic variables: share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 controls the logarithm import values from JIP database and logarithm offshoring value added from SOBA as well as control variables in Column 2. Column 4 (baseline specification) controls logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database in addition to the controls in column 3. *p<0.1; **p<0.05; ***p<0.01.

Perhaps surprisingly, column 1 shows that the impacts to manufacturing employment are even stronger and positive. This may suggest that the scale effects of robot adoption rather than the substitution effects that drive the labor-market impacts.

Table 9: CZ-level, 2SLS

	Dependent variable:					
	$\Delta\ln(L_{ct}^{MAN.})$	$\Delta\ln(L_{ct})$	$\Delta\ln(P_{ct})$	$\Delta\frac{L_{ct}}{P_{ct}}$	$\Delta\ln(L_{ct}^{SER.})$	$\Delta\ln(P_{ct}^{DEP})$
	(1)	(2)	(3)	(4)	(5)	(6)
ΔR_{ct}	4.658**	2.203**	2.003**	0.133	1.101	1.617
	(2.062)	(1.017)	(0.929)	(0.230)	(1.036)	(1.103)
CZ FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓	✓	✓
Observations	1,413	1,466	1,466	1,466	1,466	1,466
R^2	0.619	0.817	0.811	0.732	0.831	0.768

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The outcome variables are manufacturing employment, total employment (baseline), total population, (non-log) employment-to-population ratio, non-manufacturing employment (L_{ct}^{SER}), and non-working population (L_{ct}^{DEP}) in columns 1-6, respectively. *p<0.1; **p<0.05; ***p<0.01.

Turning to columns 3 and 4, we discuss the relationship with the estimates obtained in the literature and the mechanism. In column 4, we do not find a statistically significant effect on the employment-population ratio. This can be understood from column 3 (and column 2): The population positively responded to robot exposure. Thus, both employment (column 2) and population (column3) receive positive effects, cancelling the impacts to the ratio by increasing both the numerator and denominator. This finding, however, is in contrast to part of the literature. In fact, using their similar-country shift-share IV strategy, Acemoglu and Restrepo (2017) found -0.388 with the standard error of 0.091 for column (4).[12]

Note that our findings in columns 2-4 may be regarded in consistent with the findings in "local multiplier" literature (Moretti, 2010): An increase in demand for a group of people positively spillovers to other group of people in a locality. Indeed, Moretti (2010) discusses the positive spillover of local manufacturing labor demand on service labor demand, such as local restaurants, and bars worker demands for manufacturing workers there. In contrast, our results indicate that the increase in labor demand in general even has an implication for increasing the local population in general, such as housekeepers for general employees.

To further compare our results with the literature and highlight the relevance of our price-based instruments, we also conduct an analysis based on a similar country. We choose Germany as the country of comparison and take the robot adoption trends from the IFR. As Table I.1 shows, the regression results are imprecise. This is not surprising, given the discussion in Section 2: Even compared with a close innovator of robots, Germany, the trend of robot adoptions in Japan has been very unique. Therefore, the conventional identification method in the literature is not applicable in our context. In contrast, our cost-based identification method is robust to contexts.

Finally, columns 5 and 6 show suggestive evidence on spillover effects. Column 5 takes non-manufacturing employment (labeled as "L^{SER}" as abbreviation for service), defined as total employment (cf. column 2) net of manufacturing employment (cf. column 1) as the outcome variable. Column 6 takes the non-working population (labeled as "P^{DEP}" as abbreviation for dependent), defined as the total population (cf. column 4) net of employed population (cf. column 2), as the outcome variable. These results show insignificant effects on non-manufacturing employment or non-employed population and suggest the following. First, we find little evidence of spillover effects to demand for these groups of people. Second, given that there are negative effects to demand for these groups, there is no evidence about reallocations within CZ across sectors. If

[12]See their Table 7, panel A, column 3. They also report the effect on changes in log employment in the Appendix. The point coefficient is -1.656 with a standard error of 0.411.

this was the case, the reallocation happened across CZs.[13]

So far, our main outcome variables have been regarding headcounts of people, such as employment and population. Given that robot technology is characterized by the time-saving nature of routine tasks (e.g., spot welding), it is possible that the impacts on hours worked may be different from the headcount impacts. Furthermore, such hour effects may have implications for hourly wages, which reflects the hourly productivity of workers. We explore these dimensions in Table 10. In column 1, we show the baseline result (cf. Table 9, column 2), which takes log employee headcounts as the outcome variable. For columns 2 and 3, we take per-capita hours worked and hourly wages as the outcome variables, respectively. Column 2 reveals that the average hours worked decreased dramatically due to the adoption of robots. In contrast, and partly as a result of hour-reducing effects, column 3 shows that hourly wages increased due to robot adoption. These findings suggest that robots enable work-sharing or time-saving technological changes, which enhance the hour-unit productivity of employed workers.

Finally, we conduct the CZ-level analysis by subgroup of workers. We overview the takeaways, as follows. Robot-exposed regions increased the employment of both educated (more than four-year university) and non-educated (high-school graduates) workers, increased female workers more than male workers, and increased middle-aged workers (workers aged between 35 and 49) more than the other age groups of workers. Regarding wages and hours, robot-exposed regions increased wages and decreased hours worked of workers with all educational backgrounds. The impacts of robot adoption were homogeneous as found by Acemoglu and Restrepo (2017) but in the opposite direction; in Japan in 1978-2017, robot adoption improved working conditions of workers across the board while it was opposite in the US in 1992-2007. Detailed regression results are reported in Section I.

6 Discussion

In this section, we discuss the efficiency adjustment. This is motivated to address another interpretation of our primary findings in Sections 4 and 5. Note that our sample covers a very long period, 1978-2017. Therefore, it is likely that the unit efficiency of robots grew over that period, as we discussed in Section 2. This may cause time series-variation based bias, as follows. Suppose the unit efficiency in later robots is higher than in earlier ones. This may have further set of tasks

[13]Since the first and second implications contrast their predicted sign of the effect (positive spillover effects and negative reallocation effects), we acknowledge the possibility that both effects worked but canceled each other out.

Table 10: CZ-level, 2SLS

	Dependent variable:		
	$\Delta\ln(L_{ct})$	$\Delta\ln(h_{ct})$	$\Delta\ln(w_{ct})$
	(1)	(2)	(3)
ΔR_{ct}	2.213^{**}	-1.963^{***}	4.117^{***}
	(1.000)	(0.585)	(0.913)
CZ FE	✓	✓	✓
Year FE	✓	✓	✓
Demographic Controls	✓	✓	✓
Globalization Controls	✓	✓	✓
Technology Controls	✓	✓	✓
Variable	# Workers	Average Hours	Average Hourly Wage
Observations	1,453	1,453	1,453
R^2	0.818	0.827	0.948

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The outcome variables are total employment (baseline), average weekly hours, and average hourly wages in columns 1-3, respectively. *p<0.1; **p<0.05; ***p<0.01.

displaced by robots from labor due to relative cost efficiency (Acemoglu and Restrepo, 2018c). In the later years, observed robot adoption units are smaller (even when efficiency-unit robot units grew), while at the same time, labor is displaced and employed less. This generates a *spurious* positive correlation between robots and employment that is not caused by gross complements, but by (gross) substitution and unit-efficiency growth.

To alleviate this concern, we estimate robot unit efficiency. Following and extending Khandelwal et al. (2013), we consider the following CES aggregation function for robots:

$$R_{it} = \left(\sum_a \widetilde{\iota_{ai}} \left(\lambda_{ait} R_{ait}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where R_{ait} is the robot stock of application a in industry i in year t, $\widetilde{\iota_{ai}}$ is the expenditure share parameter reflecting the applicability of application a in each industry i, λ_{ait} is unobserved quality, and σ>0 is the elasticity of demand substitution. The cost-minimizing demand for robot application a is then solved as

$$R_{ait} = (\widetilde{\iota_{ai}})^{\sigma} \lambda_{ait}^{\sigma-1} r_{at}^{-\sigma} r_{it}^{\sigma-1} R_{it},$$

where r_{at} is the robot price of application a in year t, and $r_{it} = \prod_a (r_{at})^{\widetilde{\iota_{ai}}}$. Taking logs, we obtain

$$\ln R_{ait} = -\sigma \ln r_{at} + \alpha_{ai} + \alpha_{it} + \eta_{ait},$$

where $\alpha_{ai} = \sigma \ln(\widetilde{\iota_{ai}})$, $\alpha_{it} = \ln\left(C_{it}^{\sigma-1} R_{it}\right)$ and $\eta_{ait} = (\sigma - 1)\ln(\lambda_{ait})$. Regressing $\ln R_{ait}$ on $\ln r_{at}$ and fixed effects α_{ai} and α_{it} gives $\widehat{\sigma}$ and the residual $\widehat{\eta}_{ait}$. Thus, we obtain the efficiency estimate $\widehat{\lambda_{ait}} = \exp(\widehat{\eta}_{ait}/(\widehat{\sigma} - 1))$.

Several discussions follow in terms of our model choice. First, we model quality as the application-augmenting shocks. We view this is as a natural interpretation in the case of robotics, because robot quality may be conceptualized by the speed of task performance relative to that of old types of robots or human hands. Second, our extended specification (6) nests the Cobb-Douglas case. Namely, with $\sigma \to 1$ and $\lambda_{ait} = 1$, we revert to our initial specification $R_{it} = \prod_a r_{ait}^{\widetilde{\iota_{ai}}}$, with $\widetilde{\iota_{ai}} = \iota_{ai}$. Third, relative to Khandelwal et al. (2013), we have an additional expenditure share term ι_{ai}, because we have a clear pattern of applicability for each industry. Finally, compared to the IFR's quality adjustment, our treatment of the efficiency estimation is more systematic and based on a standard demand theory. Recall that Graetz and Michaels (2018) also reports quality-adjusted prices. In their data source, quality adjustment is not backed up based on a demand function. Instead, the method is called a "production-cost mark-up" method, which is "subjective but with a certain amount of knowledge through experience" (IFR, 2006).

With the unit efficiency estimate, we augment the application-level robot quantity measurement from R_{ait} to $\widehat{\lambda_{at}} R_{ait}$ and construct the industrial robot stocks. Using such a measure of efficiency-augmented robot stocks, we rerun the industry-level regression (4). Table 11 reports the 2SLS result. The column structures remain the same as in Table 4. The first-stage IV F-statistic is somewhat weaker, especially in the specification without control variables.[14] The estimated coefficients are

[14]The first-stage regression results are reported in Section H.2. The reason for the weaker first stage in column 1 of Table 11 than column 1 of Table 4 is mechanical. The quality adjustment factor λ_{ait} is estimated by the residual of the regression of lnR_{ait} on $\ln r_{at}$ and fixed effects, α_{ai} and α_{it}. By this construction, the adjustment factor $\widehat{\ln \lambda_{ait}}$ is orthogonal to the application price $\ln r_{at}$. The price aggregate, which is the weighted average of $\ln r_{at}$, is thus orthogonal to the quality adjustment factor. Therefore, using the log of the quality-adjusted robot as the dependent

Table 11: Industry-level, 2SLS, Efficiency-adjusted Quantity

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(\widetilde{R}_{it})$	2.587	0.297***	0.219*	0.378**
	(2.739)	(0.099)	(0.121)	(0.183)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	0.855	14.131	8.195	5.860
Observations	104	104	104	104
R^2	−0.440	0.981	0.986	0.980

*p<0.1; **p<0.05; ***p<0.01

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log efficiency-adjusted robot stock measure and log employment across industries and years, with the instrument of log efficiency-adjusted robot cost measure. The employment measure includes the employment of robot-producing plants. Efficiency adjustment is performed by the method described in the main text. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

similar with and without quality adjustments of robots after conditioning on the control variables. In our preferred specification of column 4, we still find a significant positive effect of robot adoption on employment. Therefore, we conclude that our results are robust to the efficiency adjustment.

variable in the first stage is adding a factor orthogonal to the instrument variable to the dependent variable and reduces the first-stage F-Statistics. Conditioning on the control variables mitigates this mechanical relationship.

7 Conclusion

How does automation affect labor demand? We study this question by focusing on a context with a long tradition in robot adoption, Japan 1978-2017. We develop a cost-based identification method for studying the impact of robots on employment, given the difficulty of applying a conventional identification method, and a newly digitized data of robot adoption. The data are characterized by three novelties: (i) a long panel covering 1978-2017 that suits the study of our context, (ii) adoption units and total values that allow systematic calculation of robot unit costs, and (iii) disaggregation of these by robot applications. Armed with these unique features, our identification hinges on industry-level application share variations during the initial period of robot adoption. We conduct a industry-level analysis and a region-level analysis. The industry-level analysis suggests that robots and labor are gross complements. Our preferred estimates mean that a one-percent decrease in robot price increased labor demand by 0.44 percent, which implies that robots and labor are gross complements. This thus implies that a one percent increase in robot adoption made by the robot price reduction increased employment by 0.28 percent. We show that these results are robust to other definitions of price measures and dropping major robot purchasers, indicating the validity of our cost-based IV. The CZ-level shift-share regressions confirm this, which shows a clear distinction from the findings in the literature and suggest across-region reallocations and time-saving technical changes.

We suggest a potential reason why we find a different result than the one in the literature: the differences in scale effects. To see this, note that our context might have been unique in strong robot demands. This may be seen, for example, in a biography of a robot innovator, Kawasaki Heavy Industry, as the incentive for producing robots: "Japan's rapid economic growth increased demands for automobiles and factories faced serious labor shortages" (KHI, 2018). If the demand for the robot-intensive industry is strong due to either domestic or international demands, then robot adoption may invoke the scale effect to the industry, mitigating the displacement effect found in, among others, Acemoglu and Restrepo (2017). We leave testing this hypothesis or other potential explanations as a future work.

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Appendix

A Other Application Examples

Out of the application list Table 1, we list some of example tasks for each category. Handling operations/Machine tending (or Handling) includes material handling, picking, and packaging. Recent developments enable food industries to package foods automatically by robots. Welding and soldering (Welding) includes several welding technologies, such as spot welding discussed in the main text, and arc welding. Dispensing includes painting and plating. Processing includes loading and unloading, polishing, and deburring. Assembling and disassembling (Assembling) includes surface mounting, as discussed in Section 2.3, and bonding. Finally, Others include robots used for education and research and to clean rooms.

B Net Elasticity of Factor Prices

The purpose of this section is to show that the compensated (net) elasticity of factor price is always negative. This implies that the net elasticity concepts cannot explain the empirical findings of positive elasticities in Sections 4 and 5. The net elasticity with respect to robot prices must be negative out of the standard profit-maximizing factor demand. To simplify the notations, we drop all subscripts in this section. The Allen-Uzawa Elasticity of Substitution (AUES) is

$$\sigma^A_{CW} \equiv \frac{D_{CW} D}{D_C D_W}.$$

We estimated the cross-price elasticity

$$\frac{\partial \ln L}{\partial \ln C} = \frac{C}{L}\frac{\partial L}{\partial C} = \frac{C}{D_W} D_{CW},$$

where the last equality holds by Shephard's lemma. We have

$$C = \frac{CR}{R} = \frac{D}{R}\frac{CR}{D} = \frac{D}{R}\theta_R. \tag{10}$$

Thus we have, with Shephard's lemma $R = D_C$,

$$\frac{\partial \ln L}{\partial \ln C} = \frac{1}{D_W} D_{CW} \frac{D}{R} \theta_R = \sigma_{CW} \theta_R. \tag{11}$$

In contrast, we have the own-price elasticity

$$\frac{\partial \ln R}{\partial \ln C} = \frac{C}{D_C} D_{CC} = \sigma_{CC} \theta_R$$

where the last equation by (10). By Euler's formula we have

$$\sigma_{CC} = \frac{-\sigma_{CW} \theta_L}{\theta_R}.$$

Thus we have

$$\frac{\partial \ln R}{\partial \ln C} = -\sigma_{CW} \theta_L. \tag{12}$$

Equations (11) and (12) imply

$$\frac{\partial \ln L}{\partial \ln C} = -\frac{\theta_R}{\theta_L} \frac{\partial \ln R}{\partial \ln C}.$$

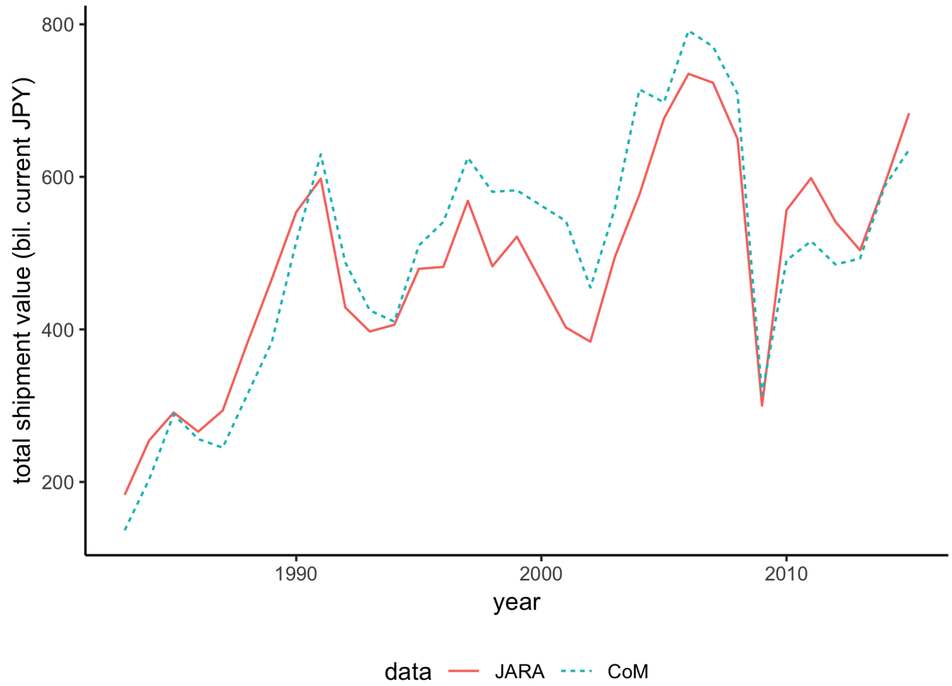
Thus, the sign must be flipped.

C Detail in the JARA

C.1 Coverage of the JARA

JARA data cover most robot producers in Japan. In 1996, 587 establishments were asked to answer the survey, among which 445 answered, for a response rate of 76 percent. To show the coverage trend of the JARA data in Japan's robot production, we compare the aggregate trend with government-based statistics. In particular, we employ Japan's Census of Manufacture (CoM) and Economic Census for Business Activity (ECBA), the latter of which was conducted jointly by METI and MIC. From these data sources, we take the aggregated total sales of industrial robots each year. The construction of aggregate statistics by CoM and ECBA is discussed in detail in Appendix G.1. Figure C.1 shows the comparison of total shipment values taken from the JARA and CoM/ECBA data. As one can see, overall, the two trends are parallel. In some years, the JARA data even surpass the total shipment values observed in the CoM/ECBA data. Therefore, the JARA covers most of the robot transactions measured in government statistics.

Figure C.1: Comparison of JARA and Census of Manufacture



Note: Authors's calculation based on JARA and CoM/ECBA data. The trend for the JARA is the sum of shipment value of any robot applications to any industries. The trend for the CoM is the sum of shipment value (net of VAT) of all products categorized as industrial robots (available from 1983 to 2016). The CoM was not conducted in 2011 and 2015. Instead, in these years, we employ data from the ECBA.

C.2 JARA Cross Tables

The cross tables we were able to access are as follows. The cross tables by application by buyer industry are available between 1978 and 2017 and are the data source for our primary analysis. The cross tables by types and buyer industry are also available, but only for the years between 1974 and 2000. From 2001 to 2017, cross tables of robot structures and buyer industries are available. This is consistent with the statement of the IFR that since 2004, the robot classifications should only be done in structures.[15] For 1982-1991, we can also access the cross tables by application and types.

In our study, we leverage the heterogeneity in these robot classifications. Robots may be categorized by several dimensions, such as applications, types, and structures. Applications are the classification of robots due to the tasks (applications) that robots are expected to perform by

[15] See `https://www.ifr.org/downloads/press2018/SourcesandMethodsWRIndustrialRobots2018.pdf`. (Accessed on October 23, 2019)

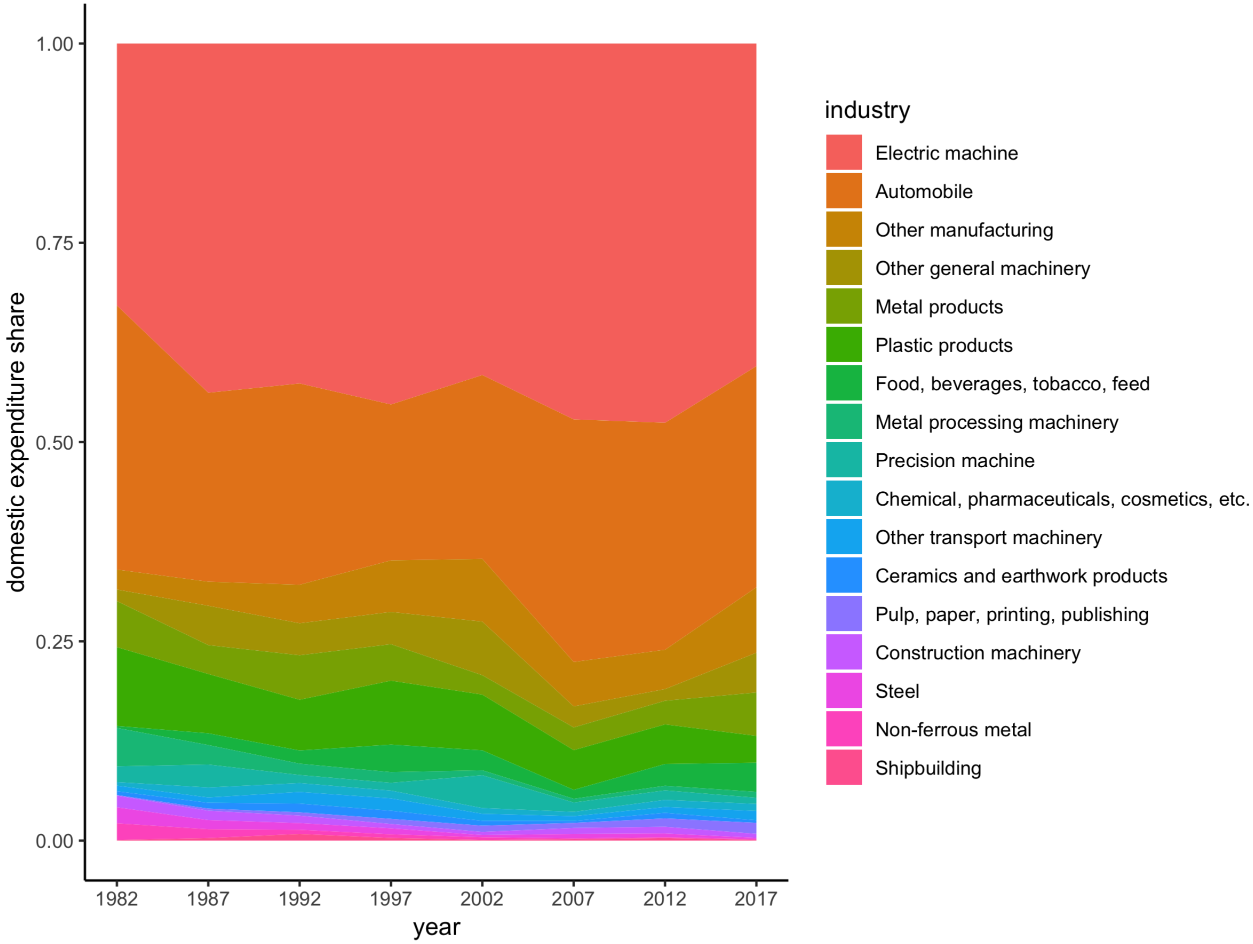
each user. Examples include Welding and soldering (WS) that are intensively needed tasks in the automobile industry, and Assembling and disassembling (AD) that are intensive in the electric machine industry. Types refer to the physical structure and features of robots. For instance, a playback robot is a type of robot that remembers pre-specified moves and plays them back over and over again. Numerical control robots receive the input by programs and move without memory based on the moves performed beforehand. Playback robots are relatively intensively used in automobile industry, while numerical control robots tend to be in electric machine industry.

Starting in 2004, the IFR and major robot producers agreed that robots should not be classified according to the above types but instead, by structures that represent the physical feature of robots. In the JARA data, the type classification discontinues in 2000 and the structure classification begins in the following year. The classifications are as follows: articulated robot, SCARA robot, polar coordinate robot, cylindrical robot, cartesian robot, and parallel link robot.

C.3 Further Raw Trends of the JARA

Figure C.2 shows the trend of expenditure shares across industries in Japan taken from the JARA data. The industries are sorted according to their value in 2017. As one can see, the distribution is historically highly skewed to particular industries within manufacturing. In particular, in 2017, the top 10 industries (industries above Chemical, pharmaceuticals, cosmetics, etc. in Figure C.2) constitute more than 97 percent of the domestic expenditure. Furthermore, the electric machine and automobile industries are noticeable significant purchasers. These two industries represent 68.2 percent of the absorption in Japan in 2017.

Figure C.2: Industry Shares



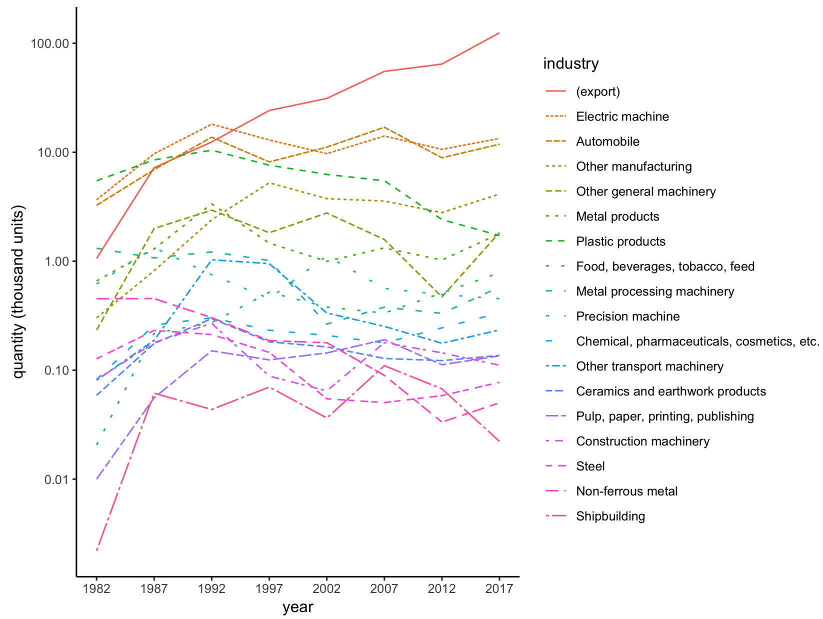
Note: Authors' calculation based on JARA data. Industries are sorted by the total quantity in 2017.

We then show the raw trends of shipment quantity and unit values for each industry, aggregated by all applications for the industry. To calculate unit values, we take the sales value and the corresponding quantity units and divide the former measure by the latter. In addition to the domestic adsorptions, we also show the trend of exports from now on for comparison. Figure C.3 shows the result. The left panel shows the quantity unit of robots, while the right shows the unit values. First, note that our data spans 1978-2017. The coverage of our data allows us to study the early period in which the quantity shipment grew rapidly in Japan. Our data show that the growth did not concentrate in a particular industry, but instead occurred across a large set of industries. As the other data source confirms, since 1990, shipments to domestic industries shrank in general, while the export trends continued to grow at a somewhat slower pace than before. These constant growth shares across domestic industries suggest that the robot penetration to domestic industries is caused not only by demand shocks to a particular set of buyer industries, but by the overall growth of the robot-producing industry.

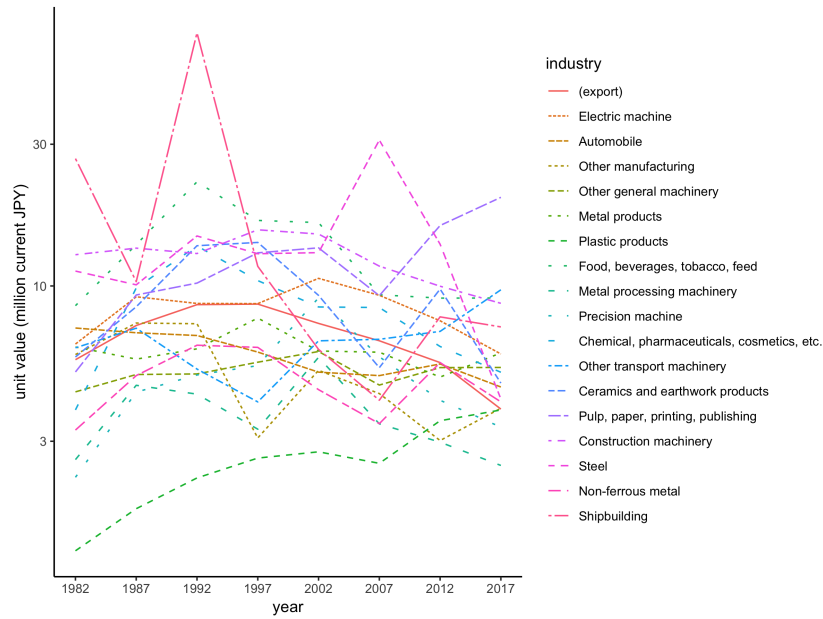
Second, in the right panel, we see that the unit-value trends for each industry are relatively constant or slightly decreasing over time, with some exceptions. The constant or decreasing unit prices would suggest that the robot producers become efficient and offer lower prices as time goes on. Note that these patterns hold for the two large buyers of industrial robots, electric machines, and automobiles.

Figure C.3: Raw Trends by Industry

(a) Quantity Units



(b) Unit Values



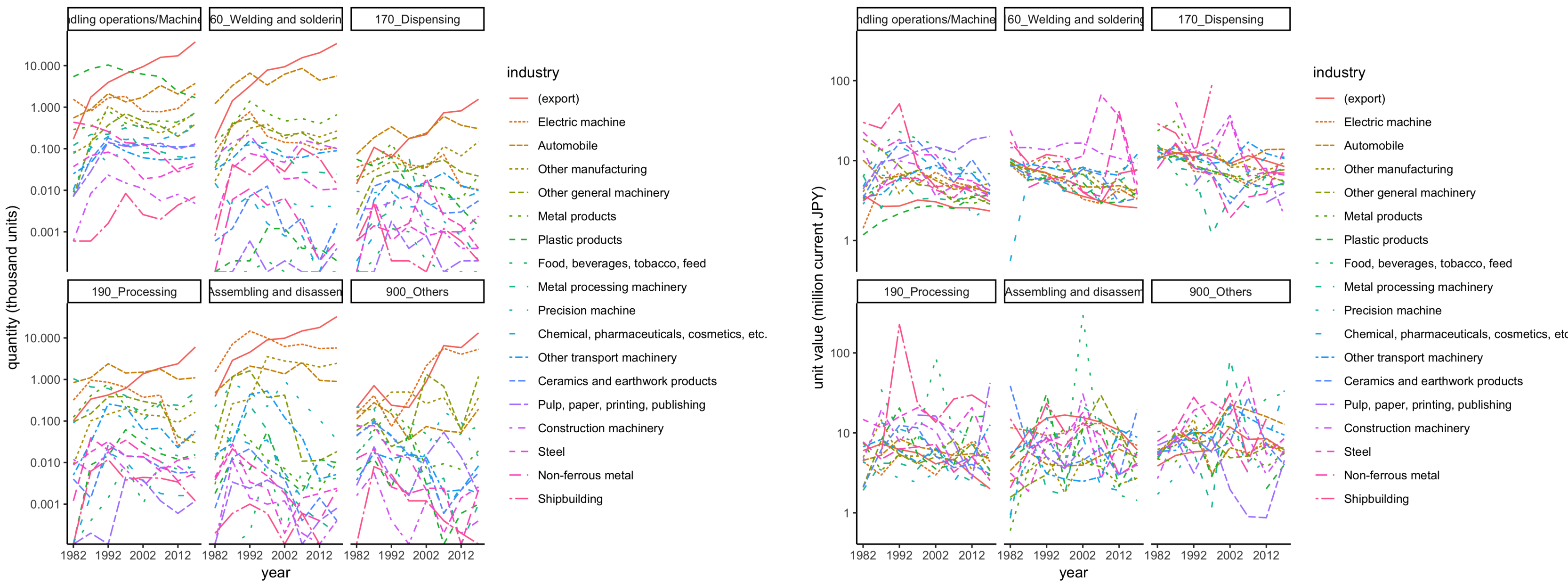
Note: Authors' calculation based on JARA data. Industries are sorted by the total quantity in 2017. Exports are not classified by industries in the survey.

With the JARA data, we are able to show the trends by industry by applications according to Table 1 in Figure C.4. Panel (a) shows the quantity and Panel (b) shows the unit value. From Panel (a), one can see that the shipment quantity increases for broad applications and broad industry during 1980s, while the increasing trend stops after the 1990s, confirming the trend we found in Figure C.3. In contrast, there is significant within-application and across-industry variation. For example, the electric machine industry intensively purchased robots for Assembling and disassembling, while the Automobile industry bought a significant amount of robots for Welding and soldering. This suggests that industries have different tasks for which they demand robots.

Panel (b) of Figure C.4 reveals the following two features. First, it shows relatively small within-application and across-industry variations. This suggests that the robot prices are not driven solely by particular industries, but by the technology for producing robots. Second, there are significant variations in trends across different applications. For example, robots for Welding and soldering show a stable decline in the unit value for a broad set of industries. This suggests that the production technology for Welding-soldering robots grew consistently over the sample period.

Figure C.4: Raw Trends by Industry and Applications

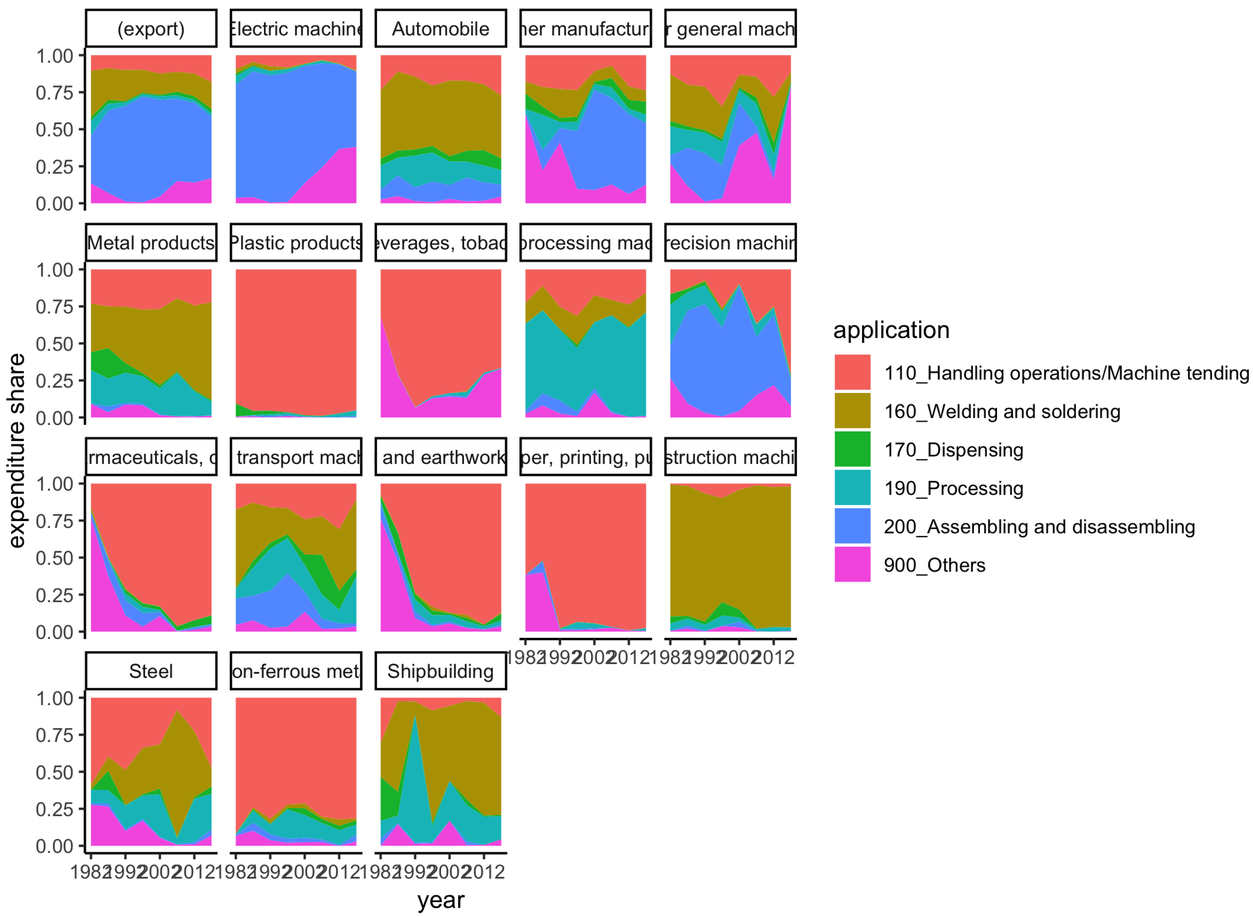
(a) Quantity Units (b) Unit Values



Note: Authors' calculation based on JARA data. Industries are sorted by the total quantity in 2017. Exports are not classified by industries in the survey. The y-axis is log scale and lines reaching the x-axis imply zero quantity in level.

To further highlight the application compositions, we show the expenditure share of applications for each industry in Figure C.5. One may see significant variations across industries. As we have discussed, the Electric machine industry and the Automobile industry intensively buy robots for Assembling and disassembling, and Welding and soldering, respectively. Furthermore, Figure C.5 reveals that the within-industry patterns of expenditure shares are stable with some exceptions in minor industries. This confirms that the expenditure share is driven by the feature of industries.

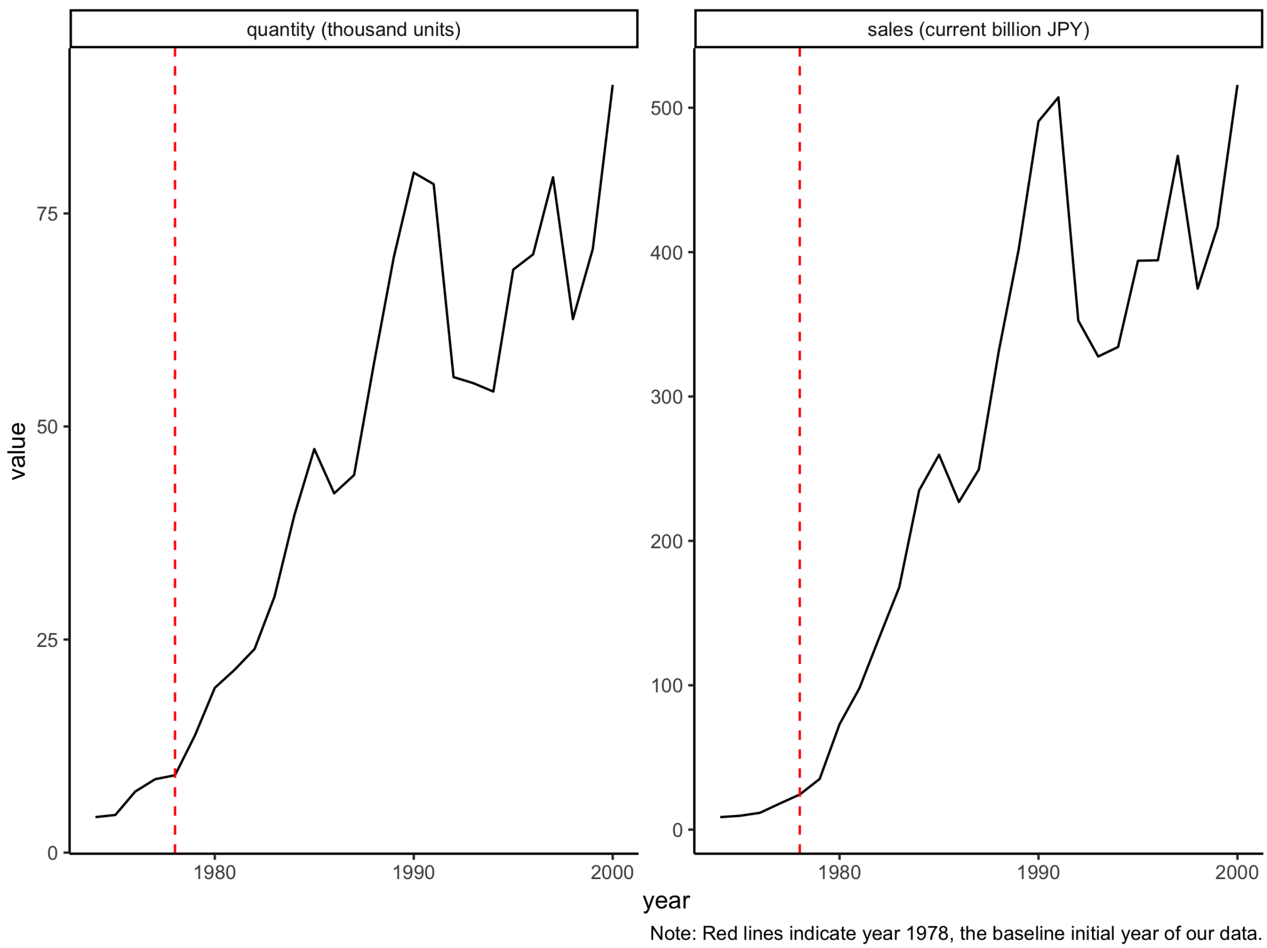
Figure C.5: Raw Trends by Industry and Applications



Note: Industries are ordered by the quantity of shipment as of 2017.

Note: Authors' calculation based on JARA data. Industries are sorted by the total quantity in 2017. Exports are not classified by industries in the survey.

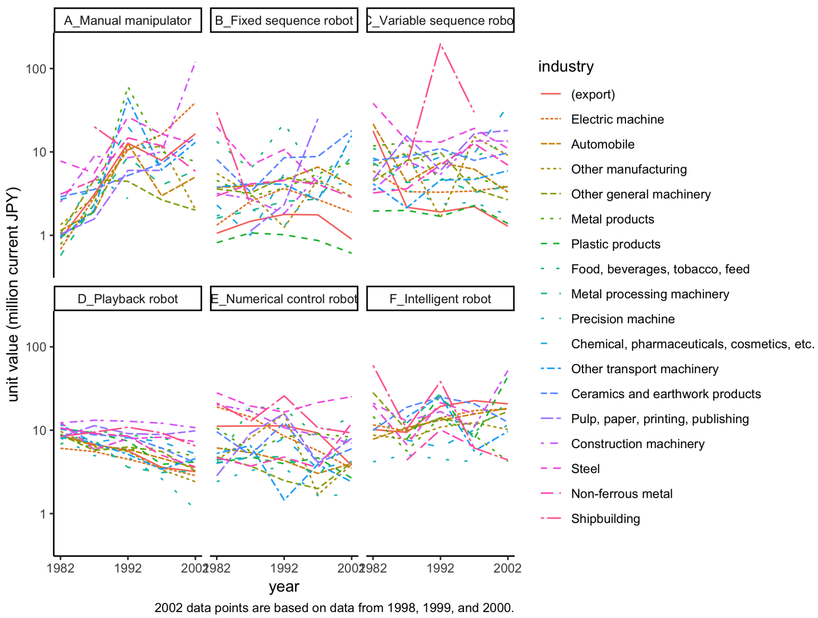
Figure C.6: Robot Trends Before and After 1978



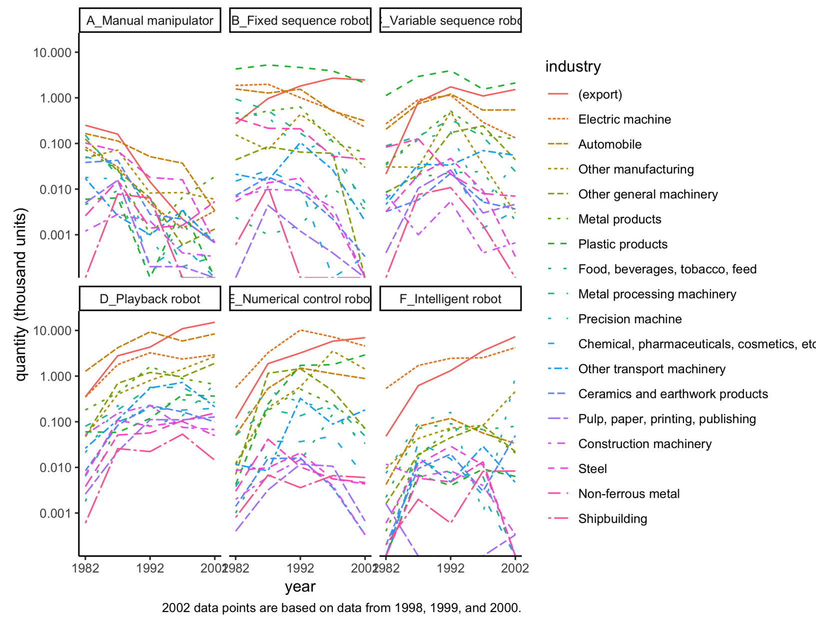
Note: Authors' calculation based on JARA data. The red dashed line indicates 1978, the initial year of our primary analysis. Trends before 1977 are taken by aggregating type-buyer industry across tables.

Figure C.7: Raw Trends by Industry and Types

(a) Quantity Units



(b) Unit Values



Note: Authors' calculation based on JARA data. Industries are sorted by the total quantity in 2017. Exports are not classified by industries in the survey. The y-axis is log scale and lines reaching the x-axis imply zero quantity in level.

Table C.1: Pooled Regression

	Dependent variable:						
	log stock units (thousand)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log unit value	-0.728^{***}	-1.449^{***}	-0.344	0.200	-1.250^{***}	-0.081	-0.230
	(0.126)	(0.253)	(0.426)	(0.301)	(0.232)	(0.318)	(0.266)
Sample	All	110, Handling	160, Welding	170, Dispensing	180, Processing	200, Assembling	900, Others
Industry FE							
Year FE							
Application FE							
Observations	818	144	129	134	138	135	138
R^2	0.039	0.188	0.005	0.003	0.176	0.0005	0.005

Note: *p<0.1; **p<0.05; ***p<0.01
Log unit values are in the unit of current million JPY.

Table C.2: Industry-Fixed Effects

	Dependent variable:						
	log stock units (thousand)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log unit value	-0.370^{***}	-0.210	-0.739^{***}	-0.237	-0.135	-0.105	-0.101
	(0.098)	(0.188)	(0.188)	(0.191)	(0.153)	(0.162)	(0.176)
Sample	All	110, Handling	160, Welding	170, Dispensing	180, Processing	200, Assembling	900, Others
Industry FE	✓	✓	✓	✓	✓	✓	✓
Year FE							
Application FE							
Observations	818	144	129	134	138	135	138
R^2	0.499	0.785	0.893	0.753	0.823	0.813	0.720

Note: *p<0.1; **p<0.05; ***p<0.01
Log unit values are in the unit of current million JPY.

Table C.3: Industry- and Year- Fixed Effects

	Dependent variable:						
	log stock units (thousand)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log unit value	-0.504^{***}	-0.388^{***}	-0.572^{***}	0.010	-0.333^{***}	-0.512^{***}	-0.333^{*}
	(0.097)	(0.139)	(0.140)	(0.198)	(0.123)	(0.138)	(0.183)
Sample	All	110, Handling	160, Welding	170, Dispensing	180, Processing	200, Assembling	900, Others
Industry FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Application FE							
Observations	818	144	129	134	138	135	138
R^2	0.545	0.912	0.950	0.828	0.903	0.897	0.770

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Log unit values are in the unit of current million JPY.

Table C.4: Industry-Year-Application Fixed Effects

	Dependent variable:
	log stock units (thousand)
log unit value	-0.245^{***}
	(0.086)
Sample	All
Industry FE	✓
Year FE	✓
Application FE	✓
Observations	818
R^2	0.659
Note:	*p<0.1; **p<0.05; ***p<0.01

D Robot Imports in Japan

Japan produces most of its robots domestically (Acemoglu and Restrepo, 2018b, among others). To confirm this, we compare the import (from the rest of the world to Japan) and the domestic sales measures of robots (from Japan to Japan). In particular, we visit Comtrade data, take HS Code 847950 (Industrial Robots for Multiple Uses), and compare the trend with domestic shipment trends from our main data source, the JARA, discussed in detail in the next section. Trade data for the HS code are available only since 1996, while JARA data exist from 1978. Table D.1 shows the result. We also calculate the shipment share by domestic producers. We obtained 97.9 percent to 99.3 percent shares, depending on the year, between 1996 and 2017. Therefore, we interpret that most of robot purchases in Japan have been domestic-sourced. In our paper, we focus only on JARA data, from which we may exploit a rich set of information that is crucial for our analysis, as we will discuss in detail.

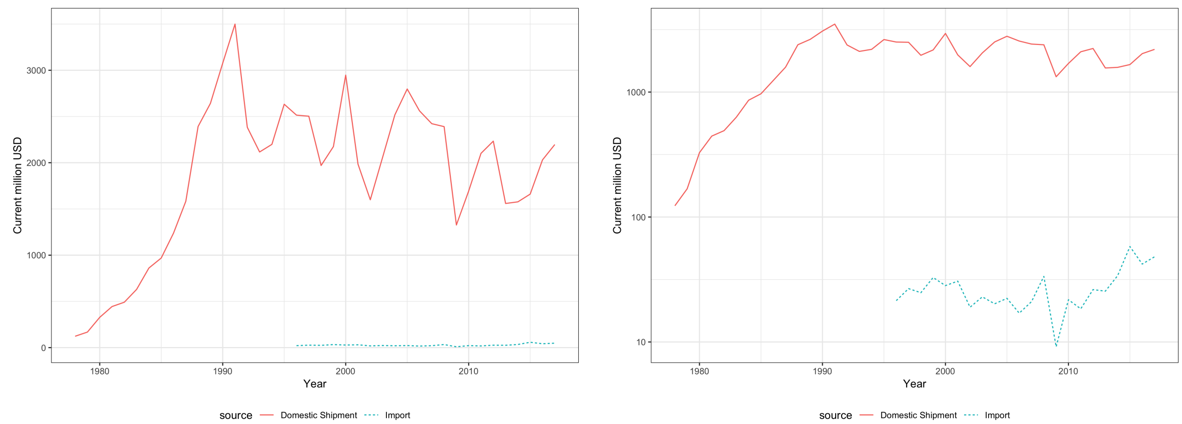
E Calculating Robot Stock

As we briefly discussed in Section 4.6, we assume alternative and flexible assumptions on the robot stock calculation. The first set of assumptions is based on the immediate withdrawal method

Figure D.1: Domestic Shipments and Import of Robots in Japan

(a) Level Scale

(b) Log-10 Scale



Note: Authors' calculation based on Comtrade and JARA data. The Comtrade trends show the total import value (reported by importer, Japan) of HS Code 847950 (Industrial Robots for Multiple Uses). The JARA trends show the total shipment from the domestic producers, aggregated by all applications and industries. The Comtrade data is denominated by current USD, while the JARA data are denominated by current JPY. To convert the monetary values, we use the FRED data, the annual current JPY-USD exchange rate.

(IWM). The IWM assumes the shipped robots are in use immediately after purchase and not in use in a specified length of years. IFR follows this method with the withdrawal period of 12 years. To better compare the results with the literature, our primary specification follows the stock definition based on IWM with 12 years. The 12-year assumption is debatable, however, as IFR admits: "This assumption was investigated in an UNECE/IFR pilot study, carried out in 2000 among some major robot companies ... This investigation suggested that an assumption of 12 years of average life span might be too conservative and that the average life/ service life was closer to 15 years." (IFR, 2018). German and US tax authorities, in contrast, suggest the standard depreciation schedules be shorter. Given these discussions, we consider three alternatives: 10, 12 (baseline), and 15 years of depreciations.

The second set of assumptions is based on the perpetual inventory method (PIM). The PIM is a standard method used when calculating capital stocks, adopted in National Accounts (OECD, 2009). A key parameter in the method is depreciation rates. There is no systematic empirical study on the value. As one measure, following Artuc et al. (2020), we use an annual 10 percent depreciation rate. As a more context-based estimate, we employ the result from Nomura and Momose (2008). Based on disposal asset data in Japan (Survey on Capital Expenditures and Disposables), Nomura

Table E.1: Industry-level, 2SLS, Different Stock Measurement

	Dependent variable:				
	$\ln(L_{it})$				
	(1)	(2)	(3)	(4)	(5)
$\ln(R_{it})$	0.255***	0.283**	0.322**	0.349***	0.284***
	(0.096)	(0.108)	(0.123)	(0.114)	(0.093)
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓	✓
Stock Measurement	10 Years	12 Years	15 Years	$\delta = 0.1$	$\delta = 0.18$
Observations	104	104	104	104	104
R^2	0.987	0.988	0.987	0.988	0.988

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The outcome variables are total employment (baseline), under age-35 employment, age 35-50 employment, and over age-50 employment in columns 1-4, respectively.*p<0.1; **p<0.05; ***p<0.01.

and Momose (2008) estimated the depreciation rate of machinery, with the category of machinery and equipment, as 18 percent. Admitting that machinery is a broader category than industrial robots, we employ 18 percent as a larger alternative than 10 percent.

Table E.1 shows the baseline regression result of specification (4) with these alternative stock measures. Column 2 shows the main regression result based on a 12-year IWM. Columns 1 and 3 show the different-year based IWM, 10 years and 15 years, respectively. Columns 4 and 5 show the results with a PIM with depreciation rates of 10 percent and 18 percent, respectively. The regression coefficients are robust to alternative choices of stock measurement of robots.

F Detail in ESS

Employment status is based on the usual employment status (the "usual method"). Any answer of mostly worked, worked besides doing housework, worked besides attending school, and worked besides doing housework and attending school are recorded as employed. For the education attainment, we define four values that are consistent across surveys: less than high-school diploma (LHS), high-school diploma (HS), technical/vocational school diploma (TVS), four-year college diploma or more (FC). For age, we define the five-year bins from age 15 up to age 79 and aggregate the age groups over 80. The survey records the annual earnings, annual days worked, and weekly hours worked in categories. Industry and occupations are encoded according to the Japan Standard Industry Classifications (JSIC) and the Japan Standard Occupation Classifications (JSOC). We convert these categorical variables into continuous variables using the mid-point of the range. Taking the 2007 survey as an example, the mean annual earnings is 3,170,263 current JPY (27,330 current USD), and the mean hours worked is 1,516 hours.

Another set of representative labor statistics is from the Basic Survey of Wage Structure that is based on the random sampling of payroll records for June. For the purpose of comparison, we report the statistics of 2007. The mean of the estimated annual salary based on the June salary and bonus payment of the previous year is 3,858,233 yen, and the mean of the estimated annual hours worked is 1,869 hours.

G Details in Other Data

G.1 Census of Manufacture

The Census of Manufacture (CoM) annually surveys manufacturing establishments in Japan.[16] The CoM asks each establishment for its product-level shipment values. The product code for industrial robots used in CoM exists since 1977. We take the CoM data since 1983 to 2016. The survey was not conducted in 2011 and 2015, because a substituting government survey, the Economic Census of Business Activity (ECBA), was conducted. We also take ECBA data to construct the complete observations of Japan's establishments that shipped robots in any years between 1983 and 2016.

[16]The survey was conducted for all establishments in years with last digit 0, 3, 5, or 8 until the Economic Census of Business Activity (ECBA) started in 2011. In other years and after 2011, all establishments with the number of employees more than three are surveyed.

The CoM and the ECBA treat the VAT in the following way. For CoM, before 2014, respondents were forced to report the shipment value gross of VAT. Since 2016, they have been allowed to choose to gross or net VAT. For the ECBA, both surveys allowed respondents to select. For consistency, we net out the VAT from all data by the legislative VAT rate from the total sales value. The VAT rate is 0 before 1988, 0.03 between 1989 and 1996, 0.05 between 1997 and 2013, and 0.08 since 2014 and onward.

The primary purpose of using the CoM and the ECBA is to take robot-producers' employment. For this purpose, we follow the following steps. First, we calculate each establishment's intensity of robot production by taking the share of robot sales among total sales. To take robot sales, we aggregate shipment values and processing fees of all products under the 1976 Japan Standard Industrial Code (JSIC) of 3498, 1984 and 1993 JSIC of 2998, 2002 JSIC of 2698 ("Industrial Robot Manufacturing," all above), and 2007 and 2013 JSIC of 2694 ("Robot Manufacturing"). Second, assuming a proportional allocation of workers for dollar sales, we multiply total workers by robot production intensity for each establishment. These steps generate robot-producing workers for each establishment, aggregating up to industry-level robot-producing workers.

Table G.1 shows the result of the specification (6) with employment, net of robot-producing workers as an outcome variable. The column structure is the same as that of our main result Table 3. One should note the very close estimates to the ones in Table 3. This solely comes from the fact that the number of robot-producing workers is very small relative to the size of the Japanese manufacturing industry. In fact, the share of robot-producing workers in manufacturing is between 0.001 and 0.004 percent throughout the sample period. Therefore, as far as the directly robot-producing workers are concerned, the reinstatement effect of automation is quite small (Acemoglu and Restrepo, 2018a).

G.2 Basic Survey on Overseas Business Activities

Basic Survey on Overseas Business Activities (BSOBA) is a firm-level census of Japanese multinational enterprises (MNEs) and their foreign subsidiaries. We take offshoring intensity measures by aggregating operating revenues in foreign subsidiaries. We take subsidiaries' industry codes when allocating revenues to each industry.

Table G.1: Industry-level, Reduced Form, net of Robot Producing Workers

	Dependent variable:			
	$\ln(L_{it}^{NRP})$			
	(1)	(2)	(3)	(4)
$\ln(r_{it}^{Z})$	-0.853^{***}	-0.466^{***}	-0.274^{*}	-0.437^{**}
	(0.130)	(0.144)	(0.151)	(0.171)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	9.1	11.047	10.912	16.703
Observations	104	104	104	104
R^2	0.975	0.984	0.985	0.987

Notes: Authors' calculation based on JARA, ESS, CoM, SOBA and JIP data. The table presents estimates of the relationship between log robot cost measure and log robot stock measure across industries and years. The employment measure excludes the employment of robot-producing plants. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

G.3 Japan Industrial Productivity Database

Japan Industrial Productivity (JIP) database is a long-run industrial aggregate of several measures starting in 1970. Among them, we use import and intangible capital. The intangible capital measure is composed of following items: ICT assets (ordered and packaged software, own-developed software), innovation assets (R and D expenditures, mineral exploration, copyright and trademark right, other product/design/research development), and competition assets (brand capital, firm-specific human capital, expenditure for restructuring). Basic concepts of these variables follow National Accounts. Detailed discussion is provided in Fukao et al. (2008).

H Further Industry-level Results

H.1 Industry-specific Prices

In this section, we assume that the prices at which each industry purchases robots may differ. In particular, we assume that the robot price of application a in industry i and year t is given by

$$r_{ait} = \frac{v^A_{ait}}{R_{ait}}, \tag{13}$$

where v^A_{ait} is purchase value of application a in industry i and year t. Armed with these variables, in Table H.1, we report the regression results of the specification (4) based on the price index (13). The results are not robust across control variables. In particular, in our preferred specification of column 4, we find a positive but insignificant coefficient estimate.

H.2 First Stage for Efficiency-adjusted Regressions

I Further CZ-level Analysis

I.1 Similar Country SSIV Result

Table I.1 shows the results of regression (9) with the standard geographic SSIV. Among the three specifications (log changes in total employment in column 1, log changes in total population in column 2, and changes in employment-to-population ratio in column 3), the point estimates show signs consistent with those of our main results in Table 9. They are not precise enough, however, to conclude the positive impacts of robots.

I.2 Heterogeneous Impacts

Table H.1: Industry-level, 2SLS, industry-specific prices

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(R_{it})$	0.429***	0.199***	0.103	0.139
	(0.079)	(0.061)	(0.101)	(0.101)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	27.262	17.462	12.754	15.404
Observations	104	104	104	104
R^2	0.968	0.987	0.987	0.988

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure, based on equation (13). The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

Table H.2: Industry-level, First Stage, Efficiency-adjusted Quantity

	Dependent variable:			
	$\ln(\widetilde{R}_{it})$			
	(1)	(2)	(3)	(4)
$\ln(r_{it}^{Z})$	-0.325	-1.564^{***}	-1.244^{***}	-1.156^{**}
	(0.352)	(0.416)	(0.435)	(0.477)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	0.855	14.131	8.195	5.860
Observations	104	104	104	104
R^2	0.949	0.969	0.973	0.977

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. The standard errors are shown in the parenthesis. Columns 1 shows the result without other control variables. Column 2 includes the demography controls. Demography controls include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. Column 3 includes the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. *p<0.1; **p<0.05; ***p<0.01.

Table I.1: Regressions with Exposure to Robots IV

	Dependent variable:		
	$\Delta \ln(L)$	$\Delta \ln(P)$	$\Delta(L/P)$
	(1)	(2)	(3)
ΔR	1.661	0.835	0.472
	(1.479)	(1.287)	(0.386)
Controls	✓	✓	✓
CZ and year FEs	✓	✓	✓
Observations	906	906	906
R^2	0.423	0.358	0.587

Notes: Authors' calculation based on IFR, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. The dependent variable is instrumented by the shift-share measure whose shift is taken from German robot adoption trends and share is taken by the baseyear industrial employment share in each CZ. As outcome variables, column 1 takes log total employment, column 2 takes log total population, and column 3 takes employment-to-population ratio. All regressions are weighted by base-year populations in each CZ. Control variables include demographic, industry, trade and capital controls in the base year. Demographic variables consists of CZ's female share and elderly (age 65 and above) share. Industry variables are CZ's manufacturing and service employment shares. Trade variable includes the import exposure from China as in Autor, Dorn, Hanson (2013). Capital control is made from the information-technology capital in each industry from JIP database. *p<0.1; **p<0.05; ***p<0.01.

Table I.2: CZ-level, 2SLS. Results by Education Groups

	Dependent variable:		
	$\Delta\ln(L_{ct})$	$\Delta\ln(L_{ct}^{HS})$	$\Delta\ln(L_{ct}^{CG})$
	(1)	(2)	(3)
ΔR_{ct}	2.203**	2.426**	3.320**
	(1.017)	(1.200)	(1.616)
CZ FE	✓	✓	✓
Year FE	✓	✓	✓
Demographic Controls	✓	✓	✓
Globalization Controls	✓	✓	✓
Technology Controls	✓	✓	✓
Group	All	High School Grad.	4-year Univ. Grad.
Observations	1,466	1,466	1,439
R^2	0.817	0.841	0.759

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The outcome variables are total employment (baseline), high-school graduate employment, and 4-year university graduate-or-more employment in columns 1-3, respectively. *p<0.1; **p<0.05; ***p<0.01.

Table I.3: CZ-level, 2SLS. Results by Sex Groups

	Dependent variable:		
	$\Delta \ln(L_{ct})$	$\Delta \ln(L_{ct}^{Female})$	$\Delta \ln(L_{ct}^{Male})$
	(1)	(2)	(3)
ΔR_{ct}	2.203**	3.112***	1.816*
	(1.017)	(1.122)	(1.028)
CZ FE	✓	✓	✓
Year FE	✓	✓	✓
Demographic Controls	✓	✓	✓
Globalization Controls	✓	✓	✓
Technology Controls	✓	✓	✓
Group	All	Female	Male
Observations	1,466	1,466	1,466
R^2	0.817	0.802	0.802

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The outcome variables are total employment (baseline), female employment, and male employment in columns 1-3, respectively. *p<0.1; **p<0.05; ***p<0.01.

Table I.4: CZ-level, 2SLS. Results by Age Groups

	Dependent variable:			
	$\Delta\ln(L_{ct})$	$\Delta\ln(L_{ct}^{a\leq 34})$	$\Delta\ln(L_{ct}^{35\leq a\leq 49})$	$\Delta\ln(L_{ct}^{50\leq a})$
	(1)	(2)	(3)	(4)
ΔR_{ct}	2.203**	1.463	4.656***	0.499
	(1.017)	(1.428)	(1.467)	(1.209)
CZ FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓
Group	All	Age ≤ 34	35 ≤ Age ≤ 49	50 ≤ Age
Observations	1,466	1,458	1,465	1,466
R^2	0.817	0.818	0.804	0.881

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of outcome variables multiplied by 100. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The outcome variables are total employment (baseline), under age-35 employment, age 35-50 employment, and over age-50 employment in columns 1-4, respectively. *p<0.1; **p<0.05; ***p<0.01.

Table I.5: CZ-level, 2SLS, Wage Effects By Education Level

	Dependent variable:			
	$\Delta \ln(w_{ct}^{MS})$	$\Delta \ln(w_{ct}^{HS})$	$\Delta \ln(w_{ct}^{TC})$	$\Delta \ln(w_{ct}^{4U})$
	(1)	(2)	(3)	(4)
ΔR_{ct}	2.275^{*}	3.595^{***}	4.842^{***}	3.213^{**}
	(1.295)	(0.929)	(1.445)	(1.613)
CZ FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓
Education	Middle School	High School	Technical College	4-year Univ.
Observations	1,402	1,402	1,402	1,402
R^2	0.899	0.951	0.836	0.879

*p<0.1; **p<0.05; ***p<0.01

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of hourly wages multiplied by 100 for different education group of workers. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The first column shows the result for the sample of middle-school graduates, the second for high-school graduates, the third for technical and vocational college graduates, and the fourth for four-year university graduates or more education. *p<0.1; **p<0.05; ***p<0.01.

Table I.6: CZ-level, 2SLS, Hours Effects By Education Level

	Dependent variable:			
	$\Delta \ln(h_{ct}^{MS})$	$\Delta \ln(h_{ct}^{HS})$	$\Delta \ln(h_{ct}^{TC})$	$\Delta \ln(h_{ct}^{4U})$
	(1)	(2)	(3)	(4)
ΔR_{ct}	-2.160^{*}	-2.253^{***}	-3.336^{***}	-0.932
	(1.117)	(0.649)	(1.017)	(0.896)
CZ FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓
Education	Middle School	High School	Technical College	4-year Univ.
Observations	1,402	1,402	1,402	1,402
R^2	0.446	0.780	0.734	0.748

*p<0.1; **p<0.05; ***p<0.01

Notes: Authors' calculation based on JARA, ESS, SOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and log difference of hours worked multiplied by 100 for different education group of workers. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are shown in the parenthesis. The demographic variables include share of high school graduates, share of 4-year university graduates, share of female workers, share of workers under age of 35, and share of workers above age of 50 from ESS. The globalization controls contain the logarithm import values from JIP database and logarithm offshoring value added from SOBA. The technology controls include logarithm stock value measures for ICT capital, innovation capital, and competition capital from the JIP database. The first column shows the result for the sample of middle-school graduates, the second for high-school graduates, the third for technical and vocational college graduates, and the fourth for four-year university graduates or more education. *p<0.1; **p<0.05; ***p<0.01.