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

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Abstract

We study the relationship between industrial robots and employment in Japan based on a unique data set that allows us to calculate the unit price of robots. We combine a standard factor demand theory and the recent task-based approach to derive a simple estimation equation between employment and robot prices. We develop an identification strategy that leverages the heterogeneous applications of robots (e.g., welding or assembling) across industries and heterogeneous price changes across applications. We find that the decline of robot prices increased the number of robots as well as employment, suggesting that robots and labor are gross complements.

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

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

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1 Introduction

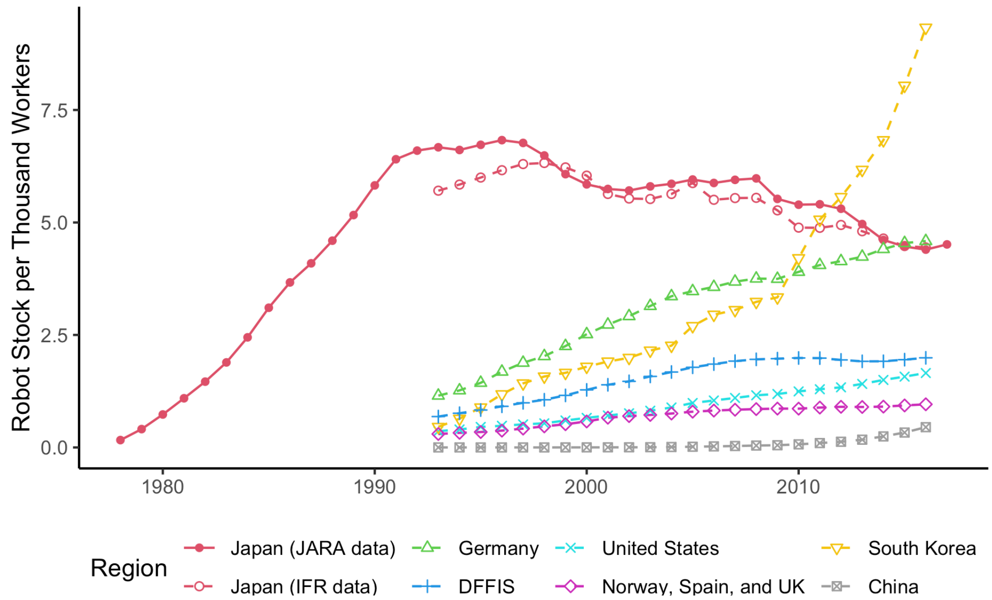
How does automation affect employment? This topic has been attracting the attention of academic researchers, policymakers, and journalists (e.g., Brynjolfsson and McAfee, 2014; Ford, 2015; Frey and Osborne, 2017; OECD, 2019). A particular example of automation is the use of industrial robots (robots hereafter). Previous studies have reported mixed evidence of the impacts of industrial robot adoption on employment.[1] Although the role of the tasks that robots can perform has been featured in a great detail in these studies, their empirical design does not take into account the cost of adopting robots, due to data limitation.

This paper analyzes the effect of robot penetration on employment in Japan using a unique data on robot prices. There are two unique features to consider when studying the Japanese experience with our data. First, Japanese manufacturers have a history of robot adoption that is about 15 years longer than that of any other country, as shown in Figure 1, which illustrates the trend of robot stock units per thousand workers for selected countries. This history enables us to examine the employment impact of robots at the early stage of the technology development. Second, Japanese robot data in our study have a unique variable related to the price of robots, and we can observe the unit price of robots by task-based classification (application). This feature leads us to propose a new identification strategy.

We first characterize the effect of robot prices on the number of robots and employment demanded to guide our empirical design. Specifically, we combine a standard factor demand theory and the recent task-based approach to derive a simple estimation equation between employment and robot prices. This model demonstrates that the adoption of robots are determined either by the decrease in robot prices relative to wages or by the technological frontier that determines the range of tasks feasibly implemented by robots. Specifically, we argue that the decrease in the relative robot price affects the demand for robots and labor through the substitution and scale effects as in a standard factor demand theory. In addition to this, thanks to the feature of the task-based model, the expansion of feasible tasks performed by robots decreases the production cost and generates a substantial scale effect, which could generate a large positive effect of robot price declines on employment. As a result, we obtain an empirical relationship between factor demand changes and the decreased price of robots, which is useful to understand the effect on employment of robotics automation measured by the robot prices.

[1] Specifically, Acemoglu and Restrepo (2020a) reported a negative impact for the US, Dauth et al. (2021) reported a neutral impact for Germany, and Dekle (2020) reported a positive impact for Japan.

Figure 1: Trends of Robot Stock per Thousand Workers, by Region



Note: Authors' calculation based on data from JARA, IFR, OECD, and National Bureau of Statistics of China (NBSC). The figure shows the trends of robot stock units for each group of countries and the robot data sources. The robot data sources are JARA and IFR. The JARA data show the robot units shipped from within Japan to other companies in Japan between 1978 and 2017. To calculate the stock units, we assume a 12-year immediate withdrawal method to match the stock unit trend of Japan observed in the IFR. The IFR data show stock unit trends from 1993 to 2016 for selected countries: the groups of countries reported in Acemoglu and Restrepo (2020a), China, Japan, and South Korea. DFFIS stands for Denmark, Finland, France, Italy, and Sweden, as selected in Acemoglu and Restrepo (2020, AR henceforth). All values are normalized by country-level employment (thousand workers) taken from OECD statistics for all countries except for China, which is taken from NBSC statistics. A detailed description of these data is given in Section 3.

We bring this model to a newly digitized dataset about industrial robots from the Japan Robot Association (JARA). JARA data consist of robot shipments by destination industry and robot application in quantity and sales values, and cover a long period starting from 1978 and ending in 2017. A robot application is the task in the production process that the robot performs, such as welding and parts assembling, and is central to our estimation strategy. Descriptive statistics from these data reveal that there are heterogeneous intensities of robot applications across industries and different price trends by robot applications. Combining these data and a conventional household survey data, we propose a new estimation strategy as follows.

We estimate the effect of the robot price decline on the robot adoption and employment change following the model solution. We construct the industrial robot price measure based on the descriptive statistics found above. Specifically, since industries have heterogeneous production processes, they utilize different robot applications with varying intensity. 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 the initial industry-level application shares of robots. The evolution of effective robot prices differs substantially across industries, reflecting the different robot price changes across applications. For example, the transportation machinery industry intensively uses welding robots, and the price of welding robots fell substantially in the sample period. Thus, the effective robot price faced by the transportation machinery industry fell substantially. In contrast, the electronic machine industry uses lots of assembling robots, but its price did not drop as much as that of welding robots. Hence, the electronic machinery industry did not enjoy the fall in effective robot price. We exploit this price variation across industries that originates from the heterogeneous usage of applications as the source of identification. To implement the idea, we construct a Bartik-style industry-year-level robot price index to estimate the impacts of robot price on robot adoption and employment.

In our empirical analysis, 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. Therefore, these findings imply that robots and workers are gross complements. The credibility of our industry-level analysis hinges on the exogeneity of robot prices. This key assumption could be violated when the robot price is affected by robot demand. We address this potential price endogeneity by the following three methods. First, we construct alternative prices based on the leave-one-industry-out price and export price that are less likely to reflect the domestic industry demand. Second, we reconstruct the analysis sample by dropping industries that adopts robots intensively (automobiles and electric machine), because the demand shock to the large adopter may propagate to the robot price. Third, we use the initial application share by industry as an instrumental variable (IV) as suggested by Goldsmith-Pinkham et al. (2020), so that we can completely relax the exogeneity assumption of robot prices by applications. All of these methods show the robustness of our baseline results and so establish the robustness of our baseline results. We then argue that the scale effect induced by robot adoption was substantial and dominated the substitution effect in Japan. Namely, we estimate that the elasticity of industrial real output to our robot price measure is -0.62, and the elasticity of industrial output price to robot price is 0.26. These figures suggest that Japanese manufacturers exploited the benefit of robot adoption to reduce the production cost and the output price to expand output.

Following the recent literature on the effect of robots on employment, we then conduct an local-labor market analysis (e.g., Acemoglu and Restrepo, 2020a, AR hereafter; Dauth et al., 2021). First, we use commuting-zone (CZ) as the unit of analysis to allow for spillover effects across industries. Second we regress the changes in labor market outcomes on the number of robots using the instrumental variable of the shift-share measure of the robot adoption cost across CZs. Our result indicates that one robot unit per 1,000 workers increases employment by 2.2 percent, corroborating the finding that the robots and labor are gross complements at the industry level. This contrasts with the finding by AR, whose corresponding estimate was -1.6 percent. We also find that the across-industry-within-region spillovers are limited, in the sense that the positive employment effect was mostly found in the manufacturing employment, but not the number of people employed in non-manufacturing sector or those who are dependent. This finding also corroborates our interpretation of the empirical results that the positive employment effect of robot emerges because of the balance of the substitution and scale effects, and because the latter dominates the former.

We contribute to the literature by proposing a robot-cost based identification strategy to estimate the causal effect of robot penetration on labor demand. We do so by drawing on the unique features of the Japan Robot Association's statistics, which include the sales value and quantity of shipments at a finely disaggregated level across robot applications. The widely used data set by the International Federation of Robotics (IFR) does not record the sales values at the same level.[2] Our newly digitized data also contribute to the literature by offering the robot price measures by application that can be used to construct an IV for robot penetration outside of Japan, given that Japan is a major exporter of robots in the world market.

Another contribution to the literature is that our study provides additional evidence on the impact of robots on employment from Japan, a country with longest tradition of robot adoption. As we mentioned, the literature has found mixed evidence from different contexts. 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. In contrast, AR analyzed US regional labor markets and concluded that robot penetration into a

[2]For instance, IFR data are used by Acemoglu and Restrepo (2020a), Dauth et al. (2021); Graetz and Michaels (2018); Artuc et al. (2020); Bessen et al. (2019); Koch et al. (2019); Humlum (2019). Among them, Graetz and Michaels (2018) used the robot price taken from a survey of a subset of robot producers and show that the cost reduction was a critical factor behind robot adoption. They did not, however, use the price information in their main regression analysis, because the IFR price index does not have a rich variation that would allow a formal statistical analysis.

local labor market reduces the employment-to-population ratio and the earnings of all workers regardless of skill level. On the other hand, Dauth et al. (2021) 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. A recent study on Japan by Dekle (2020), which was done independently from us, found that robot penetration increased employment.[3] These studies suggest that the empirical results from three large economies are conflicting. Furthermore, the theoretical discussion by Berg et al. (2018) and Caselli and Manning (2019) contend with some of the results found in the empirical literature claiming that technological progress should benefit some workers under fairly general assumptions. Our study brings to the literature new empirical results based on a newly proposed identification strategy, which are consistent with these theoretical predictions.

2 Model

This section develops an equilibrium task-based model of the allocation of industrial robots and workers. By doing so, we explicitly define robotics automation considered throughout the paper and derive the log-linearized factor demand equations with respect to the robotics automation that motivates our estimation strategy.

2.1 Environment

We consider a production economy with T periods indexed by $t = 0, 1, \dots, T$ and I industries indexed by $i = 1, \dots, I$. Production factors are labor and robots, where robots are defined as the combination of robots applied to each application, as detailed in a later section. In this sense, I occasionally say robots are the combination of applications. Households own labor and robots, rents them inelastically to producers, and consume industrial goods. Producers in each industry hire labor and robots, allocate them in a fixed task space $\Omega \equiv [0, 1]$ to produce industrial goods (Acemoglu and Autor, 2011). Without loss of generality, each task $\omega \in \Omega$ is ordered according to the comparative advantage of robots. For example, robots have a comparative advantage in the

[3] Dekle (2020) implemented an industry-level analysis and addressed the endogeneity using two sets of IVs, reflecting the replaceability measures interacted with the growth in computer processing memory and the industry dependence on middle-aged workers interacted with the national growth of the elder population. Thus, his identification strategy is different from ours.

spot welding task compared to the human-resource management task. In this case, the index for spot welding is smaller than that of human-resource management.

All markets are competitive and markets clear in equilibrium. The price of industry-i good is P_{it}, the price of task ω in industry i is $p_{it}(\omega)$, and the spot prices of hiring labor and robots are w_{it} and p_{it}^R, respectively.[4] Note that since robots are the combination of applications, their price p_{it}^R reflects the cost minimizing solution. We will discuss this problem and the measurement of p_{it}^R in a later section.

Households do not save but chooses consumption of each industrial good in each period to maximize the utility function

$$U_t = \left(\sum_i \alpha_{it} C_{it}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1}$$

where C_{it} is the consumption of industry-i output in period t, $\alpha_{it} > 0$ represents the expenditure share and satisfies $\sum_i \alpha_{it} = 1$ for any t, and $\varepsilon \geq 0$ is the output demand elasticity. Household income is given by $I_t = \sum_i (w_{it} L_{it} + r_{it} R_{it})$.

Extending Acemoglu and Restrepo (2020, AR), producers in each industry i produce output with the following production function

$$Y_{it} = \left[\int_{\omega\in\Omega} (y_{it}(\omega))^{\frac{\sigma-1}{\sigma}} d\omega\right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where $y_{it}(\omega)$ is the input amount of the task ω, and $\sigma \geq 0$ is the elasticity of substitution between tasks. Each task ω can be produced by labor or robots as follows:

$$y_{it}(\omega) = a_{i,L}(\omega) l_{it}(\omega) + a_{i,R}(\omega) r_{it}(\omega), \tag{3}$$

where $a_{i,L}(\omega)$ and $a_{i,R}(\omega)$ are the industry-i productivity of performing task ω by labor and robots, respectively. As mentioned above, each task $\omega \in \Omega$ is ordered according to the comparative advantage of robots, so that we have $a_{i,R}(\omega)/a_{i,L}(\omega)$ is a non-increasing function for any i. Following AR, we impose the following assumption:

$$a_{i,R}(\omega) = 0 \text{ if } \omega > \bar{\omega}, \tag{4}$$

[4]We assume that factors are homogeneous so that they are priced at the same rate no matter what tasks they perform. It is routine to relax this assumption to introduce some heterogeneity in labor, such as educational attainment.

where $\bar{\omega} \le 1$ is an exogenous parameter. This assumption means that robots are not applicable at all to the tasks whose indices are large enough. Therefore, we call $\bar{\omega}$ the automation technological threshold. In the following subsection, we will characterize the equilibrium task threshold $\omega^* \le \bar{\omega}$ that determines the task allocation between robots and labor.

Discussion of Underlying Assumptions We do not impose any restrictions on the automation technological threshold $\bar{\omega}$ except for $\bar{\omega} \le 1$. Specifically, past studies (including AR) assumed that the unit cost of using robots is smaller than that of using labor at the equilibrium threshold ω^*. This assumption implies that the technological frontier $\bar{\omega}$ always binds and entails $\omega^* = \bar{\omega}$. In other words, it excludes the situation where the automation technological threshold $\bar{\omega}$ is so large in the unit space [0, 1] that the allocation of robots and labor is determined by their relative cost at margin, but not the technological possibility $\bar{\omega}$. It is routine to show that this assumption is equivalent to assuming that the unit cost of using labor is greater than that of using robots at the task threshold, or formally,

$$\frac{w_{it}}{a_{i,L}(\bar{\omega})} > \frac{p_{it}^R}{a_{i,R}(\bar{\omega})}. \tag{5}$$

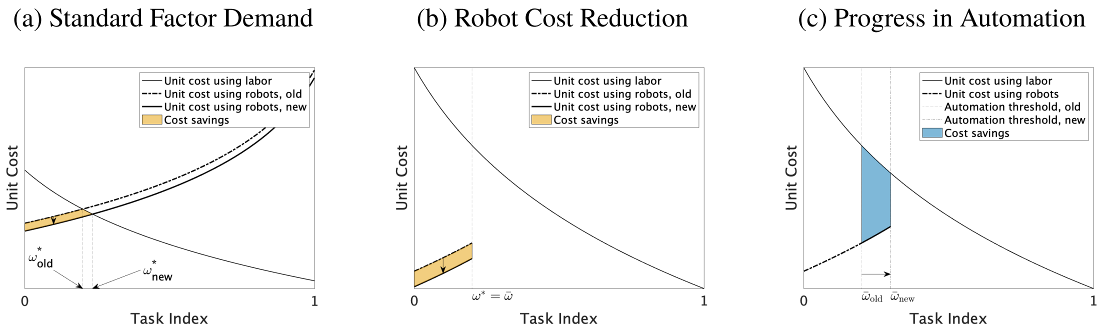
By not imposing this assumption, we allow the situation in which the automation technological threshold is not binding, or $\omega^* < \bar{\omega}$. Under such a situation, the allocation of tasks between robots and labor depends on the relative unit price. It is essential to relax this assumption in the past literature since the price is a relevant factor for the introduction of robots, and the cases where robots can be introduced technically but are not introduced due to economic incentives are pervasive.

In the following, we will characterize industrial factor demands $L_{it} = \int_{\omega \in \Omega} l_{it}(\omega)\, d\omega$ and $R_{it} = \int_{\omega \in \Omega} r_{it}(\omega)\, d\omega$. Specifically, we consider shocks to the level of automation technological threshold $\bar{\omega}$ and the log of price of robots p_{it}^R. We call these shocks "robotics automation" in general. Note that our robotics automation is another strict generalization of the past literature of automation, since we consider the shock to the price of robots p_{it}^R in addition to the shock to the automation technological threshold $\bar{\omega}$. In contrast, the automation literature has only considered the shock to the technological threshold $\bar{\omega}$.

2.2 Task Allocation and the Changes in the Unit Cost

Solving this model involves the characterization of the following producer task allocation problem. Let us focus on an industry i. Since tasks are ordered according to robots' comparative advantage,

Figure 2: Unit Costs, Shocks, and Cost Savings



Note: The diagrams show the allocation of robots and workers to tasks. The horizontal axis shows the task space [0, 1], and the vertical axis shows the unit cost of performing each task by robots or workers. A cost-minimizing producer chooses the threshold ω^* so that tasks $\omega < \omega^*$ are allocated to robots and tasks $\omega \geq \omega^*$ are allocated to workers. Each diagram differs by the automation threshold and the type of the shock considered. Figure 2a shows the case where the automation technological threshold is slack and $\bar{\omega} = 1$ and the shock is the robot cost reduction, so that the implication to the unit cost reduction is similar to the one in the standard factor demand model. Figure 2b and 2c show the case where the automation technological threshold is binding $\omega * = \bar{\omega}$ and the shock is the robot cost reduction and automation (a rightward shift of the automation technological threshold), respectively.

the optimal task allocation can be given by an (equilibrium) threshold task $\omega_i^* \leq \bar{\omega}$ such that robots perform tasks indexed $\omega \leq \omega_i^*$ and labor performs tasks indexed $\omega > \omega_i^*$ for each industry i.

Figure 2 visualizes the task allocation problem in a diagram of the unit cost of performing each task. The task is ordered by the comparative advantage of robots compared to labor, so that a cost-minimizing producer chooses the threshold ω^* to allocate robots to tasks $\omega < \omega^*$ and workers to tasks $\omega \geq \omega^*$. In Figure 2a, the automation technological threshold is slack and $\bar{\omega} = 1$. Therefore, a producer chooses the threshold ω^* at the point where the two unit cost curves cross and the use of either robots or workers is equally cost-effective. In contrast, Figures 2b and 2c show a situation in which the automation technological threshold is binding. In this case, a producer allocates robots to all the tasks in which robots are productive.

Since this equilibrium threshold ω^* plays a key role in explaining the cost savings brought by robots, it is worth discussing the effect of robotics automation on the unit cost of industrial production here. The idea is visualized in Figure 2. In all figures, the unit cost of production is the area under the unit cost line of a factor that is allocated to each task. In Figures 2a and 2b, we consider the shock to the robot cost p_{it}^R. In Figure 2a, as the robot cost reduces, a producer finds it cost-effective to allocate the set of tasks to robots, so that ω^* shifts rightward. The cost implication of this shock is identical to that in the standard factor demand theory since there is no automation technological threshold in Figure 2a. In contrast, in Figure 2b, the robot cost reduction does not induce the task allocation change since the productivity of robots is zero above the automation technological threshold. In Figure 2c, we consider the case in which the automation technological threshold is binding, and the shock is a progress in automation, or a rightward shift of the automation technological threshold. In this case, the tasks in which robots become productive are allocated to robots after the shock since the threshold was initially binding and allocating robots would have been more cost effective. In all cases, the cost-savings due to the shocks is depicted in the shaded area.

We formalize the above idea in the following. In our framework, the unit cost of production is implied by the cost minimization problem with production function (2) as follows:

$$P_{it} = \left(\int_{\omega\in\Omega} \left(p_{it}(\omega)\right)^{1-\sigma} d\omega\right)^{\frac{1}{1-\sigma}}.$$

Since the competitiveness in the task market implies that the task price is equal to the marginal cost of performing the task, we have

$$P_{it} = \left(A_{i,R}\left(\omega_i^*\right)\left(p_{it}^R\right)^{1-\sigma} + A_{i,L}\left(\omega_i^*\right)\left(w_{it}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}},$$

where $A_{i,R}\left(\omega_i^*\right) \equiv \int_0^{\omega_i^*}\left(a_{i,R}(\omega)\right)^{\sigma-1} d\omega$ and $A_L\left(\omega_i^*\right) \equiv \int_{\omega_i^*}^1\left(a_{i,L}(\omega)\right)^{\sigma-1} d\omega$ are the functions of the equilibrium threshold that represents the cost (in)efficiency of robots and labor, respectively. Log-linearizing this price index with respect to the values in the initial period $t = 0$, we have

$$d\ln P_{it} = s_{i0}^R d\ln p_{it}^R + \left(1 - s_{i0}^R\right) d\ln w_{it} + S_{i0} d\bar{\omega}, \tag{6}$$

where $s_{i0}^R \equiv p_{i0}^R R_{i0} / \left(p_{i0}^R R_{i0} + w_{i0} L_{i0}\right)$ is the robot cost share among the total cost of robots and labor in $t = 0$, and

$$S_{it} \equiv \frac{1}{1-\sigma}\frac{\left(\frac{p_{it}^R}{a_{i,R}\left(\omega_i^*\right)}\right)^{1-\sigma} - \left(\frac{w_{it}}{a_{i,L}\left(\omega_i^*\right)}\right)^{1-\sigma}}{\left(P_{it}\right)^{1-\sigma}}$$

defines the marginal cost savings due to the change in the automation technological threshold. Note that, if the condition (5) holds as assumed in the past literature, we have $S_{it} < 0$. Intuitively, when the task threshold is technologically binding, the expansion of the tasks robots can perform implies the reduction in the unit cost of production (Figure 2c). In other words, S_{it} is the potential cost savings that have not been realized because robots have cheaper unit cost than labor but cannot be introduced due to technical limitations. In contrast, if the condition (5) does not hold, which we allow in our setup, the unit cost of robots must be equal to that of labor at the equilibrium threshold, or $p_{it}^R / a_{i,R}\left(\omega_i^*\right) = w_{it} / a_{i,L}\left(\omega_i^*\right)$, implying $S_{it} = 0$. This means that when the automation technological threshold is slack, the increase in the threshold does not save any costs because it does not improve the equilibrium task allocation.

At this point, it is worthwhile to compare our theoretical implications to those of others. Namely, the implications of our model extend ones of both the standard factor demand model and the recent model of automation popularized by AR. On one hand, if $\bar{\omega} = 1$, we do not have any margin to increase the threshold $\bar{\omega}$ at the maximum $\bar{\omega} = 1$, and thus the model reduces to the one with the standard CES production function. Indeed, the changes in the unit cost (6) become $d \ln P_{it} = s_{it}^R d \ln p_{it}^R + \left(1 - s_{it}^R\right) d \ln w_{it}$ as there is no cost savings due to the change in technological threshold. On the other hand, if we impose assumption (5), then our model reduces to the one in the past automation literature. In this case, producers want to adopt robots for all the tasks in which robots are applicable, or $\omega_i^* = \bar{\omega}$. Furthermore, as mentioned above, our robotics automation considers a broader set of shocks than standard automation models, as it includes the changes in the robot price p_{it}^R as well as the automation technological threshold $\bar{\omega}$.

2.3 The Model Solution

Using the change in the unit cost of production (6), we can characterize our estimating equations. To do so, we first solve the household expenditure-minimization problem with utility function (1) to get $C_{it} = \left(\frac{p_{it}}{P_t}\right)^{-\varepsilon} I_t$, where $P_t = \left(\alpha_{it}\left(p_{it}\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ is the ideal price index. To derive the factor demand of producers, we solve the cost minimization problem with the production functions (2) and (3), and combine the solution with the good market clearing condition to get

$$R_{it} = A_{i,R}\left(\omega_i^*\right)\left(\frac{r_{it}}{P_{it}}\right)^{-\sigma}\left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} I_t, \tag{7}$$

$$L_{it} = A_{i,L}\left(\omega_i^*\right)\left(\frac{w_{it}}{P_{it}}\right)^{-\sigma}\left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} I_t. \tag{8}$$

Since we impose the free mobility of labor in the long-run, we have $w_{it} = w_t$. We approximate the initial period robot share $s_{i0}^R = s_0^R$ for each i and t, reflecting the small variation in the robot share observed in the initial (the 1970's) phase in Japan. With these assumptions, factor demand functions (8) and (8) combined with the change in the unit cost with respect to the change in robot price, wage, and the automation technological threshold (6) imply

$$d \ln L_{it} = a_i^L + a_t^L + (\sigma - \varepsilon) s_{i0}^R d \ln p_{it}^R + (\sigma - \varepsilon) S_{i0} d\bar{\omega} \tag{9}$$

where $a_i^L \equiv d \ln A_{i,L} \left(\omega_i^*\right)$ and $a_t^L \equiv \left(-\sigma + (\sigma - \varepsilon)\left(1 - s_0^R\right)\right) d \ln w_t + \varepsilon d \ln P_t + d \ln I_t$ are the industry- and time-fixed effects for the labor demand and accordingly for the robot demand. Equation (9) shows the relationship between labor demand changes and robot price changes and the automation shocks up to the fixed effects.

When bringing equation (9) to estimation, we encounter a problem that we do not directly observe the change in the threshold $d\bar{\omega}$. To overcome this problem, we consider a flexible relationship between the cost savings and the change in robot price using the following linear projection:

$$S_{i0} d\bar{\omega} = \rho d \ln p_{it}^R + \epsilon_{it}, \ \epsilon_{it} \perp d \ln p_{it}^R. \tag{10}$$

Note that the linear projection is without loss of generality, and the correlation between the two shocks is captured by parameter ρ. Specifically, suppose that there is a technological advancement in industry i and year t. This may be represented by a robot price reduction $-d \ln p_{it}^R > 0$ as well as an expansion of the robot tasks $d\bar{\omega} > 0$, or a cost savings $-S_{i0} d\bar{\omega} > 0$. In this case, we have $\rho > 0$.[5]

Using equations (9) and (10), we derive:

$$d \ln R_{it} = a_i^R + a_t^R + b^R d \ln p_{it}^R + e_{it}, \tag{11}$$

$$d \ln L_{it} = a_i^L + a_t^L + b^L d \ln p_{it}^R + e_{it}, \tag{12}$$

[5]This condition holds if the expansion of the tasks robots can perform is brought by profit-maximizing robot innovators who wish to sell their products to robot users. This is because robot users have a high willingness to pay (WTP) for robots that can achieve significant cost savings. Due to the lack of data on the robot producer side, we omit the formal modeling of robot production and instead allow any correlation between the robotics automation shocks.

where

$$
\begin{aligned}
a_i^R &\equiv d \ln A_{i,R}\left(\omega_i^*\right), \\
a_t^R &\equiv (\sigma - \varepsilon)\left(1 - s_0^R\right) d \ln w_t + \varepsilon d \ln P_t + d \ln I_t \\
b^R &\equiv -\sigma + (\sigma - \varepsilon)\left(s_0^R + \rho\right),\ e_{it} \equiv (\sigma - \varepsilon)\,\epsilon_{it},
\end{aligned}
$$

and

$$
b^L \equiv (\sigma - \varepsilon)\left(s_0^R + \rho\right). \tag{13}
$$

The coefficients of the interest are b^R and b^L, the one on the robot price change $d \ln p_{it}^R$. To interpret them, take b^L as an example. It represents the difference in the elasticity of task demand σ and of output demand ε rescaled by the robot share s_{it}^R and the shock correlation ρ. Recall that σ governs the size of the substitution effect, while ε the scale effect in the standard factor demand theory. Therefore, if $\rho > 0$, a relatively large output elasticity ε would imply that the regression coefficient satisfies $b < 0$ provided that $\varepsilon > \sigma$. In this case, the fall in robot price p_{it}^R increases the employment. In addition, our generalized model implies that b also depends on an additional element ρ, which rescales the effect of price changes on labor demand via the correlation between the price shock and the shock to the technological threshold.

The interpretations of the remaining parameters are the following. The industry fixed effects a_i^R and a_i^L absorb the changes in factor share parameters in each industry. The time fixed effects a_t^R and a_t^L absorb the sum of (i) the changes in factor demand due to wage changes that are constant across industries, and (ii) the changes in total demand. The error term e_{it} reflects the linear projection error ϵ_{it} between the price shock and the automation threshold shock. Note that since ϵ_{it} is orthogonal to the price shock $d \ln p_{it}^R$ by definition, OLS regression of equations (11) and (12) give an unbiased and consistent estimator of b^R and b^L, respectively. Therefore, we need to obtain the measures of R_{it}, L_{it}, and p_{it}^R to implement these regressions. The next section is devoted to provide the data sources for such a purpose.

3 Data

The goal of our empirical analysis is to estimate the factor demand equations for robot and labor as the function of robot price, namely equations (11) and (12). The required variables are the robot price, robot quantity, and employment by industry i and year t. We explain the data sources to construct these variables. We first describe the most unique data of ours, robot data and their some summary statistics, followed by the data source of employment and other control variables in the regression.

3.1 Robot Data

Our main data source is derived from the *Japan Robot Association* (JARA, henceforth). The JARA data are based on an establishment-level survey targeted at Japanese robot producers, which is the Japanese data source in the International Federation of Robotics data, a leading source of information in the robot literature. We digitize the Appendix Tables to the *Survey Report on Company Conditions of Manipulators and Robots* (survey tables, henceforth) from the JARA annual survey report.[6] The survey is available starting from 1974, and we focus on the years after 1978 in our main analysis because the shipment variable disaggregated by application became available from that year. The feature of JARA data is the availability of the monetary value of shipments, in addition to the units of robots by robot application, destination industry, and year. The shipment monetary value allows us to calculate the time series of the unit value of robots by application, which will be the core of our identification strategy. One may realize that the quality upgrading of robots is presumably substantial from 1978 to 2017. Nevertheless, our empirical results are robust to this exercise, as shown in Appendix B. In addition, we will check the robustness of our key results without relying on the measurement of robot prices by application in Section G.1.

Recall that Figure 1 shows the trends of robot stock units for each of the selected countries and data sources. Line colors and dot shapes indicate country groups, while line types indicate data sources (solid line for JARA, dashed line for IFR).[7] Two findings stand out from the figure. First, Japan experienced a very different trajectory than that of other countries, as mentioned before. A rapid increase occurred in the 1980s, and the trend has been stable or even decreasing from the 1990s and onward in Japan. In contrast, other large robot adopters are Germany and other European countries, South Korea, and the US. Recently, China has rapidly accelerated its robot adoption, though the per-worker measure is still smaller than other country groups listed in the figure.All of these countries, except for Japan, increased the stocks rapidly in the 1990s and 2000s. Although

[6]The JARA is a non-profit organization of robot-producing member companies. As of October 2019, there are 53 full member companies and 194 associate member companies. See `https://www.jara.jp/about/index.html` (In Japanese. Accessed on October 22, 2019). JARA sends an annual questionnaire to member companies and publicizes the survey tables to its member companies.

[7]To calculate robot stock in 1978, we assume that the robot stock is quantitatively smaller before 1978, relative to after. This assumption is warranted given the trends for 1974-1978, as shown in Figure F.3.

there are no data available for these countries before 1993, the novelty of robotics technology suggests that stocks before 1993 would have not been more than those of 1993. Therefore, Japan had a quite unique trend in robot adoption.[8]

Second, Japan's trends overlap well between the IFR and JARA datasets, as is predicted since the IFR creates its Japanese series based on JARA data. The two series do not completely overlap, partly due to robot category adjustments, which are mentioned below. Furthermore, recall that the IFR series show the total adoption, while the JARA series show the adoption of robots shipped from Japan. Therefore, the small discrepancy between the two datasets reveals Japan's small robot import share.[9] We confirm this fact more directly using the import statistics in Appendix F.13.

A major discrepancy between JARA and IFR data is robot classification. Namely, in JARA data, robots used in "clean rooms" (or clean-room robots) are included in the "Others" application in Table 1. Clean rooms are an environment free from dust and other contaminants, mainly used in the electric and electronics industry. There is a growing usage of machines in this clean environment to avoid contaminants brought by human labor. Our own interview with a JARA official revealed that the statistics started covering the robots used in the clean rooms of electric machinery industry from the mid-1990s. We in fact find a sudden increase of the Others application category shipped to the electric machinery industry. In contrast, IFR data do not count clean-room robots.

We demonstrate the validity of Japanese robot data based on three points, in contrast to the leading research in the literature, which avoids using Japanese statistics, citing a classification issue (e.g., Graetz and Michaels, 2018, AR). First, as above, we have spotted the source of classification differences (i.e., the inclusion/exclusion of clean-room robots). Second, this change in coverage is not large enough to create a discontinuity in the aggregate time series, as can be confirmed from Figure 1. Third, we show the robustness of our main results to dropping the Others application in Table 5.

[8]The decrease of robot stock after the mid-1990s in Japan is arguably explained by the depreciation of robot capital and the decline of the manufacturing sector. The reason why the replacement investment was not vigorous in Japan is consistent with the declining trend of capital investment in general in Japan, reflecting the low return to capital, as reported by Miyagawa et al. (2018).

[9]Thus, the error due to missing the imports of robots by using the JARA data is considerably small in the case of Japan, which differs from other settings. For instance, Humlum (2019) used the *import statistics* of robots when analyzing the labor-market impact in Denmark, based on the fact that most robots in Denmark are imported. In this sense, our assumption behind the strategy to obtain data is in stark contrast relative to this literature's.

3.2 Industrial Adoption, Application, and Price of Robots

We provide some descriptive statistics using the robot data described in Section 3.1. Not only do these statistics provide further understanding of Japanese robot adoption, they also lead to the idea and rationale for our identification strategy. After describing the industry shares of robots, we show some relevant trends of the application shares of robot shipments by industry, and then robot price at the application level. To smooth the year-level volatility and focus on long-run structural changes, 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). From now on, we keep using this five-year aggregated measure of robots.

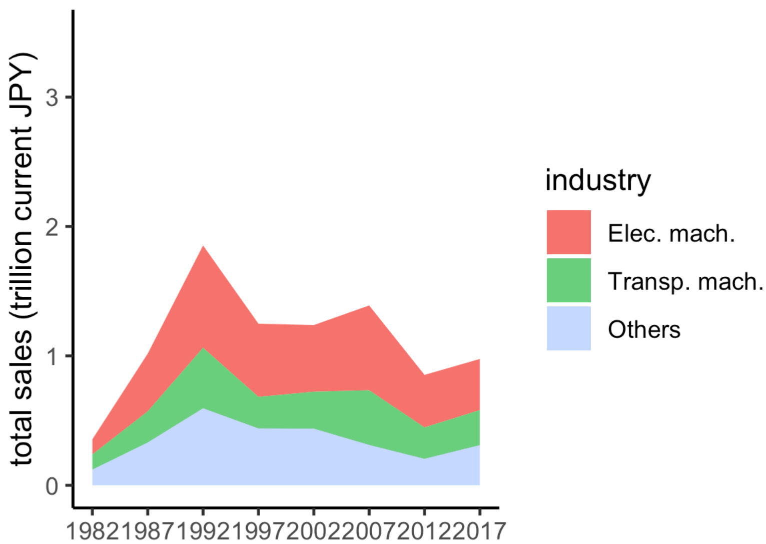
First, we study who purchased robots in Japan. Figure 3 shows the decomposition of the sales of robots to destination industries.[10] Figure 3 reveals that significant shares of robots are purchased by electric machine and transportation machine (including automobiles) industries. These two industries represent 68.2 percent of the domestic absorption in 2017. Given this feature of the data, we will study the application shares at the industry level, with an emphasis on these two industries. At the same time, it leads to a caution about the identification: Since these buyers are large, their demand might affect observed unit values. We argue these issues in depth in Section 4.3.

Robot Applications To construct a robot price measure in equations (11) and (12), it is worthwhile to scrutinize robotics technology. In particular, we study the robot applications as the source of variation for the identification in our context. Namely, recall that the definition of an industrial robot (ISO 8373) reads: "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 this definition is clear and widespread in the literature, it includes a fairly broad set of machine and thus has different functionalities depending on the particular applications. The mechanical difference of the robots that enables to perform these heterogeneous applications is called the type of robots and is one of the robot supply-side characteristics.

The JARA's survey questionnaire asks for the robot unit quantity and monetary value of industrial robots that the producer ships by each application, type, as well as destination industry. We focus on the disaggregation by applications, which means the specified tasks for each robot, in our

[10]In appendix F.6, we also show the decomposition into export and domestic sales.

Figure 3: Destination Industries of Robot Shipments



Note: Authors' calculation based on JARA data. The figure shows the decomposition of aggregated domestic industries into three categories: electric machine (red), transportation machine (green), and aggregated other domestic industries (purple).

main analysis.[11] The full list of the application and type categories is given in Table 1.

A different mix of robot applications is used in different industries. For example, consider the task of spot welding (SW) in the manufacturing process. SW combines two or more metal sheets together by applying pressure and heat to the weld area, called a spot. The task may be conducted by human labor or robots. The robots for SW tasks are called SW robots. SW robots are adopted in the automobile industry, as a critical task of automobile industry is welding to produce a complex output such as a car body. Furthermore, SW requires intensive movements in a repetitive way to assemble large and complex automobile body shapes. Therefore, SW robots are typically categorized as playback robots, which are a type of robots that can repeat the same but complex process with one-time teaching. Another example of a robot application is surface mounting (SM).

[11]In contrast, robot types refer to a robot categorization based on the mechanical way in which robots work, while 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. Thus, consistent time series are available only for the aggregation by application and destination industry. The structure categorization is further discussed in Appendix F.3.

Table 1: Classifications of Robots

	Classification by Application	Classification by Type
Classification	Handling operations/Machine tending (Tending)	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. The Others application includes robots for education, clean-room use of robots, and the unclassified. "SAL control robot" stands for sensory-control, adaptive-control, and learning-control robot.

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. Robots deployed for SM are different in their type from those used for spot welding (SW) since the tasks they perform are different.

To formally study these heterogeneous intensities of robot applications across industries, Table 2 shows the application-expenditure shares for the large robot purchasers, electric machines, transportation machinery, along with the other aggregated industries in Japan. For instance, in the electric machine industry, assembling robots were 76.2 percent of the total purchase and welding robots were 3.0 percent in 1982. In contrast, in the transportation machinery industry, assembling robots were 7.1 percent of the total purchase and welding robots were 46.3 percent in the same year. Another takeaway from Table 2 is that the within-industry expenditure shares are fairly constant over years, even though there has been a significant change in prices and quantities in robot adoption.[12] These points suggest a stable industrial specificity regarding robot use for different tasks, and robot applications are neither substitutes nor complements to each other.

Evolution of Robot Prices by Applications Given these considerations, we assume that robots are homogeneous goods conditional on application and year, and thus the robot price at the application-year level is the same for all buyer industries i. In fact, the difference of mechanical types by robot applications creates a price variation by robot applications. For example, the

[12] An exception is the decrease in assembling robots and the increase of other robots shipped for the electric machinery industry. The reason is the classification change, in which the JARA statistics started to include the clean-room robots, as mentioned in Section 3.1. To study the robustness about this classification change, we perform a sensitivity analysis about dropping the Others application in Section 4.3 and confirm that this change does not pose an identification threat.

Table 2: Application Expenditure Share by Industry and Year (%)

Industry	Application	1982	1987	1992	1997	2002	2007	2012	2017
Elec. mach.	Tending	9.4	4.6	7.4	8.2	5.6	3.2	5.4	10.3
	Welding	3.0	2.2	3.1	1.0	0.5	0.3	0.5	0.5
	Dispensing	1.7	0.9	0.3	0.3	0.2	0.3	0.1	0.1
	Processing	6.0	3.2	2.9	2.5	1.1	1.8	0.2	0.3
	Assembling	76.3	84.9	85.8	87.3	79.1	70.3	57.1	50.8
	Others	3.7	4.2	0.5	0.9	13.6	24.1	36.7	38.1
Transp. mach.	Tending	23.5	11.1	14.1	20.2	17.3	17.3	19.8	26.5
	Welding	46.4	53.0	46.8	39.5	50.1	47	44.7	42.9
	Dispensing	4.6	4.9	3.9	4.3	3.7	7.6	10.3	7.6
	Processing	15.9	12.1	23.9	19.8	16.0	11.0	11.4	10.7
	Assembling	7.1	13.9	9.7	15.3	9.5	15.8	12.0	7.8
	Others	2.5	5.0	1.6	0.9	3.4	1.3	1.7	4.5
Others	Tending	47.3	42.8	47.3	54.5	40.3	42.1	51.6	40.9
	Welding	13.7	14.0	17.5	14.0	8.3	16.4	16.8	16.4
	Dispensing	6.3	5.0	2.7	1.7	1.1	2.4	2.2	3.1
	Processing	15.7	12.7	9.9	8.9	5.4	9.7	6.7	5.8
	Assembling	2.3	13.1	9.5	12.2	30.0	17.4	14.2	11.6
	Others	14.7	12.4	13.1	8.6	15.0	12.0	8.6	22.1

Note: Authors' calculation based on JARA data. The table shows application-expenditure shares in percentages for the three industry aggregates: electric machine (Elec. mach.), transportation machine (Transp. mach.), and aggregated other industries (Others). Sums over application within each industry and year equals 100 percent, up to rounding error. The application list is discussed in the main text and shown in Table 1.

technological progress of playback robots reduced the price of welding robots relatively faster than that of assembly robots in recent decades. Our data allow to measure such trends. Specifically, to compute the application-level robot price p^R_{at} in the data, we sum the values and quantities across all industries to calculate the average unit value for each application and year. Formally,

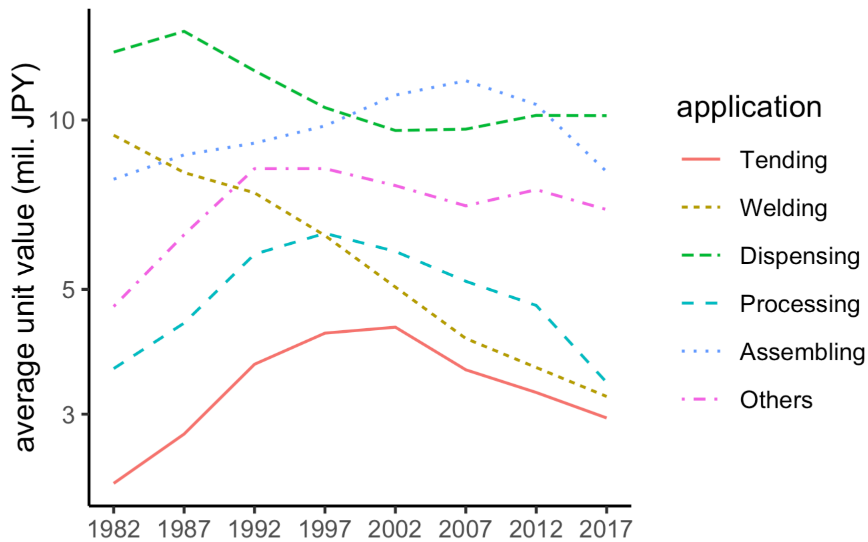
$$p^R_{at} = \frac{\sum_i v_{ait}}{\sum_i R_{ait}}, \tag{14}$$

where v_{ait} is the sales value of application a to industry i in year t.

To see how the prices evolved, Figure 4 shows the trends of the price for each application, aggregated across industries. For example, robots for welding and soldering show a stable decline in the unit value. This suggests that the production technology for welding-soldering robots improved consistently over the sample period.

It is worthwhile to document the potential reasons why welding robots became cheaper. Almost

Figure 4: Unit-Value Trends of Robot by Applications



Note: Authors' calculation based on JARA data. The figure shows industry 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.

all of the welding robots are classified as playback robots, a type of robot that repeats the same sequence of motions in all its operations. During the 1982-1991 period, the unit value of the playback robots declined.[13] Indeed, a review of articles in a business database of newspaper and magazine articles (the Nekkei Telecom database) between 1975 and 1985 reveals two important technological developments during the period: the adoption of numerical control technology and the substitution of the hydraulic actuator with the electronic motor actuator (Nikkei, 1982, 1984). This episode suggests that the price reduction was caused by the technological change in this application.

3.3 Other Data

We obtain labor-market outcome variables from the Employment Status Survey (ESS). We also obtain control variables from the Census of Manufacture (CoM), the Basic Survey on Overseas Business Activities (BSOBA), and the Japan Industrial Database (JIP). We briefly explain these

[13]See Figure F.4 and F.5 in Appendix F.5. The type-application cross-tabulation tables are only available between 1982 and 1991. Further details of the JARA dataset are discussed in the Online Data Appendix.

data sources in this subsection.

For employment variables, we take the 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 people who live in Japan and are age 15 or above, which is roughly one percent of this population. We obtain the regional and industrial employment and population variables for each demographic group, such as residential 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.9.

The CoM, which is conducted by Japan's Ministry of Economy, Trade and Industry (METI), is an annual survey of manufacturing establishments in Japan. It takes the universe of establishments with more than three employees. The strength of the dataset is the fine industry coding employed. The CoM records the 4-digit Japan Standard Industry Classification (JSIC) for each establishment. Furthermore, the survey asks each respondent for their major products and product codes. 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. See Section F.10 for details.

The BSOBA, which is also administered by the METI, is an annual survey of the universe of Japanese multinational enterprises (MNEs). Since offshoring and multinational production are concurrent phenomena that change the labor demand (e.g, Hummels et al., 2014), we control them with variables constructed from the BSOBA. Section F.11 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). We use the gross trade (exports and imports) and intangible capital values 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 F.12. Finally, throughout this paper, we work with 13 industry classifications (12 manufacturing and one "others" aggregates) that are consistent with the main datasets we describe above. The industries are: Steel; Non-ferrous metal; Metal products; General machine (includes robot producers); Electric machine; 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.

4 Empirical Analysis

Based on the data overview in Section 3.2, we construct the variables and the econometric model that uses the variables. We then report the main empirical results and the validation exercise of our main identification assumption, followed by some robustness checks.

4.1 Estimation Strategy

First, to construct the robot stock, we follow the immediate withdrawal method (IWM), which is a standard method and is also used by the IFR (IFR, 2018).[14] Using this robot stock measure, we next consider the robot aggregates at the industry level. Robot applications are aggregated and perform services for production in each industry. Motivated by the observation that the expenditure shares are roughly constant across applications in each industry (Table 2), we assume that the robots are aggregated by a Cobb-Douglas function:

$$R_{it} = \prod_a (R_{ait})^{s_{ai}}, \tag{15}$$

where a is robot application and R_{ait} is the robot stock of application a in industry i in year t. This robot aggregate measure can be understood as the service of robots that performs the tasks in production.We use the initial-year expenditure share as the weight of function (15), s_{ai}.These assumptions imply that the price indicator for robots in industry i is given by

$$p_{it}^R = \prod_a \left(p_{at}^R\right)^{s_{ai}} \iff \ln\left(p_{it}^R\right) = \sum_a s_{ai} \ln\left(p_{at}^R\right), \tag{16}$$

where p_{at}^R is computed in equation (14). As we have discussed in the data section, we treat this robot price measure as exogenous to robot-adopting industries as they are determined by the industry's baseline application share and application prices that are driven by technological changes. Nonetheless, we provide some justification analysis of this identification assumption in Section 4.3.

[14] Recall that the JARA data have only the flow shipment variable, whereas we are concerned about the stock of robots that performs tasks and its impact on employment. The IWM method sums the robot investment in past 12 years to construct the robot stock, assuming that the robot works immediately after installation for the first 12 years, and then stop working in the year 13. We discuss the robustness to other choices of stock measure construction in the robustness section below.

Given the measure of robot prices, we estimate the robot and labor demand equations:

$$\ln(R_{it}) = \beta^R \ln\left(p_{it}^R\right) + X_{it}\gamma^R + \xi_i^R + \tau_t^R + u_{it}^R, \tag{17}$$

$$\ln(L_{it}) = \beta^L \ln\left(p_{it}^R\right) + X_{it}\gamma^L + \xi_i^L + \tau_t^L + u_{it}^L, \tag{18}$$

where L_{it} is employment in industry i in year t, R_{it} is the stock of robots in industry i in year t, X_{it} is the set of time-varying control variables in industry i in year t described below in Section 4.1, ξ_i is the industry fixed effect, and τ_t is the year fixed effect.[15]

Our coefficient of interest are β^R and β^L. The parameter β^R is the gross own-price elasticity of robot demand with respect to robot price, and β^L is the gross cross-price elasticity of labor demand with respect to robot price. Note that all the elasticity estimates in equations (17) and (18) are gross instead of net, thus they contain both the substitution effect and the scale effect, where the latter arises due to the productivity gain made possible by robot adoption (Cahuc et al., 2014). Although it would be informative to separate the gross estimates into each mechanism, to do so, we would need the exogenous determinant of production scale apart from the exogenous source of robot price variation for such a purpose. The lack of such an exogenous variation prevents us from separating two effects.[16] 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.

We assume that the variation in p_{at}^R is exogenous to demand industries. We will also conduct a robustness check using several price measures that are presumably less endogenous to robot adopters, such as leave-one-out robot prices and export robot prices, in the following section. Furthermore, note that the i-level variation comes from the initial share s_{ai0} across industries. In this regard, our identification assumption is that the initial application shares are uncorrelated with unobserved labor-market growth factors after conditioning on the fixed effects and control variables (Goldsmith-Pinkham et al., 2020). In other words, the endogeneity of p_{at}^R does not give industry i-level variation, which alleviates the concern about using application prices as shifters of the IV.[17]

[15] To avoid yearly noises, we aggregate robot measures at every five years. In contrast, we use the final year of these 5-year bins for the employment statistics. For example, we take robot stock measures computed from the average across 1978-1982 and examine employment in 1982. We regard this as naturally capturing the lagged impact on employment (cf. Autor et al., 2020). Furthermore, this formulation leaves 1979 employment from ESS data (introduced in Section 3.3) unused for the baseline analysis, which allows us to examine some pre-trend analysis in Appendix Table G.2.

[16] Limiting attention to the gross effect is standard in the literature. For instance, AR estimate the gross effect of robots via the exposure-to-robot IV method in their general equilibrium framework.

[17] The recent development of econometric theories, for instance, Borusyak et al. (2021) discuss the identification

To control for the potential confounders in the regressions, we control for industry fixed effects and time fixed effects. As further possible industry- and time-varying explanations for industrial employment changes, we consider the following three elements: (i) demographics, which may change the adoption incentive of robots and labor supply, (ii) globalization and (iii) technology, both of which can change the competition and production environment, and thus the motive for robot adoption and employment at the same time. Detailed description of these variables are relegated to Appendix A. Furthermore, in all industry-level regressions, we cluster the standard error and estimate the cluster-robust standard error by the cluster bootstrap method to account for the small number of clustering units, which is 13 industries.

4.2 Main Results

In Table 3, Panel A shows the OLS estimates of robot demand equation (17). 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 adds globalization controls, and column 4 adds technology controls. This column structure is the same for the other panel in Table 3. Our preferred specification is column 4 as it includes all potential confounders discussed in Section 4.1. In all specifications, we find consistently negative and significant estimates. This result is not surprising, given that the price reduction increases the robot quantity demanded. According to column 4, controlling for fixed effects and other factors affecting industrial employment, a one-percent decline in robot prices drives a 1.54 percent increase in robot adoption.

Panel B of Table 3 shows the OLS estimates of labor demand equation (18). In all specifications, we find consistently negative and significant estimates. To clarify, the negative coefficient implies that the fall of the effective robot price induces 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.

To interpret these estimates, recall that the coefficient β^L corresponds to the terms in equation (13). Therefore, the negative β^L corresponds to a larger demand elasticity ε than the substitution elasticity σ. Intuitively, cheap robots and the automation allows to produce goods at a reasonable cost, expand a lot due to higher demand, and thus hire more workers. This effect dominates the substitution away from labor to robots, making the overall relationship between robot price changes

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 the standard SSIV estimators over-reject the null of no effects in the presence of cross-regional correlations.

Table 3: Robot and labor demand estimates of Industry-level Analysis

	(1)	(2)	(3)	(4)
Panel A: Robot demand	*Dependent variable:* $\ln(R_{it})$			
$\ln(p^R_{it})$	-1.175^{***}	-1.852^{***}	-1.322^{***}	-1.542^{***}
	(0.426)	(0.314)	(0.300)	(0.294)
R^2	0.969	0.979	0.984	0.986
Panel B: Labor demand	*Dependent variable:* $\ln(L_{it})$			
$\ln(p^R_{it})$	-0.841^{***}	-0.465^{***}	-0.272^{**}	-0.437^{***}
	(0.099)	(0.073)	(0.116)	(0.075)
R^2	0.975	0.984	0.985	0.987
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
Observations	104	104	104	104

Notes: Authors' calculation based on JARA, ESS, BSOBA and JIP data. The table presents OLS regression estimates of robot and labor demand based on industry and year panel data following equations (17) and (18). All columns control the industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. 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 BSOBA. Column 4 includes logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. The industry-level cluster-bootstrap standard errors are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

and employment negative. We will provide some evidence of the demand elasticities in Section 4.5.

One may be concerned about the issue of robot quality upgrading. Indeed, our sample covers a long period, 1978-2017, and the unit efficiency of robots have grown over that time. If an industry specializes in the application of robots whose quality grew rapidly, the efficiency-adjusted prices drop even faster than the raw price series of robots. At the same time, the employment growth in such a industry may have increased, causing a bias. To alleviate this concern, we extend our robot aggregation function (15) to perform a quality adjustment method developed in Khandelwal et al.

(2013). Specifically, we allow the aggregation of robots with a Constant Elasticity of Substitution (CES) and estimate the robot unit efficiency using our application-industry-time-level variation of robot prices. The intuition of this method is that the sales component that cannot be explained by the CES demand structure with the observed price is attributed to the quality component. While the technical details of the quality-adjustment method are out of our focus, our qualitative results are maintained in this exercise. Therefore, a detailed discussion is relegated to Appendix B.

4.3 Validating Identifying Assumptions

A contribution of this paper is the new identification method based on the robot price index (16). We thus argue that our choice of robot price index is an appropriate exogenous variable using three robustness exercises. First, we consider alternative price measures to address the potential reverse causality from industrial employment growths to the robot price. Second, we check dropping big robot buyers from our main sample to address their potential price-setting effects. We also explore the role of applications by removing each application when computing robot price index (16). These exercises care about the issue that robot price (14) may be affected by robot and labor demand shocks, and the results will show that our main empirical results prevail even with these considerations.

Alternative Price Measures The concern for the endogeneity of robot prices may arise when robot and labor demand shocks, such as industrial total factor productivity (TFP) growth, affect the application robot price. To alleviate this concern, we consider application-level price measure alternatives that do not depend on the own industries' robot prices, instead of the industry-aggregated one in equation (14). The first measure is the leave-one-out price that leaves out the own industry when calculating robot prices. Namely, we construct the following application-level robot price:

$$p_{ait}^{R,LOO} = \frac{\sum_{i' \neq i} v_{ai't}}{\sum_{i' \neq i} R_{ai't}}. \tag{19}$$

Then we construct the industrial price index based on equation (16), but replacing p_{at}^{R} with $p_{ait}^{R,LOO}$. This measure is supposed to take the variation that is external to each industry.

Next, the leave-one-out price measure may still contain feedback bias because the shock to own industry may propagate to the prices faced by the other industries. To address this further concern, we consider the second measure of application-level robot prices using export prices as follows:

$$p_{at}^{R,EXP} = \frac{v_{a,exp,t}}{R_{a,exp,t}}. \tag{20}$$

We again aggregate this export price measure to the industrial price index using equation (16). Using this measure, we take the variation further external to each domestic industry.

Furthermore, we turn to the issue of robot quality upgrading. Our sample covers a very long period, 1978-2017, and the unit efficiency of robots have grown over that time. If an industry specializes in the application of robots whose quality grew rapidly, the efficiency-adjusted prices drop even faster than the raw price series of robots. At the same time, the employment growth in such a industry may have increased, causing a bias. To alleviate this concern, we extend the quality adjustment method in Khandelwal et al. (2013). Specifically, we extend our robot aggregation function into the Constant Elasticity of Substitution (CES) and estimate the robot unit efficiency using our application-industry-time-level variation of robot prices. Intuitively, the sales component that cannot be explained by the CES demand structure with the observed price is attributed to the quality component. The technical details of this quality adjustment method is laid out in Appendix B.

We report the results based on these alternative robot prices in Table 4. Column 1 shows the baseline estimates (thus the same as Table 3, Panel C, column 4). Columns 2 and 3 are based on leave-one-out prices (19) and export prices (20), respectively. The estimates reveal that a one percent decrease of leave-one-out robot prices and export robot prices increases employment by 0.5%. Therefore, we find that the estimates are robust to these price measures, and the endogeneity of the price measure poses minimal threat to our identification strategy.

Sensitivity to the Selection of Industry and Application Next, we consider the exercise of dropping large robot buyer industries. The endogeneity of robot prices may be most severe to big robot buyers, such as the electric machinery industry and the transportation machinery industry because their demand may affect robot prices greatly. If their output demand surges, it may enhance both robot and labor demands, and the increase in robot demand affects prices. In this case, there is a spurious correlation between robot price and robot/labor demands. While this concern is already partly addressed by using an arguably exogenous price series in the above analysis, we address this concern in a more direct way by dropping the two large robot-purchasing industries. The resulting sample is made from smaller industries, whose robot prices are thus less endogenous to robot demand-side shocks. Panel B of Table 4 shows the main specification (18) with a varying

Table 4: Verifying Identification in the Industry-level Analysis

Panel A: Alternative Price Measures

	Dependent variable:		
	$\ln(L_{it})$		
	(1)	(2)	(3)
$\ln(p^R_{it})$	-0.437^{***}	-0.525^{***}	-0.412^{***}
	(0.071)	(0.097)	(0.051)
Price Measure	Benchmark	Leave-one-out	Export
Controls	✓	✓	✓
Observations	104	104	104
R^2	0.988	0.987	0.987

Panel B: Dropping Major Industries

	Dependent variable:		
	$\ln(L_{it})$		
	(1)	(2)	(3)
$\ln(p^R_{it})$	-0.650^{***}	-0.609^{***}	-0.834^{***}
	(0.069)	(0.114)	(0.159)
Dropped Industries	Elec.	Transp.	E&T
Controls	✓	✓	✓
Observations	96	96	88
R^2	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 price measure and log employment across industries and years. In panel A, each column is different in the price measures. Column 1 shows the result with the instrumental variable of the benchmark industry-aggregate robot price (14). Column 2 shows the result with the leave-one-out robot price (19). Column 3 shows the result with the export robot prices (20). Column 4 shows the result with robot quality-adjusted price measure with the quality estimated by the method of Khandelwal et al. (2013). In panel B, each column is different in industries to be dropped from the sample. 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. All specifications control the industry and year fixed effects, demography controls, globalization controls, and technology controls defined in Section 4.1. All regressions are weighted by purchase values of robots in each year. The industry-level cluster-bootstrapped standard errors are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

sample. Column 1 shows the baseline estimates. Column 2 drops electric machinery, column 3 drops transportation machinery, and column 4 drops both. The coefficients are consistently negative across columns. The findings in this subsection overall suggest that the concern about endogeneity due to large industries' demand is minimal.

Furthermore, we check how our main result varies by changing the set of applications in the empirical specification. To do so, we drop each application from Table 1 and perform our main regression in equation (18). Table 5 reports the results. Column 1 shows the result with all applications, and thus the same result as column 4 of Panel C in Table 3. Columns 2-7 report the results that drop each of the applications one by one, in the order of applications in Table 1. Our empirical finding does not qualitatively vary by dropping any applications, except for the case of dropping the Welding application. This result is consistent with the previous result obtained by dropping the transportation machinery industry in Table 4, because the industry intensively uses welding robots. These results suggest that the violation of the exogeneity assumption on the initial share of welding robots leads to a substantial inconsistency of the 2SLS estimator. We will further demonstrate the plausibility of the exogeneity assumption in the next analysis.

Table 5 also clarifies that our findings are not driven by the "Others" application, as can be confirmed in column 7. Since the Others application contains clean-room robots, as discussed in Section 3.1, this result is relevant from the following two viewpoints. First, due to the surge in the use of clean-room robots in the electric machine industry, the application share in electric machine industry has changed since the initial years (cf. Figure 2). Since the share component s_{ai} is taken at the initial years, robot measures in later periods may not capture the actual robot price and quantity in the industry. Second, one of the robot categorization differences between Japan and other robot-adopting countries is the treatment of clean rooms; IFR does not count clean-room robots, while JARA does. For these two reasons, the robustness to the exclusion of the Others industry is reassuring; it shows that our result is not driven by the varying application shares over time and the cross-country differences in robot definitions.

Pushing toward this direction further, we consider the role of each application in identifying the robot price effects on employment by using only the initial application share as the instrumental variable. This exercise has a close connection with the idea of Goldsmith-Pinkham et al. (2020), and validates that our results are robust to the lack of exogeneity assumption of the application-level robot prices (16). Detailed arguments are made in Appendix G.1.

Table 5: Alternative Set of Applications

	Dependent variable:						
	$\ln(L_{it})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(p_{it}^R)$	-0.437^{***}	-0.332^{***}	-0.513^{***}	-0.408^{***}	-0.420^{***}	-0.400^{***}	-0.451^{***}
	(0.071)	(0.033)	(0.072)	(0.069)	(0.068)	(0.107)	(0.073)
Dropped Applications	(None)	Tending	Welding	Dispensing	Processing	Assembling	Others
Observations	104	104	104	104	104	104	104
R^2	0.987	0.989	0.987	0.987	0.987	0.989	0.984

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 varying instrumental variables of log robot cost measure. Columns 1 shows the main-specification result reported in column 4 of Panel C in Table 3. Column 2-7 drop one application from the application lists in Table 1. The employment measure includes the employment of robot-producing plants. All columns control the demography, globalization, and capital controls as well as industry and year fixed effects. 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. Globalization controls are the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Capital controls are logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. Standard errors are shown in the parenthesis. All regressions are weighted by purchase values of robots in each year. *p<0.1; **p<0.05; ***p<0.01.

4.4 Heterogeneity

The analysis so far has suggested the robot price reduction has increased overall employment. To study more heterogeneous impacts across demographic groups, we consider our main empirical specification (18) with the employment of several subgroups of workers as outcome variables. Table 6 shows the results. In column 1, we show our baseline estimate (the same as Table 3, Panel C, 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 (equal to or more than 50 years old, column 6). Perhaps surprisingly, our finding that robots and labor are gross complements is robust to all of these subgroups. Moreover, the sizes of the estimated coefficients do not differ substantially across demographic groups.[18] These findings suggest that the positive employment effects are broadly shared by society as a whole.

4.5 Mechanism: The Scale Effects

Our theoretical analysis suggests that the robot price reduction and automation induce producers to expand since they can reduce the cost of production and thus the output price. We show some additional evidence that bolsters this interpretation of our main results in Table 3.

Output Volume We examine if and how much the reduced robot price changes output volume. For this purpose, we study four outcome measures: real output Y_{it} in 2000 JPY, nominal output PY_{it}, nominal export EX_{it}, and nominal domestic absorption AB_{it}, all at the sector level. Three variables, Y_{it}, PY_{it}, and EX_{it}, are taken from the JIP database, and the absorption is defined by $AB_{it} \equiv PY_{it} - EX_{it}$. As mentioned in the Data Section, the JIP database only covers years 1978-2012. Therefore, the last year in the main analysis, 2017, is dropped throughout the analysis in this section, which results in the sample size of 91, with 13 industries times 7 time periods.

Table 7 shows the regression result of the log of our four output measures on the log robot price measure p^R_{it}. We find a piece of evidence that robot price reduction induces increases of real output, nominal output, and nominal domestic absorption at the industry-year level. The finding is robust to including the globalization and technology control variables. Perhaps surprisingly, we do not find evidence that the drop of robot price causes export growth. As we show in Appendix F.14, the

[18]We also study the heterogeneity in the period of analysis, leveraging our long sample period. We find suggestive evidence that the positive employment impact is found in the late period of our sample. See Appendix G.2 for detail.

Table 6: Industry-level Estimates for each Demographic Group

	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)
$\ln(p_{it}^{R})$	-0.437^{***}	-0.430^{***}	-0.467^{***}	-0.429^{***}	-0.505^{***}	-0.613^{***}
	(0.073)	(0.087)	(0.050)	(0.056)	(0.068)	(0.049)
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 price measure and various log employment outcomes across industries and years. 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. 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 industry cluster-bootstrap standard errors are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Robot Price, Output Quantity, and Output Prices

	Dependent variable:					
	$\ln(Y_{it})$	$\ln(PY_{it})$	$\ln(EX_{it})$	$\ln(AB_{it})$	$\ln(P_{it})$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(p^R_{it})$	-0.621^{***}	-0.561^{***}	0.155	-0.834^{***}	-0.053	0.259^{**}
	(0.229)	(0.102)	(0.349)	(0.111)	(0.121)	(0.107)
Drop Electrics						✓
Observations	91	91	91	91	88	80
R^2	0.987	0.997	0.989	0.996	0.975	0.777

Note: The table shows the regression results of each outcome variable on the robot price measure (16) as well as other controls. Outcome variables are indicated at the top of each column. Y_{it} is sectoral real output, PY_{it} is sectoral nominal output, EX_{it} is sectoral (nominal) export, $AB_{it} \equiv PY_{it} - EX_{it}$ stands for sectoral (nominal) domestic absorption, and P_{it} represents the sectoral output price index. All regressions control for the industry and year fixed effects, demographic controls (female share, college-graduate share, age 35-49 share, age >50 share), globalization controls (industry's log import and log foreign production values), and technology controls (the log stock values of Computerized information, Innovative property, and Economic competencies). Standard errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

export share of the nominal output is not negligible in certain industries, but the export elasticity with respect to the robot price is small. Therefore, the invariance of export share with respect to the robot price does not affect the strong finding about the total demand boost due to robot price reduction. Instead, the demand boost is mainly absorbed in the domestic economy. This finding implies that the positive employment effect is not likely to be unique to Japan, which is the net exporter of the robot-intensive industry (e.g., automobile) since it is not export that expanded due to the availability of cheap robots but domestic absorption. Therefore, other countries might also tap into the domestic demand by making industries productive with robotization.

Output Price Since the scale effect works through the reduction in the sectoral output price, we also analyze this variable. Unfortunately, the JIP database does not record the price deflator separated by industry. Therefore, we draw on the price index assembled by the Bank of Japan (BOJ). The BOJ output price indices aggregate domestic and export destinations. Furthermore, there are some unavailable industries such as non-manufacturing and other-manufacturing aggregates. Since the revision of industry codes prevents the Electric machine industry incomparable across years, we use BoJ's "reference series" for the Electric machine industry that are less consistent across time than the series for other industries. As a result, we obtain 11 industries (10 if we exclude the reference Electric machine industry) for 8 time periods, totaling a sample size of 88. In addition, the price series for the reference Electric machine industry shows a strikingly different trend that is likely to be not related to robotization, as shown in Appendix C. Therefore, we report the result with and without the Electric machine industry for the regression analysis of output prices.

Columns 5 and 6 of Table 7 show the result of the regression analysis of log output prices. When we drop the reference Electric machine industry, we find a significant and robust positive effect of robot price reduction on the output price reduction, as predicted by the scale effect mechanism. Quantitatively, a one-percent drop of the robot price measure in an industry and year implies a 0.26 percent reduction in the quality-controlled output price when we control for all covariates. As discussed above, including the Electric machine industry would add significant noise to the regression, and the coefficients would turn insignificant.

4.6 Further Robustness Checks

We briefly discuss additional robustness checks, netting out robot-producing workers and alternative stock measures. First, we drop robot-producing workers from the employment to study the net effect of robotization on employment that excludes the mechanical increase of workers who produce robots (Acemoglu and Restrepo, 2018b). Appendix F.10 discusses in detail how to generate robot-producing worker employment and the regression results when robot producers are netted out of the outcome variable. The main findings are qualitatively unchanged.

Next, we check alternative measures of robot stocks. Recall that our main specifications follow the literature and IFR suggestion and aggregate the 12-year flows of robots, which is called the immediate withdrawal method (IWM). As several authors argue, another choice is 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 IWM with varying withdrawal years and PIM with a few depreciation rates. We find that the variation in the definition of stock variables has minimal impacts on the regression results. We discuss further the details and empirical results in Appendix Section F.8.

5 Local Labor Market Effects

The previous section reveals that robots and employment are gross complements at the industry level. This section attempts to (i) compare our estimates with those in the existing studies in the literature such as Acemoglu and Restrepo (2020a) and Dauth et al. (2021), and (ii) provide evidence of some region-level spillover mechanisms that the industry-level analysis does not capture. Existing studies are different from our approach in two important ways. First, they use commuting zone as the unit of analysis instead of industry. Second, they examine the effects on employment of the robot exposure measure created from the quantity of robots instead of robot the price. In this section, we modify the unit of analysis and the empirical model specification to make our estimates comparable to the estimates from the existing studies.

Specifically, we first modify the unit of analysis from the industry to the local labor market, or more specifically, Commuting Zones (CZs) delineated by Adachi et al. (2020).We then consider the empirical specification such that employment is regressed on the quantity of robot following AR:

$$\Delta Y_{ct} = \beta^{CZ} \Delta R_{ct} + X_{c,t-15} \gamma^{CZ} + \xi_i^{CZ} + \tau_t^{CZ} + u_{it}^{CZ}, \tag{21}$$

where Y_{ct} is labor market outcomes including employment in commuting zone c in year t and R_{ct} is the robot exposure measure defined below. The time difference operator Δ represents the long-run (15-year) differences, so that $\Delta Y_{ct} \equiv Y_{ct} - Y_{c,t-15}$, for instance. The vector of control variables $X_{c,t-15}$ includes the same control variables in the industry-level analysis prorated to each CZ according to the industry composition. Based on the industrial robot adoption and price measures, we employ the shift-share method to construct a CZ-level robot exposure measure, as in AR:

$$\Delta R_{ct} = \sum_i l_{cit} \frac{\Delta R_{it}}{L_{it}}, \tag{22}$$

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

A major concern of specification (21) in the literature is the endogeneity of ΔR_{ct}. While AR address this concern by instrumenting ΔR_{ct} by the penetration of robots in other developed countries, we instead use $\Delta \ln (r_{ct})$ as IV because Japan is unique in its adoption of robot and the comparable country is absent (Figure 1). 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:

$$\Delta \ln (r_{ct}) = \sum_i l_{cit_0} \Delta \ln (r_{it}) . \tag{23}$$

A few comments on the specification follow. First, the fixed effects in specification (21) control 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 with the ones in the literature, such as AR. Note that our specification also allows differential trends across CZs as we assess many (in particular, the five first differences) time periods.

The first-stage regression of the 2SLS estimator in equation (21) is highly significant and shown in Appendix G.3. Table 8 shows the 2SLS results of specification (21).[19] All columns report the preferred specification with the full set of our control variables.[20] First, as our primary interest, column 1 shows that overall employment increased in CZs that were exposed to robots, confirming that the findings in Section 4 also holds in the first difference-based specification (21) with two-way fixed effects. This positive estimate, 1.943 with a standard error of 0.952, contrasts with the comparable estimate for the US, -1.656 with a standard error of 0.411, reported by AR in their Appendix.[21]

Next, using columns 2 and 3, we discuss the relationship with the estimates obtained in the literature and the mechanism. Column 2 shows that the regional population responded positively to robot exposure. The estimated impact on the population is similar to the impact on employment reported in Column 1. Thus, both employment (column 1) and population (column 2) experience quantitatively similar positive effects, cancelling the impacts to their ratio by increasing both the numerator and denominator. This implies that, Column 3 shows that robot penetration does not affect the employment-population ratio in a statistically significant way. This finding, however, is in contrast to part of the literature. For example, using their similar-country shift-share IV strategy, AR found -0.388 with the standard error of 0.091 as the impact on employment-population ratio.

Turning to the sectoral employment analysis, column 4 shows that the impact of robots on manufacturing employment is positive and significant. The estimated impact is three times larger than the impact on total employment. Since it is the manufacturing sector that primarily adopted industrial robots, this large impact on manufacturing employment can be considered as a direct effect of robot adoption on employment. It suggests that the scale effects of robot adoption are substantially larger than the substitution effects, as is discussed in detail in Section 4.5.

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

[20]The standard deviation of robot exposure measures is 5.25 in the raw data and 2.17 when residualized.

[21]Appendix **??** discusses how to interpret the coefficient differences between the industry-level analysis and the CZ-level analysis through labor supply elasticities.

Table 8: CZ-level 2SLS Regression

	Dependent variable: 100×					
	$\Delta\ln(L_{ct})$	$\Delta\ln(Pop_{ct})$	$\Delta\frac{L_{ct}}{Pop_{ct}}$	$\Delta\ln(L_{ct}^{MAN.})$	$\Delta\ln(L_{ct}^{SER.})$	$\Delta\ln(Pop_{ct}^{DEP})$
	(1)	(2)	(3)	(4)	(5)	(6)
ΔR_{ct}	1.943**	1.753**	0.124	5.923***	0.809	1.391
	(0.950)	(0.869)	(0.213)	(2.010)	(0.975)	(1.021)
CZ FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓	✓	✓
Observations	1,265	1,265	1,265	1,265	1,265	1,265
R^2	0.821	0.812	0.751	0.612	0.833	0.771

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 at the commuting zone (CZ) level. 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. The standard errors are clustered at the CZ level and reported in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Furthermore, the CZ-level analysis allows us to test the "local multiplier" hypothesis in Moretti (2010); An increase in demand for manufacturing employment has a positive spillover to the labor demand in other industries (e.g., service) in a locality. To study this, column 5 takes non-manufacturing employment (labeled as "L^{SER}" as abbreviation for service), defined as the total employment (cf. column 1) minus the manufacturing employment (cf. column 4), as the outcome variable. The estimated coefficient is only imprecisely estimated and does not reject null. Thus, we find little evidence of spillover effects to employment in the non-manufacturing sector. The findings from columns 4 and 5 imply the absence of reallocation within CZs across sectors; rather, the reallocation might have happened across CZs. Finally, column 6 takes the non-working population (labeled as "P^{DEP}" as abbreviation for dependent), defined as the total population (cf. column 2) minus the employed population (cf. column 1), as the outcome variable. The estimated impact is not statistically significant. Thus, the robot impact does not spill over to the size of the dependent population.

Our analysis marks a sharp contrast between Japan and the other developed countries in the timing of robot adoption and its impact on labor-market outcomes. In Appendix D, we discuss a potential reason for the large scale effects in Japan. Indeed, Japan adopted robots earlier than other high-income countries. We argue that this is not likely due to the proximity to domestic robot producers, but to unique employment practices such as long-term contracts, seniority-based wage setting, and company-level unions instead of occupation-level unions. These employment practices could mitigate the objection to robot adoptions of workers under threat of automation, enabling a smooth adoption of robots with a large productivity gain and thus scaling the production.

5.1 Hours Worked and Wages

So far, our main outcome variables have been the headcounts of people, such as employment and population. Given that robot technology is characterized by the time-saving nature of routine tasks (e.g., welding and assembly), 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 9. In column 1, we show the baseline result (cf. Table 8, column 1), 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; one robot per 1,000 employees reduced the hours

Table 9: CZ-level 2SLS Regression of Other Labor Market Outcomes

	Dependent variable: $100 \times$		
	$\Delta \ln(L_{ct})$	$\Delta \ln(h_{ct})$	$\Delta \ln(w_{ct})$
	(1)	(2)	(3)
ΔR_{ct}	1.943^{**}	-1.928^{***}	4.020^{***}
	(0.952)	(0.520)	(0.859)
CZ FE	✓	✓	✓
Year FE	✓	✓	✓
Demographic Controls	✓	✓	✓
Globalization Controls	✓	✓	✓
Technology Controls	✓	✓	✓
Variable	# Workers	Average Hours	Average Hourly Wage
Observations	1,265	1,265	1,265
R^2	0.821	0.856	0.954

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 at the commuting zone (CZ) level. 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. The standard errors are clustered at the CZ level and reported in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

worked by 2 percent. Column 3 shows that robots increased hourly wages even more drastically: One robot per 1,000 employees increased the hourly wages by 4 percent. These findings, combined with the positive impact on employment, suggest that robots enable work-sharing or time-saving technological changes, which enhance the hour-unit productivity of employed workers.

At this point, it is worthwhile to mention local labor supply (migration) elasticity, because it affects how the local adoption of robots induces the labor demand shift and eventually affects employment and wages. Namely, if labor is geographically immobile and the local labor supply is inelastic, the effects of a labor demand shift show up in wages more than in employment. Our empirical findings in Tables 8 and Table 9 suggest that the local labor supply elasticity induced by robot adoption is 0.483 and is significantly lower than 1.[22]

Previous studies in the literature report that some new technologies are skill-biased technological changes, and thus the impacts of new technology may differ by educational background (Autor et al., 2003; Webb, 2020). To consider such potentially heterogeneous impacts, we now examine the impacts of robot adoption on hours and wages by the educational background of workers. Table 10 reports the results. Consistent with the findings in Table 9, we find that hours worked decreased significantly due to robot adoption, except for the hours worked among middle-school and four-year university graduates. An additional robot per 1,000 workers in the labor market decreases the hours worked of high-school graduates by about 2 percent and that of technical college graduates by about 2.5 percent. In terms of hourly wages, all workers, except for middle-school graduates, gained from the adoption of robots in the locality. An additional robot per 1,000 workers increases the hourly wage growth by 3.5 percent among high school graduates, by 4.1 percent among technical-college graduates, and by 4.6 percent among 4-year university graduates. Thus, the return to robots is about 30 percent higher among 4-year university graduates than among high-school graduates. This implies that the robots were also skill-biased technical change in the Japanese context. Therefore, the impacts of robot adoption were heterogeneous, as found by AR, but in the opposite direction; in Japan in 1978-2017, robot adoption improved the working conditions of workers across the board, while it was opposite in the US in 1992-2007. Detailed regression results are reported in Section G.

6 Conclusion

We study the effect of robotization on employment in the context of Japan during the 1978-2017 period. We develop a model that combines the standard factor demand theory and a recently evolving task-based framework to examine the role of robot price reduction on factor demands. We use newly digitized data of robot adoption that have three novelties: (i) a long panel covering 1978-2017 that suits the study of our context, (ii) adoption units and total values that allow a systematic calculation of robot unit costs, and (iii) disaggregation of these variables by robot application. Armed with these unique features, we use application share variations in each industry in the

[22] In Table 8, Column 1 shows that the employment elasticity with respect to robots is 1.943. In Table 9, Column 3 shows that the wage elasticity with respect to robots is 4.020. These estimates suggest that the local labor supply elasticity induced by robot adoption is 1.943/4.020 = 0.483. The estimated elasticity is more elastic than the previous empirical findings in Japan, 0.271, by Barro and Sala-I-Martin (1992) using 47 prefectures as the geographic units.

Table 10: CZ-level 2SLS Regression of Hours and Wages By Education Level

	Dependent variable: 100 ×			
	$\Delta\ln(h_{ct}^{MS})$	$\Delta\ln(h_{ct}^{HS})$	$\Delta\ln(h_{ct}^{TC})$	$\Delta\ln(h_{ct}^{4U})$
	(1)	(2)	(3)	(4)
ΔR_{ct}	-1.499	-2.045^{***}	-2.450^{***}	-1.260
	(0.993)	(0.588)	(0.906)	(0.855)
R^2	0.446	0.780	0.734	0.748
	Dependent variable: 100 ×			
	$\Delta\ln(w_{ct}^{MS})$	$\Delta\ln(w_{ct}^{HS})$	$\Delta\ln(w_{ct}^{TC})$	$\Delta\ln(w_{ct}^{4U})$
	(1)	(2)	(3)	(4)
ΔR_{ct}	1.621	3.546^{***}	4.113^{***}	4.613^{***}
	(1.172)	(0.885)	(1.309)	(1.370)
R^2	0.495	0.811	0.781	0.762
Group	Middle School	High School	Technical College	4-year Univ.
CZ FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓
Observations	1,265	1,265	1,265	1,265

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 at the commuting zone (CZ) level. All regressions control demographic variables, globalization controls, and technology controls described in Section 4.1 as well as the industry and year fixed effects. All regressions are weighted by initial-year population. The standard errors are clustered at the CZ level and reported in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

initial period of robot adoption for the source of identification. Our preferred estimates show that a one-percent reduction in robot price measure increases employment by 0.43 percent, implying that robots and labor are gross complements, which is robust to changes of price variables and the sources of identification such as the initial application shares. We also provide suggestive evidence of the significant scale effect of robot price reduction, bolstering our theoretical mechanism. The CZ-level shift-share regressions confirm this, which shows a clear distinction from the findings in the literature.

The identification strategy developed in this paper is potentially applicable to other contexts. The effective robot price series by industry-year level might serve as the explanatory variable for analyzing the effect of robot adoption in the other countries because Japanese manufacturers export robots worldwide. Reexamination of the effect of robot penetration on employment drawing on the new identification strategy would be complementary to the existing evidence of the labor market effect of robotization.

References

Acemoglu, Daron and David Autor, "Skills, tasks and technologies: Implications for employment and earnings," in "Handbook of labor economics," Vol. 4, Elsevier, 2011, pp. 1043–1171.

_ **and Pascual Restrepo**, "Demographics and Automation," Technical Report, National Bureau of Economic Research, No.24421 2018.

_ **and** _ , "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment," *American Economic Review*, 2018, *108* (6), 1488–1542.

_ **and** _ , "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020, *128* (6), 2188–2244.

_ **and** _ , "Unpacking Skill Bias: Automation and New Tasks," *AEA Papers and Proceedings*, May 2020, *110*, 356–61.

Adachi, D, Taiyo Fukai, Daiji Kawaguchi, and Yukiko Saito, "Commuting Zones in Japan," Technical Report, RIETI Discussion Paper 2020.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales, "Shift-Share Designs: Theory and inference," *The Quarterly Journal of Economics*, 2019, *134* (4), 1949–2010.

Antras, Pol, Teresa C Fort, and Felix Tintelnot, "The Margins of Global Sourcing: Theory and Evidence from US Firms," *American Economic Review*, 2017, *107* (9), 2514–64.

Arkolakis, Costas, Natalia Ramondo, Andrés Rodríguez-Clare, and Stephen Yeaple, "Innovation and Production in the Global Economy," *American Economic Review*, 2018, *108* (8), 2128–73.

Artuc, Erhan, Paulo Bastos, and Bob Rijkers, "Robots, Tasks and Trade," 2020.

Autor, David, David Dorn, and Gordon H Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–68.

_ , David Mindell, and Elisabeth Reynolds, "The Work of the Future: Building Better Jobs in an Age of Intelligent Machines," *MIT Work of the Future. Accessed December*, 2020, *6*, 2020.

Autor, David H, Frank Levy, and Richard J Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

Barro, Robert T. and Xavier Sala-I-Martin, "Regional Growth and Migration: A Japan-United States Comparison," *Journal of The Japanese and International Economies*, 1992, *6* (4), 312–346.

Berg, Andrew, Edward F Buffie, and Luis-Felipe Zanna, "Should We Fear the Robot Revolution? (The correct answer is yes)," *Journal of Monetary Economics*, 2018, *97*, 117–148.

Bessen, James E, Maarten Goos, Anna Salomons, and Wiljan Van den Berge, "Automatic Reaction - What Happens to Workers at Firms that Automate?," *Boston Univ. School of Law, Law and Economics Research Paper*, 2019.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-Share Research Designs," Technical Report, National Bureau of Economic Research, No. 24997, forthcoming in *Review of Economic Studies*, 2021.

Brynjolfsson, Erik and Andrew McAfee, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, WW Norton & Company, 2014.

Cahuc, Pierre, Stéphane Carcillo, and André Zylberberg, *Labor Economics*, MIT press, 2014.

Caselli, Francesco and Alan Manning, "Robot Arithmetic: New Technology and Wages," *American Economic Review: Insights*, 2019, *1* (1), 1–12.

Corrado, Carol, Charles Hulten, and Daniel Sichel, "Measuring Capital and Technology: an Expanded Framework," in "Measuring Capital in the New Economy," University of Chicago Press, 2005, pp. 11–46.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner, "The Adjustment of Labor Markets to Robots," *Journal of the European Economic Association*, 05 2021. jvab012.

Dekle, Robert, "Robots and Industrial Labor: Evidence from Japan," *Journal of the Japanese and International Economies*, 2020, *58*, 101108.

Diamond, Rebecca, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 2016, *106* (3), 479–524.

Flath, David, "Distribution Keiretsu, Foreign Direct Investment, and Import Penetration in Japan," *Japanese Economy*, 2005, *33* (2), 26–53.

Ford, Martin, *Rise of the Robots: Technology and the Threat of a Jobless Future*, Basic Books, 2015.

Fort, Teresa C, Justin R Pierce, and Peter K Schott, "New Perspectives on the Decline of US Manufacturing Employment," *Journal of Economic Perspectives*, 2018, *32* (2), 47–72.

Freeman, Richard B and Martin L Weitzman, "Bonuses and employment in Japan," *Journal of the Japanese and International Economies*, 1987, *1* (2), 168–194.

Frey, Carl Benedikt and Michael A Osborne, "The Future of Employment: How Susceptible are Jobs to Computerisation?," *Technological forecasting and social change*, 2017, *114*, 254–280.

Fukao, Kyoji, Tsutomu Miyakawa, and Takehiko Yasuda, *Productivity and Japan's Economic Growth*, University of Tokyo Press, 2008.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, August 2020, *110* (8), 2586–2624.

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

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, "Long-Run Implications of Investment-specific Technological Change," *The American Economic Review*, 1997, pp. 342–362.

Humlum, Anders, "Robot Adoption and Labor Market Dynamics," Technical Report, Working Paper 2019.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang, "The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data," *American Economic Review*, 2014, *104* (6), 1597–1629.

IFR, *World Robotics 2006*, International Federation of Robotics, 2006.

_ , *World Robotics 2018*, International Federation of Robotics, 2018.

Ito, Takatoshi and Takeo Hoshi, *The Japanese Economy*, MIT press, 2020.

Jeong, Dae Yong and Ruth V. Aguilera, "The Evolution of Enterprise Unionism in Japan: A Socio-Political Perspective," *British Journal of Industrial Relations*, 2008, *46* (1), 98–132.

Karabarbounis, Loukas and Brent Neiman, "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 2014, *129* (1), 61–103.

Khandelwal, Amit K, Peter K Schott, and Shang-Jin Wei, "Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters," *American Economic Review*, 2013, *103* (6), 2169–95.

KHI, *Half a Century of Kawasaki Robotics: The Kawasaki Robot Story 1968 - 2018*, Kawasaki Heavy Industry, Ltd., 2018.

Koch, Michael, Ilya Manuylov, and Marcel Smolka, "Robots and Firms," Technical Report, CESifo Working Paper 2019.

Koike, Kazuo, *Understanding Industrial Relations in Modern Japan*, MacMillan Press, 1988.

Kolesár, Michal, Raj Chetty, John Friedman, Edward Glaeser, and Guido W Imbens, "Identification and Inference with Many Invalid Instruments," *Journal of Business & Economic Statistics*, 2015, *33* (4), 474–484.

Miyagawa, Tsutomu, Miho Takizawa, Konomi Tonogi, and Kyoji Fukao, "Declining Rate of Return on Capital and the Role of Intangibles in Japan," in Deb Kusum Das, ed., *Productivity Dynamics in Emerging and Industrialized Countries*, London: Taylor & Francis, 2018.

Moretti, Enrico, "Local multipliers," *American Economic Review*, 2010, *100* (2), 373–77.

Nikkei, "Factory Automation toward Unmanned Factory (Kanzen Mujinka Kojo he FAka no Uneri)," *Nikkei Sangyo Shimbun*, August 23 1982.

—, "Spot Welding Robot (Spot Yousetsu Robot)," *Nikkei Sangyo Shimbun*, May 23 1984.

Nomura, Koji and Fumio Momose, "Measurement of Depreciation Rates based on Disposal Asset Data in Japan," Technical Report, OECD Working Party on National Accounts 2008.

OECD, *Measuring capital*, Organization for Economic Cooperation and Development, 2009.

—, *How's Life in the Digital Age?* 2019.

Rotemberg, Julio, "Instrument Variable Estimation of Misspecified Models," Technical Report, Massachusetts Institute of Technology 1983.

Tachibanaki, Toshiaki, Tomohiko Noda, Torben M. Andersen, and Alan Kirman, "Enterprise Unionism: The Japanese System at Work," *Economic Policy*, 1996, *11* (23), 471–485.

Webb, Michael, "The Impact of Artificial Intelligence on the Labor Market," Technical Report, Stanford University 2020.

Appendix

A Control Variables and Summary Statistics

In this section, we discuss the set of control variables in our main analysis. 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, 2018a). The lack of demographic variables may bias the estimates of regression coefficients. 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 employ workers (Fort et al., 2018). To alleviate this concern, we control for offshoring, import competition, 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 export platforms (e.g., Arkolakis et al., 2018).

Third, technological changes other than robots, such as increases in information and communications technologies (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 F.12.

Table A.1 shows the summary statistics of these control variables as well as other variables used in the main regression specifications (17) and (18).

Table A.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Robot Stock	104	8,761.046	15,638.330	25.116	492.436	5,616.348	69,779.880
Robot Price (million JPY)	104	5.396	1.463	2.408	4.359	6.341	9.478
Robot Purchases (billion JPY)	104	17,429.730	30,903.520	51.340	1,519.550	17,031.090	158,054.600
Employment (thousand)	104	4,887.663	13,316.480	163.044	450.847	1,518.707	55,030.380
High School Graduate Share	104	0.506	0.052	0.348	0.480	0.539	0.613
College Graduate Share	104	0.198	0.086	0.053	0.135	0.245	0.491
Female Share	104	0.307	0.127	0.094	0.203	0.402	0.588
Age $\leq$ 35 Share	104	0.310	0.059	0.202	0.267	0.344	0.476
Age $\geq$ 50 Share	104	0.317	0.077	0.122	0.266	0.377	0.461
Foreign Value Added (billion JPY)	104	2,942.763	7,028.600	0	0	2,449.6	49,337
Import (billion JPY)	104	3,496.364	4,825.271	142.424	592.385	4,164.628	25,135.200
IT Asset (billion JPY)	104	1,115.569	3,836.960	0	4.2	393.0	24,132
Innovation Asset (billion JPY)	104	7,047.061	13,958.690	0	21.8	6,391.2	71,401
Competitive Asset (billion JPY)	104	1,223.020	3,757.351	0	10.2	628.5	18,431

B Robot Quality Adjustment

Since Cobb-Douglas aggregation (15) does not allow quality upgrading across applications, we modify it to the following CES aggregation

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

where R_{ait} is the robot stock of application a in industry i in year t, $\widetilde{s_{ai}}$ is the time-constant expenditure share parameter reflecting the applicability of application a in each industry i, λ_{ait} is time-varying unobserved quality that captures the quality upgrading over time, and σ is the elasticity of substitution between robot applications. Cost minimization implies the demand for robot application a as

$$R_{ait} = (\widetilde{s_{ai}})^{\sigma} \lambda_{ait}^{\sigma-1} (p_{at}^{R})^{-\sigma} (p_{it}^{R,QA})^{\sigma-1} R_{it},$$

where p_{at}^{R} is the price of robot application a in year t, and

$$p_{it}^{R,QA} = \left(\sum_{a} \widetilde{s_{ai}} \left(p_{at}^{R} / \lambda_{ait} \right)^{1-\sigma} \right)^{1/(1-\sigma)} \tag{24}$$

is the quality-adjusted robot price index. Taking logs, we obtain

$$\ln R_{ait} = -\sigma \ln p_{at}^{R} + \alpha_{ai} + \alpha_{it} + \eta_{ait}, \tag{25}$$

where R_{ait} is the robot stock, $\alpha_{ai} = \sigma \ln (\widetilde{s_{ai}})$, $\alpha_{it} = \ln \left((p_{it}^{R})^{\sigma-1} R_{it} \right)$ and $\eta_{ait} = (\sigma - 1) \ln (\lambda_{ait})$. Regressing $\ln R_{ait}$ on $\ln p_{at}^{R}$ and fixed effects α_{ai} and α_{it} gives $\widehat{\sigma}$ and the residual $\widehat{\eta}_{ait}$. Thus, we obtain the quality estimate

$$\widehat{\lambda_{ait}} = \exp \left(\widehat{\eta}_{ait} / (\widehat{\sigma} - 1) \right). \tag{26}$$

Several discussions follow in terms of our model choice. First, our extended specification nests the Cobb-Douglas case. Namely, with $\sigma \to 1$ and $\lambda_{ait} = 1$, we revert to our initial specification $R_{it} = \prod_{a} (p_{ait}^{R})^{\widetilde{s_{ai}}}$, with $\widetilde{s_{ai}} = s_{ai}$. Second, we model quality as application-augmenting shocks. We interpret this 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. Third, relative to Khandelwal et al. (2013), we have an additional expenditure share term

s_{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).

To obtain quality measure $\widehat{\lambda_{ait}}$ from equation (25), it is necessary to have an estimate for robot demand elasticity $\widehat{\sigma}$. For this purpose, we follow two strategies. The first one is the fixed-effect regression as in equation (25), as it contains application-industry and industry-time specific fixed effects. Therefore, any unobserved robot qualities that are invariant across time (e.g., industry-specific applicability of a particular robot application, such as the Transportation machine industry's intensive use of Welding robots) and across applications (e.g., industry-specific readiness to adopt robots in each period) do not cause bias for the estimates of σ. Second, a remaining concern for endogeneity is that time t-varying application a-industry i-specific quality upgrading may still cause both the measured robot price and the measured quantity, biasing the estimate of σ. To alleviate this concern, we use a leave-one-industry-out counterpart $r_{-i,at}$ as a cost shifter that is independent of industry-specific quality shock. The premise is that the industry-specific quality upgrading is uncorrelated across industries, so that the variation in leave-one-out price $r_{-i,at}$ captures the cost component for industry i.

We report our estimates of the robot application elasticity of substitution σ in Table B.2. Column 1 reports the result with OLS regression of equation (25), and column 2 shows that with the instrumental variable of leave-one-industry-out robot price. We find that robots are complementary to each other, and specifically, σ is in the range of 0.3 to 0.5. This is broadly consistent with our idea of robot applications since different applications perform separate sets of tasks, which makes substitution across applications hard.

Based on these results, we use $\sigma = 0.3$ and $\sigma = 0.5$ for our robustness analysis with the quality-adjusted price. Table B.3 shows the regression result of our main specification with the employment outcome variable, equation (18). Column 1 shows the result with $\sigma = 0.3$ and column 2 reports the one with $\sigma = 0.5$. We confirm that the quality adjustment does not affect our qualitative conclusion that the reduction of robot prices increases employment, while the quantitative implication is smaller. Intuitively, the robot price decline of a given robot application, combined with our estimation result of $\sigma < 1$ and roughly constant application expenditure share

Table B.2: Estimates of the Elasticity of Substitution across Robot Applications

	Dependent variable:	
	$\ln(R_{ait})$	
	(1)	(2)
$\ln(r_{at})$	0.468	0.299
	(0.172)	(0.179)
Application-Industry FE	✓	✓
Industry-Year FE	✓	✓
Estimator	FE	FE-IV
Observations	652	652
R^2	0.939	0.939

Notes: Authors' calculation based on JARA data. The table shows σ estimates implied by equation (25) and the relationship between the log robot stock quantity $\ln(R_{ait})$ and log robot average price $\ln(p^R_{at})$. The first column shows the fixed-effect (FE) estimate. The second column reports the FE-IV estimate with the leave-one-out robot price $\ln(p^R_{-i,at})$. In both IV specifications, the first stage has the F-value of 5837 (p<0.001). Standard errors are in parentheses. As we do not have a priori null hypothesis, we do not report significance against any values.

(Table 2), implies that the quality of robots must have been upgraded to keep the expenditure share constant. Therefore, part of the positive employment impact of robot price reduction in the main empirical result is absorbed when we take into account such quality upgrading in the regression. This also explains the larger coefficient in column (2) compared to column (1) since the larger the EoS, the smaller the quality-adjusted price declines due to greater technological progress to maintain a constant expenditure share.

C Output Price Trends

In Figure C.1, we show the trend of sectoral output prices. In the 1980s and 90s, industries experienced a modest reduction in the output price index, which is consistent with long-run technological growth, followed by a slowdown and even some reversal afterward in some industries.[23] Notably, the electric machine industry shows a very stark price reduction during the period. Since the electric machine industry includes ICT goods, this rapid price drop is consistent with the large macroeco-

[23]The prices of Non-ferrous metal and Steel increased substantially in the mid-2000s, reflecting the substantial increases in commodity prices, such as those of aluminum, copper, and iron ore.

Table B.3: Employment effect of Quality-adjusted Prices

	Dependent variable:	
	$\ln(L_{it})$	
	(1)	(2)
$\ln(p_{it}^{R,QA})$	-0.024^{**}	-0.041^{**}
	(0.010)	(0.020)
EoS σ	0.3	0.5
Observations	104	104
R^2	0.986	0.986

Notes: Authors' calculation based on JARA, ESS, CoM, SOBA and JIP data. The table presents estimates of the relationship between log quality-adjusted robot price measure and log employment across industries and years. Each column shows the result with quality estimates based on alternative estimates of the elasticity of substitution (EoS) between applications. Column 1 uses the EoS value of 0.3, while column 2 uses 0.5. All specifications control the industry and year fixed effects, demography controls, globalization controls, and technology controls defined in Section 4.1. All regressions are weighted by purchase values of robots in each year. The industry-level cluster-bootstrapped standard errors are shown in the parenthesis. *p<0.1; **p<0.05.

nomics literature on the decline and its implication for investment good prices (e.g., Greenwood et al., 1997; Karabarbounis and Neiman, 2014). Since the great reduction of the electric machine price does not necessarily reflect robot penetration, including the electric machine in the regression model would introduce significant noise in the coefficient estimates. For this reason, we drop the electric machine industry from the regression analysis of output prices.

D Early adoption of Robots in Japan

Japanese industries adopted robots about 15 years earlier than their US and European counterparts, as we mentioned in the introduction and data section. What accounts for this early adoption of robots? One might think that the availability of domestic robot producers trivially explains the early adoption in Japan. Robot technology, however, was more advanced in the US than in Japan in the early 1970s. For instance, the first domestic industrial robot in Japan was produced in 1969 by Kawasaki-Unimation, the joint venture of Kawasaki Heavy industry Inc. and US-based Unimation Inc, allegedly the first industrial robot producer in the world. Kawasaki signed a technical license

Figure C.1: Output Price Trend

Note: Authors' computation based on BOJ data. The output price index is normalized at 100 in 2005.

agreement with Unimation in 1968 and sent its engineers to the United States to acquire technical knowledge and import sample machines. Thus, the presence of domestic robot producers does not solely explain the early adoption of robots by Japanese industries.

We argue that the Japanese employment practices of large manufacturing firms throughout the analysis period promoted the earlier adoption of robots to production sites compared with the Western counterparts. Standard textbooks of the Japanese economy list the features of the practice as a combination of (i) long-term employment, (ii) seniority-wage, (iii) large bonus payments that are associated more with companies' performance rather than individual performance, and (iv) enterprise-level labor unions (Flath, 2005; Ito and Hoshi, 2020). Among these features, long-term employment and seniority wage are allegedly combined with a unique job rotation system of shop floor workers. In particular, based on interviews with shop floor workers and labor unions of the automobile industry in the 1970s in both Japan and the US, Koike (1988) documents that the Japanese automobile shop floor workers experienced a wider range of operations on the production line than did their US counterparts. This practice helps workers obtain an overview of the whole production process, which might have mitigated the plant's concern about adopting robots and thus reduced the cost of adoption.

In addition, enterprise-level labor unions tend to welcome the introduction of new technology that improves the work environment or labor productivity, because workers who become redundant can be relocated to other workplaces of the same firm, and they receive a part of the productivity gain due to the profit sharing nature of the wages and bonus determination (Freeman and Weitzman, 1987).[24] A comment by the CEO of a machine tool manufacturer substantiates the claim that Japanese employment practices mitigated labor unions' opposition to the adoption of new technology. In an interview with Tsuyoshi Higuchi of Nikkei newspaper, Teruyuki Yamasaki, the CEO of Yamazaki Iron Work (Currently, Yamazaki Mazak Corporation), commented based on his experience in both Japan and Europe that

> Indeed, Japanese managers are enthusiastic about technological innovation and, in addition, since Japanese firms adopt life-long employment, labor unions are open to automation or labor-saving technology that improve the work environment. In the western countries, labor unions are typically organized by occupation; thus, for example, transferring a lathe operator to another occupation is very difficult. (Nikkei, evening edition, February 15, 1982, page 3.)

Without the fear of job loss, labor unions *welcomed* the introduction of robots at production sites as a deliverer that releases union members from hard tasks. For instance, KHI (2018) describes the *Kawasaki-Unimate 2000*, one of the first robot brands in Japan, that: "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." Apparently, the number of shop floor workers involved in spot welding tasks was reduced, but the workers were released from the hardship associated with these tasks.

Our own interviews with high-rank managers and officers of robot manufacturers bolster the argument above. In interviews with three major robot manufacturers, we asked why Japanese manufacturers vigorously adopted robots as early as the 1980s, ahead of their US or European counterparts. In response, all interviewees unanimously pointed to the Japanese employment practices, claiming that the adoption of robots did not lead to job loss.[25]

[24]Tachibanaki et al. (1996) and Jeong and Aguilera (2008) also document that the employment practices of Japan allow workers' relocation within a company through retraining.

[25]Interviews with Mr. Tomonori Sanada and Mr. Seiji Amazawa of Kawasaki Heavy Industries, Ltd. on April 6th,

2021, with Mr. Kazuyoshi Toyokawa of Yasukawa Electronic Corporation on April 9th, 2021, and with Dr. Shinsuke Sakakibara of Fanuc Corporation on April 22nd.

Online Appendix

E Theory Appendix

F Data Appendix

F.1 Coverage of JARA data

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 F.10. Figure F.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.

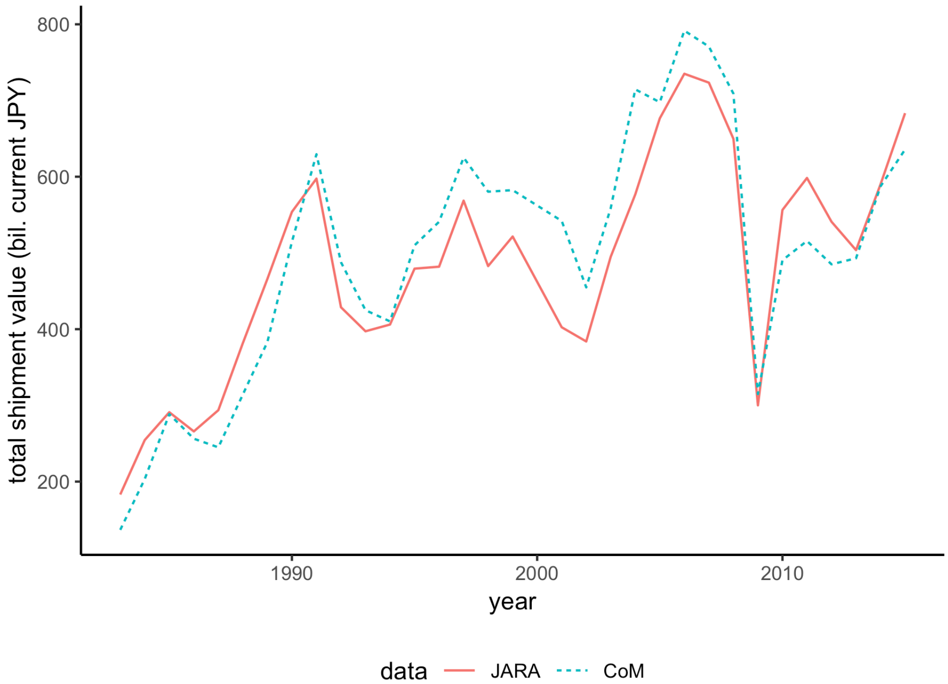
F.2 Raw Trends of Robot Stock Units, by Country

Figure F.2 shows the raw trend of the number of robot units across the selected world regions in Figure 1. Our main claims are unchanged; Japan had a unique trend of robot stocks that emerged and grew fast in the 1980s and plateaued and slightly declined afterward. In Figure F.2, China adopted robots very rapidly, and is the largest robot adopter since 2016. Due to the size of the country, however, when normalized by employment, China's robot stock is still smaller than that of any of the countries considered in these figures (recall Figure F.2).

F.3 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

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



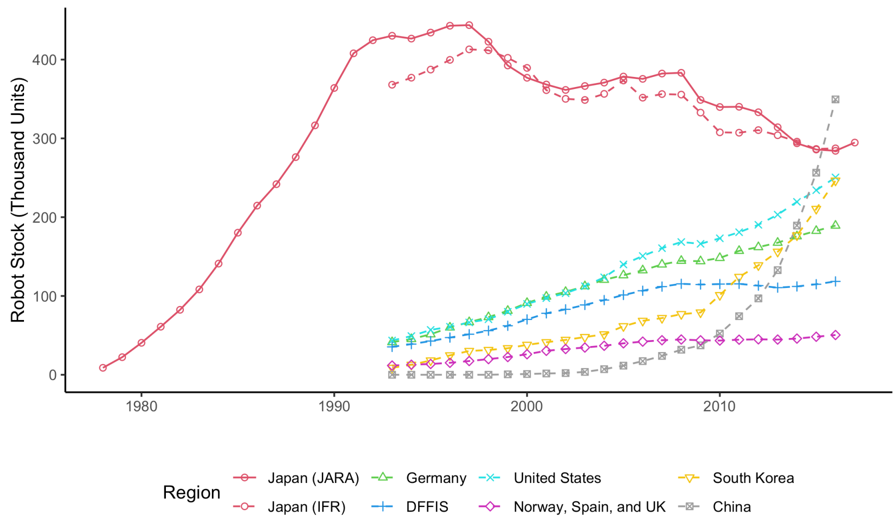
Note: Authors' calculation based on JARA and CoM/ECBA data. The trend for the JARA is the sum of shipment value of any robot applications to any industries. The trend for the CoM is the sum of shipment value (net of VAT) of all products categorized as industrial robots (available from 1983 to 2016).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

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.[26] 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 according to 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 each user. Examples include Welding and soldering (WS), which are intensively needed tasks in the automobile industry, and Assembling and disassembling (AD), which 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

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

Figure F.2: Raw Trends of Robot Stock Units, by Country



Note: Authors' calculation based on JARA, IFR, OECD, and National Bureau of Statistics of China (NBSC). The figure shows the trends of robot stock units for each group of countries and data source. As sources, we use JARA and IFR, which are explained in detail in the data section. The JARA data show the application-aggregated robot shipment units from within Japan to Japan between 1978 and 2017. To calculate the stock units, we assume a 12-year immediate withdrawal method to match the stock unit trend of Japan observed in the IFR. The IFR data show stock unit trends from 1993 to 2016 for selected countries: the groups of countries reported in Acemoglu and Restrepo (2020a), China, Japan, and South Korea. DFFIS stands for Denmark, Finland, France, Italy, and Sweden, as selected in AR.

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 the automobile industry, while numerical control robots tend to be in the 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 features of robots. In the JARA data, the type classification was discontinued in 2000 and the structure classification began in the following year. The structure classifications are as follows: articulated robot, SCARA robot, polar coordinate robot, cylindrical robot, cartesian robot, and parallel link robot.

F.4 Robot Trend in The Very Early Period

Figure F.3 shows the robot trends starting in 1974, leveraging the tables by types of robots that start from that year (recall the coverage of years in Table 1). By doing so, we can gauge the robot adoption in Japan in years before 1978, the starting year of our sample period. Consistent with the fact that robot adoption in Japan expanded quantitatively beginning in the late 1970s, the robot units and their monetary values are small in 1974-1977 relative to the later periods. This finding corroborates our choice of stock measures that assume no robot adoption before 1977. We also consider the exercise in which we allocate the total robot quantity and sales to each application in 1974-1977 by application shares in 1978-1982. Since these values are quantitatively negligible compared to the observed application-level quantities and sales after 1982, this exercise does not affect our empirical results, which are available upon request.

F.5 Robot Price Trend by Type

Figures F.4 and F.5 show the expenditure shares and unit value trends of each robot type, respectively. Figure F.4 reveals that, among others, the Welding application uses playback robots most intensively. Figure F.5 shows the secular declining trend of playback robots. This monotonic price decline of playback robots makes a sharp contrast to the price trends of other robot types and reduced the price of welding robots. These findings corroborate Table 2 and Figure 4, and support the idea that the price decline was caused by the mechanical specification of robots, classified by the types of robots.

F.6 Domestic Sales and Export of Japanese Robots

Figure F.6 reveals that the growth of robot adoption within Japan expanded during the 1980s, while the trend is stagnant afterward. In contrast, starting around 1990, the export trend grew rapidly. Although the structural break before and after 1990 is an interesting phenomenon in itself, we instead focus on the domestic adoption trend and its industrial variation.

F.7 Technical Details of Robot Applications

We provide the technical details of robot applications to bolster the interpretation that the robot price movement is caused by technological changes. Following Section 3.2, we describe the two prominent robot applications: spot welding (SW) and surface mounting (SM).

SW requires intensive movements in all directions within three-dimensional spaces to weld metal sheets to assemble complex automobile body shapes. Therefore, SW robots are typically structured as articulated robots, which are equipped with multiple joints (typically six) that enable smooth movements along any direction.

In contrast, SM requires quick and accurate movements 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.[27]

F.8 Calculating Robot Stock

As we briefly discussed in Section 4.6, we make alternative and flexible assumptions on the robot stock calculation. The first set of assumptions is based on the immediate withdrawal method (IWM). The IWM assumes that shipped robots are in use immediately after purchase and not in use after a specified length of time. IFR follows this method with a withdrawal period of 12 years. To better compare the results with those in 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 using shorter standard depreciation schedules. Given these discussions, we consider three alternatives: 10, 12 (baseline), and 15 years of depreciation.

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 this 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 disposable asset data in Japan (Survey on Capital Expenditures and Disposables), Nomura 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 F.1 shows the baseline regression result of specification (**??**) 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 the stock measurement of robots.

[27] As is discussed in detail in Appendix F.3, robot structure is the mechanical aspect of robots.

Table F.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***
	(0.071)	(0.071)	(0.030)	(0.091)	(0.085)
Stock Measurement	10 Years	12 Years (Main)	15 Years	$\delta = 0.1$	$\delta = 0.18$
Industry FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓	✓
IV F-stasitic	77.219	27.527	21.872	194.3	434.083
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 log robot stock measure and log employment across industries and years, with the instrument of log robot cost measure, with various robot stock measures. In Column 1, the stock measure is calculated by the assumption that robots are used for 10 years continuously after purchase and depreciated afterwards. Column 2 and 3 assumes in similar ways but with the different length of years of 12 years and 15 years, respectively. Columns 4 and 5 assumes the exponential depreciation after purchase, with the annual depreciation rate of 10% and 18%. The employment measure includes the employment of robot-producing plants. All columns control the industry and year fixed effects. All regressions control the demography controls (explained in the main text), the logarithm import values from JIP database, the logarithm offshoring value added from SOBA, and the logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. All of them are weighted by purchase values of robots in each year. The industry-level cluster-bootstrapped standard errors are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

F.9 Detail in ESS

In the 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 educational 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), and 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. We convert these categorical variables into continuous variables using the mid-point of each 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. Industry and occupations are encoded according to the Japan Standard Industry Classifications (JSIC) and the Japan Standard Occupation Classifications (JSOC).

F.10 Details of the Census of Manufacture

The Census of Manufacture (CoM) annually surveys manufacturing establishments in Japan.[28] The CoM asks each establishment for its product-level shipment values. The product code for industrial robots used in CoM has existed since 1977. We take the CoM data from 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.

The CoM and the ECBA treat the VAT in the following way. For CoM, before 2014, respondents were required 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 adopt 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 the 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.

[28]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 more than three employees are surveyed.

Table F.2: Industry-level, Reduced Form, Removing Robot-Producing Workers

	Dependent variable:			
	$\ln(L_{it}^{NRP})$			
	(1)	(2)	(3)	(4)
$\ln(r_{it}^{Z})$	-0.841^{***}	-0.466^{***}	-0.274^{*}	-0.437^{***}
	(0.094)	(0.120)	(0.151)	(0.077)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-stasitic	7.611	34.718	19.411	27.527
Observations	104	104	104	104
R^2	0.975	0.984	0.985	0.987

Table F.2 shows the result of the specification (**??**) 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 that the estimates are very close to the ones in Table 3, Panel B. 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 direct robot-producing workers are concerned, the reinstatement effect of automation is quite small (Acemoglu and Restrepo, 2020b).

F.11 Details of the Basic Survey on Overseas Business Activities

The Basic Survey on Overseas Business Activities (BSOBA) is a firm-level census of Japanese multinational enterprises (MNEs) and their foreign subsidiaries. For all MNEs, all subsidiaries and each subsidiary's subsidiaries must be reported, which we call subsidiaries collectively. 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 foreign sales variables for each industry and headquarters location. We take offshoring intensity measures by aggregating operating revenues in foreign subsidiaries. We take subsidiaries' industry codes when allocating revenues to each industry.

F.12 Details of the Japan Industrial Productivity Database

Japan Industrial Productivity (JIP) database is a long-run industrial aggregate of several measures starting in 1970. The industrial data contain KLEMS variables and variables regarding trade, and these data are a part of the world KLEMS data project. Among them, we use import and intangible capital to control for recent developments of foreign competition and technologies, both of which are argued to be sources of impact factors to labor demand in recently developed economies (e.g., Autor et al., 2003, 2013). The JIP database measures intangible capital of the following broad categories: computerized information (e.g., ordered and packaged software, own-developed software), innovative property (e.g., R and D expenditures, mineral exploration, copyright and trademark right, other product/design/research development), and economic competencies (brand capital, firm-specific human capital, expenditure for restructuring). Basic concepts of these variables follow National Accounts. Further details are provided in Corrado et al. (2005) and Fukao et al. (2008).

F.13 Robot Imports in Japan

Japan produces most of its robots domestically (Acemoglu and Restrepo, 2018a, among others). To confirm this, we compare the import (from the rest of the world to Japan) and the domestic sales (from Japan to Japan) measures of robots. 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 F.7 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 the results as indicating that most 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.

F.14 Industry Export Share

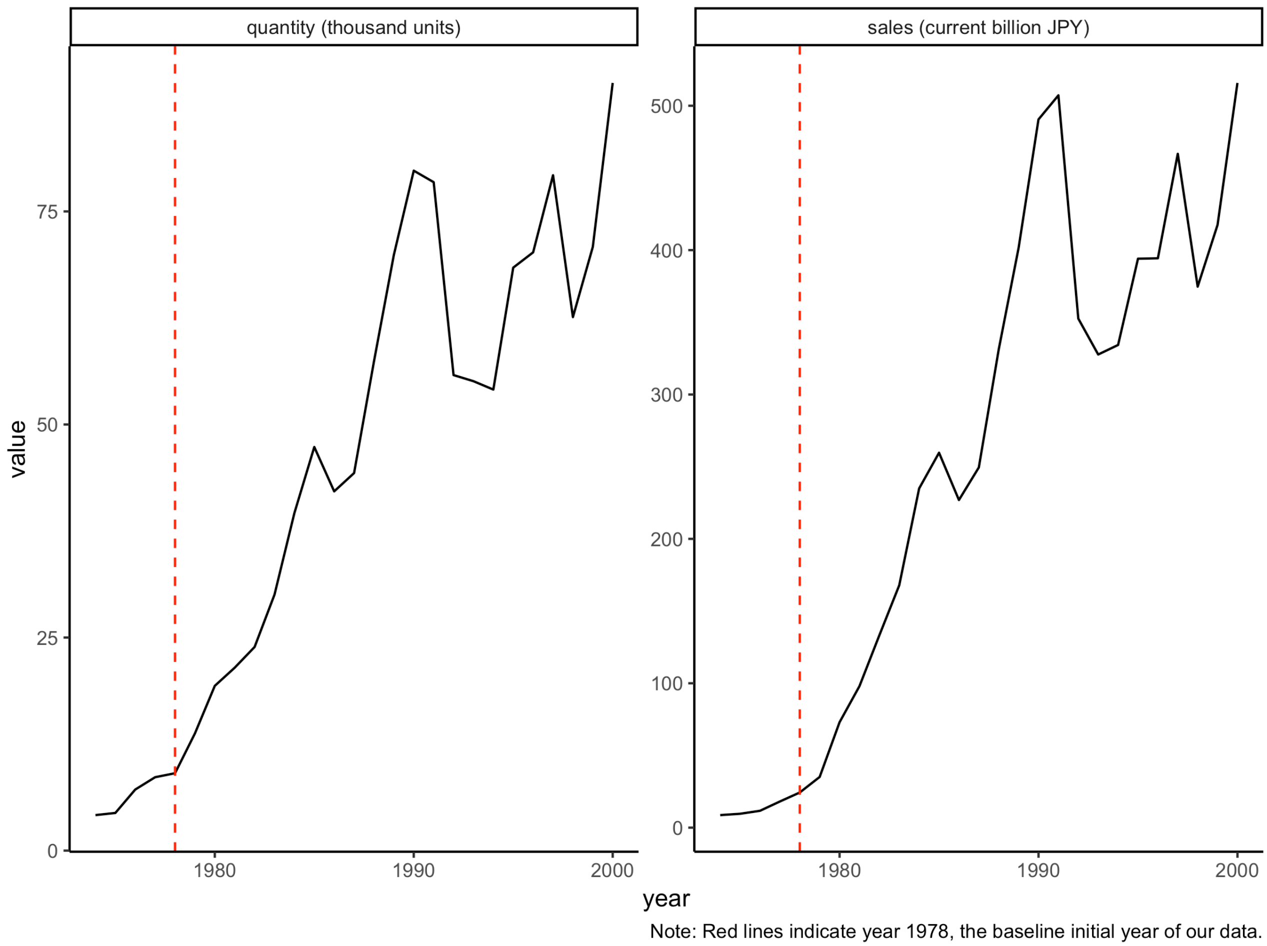
We report the export shares of the nominal output, EX_{it}/PY_{it}, in Table F.3. Since the export share is small relative to the domestic absorption, the impact of the robot prices on the total output, if any, is likely to be observed in the domestic absorption component as opposed to the export component.

Table F.3: Export Share

Industry	1982	1987	1992	1997	2002	2007	2012
Steel	0.129	0.126	0.071	0.082	0.107	0.136	0.142
Non-ferrous metal	0.140	0.050	0.048	0.079	0.160	0.287	0.435
Metal products	0.104	0.085	0.046	0.053	0.073	0.103	0.125
General machine	0.223	0.244	0.190	0.241	0.277	0.368	0.409
Electric machine	0.260	0.311	0.243	0.268	0.312	0.373	0.356
Precision machine	0.364	0.393	0.316	0.352	0.392	0.453	0.406
Transport machine	0.331	0.383	0.250	0.251	0.299	0.338	0.345
Food	0.012	0.008	0.006	0.006	0.006	0.009	0.010
Paper	0.023	0.022	0.018	0.016	0.020	0.028	0.033
Chemical	0.089	0.087	0.081	0.098	0.125	0.175	0.192
Ceramics	0.070	0.074	0.051	0.061	0.079	0.120	0.157
Other manuf.	0.055	0.061	0.049	0.051	0.064	0.078	0.101
Non-manuf.	0.000	0.000	0.000	0.000	0.000	0.000	0.004

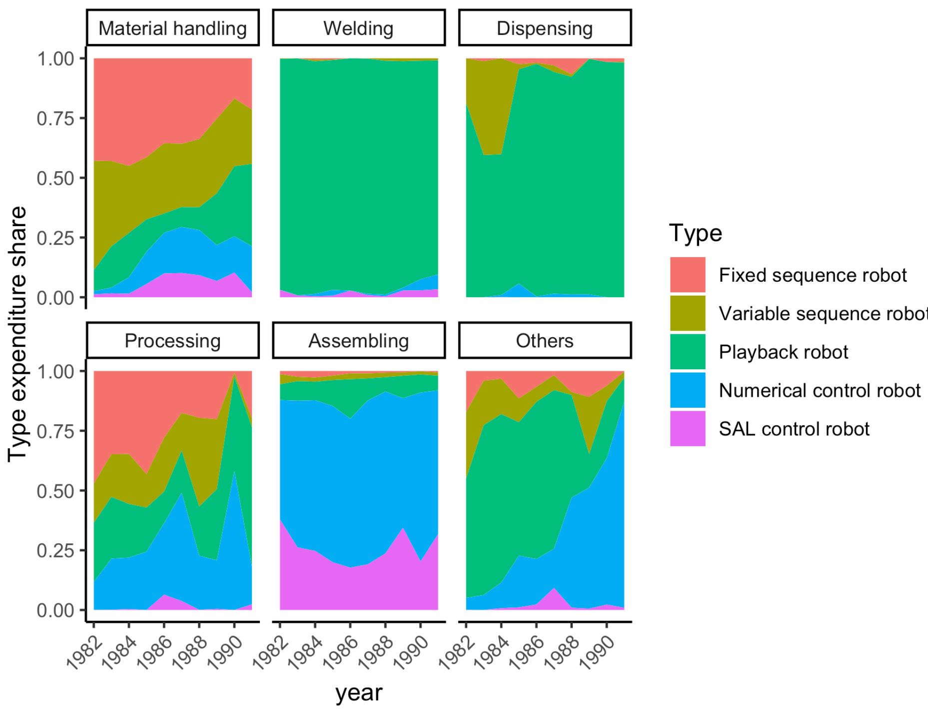
Note: The authors' calculation from the JIP database, sectoral growth accounting and export statistics. Value 0 means all goods are absorbed in the domestic economy, while value 1 means all are exported.

Figure F.3: Robot Trends Before and After 1978



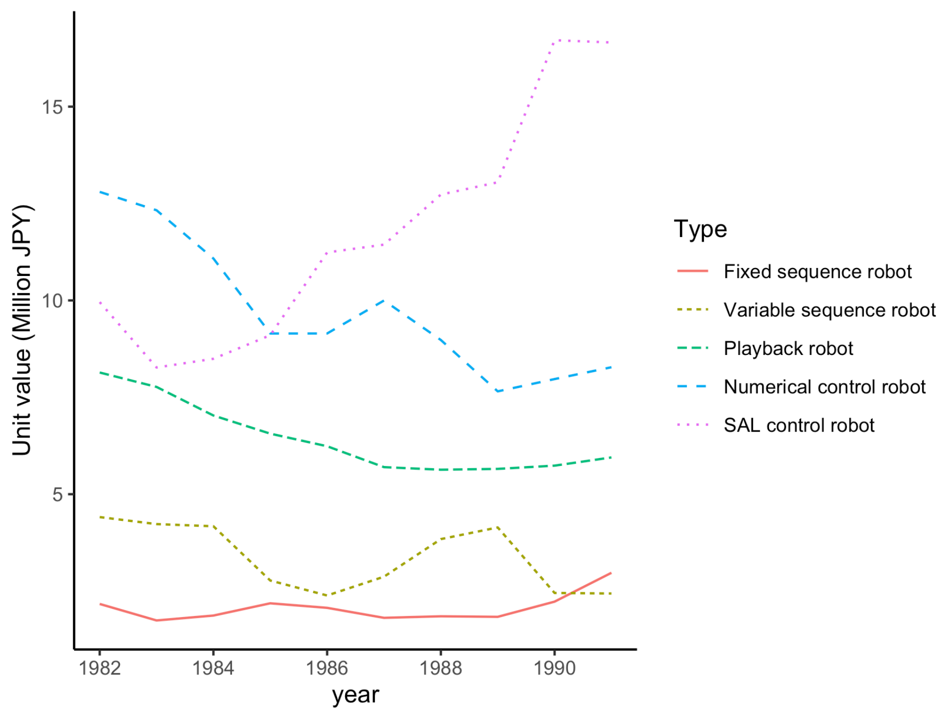
Note: Authors' calculation based on JARA data. The red dashed line indicates 1978, the initial year of our primary analysis. Trends before 1977 are taken by aggregating type-buyer industry across tables.

Figure F.4: Expenditure Shares by Robot Type



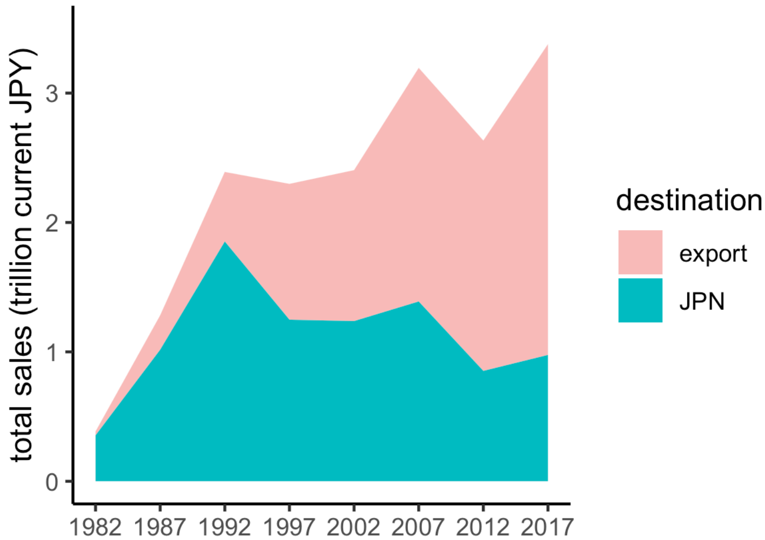
Note: Authors' calculation based on JARA, 1982-1991. The figure shows the type-expenditure shares for five robot type aggregates: fixed sequence robot, variable sequence robot, playback robot, numerical control robot, and intelligent robot.

Figure F.5: Unit-Value Trends by Robot Type



Note: Authors' calculation based on JARA data, 1982-1991. The figure shows the aggregated unit-value trends for each robot type for five robot type aggregates: fixed sequence robot, variable sequence robot, playback robot, numerical control robot, and intelligent robot.

Figure F.6: Destination Countries of Japanese Robot Shipments

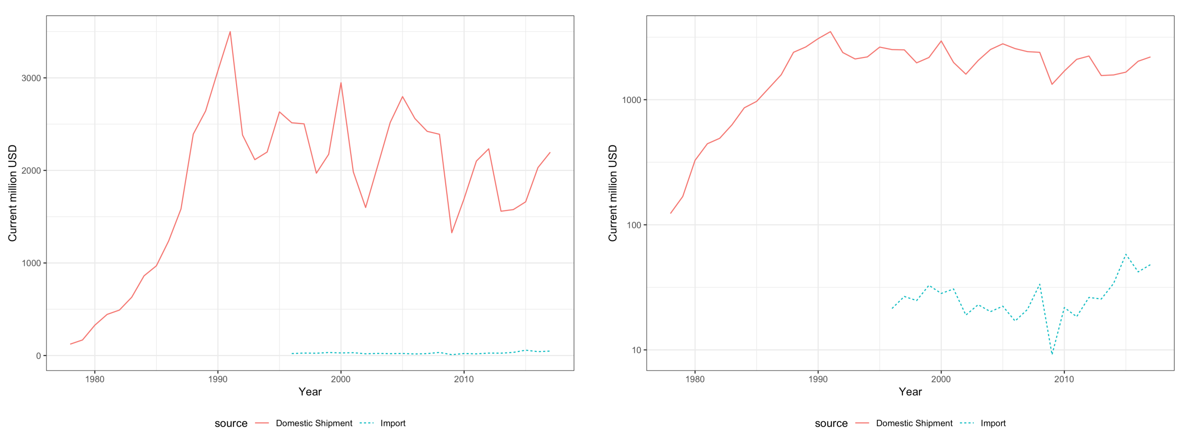


Note: Authors' calculation based on JARA data. The figure shows the sales of exports (pink) and aggregated domestic industries (green). The figure shows the decomposition of aggregated domestic industries into three categories: electric machine (red), transportation machine (green), and aggregated other domestic industries (purple).

Figure F.7: Domestic Shipments and Imports 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 shipments from domestic producers, aggregated by all applications and industries. The Comtrade data are 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.

G Additional Empirical Results

G.1 Rotemberg Decomposition of the Robot Price Index

One of our premises in the main analysis is that our robot price measure (16) is exogenous to the labor demand of robot users. Although we have already shown some supporting evidence in Section 4.3, it is still a contestable assumption. In this section, we argue that our results are not driven by this assumption by employing the identification strategy that hinges solely on the exogeneity of the initial period application share component. For this purpose, we allow the robot price measure (16) to be an endogenous variable. To obtain an exogenous force that shifts the robot price measure but not the employment directly, we take the initial application share and use it as an instrumental variable. The premise is that, as we have discussed in Section 3.2, the initial application share is related to the cost of robot adoptions each industry perceives, while it does not directly affect the future labor demand trends. This assumption is weaker than assuming our robot price measure (16) is exogenous, as it is free from imposing any restriction on the application-level price measure (14).

Our exercise can be understood in light of Goldsmith-Pinkham et al. (2020, GPSS). Namely, recall that a shift-share measure is the average of "shift" weighted by "share." One can use only the share part as the source of exogenous variation. In this case, there are a number of IVs that correspond to the dimension of the share components. Therefore, there are six IVs for the endogenous variable as tabulated in Table 1 with six just-identified IV estimates $\hat{\beta}_a^R$ using each application-a share as IV. This is a useful way to understand our exercise because we can compute the relevance of each IV estimate by a measure called Rotemberg weight $\hat{\alpha}_a$ for each application a (Rotemberg, 1983). Using this measure, the IV estimate with a large Rotemberg weight contributes to a large inconsistency if the corresponding IV does not satisfy the exogeneity assumption. Therefore, examining the Rotemberg weight gives an insight to validate the identification assumption.

Formally, take our estimation equation (18) as example and we decompose our estimator $\hat{\beta}$ into Rotemberg weight $\hat{\alpha}_a$ and IV coefficient $\hat{\beta}_a$ that satisfy

$$\hat{\beta} = \sum_a \hat{\alpha}_a^R \hat{\beta}_a^R, \tag{27}$$

Table G.1: Rotemberg Decomposition

Application	Rotemberg Weight	IV Coefficient
Welding and soldering	0.415	-0.794
Assembling and disassembling	0.243	-0.095
Handling operations/Machine tending	0.194	-0.384
Processing	0.018	-1.201
Dispensing	0.013	-0.199
Others	0.118	0.125

Note: Rotemberg decomposition following Goldsmith-Pinkham et al. (2020, GPSS). Following GPSS Section 3.C, we aggregate the time dimension and report an application-level decomposition. Column "Rotemberg Weight" indicates the weight for the IV specification based on each robot application that aggregates to the original Bartik specification due to Rotemberg (1983). Column "Coefficient" shows the IV regression coefficient for each regression..

where $\hat{\alpha}_a^R \equiv \sum_t \hat{\alpha}_{a,t}^R$ and $\hat{\beta}_a^R \equiv \sum_t \left(\hat{\alpha}_{a,t}^R / \hat{\alpha}_a^R\right) \hat{\beta}_{a,t}^R$ with

$$\hat{\alpha}_{a,t}^R \equiv \frac{\sum_i s_{ai} \ln\left(p_{at}^R\right) \ln\left(p_{it}^R\right)^\perp}{\sum_{(a',i,t')} s_{a'i} \ln\left(r_{a't'}\right) \ln\left(p_{it'}^R\right)^\perp}, \text{ and } \hat{\beta}_{a,t}^R \equiv \frac{\sum_i s_{ai} \ln\left(L_{it}\right)^\perp}{\sum_i s_{ai} \ln\left(p_{it}^R\right)^\perp},$$

and for any variable X, $X^\perp$ is the residualized X with respect to the set of control variables in our main specification (Table 3, Column 4).

Following these arguments, we show the decomposition result in Table G.1. We find that for all robot applications, Rotemberg weights are positive. Furthermore, the Welding and soldering application is associated with highest weights, followed by Assembling and disassembling and Handling operations/Machine tending. These patterns are consistent with the high adoption value of these applications, and thus our empirical results are largely driven by these applications. The large Rotemberg Weight for welding and soldering robots reflects that the substantial price variation of welding and soldering robots plays a crucial role for identification. This fact reflects the relevance of our results, as well as the sensitivity to misspecification, especially for these applications. We will examine this point later in Table 5.

As for the IV coefficients, our main result of the positive impact of robot adoption on employment can be found in all applications but the "Others" application. In particular, we find that Welding and soldering and Handling operations/Machine tending have large negative coefficients. Again, it is reassuring that our main finding is driven by robots used for these quantitatively sizable applications, but at the same time, if there is a misspecification for these applications, the bias could be quantitatively severe.

Initial Application Shares and 1979-1982 Employment Growth To further check the plausibility of our identification assumption, we show the results of several alternative estimators suggested by GPSS. Since our identification assumption is the share exogeneity, one could use all application shares separately as IVs and perform 2SLS instead of using our Bartik-style IV (16). We also report the results of the limited-information-maximal-likelihood (LIML) estimator and modified-bias-corrected-two-stage-least-square (MBTSLS) estimator (Kolesár et al., 2015). Table G.4 reports the coefficient of the main specification (18) for each of these estimators. The findings are not sensitive to the choice of estimators, as we do not find any significant differences between any pairs of estimates considered.

Furthermore, Table G.2 reports the regression results of 1979-1982 employment growth on the initial application shares. Note that the employment data in our main analysis start from 1982, as explained in footnote 15. We use the 1979 ESS to perform the analysis of initial employment growth with respect to the application share variable $s_a i$, our source of identification based on Goldsmith-Pinkham et al. (2020). To do so, we regress the industrial employment growth rate from 1979 to 1982 on the industry's expenditure on applications, as well as demographic controls. Since we have 6 applications from Table 1, we regress 6 such regressions. The results are shown in Table G.2. We find that the 1979-1982 employment growth is not predicted by the application shares in a statistically significant manner. This bolsters our interpretation that the robot application shares are not determined by the pre-trend, which also applies to the main analysis period.

G.2 Heterogeneity by Sample Periods

We study heterogeneity in the period of analysis, leveraging our long sample period. Recall that the actual data points are eight points: 1978-1982, 1983-1987, 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012, and 2013-2017. We experiment with how many data points we can drop to sustain our current estimation results. Table G.3 shows the result. We find suggestive evidence that the positive employment impact is found in the late period of our sample. We find that the result does not change substantially when we drop one or two sample periods, 1978-1982 or 1983-1987. Dropping the other two sample periods, however, makes the estimation results fragile, as indicated by the inflated standard errors. Dropping three time periods renders very noisy results, including small first-stage F statistics.[29] These results indeed suggest that drawing on a long-time period is indispensable to stably estimate the impact of robot adoption on employment, at least in the

[29]The results are available upon request.

Table G.2: Application Shares and 1979-1982 Employment Growth

	Employment Growth					
	Tending	Welding	Dispensing	Processing	Assembling	Others
	(1)	(2)	(3)	(4)	(5)	(6)
Application Share	−0.100	0.146	−0.502	0.117	0.250	−0.091
	(0.067)	(0.140)	(0.594)	(0.113)	(0.132)	(0.122)
Observations	13	13	13	13	13	13
R^2	0.948	0.939	0.936	0.939	0.955	0.934

Notes: Authors' calculation based on JARA and ESS data. The table presents estimates of the relationship between the initial application shares and and employment growth rate between 1979 and 1982 across industries. Each column indicates the regression model with differing application shares s_{ai} as the regressor. All columns control the demography control variables. Standard errors are shown in the parenthesis. All regressions are weighted by purchase values of robots in each year. *p<0.1; **p<0.05; ***p<0.01.

Japanese context.

G.3 The First Stage of the CZ-level specification (21)

Table G.5 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.

G.4 Heterogeneous Impacts with the CZ-level Analysis

Table G.6 shows the heterogeneous effects of regional robot adoption on employment across education groups (panel A), sex (panel B), and age (panel C). We find some heterogeneity of the positive employment impact found in Table 8; Panel A reveals that high-school graduates' employment increased but not strong evidence of 4-year university graduates employment increase; Panel B shows that both female and male workers increased; and Panel C indicates that relatively

Table G.3: Industry-level 2SLS Regression with Varying Sample Periods

	Dependent variable:					
	$\ln(L_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(R_{it})$	0.283^{***}	0.139^{*}	0.293^{***}	0.121	−0.001	0.355^{***}
	(0.071)	(0.075)	(0.049)	(0.187)	(0.073)	(0.067)
Sample Period	1978-2017	1978-2012	1983-2017	1978-2007	1983-2012	1988-2017
IV F-stasitic	27.527	44.793	18.104	7.644	57.023	13.069
Observations	104	91	91	78	78	78
R^2	0.988	0.990	0.989	0.991	0.992	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. Each columns take varying sample periods. Column 1 shows the benchmark case, 1978-2017 (8 sample periods). Columns 2 and 3 shows the result with one-sample year dropping, thus keeping 1978-2012 for column 2 and 1983-2017 for column 3. Columns 4, 5, and 6 show the result with two-saple years dropping, thus keeping 1978-2007, 1983-2012, and 1988-2017, respectively. 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. 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. The industry-level cluster-bootstrap standard errors are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

young workers' employment increased, especially for those between ages of 35 and 49.

G.5 Exposure-to-robots IV

In this section, we formally define the exposure-to-robot IV (the conventional IV) used in AR and list the pros and cons of it and our robot cost-based IV. By doing so, we make explicit the comparison between the conventional method and ours. AR takes the same regression specification as our main one in the CZ-level analysis, equation (21). The methods of AR and ours diverge in the IV. While our IV is the region-level robot price measure defined in equation (23), AR defines the "exposure to robot" as follows:

$$Z_{ct} = \sum_{i} l_{cit_0} \frac{\Delta R_{it}^{\text{similar countries}}}{L_{it}}, \tag{28}$$

Table G.4: Alternative Estimators

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(R_{it})$	0.283^{**}	0.223^{***}	0.185^{**}	0.185^{**}
	(0.108)	(0.057)	(0.076)	(0.076)
Estimator	Bartik	2SLS	LIML	MB2SLS
Observations	104	104	104	104
R^2	0.988	0.988	0.991	0.991

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 varying set of estimators. Column 1 shows our main result with the Bartik-style IV. Column 2 shows results with plain 2SLS wth application shares for all applications as the set of IVs. Column 3 and 4 show the limited information maximum likelihood (LIML) and modified bias-corrected 2SLS (MB2SLS) suggested by Kolesar et al. (2014). All columns control the demography, globalization, and capital controls as well as industry and year fixed effects. 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. Globalization controls are the logarithm import values from JIP database and logarithm offshoring value added from SOBA. Capital controls are logarithm stock value measures for ICT capital, innovation capital, competition capital from the JIP database. The standard errors are shown in the parenthesis. All regressions are weighted by purchase values of robots in each year. *p<0.1; **p<0.05; ***p<0.01.

where $\Delta R_{it}^{\text{similar countries}} = R_{i,t+1}^{\text{similar countries}} - R_{i,t}^{\text{similar countries}}$ is the robot stock change in the other countries that are in the similar technological level. For instance, AR takes Denmark, Finland, France, Italy, and Sweden as being the countries that are similar to the US, based on the similarity of robot absorption trends in Figure 1. The premise is that while robot stock trends in the other countries are driven by robot technological progress, as well as the demand shocks in each country, the demand shock component is uncorrelated with the one in the US, AR's country of analysis. If there is a positive demand correlation between countries, such as the ones brought by multinational enterprises that demand the same type of robots across different countries, the coefficient of interest β^{CZ} in equation (21) would be biased upward.

There are pros and cons in both our method and the conventional one. On the one hand, our method's strength is that it relaxes the identification assumption of the conventional method in the following sense. First, our robot cost-based method does not require the researcher to select the

Table G.5: CZ-level First Stage Regression

	Dependent variable:			
	ΔR_{ct}			
	(1)	(2)	(3)	(4)
Δr_{ct}^{Z}	-35.683^{***}	-37.178^{***}	-33.564^{***}	-27.042^{***}
	(3.398)	(3.494)	(3.082)	(3.253)
CZ FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
IV F-statistics	110.261	113.198	118.624	69.09
Observations	1,265	1,265	1,265	1,265
R^2	0.943	0.947	0.953	0.974

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 at the commuting zone (CZ) level.. 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. The standard errors are clustered at the CZ level and reported in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

countries of comparison. This ties the researcher's hand and frees her from the issue of finding the "correct" set of comparison countries. Second, our method does not use other countries' information regarding robot stock, so it is free from the independent demand shock assumption mentioned above. On the other hand, the first drawback of our method is the high data requirement; it is JARA's data on total robot monetary value data that make implementing our cost-based method possible. Recall that the IFR does not have such data. Second, our method has its own identification threat, the price endogeneity. Although we have shown the validity checks in Section 4.3, it is not always the case that there are convincing ways to defend the identification assumption of our method.

Given the method of the exposure-to-robot IV (28), we move on to apply the method in our setting. We do so and compare the results with our main ones to better understand if our empirical results are driven by the unique identification strategy (the robot cost-based IV) or context (Japan). For this purpose, we use robot stocks in Germany (columns 1-3) and South Korea (columns 4-6) taken from IFR, given their relatively early robot adoption trends that are closer to Japan's than any other countries' (cf. Figure 1). Specifically, we construct the exposure to robots since 1992 for every 5 years, and stack three time periods (1992-1996, 1997-2001, 2002-2007), because IFR data are only available only since 1992.

Table G.7 shows the results. We consider three outcome variables, log changes in total employment in column 1 and 4, log changes in total population in column 2 and 5, and changes in the employment-to-population ratio in column 3 and 6. Note that the employment-to-population ratio is one of the main outcome variables in AR. The point estimates show positive signs for German SSIV and negative ones for South Korean SSIV. They are not precise enough, however, to make conclusions about the employment impact of robots. We interpret these results for the following two potential reasons: (i) Neither the German or South Korean SSIV strategy correlates with Japanese robot adoption pattern, so that it does not capture true employment impacts. Or, (ii) in the analysis period, the substitution effects and the scale effects of robots cancel out, and we could not detect statistically significant non-zero employment effects.

Table G.6: Heterogeneous Effects of Robots at the CZ level

Panel A: Education	Dependent variable: 100 ×		
	$\Delta \ln(L_{ct})$	$\Delta \ln(L_{ct}^{HS})$	$\Delta \ln(L_{ct}^{CG})$
	(1)	(2)	(3)
ΔR_{ct}	1.943**	2.894**	2.455
	(0.952)	(1.131)	(1.501)
Group	All	High School Grad.	4-year Univ. Grad.
Controls	✓	✓	✓
Observations	1,265	1,265	1,265
R^2	0.821	0.850	0.768

Panel B: Sex	Dependent variable: 100 ×		
	$\Delta \ln(L_{ct})$	$\Delta \ln(L_{ct}^{Female})$	$\Delta \ln(L_{ct}^{Male})$
	(1)	(2)	(3)
ΔR_{ct}	1.943**	1.908*	1.934**
	(0.952)	(1.064)	(0.974)
Group	All	Female	Male
Controls	✓	✓	✓
Observations	1,265	1,265	1,265
R^2	0.821	0.819	0.803

Panel C: Age	Dependent variable: 100 ×			
	$\Delta \ln(L_{ct})$	$\Delta \ln(L_{ct}^{a\leq 34})$	$\Delta \ln(L_{ct}^{35\leq a\leq 49})$	$\Delta \ln(L_{ct}^{50\leq a})$
	(1)	(2)	(3)	(4)
ΔR_{ct}	1.943**	2.327*	3.642***	0.818
	(0.952)	(1.330)	(1.336)	(1.123)
Group	All	Age ≤ 34	35 ≤ Age ≤ 49	50 ≤ Age
Controls	✓	✓	✓	✓
Observations	1,265	1,265	1,265	1,265
R^2	0.821	0.825	0.823	0.889

Notes: Authors' calculation based on JARA, ESS, BSOBA 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 outcome variables are employment of the group indicated in Group row of each panel. All regressions control demographic variables, globalization controls, and technology controls as well as the industry and year fixed effects discussed in Section 4.1. All regressions are weighted by initial-year population. The standard errors are clustered at the CZ level and reported in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table G.7: Regressions with exposure to robots IV

	Dependent variable:					
	$\Delta \ln(L)$	$\Delta \ln(Pop)$	$\Delta(L/Pop)$	$\Delta \ln(L)$	$\Delta \ln(Pop)$	$\Delta(L/Pop)$
	(1)	(2)	(3)	(4)	(5)	(6)
ΔR	1.661	0.835	0.472	−3.495	−2.708	−0.764
	(1.479)	(1.287)	(0.386)	(2.560)	(2.215)	(0.672)
IV	Germany	Germany	Germany	Korea	Korea	Korea
Controls	✓	✓	✓	✓	✓	✓
CZ and year FEs	✓	✓	✓	✓	✓	✓
First stage F-stat	557.638	557.638	557.638	117.415	117.415	117.415
Observations	906	906	906	906	906	906
R^2	0.423	0.358	0.587	0.411	0.352	0.574

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 ("exposure to robots" in Acemoglu and Restrepo, 2020) 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 (column 1-3) and Korean (column 4-6) robot adoption trends, and whose share is taken by the baseyear industrial employment share in each CZ. As outcome variables, column 1 (4 for Korean exposure IV) takes log total employment, column 2 (5 for Korean exposure IV) takes log total population, and column 3 (6 for Korean exposure IV) 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.