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

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Abstract

This paper studies the relationship between industrial robots and employment in Japan based on a unique dataset that allows us to calculate the unit price of robots. Our model combines standard factor demand theory with a recent task-based approach to derive a simple estimation equation between robot prices and employment, and our identification strategy leverages heterogeneous applications of robots across industries and heterogeneous price changes across applications. We find that the decline in robot prices increased both the number of robots and employment by raising the productivity and production scale of robot-adopting industries.

Keywords: Automation, Industrial robots, Robotic applications, Employment, Factor demand elasticity.

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

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1 Introduction

As companies worldwide aim to increase productivity and cut costs, the effect of automation on employment has been attracting increasing attention by academic researchers, policymakers, and journalists (e.g., Brynjolfsson and McAfee, 2014; Ford, 2015; Frey and Osborne, 2017; OECD, 2019), but the evidence so far has been mixed, particularly regarding the use of industrial robots (robots hereafter). While academic studies to date have examined the effect of the specific tasks that robots perform in great detail, data limitations prevent their empirical designs from taking into account the cost of adopting robots.

This paper analyzes the effect of industrial robot adoption on employment in Japan. A unique feature of our Japanese robot data is that we can observe the unit price of robots according to their task-based classification, which allows us to study the effect of robot price reductions on changes in industrial employment. Empirically, we show that declining robot prices have historically driven growth in industrial employment, and we provide several robustness checks supporting the validity of using robot prices in our design. We also empirically show that robots significantly reduce production costs and thus expand production scale. We further examine several local labor market effects.

To guide our empirical design, we begin by characterizing the effect of robot prices on the demand for both robots and labor. Although a standard factor demand framework is useful to analyze the effect of robot price reduction on the labor demand, it is not able to account for a sizable employment effect due to the small cost share of robots among overall production. To overcome this issue, we combine standard factor demand theory with a recently developed task-based approach to derive a simple and estimatable equation relating employment and robot prices. This model demonstrates that the adoption of robots is determined either by a decrease in robot prices relative to wages or by an advance in the technological frontier regarding the range of tasks that can feasibly be performed by robots. Following standard factor demand theory, we argue that a decrease in the relative price of robots affects the demand for robots and labor through substitution and scale effects. However, in addition to this, the task-based framework shows that an expansion in the feasible tasks performed by robots decreases production costs and generates a substantial scale effect, creating a large positive effect of lower robot prices on employment. Taken together, we obtain a relationship between factor demand changes and declining robot prices which can be directly mapped to regression analysis using our data on industrial employment and robot prices.

Japan is known worldwide for its long history at the forefront of industrial robotics, and we are able to implement our study using the newly digitized data on industrial robots from the Japan Robot Association (JARA) which begins more than a decade earlier than data available elsewhere (see Figure 2 in the data section). The JARA data consists of robot shipments (both in units and sales value) by destination industry and robot application from 1978 to 2017. A robot application is a set of tasks in the production process that robots perform, such as welding and parts assembly, and is central to our estimation strategy. Descriptive statistics from the data reveal that there are heterogeneous intensities of robot applications across industries as well as different price trends among these various applications. We use the data from JARA and a national household survey to estimate the equation derived from our theoretical model.

Our industrial robot price measure is based on the heterogeneous use of applications across industries and heterogeneous price trends across robot applications. Exploiting these inter-industry variations, we construct a robot price index for each industry by averaging the robot price by application, weighted by the initial industry-level robot share for each application. The price of industrial robots faced by firms differs substantially across industries due to the variation in robot prices across applications. For example, the transportation machinery industry intensively uses welding robots, whose price fell substantially during the sample period, so the effective robot price faced by the transportation machinery industry also fell substantially. In contrast, the electronic machine industry primarily uses assembly robots, whose price did not drop as much as that of welding robots, so the electronic machinery industry did not enjoy as large a decline in the effective robot price. Our identification strategy exploits this price variation across industries that originates from the heterogeneous use of applications, and we implement this by constructing a Bartik-style industry-year-level robot price index to estimate the impact of robot price on robot adoption and employment.

In our empirical analysis, we show that a one percent decrease in the price of robots increased robot adoption by 1.54 percent. Perhaps more surprisingly, we also find that a one percent decrease in the robot price increased employment by 0.44 percent, so a large availability of robots actually *raised* employment, suggesting that the scale effect induced by robot adoption was substantial and dominated the substitution effect. As we found a large and significant elasticity of industrial real output to our robot price measure, this suggests that Japanese manufacturers successfully pursued robotic adoption to reduce production costs and output prices and to expand output.

One possible concern with our analysis involves potential price endogeneity, which could arise when the robot price is affected by robot demand. We addressed this concern through several methods, first constructing alternative price measures based on the leave-one-industry-out price and the export price, both of which are less likely to reflect domestic industry demand shocks. Secondly, we reconstructed the analysis sample by dropping industries that adopt robots intensively (i.e. automobiles and electric machines) because of the potential for a demand shock to these large adopters propagating to the robot price. After dropping these industries, the remaining industries should face exogenous robot price movements. Thirdly, we also dropped each of the applications from the analysis one by one to confirm that no single application drove our results. All of these exercises support the robustness of our baseline results.

Next, following the recent literature on the effect of robots on employment (e.g., Acemoglu and Restrepo, 2020a, AR hereafter; Dauth et al., 2021), we conducted an analysis of the local labor market, which departs from the industry-level analysis in two important ways. First, we used the commuting-zone (CZ) as the unit of analysis to allow for spillover effects across industries. Second we regressed the changes in labor market outcomes on the number of robots using the instrumental variable of the shift-share measure of robot prices across CZs. Our results indicate that one robot unit per 1,000 workers increases employment by 2.2 percent, corroborating our industry-level finding that a decline in robot prices increases employment. 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, as the positive employment effect was predominantly found in the manufacturing sector but not in the non-manufacturing sector or for those who were not employed and dependent on working family members.

This study contributes to the literature by proposing a strategy of using robot prices 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 dataset which includes unit shipments and sales values at a finely disaggregated level across robot applications that is not available in other widely used datasets such as that of the International Federation of Robotics (IFR).[1] Thus, our newly digitized JARA data also contribute to the literature by offering 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 to global markets.

Another contribution to the literature is the evidence provided on the impact of robots on

[1]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. (2021); Humlum (2019). Among these studies, Graetz and Michaels (2018) use the robot price taken from a survey of a subset of robot producers to show that the cost reduction was a critical factor behind robot adoption. They do not, however, use price information in their main regression analysis because the IFR price index does not possess the rich variation that would allow a formal statistical analysis.

employment in Japan, a large economy with the longest tradition of robot adoption globally. To date, the literature has found conflicting evidence from different contexts, with Graetz and Michaels (2018) reporting that robot penetration increased labor productivity and wages in their country-industry level analysis of the Organisation for Economic Co-operation and Development (OECD) while AR's analysis of US regional labor markets finds that robot adoption reduced the employment-to-population ratio and the earnings of all workers regardless of skill level. Meanwhile, the Dauth et al. (2021) analysis of German regional labor markets finds that the penetration of robots decreased employment in the manufacturing sector but increased employment in the service sector. Finally, a recent study on Japan by Dekle (2020), conducted independently from us, finds that robot penetration increased employment.[2] While the empirical results from these three large economies do not provide a consensus, the theoretical discussion by Berg et al. (2018) and Caselli and Manning (2019) contend with some of the results found in the empirical literature by claiming that technological progress should benefit at least some workers under fairly general assumptions. Our study brings to the literature a newly proposed identification strategy and empirical results that are consistent with these theoretical predictions.

2 Model

We begin by developing a simple task-based model of the allocation of industrial robots and workers and derive the change in labor demand due to an enhanced availability of robots (EAR). The model explicitly defines EAR in terms of automation, in which robots can perform a larger set of tasks, and a reduction in the price of robots. We show that the change in labor demand is characterized by two effects, (i) a shift in the task allocation from labor to robots and (ii) a cost savings due to EAR. Finally, we use the change in the robot price as a proxy for EAR to derive a regression equation.

2.1 Setup

We consider an economy with T periods indexed by $t = 0, 1, \ldots, T$ and I industries indexed by $i = 1, \ldots, I$. Production factors are labor and robots, where robots are defined as the combination of robots used in each application, as described in detail later. Households own labor and robots,

[2] Dekle (2020) implements an industry-level analysis using a different identification strategy than the current study. He addresses endogeneity using two sets of IVs, reflecting the interaction between replaceability measures and the growth in computer processing memory as well as the industry dependence on middle-aged workers with the national growth of the elder population.

rent them inelastically to producers, and consume industrial goods 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 $I_t = \sum_i \left(w_{it} L_{it} + p_{it}^R R_{it} \right)$, where L_{it} is labor employment, R_{it} is robot use, w_{it} is the wage, and p_{it}^R is the rental price of robots.[3] For simplicity, we do not incorporate specific robot applications in the model section, but provide in Appendix A a microfoundation in which each robot application performs tasks which aggregate to the robot measure R_{it}. In each year t, each industry i allocates labor and robots to a fixed task space $\Omega \equiv [0, 1]$ to produce industrial goods (Acemoglu and Autor, 2011) following production function

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

where $y_{it} (\omega)$ is the input amount of the task ω, and $\sigma \geq 0$ is the elasticity of substitution between tasks.

All markets are competitive and markets clear in equilibrium. Therefore, all industrial producers are price takers.[4] We assume that labor is mobile across industries, so in equilibrium $w_{it} = w_t$.

A Task-based Framework As in Acemoglu and Restrepo (2020), or AR, 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 productivities of performing task ω by labor and robots, respectively. Without loss of generality, each task $\omega \in \Omega$ is ordered in terms of the comparative advantage of robots so that $a_{i,R} (\omega) / a_{i,L} (\omega)$ is a non-increasing function for any i. Following AR, we impose the following two assumptions: First, there exists a "technological frontier" $\bar{\omega}_{it} \in [0, 1]$

[3]For simplicity, labor is homogeneous, but this assumption can be relaxed routinely to introduce some labor heterogeneity such as educational attainment.

[4]This assumption is likely to hold for industries with low intensity of robot adoption but can be problematic for other industries. We address this concern in the empirical analysis by dropping large robot buyers and find that our results are qualitatively unchanged.

such that

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

This assumption means that robots are not feasible for tasks with task indices that are sufficiently large. Using this notation, we define automation as the extension of the task space that robots can perform, or $d\bar{\omega}_{it} > 0$. Second, we assume that automation is always cost-saving at the technological frontier:

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

Under this assumption, producers always find it cost-minimizing to allocate robots to tasks in which robots have become newly feasible to operate due to advances in automation. This brings a sizable cost savings in production, but note that even under this assumption, the price of robots remains relevant for factor demand. Specifically, as we see in the following sections, labor demand is affected by both the task-based force (automation) and the standard force (factor price changes).

2.2 Solution

Solving this model involves the characterization of the following producer task allocation problem. Let us focus on industry i in year t. Since tasks are ordered according to robots' comparative advantage, the optimal task allocation can be given by an (equilibrium) threshold task $\omega_{it}^{*} \leq \bar{\omega}_{it}$ such that robots perform tasks indexed $\omega \leq \omega_{it}^{*}$ and labor performs tasks indexed $\omega > \omega_{it}^{*}$. As in AR, it is routine to show that under condition (5), producers allocate robots to all the tasks in which robots are feasible to operate, so $\omega_{it}^{*} = \bar{\omega}_{it}$.

Given the solution to the task allocation problem, the factor demands for each industry can be obtained by integrating the task-level factor demands across tasks. Note that the household expenditure minimization problem with utility function (1) yields $C_{it} = \left(\frac{p_{it}}{P_t}\right)^{-\varepsilon} I_t$, where $P_t = \left(\alpha_{it}(p_{it})^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ is the ideal price index. Combining this with the cost-minimizing solution of the producer's problem, we obtain

$$R_{it} = A_{i,R}(\bar{\omega}_{it}) \left(\frac{p_{it}^{R}}{P_{it}}\right)^{-\sigma} \left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} I_t, \tag{6}$$

$$L_{it} = A_{i,L}(\bar{\omega}_{it}) \left(\frac{w_{it}}{P_{it}}\right)^{-\sigma} \left(\frac{P_{it}}{P_t}\right)^{-\varepsilon} I_t., \tag{7}$$

where $A_{i,R}(\bar{\omega_{it}}) \equiv \int_0^{\bar{\omega}_{it}} \left(a_{i,R}(\omega)\right)^{\sigma-1} d\omega$ and $A_{i,L}(\bar{\omega_{it}}) \equiv \int_{\bar{\omega_{it}}}^1 \left(a_{i,L}(\omega)\right)^{\sigma-1} d\omega$ are the functions of the technological frontier that represent the cost (in)efficiency of robots and labor, respectively. Furthermore, the output price P_{it}, or the unit cost of production, is given by

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

Notice that equations (6) and (7) include both a standard and a task-based mechanism of the effect of the change in factor prices on factor demand. On the one hand, the elasticity of factor substitution σ governs the substitution effect, or the effect of the change in the relative factor cost on the change in the demand for factors. By contrast, the elasticity of output substitution ε in the household utility function controls the scale effect, or the effect of a change in the relative output price on factor demands via a change in household output demand. On the other hand, factor productivities $A_{i,R}$ and $A_{i,L}$ and unit cost of production P_{it} depend on the technological frontier, which is not considered in the traditional factor demand theory. From this point, we focus our discussion on the labor demand equation (7), as the robot demand equation behaves in a similar manner.

Log-linearizing equation (7) with respect to the technological frontier $\bar{\omega_{it}}$ and factor prices, we have

$$d\ln L_{it} = d\ln A_{i,L}\left(\bar{\omega}_{it}\right) + (\sigma - \varepsilon)\, d\ln P_{it} + a_t^L, \tag{8}$$

where $a_t^L \equiv d\ln w_t^{-\sigma} P_t^{\varepsilon} I_t$ is a time fixed effect common across industries. This equation clarifies the mechanisms through which the effect on labor demand takes place. The first term characterizes the task shift, or the effect in which automation reallocates tasks from labor to robots. The second term indicates the cost saving, which operates through the substitution and scale effects mentioned above to drive the change in labor demand. These terms can be solved as follows:

$$d\ln A_{i,L}\left(\bar{\omega}_{it}\right) = -a_{i0,L}^M d\bar{\omega}_{it} \tag{9}$$

$$d\ln P_{it} = S_{i0} d\bar{\omega}_{it} + s_{i0}^R d\ln p_{it}^R + \left(1 - s_{i0}^R\right) d\ln w_t, \tag{10}$$

where $a_{i0,L}^M \equiv \frac{\left(a_{i,L}(\bar{\omega}_{i0})\right)^{\sigma-1}}{A_{i,L}(\bar{\omega}_{i0})}$ is the marginal (log-)labor productivity, $s_{i0}^R \equiv \frac{p_{i0}^R R_{i0}}{p_{i0}^R R_{i0} + w_{i0} L_{i0}}$ is the initial robot cost share, and $S_{i0} \equiv (1-\sigma)^{-1}\left[\left(p_{i0}^R / a_{i,R}\left(\bar{\omega}_{i0}\right)\right)^{1-\sigma} - \left(w_{it} / a_{i,L}\left(\bar{\omega}_{i0}\right)\right)^{1-\sigma}\right] / \left(P_{i0}\right)^{1-\sigma}$ is the marginal (log-)cost saving. These equations clarify the effects of each EAR element on each mechanism of the labor demand effect. First, the task shift only depends on automation through marginal labor productivity, as the assumption in equation (5) means that factor price changes do not affect the task shift. Second, the unit cost change depends on both automation (because equation (5) implies that there is a cost saving by switching from labor to robots on the margin of the technological frontier) and the factor price change (because of the standard force that factor price changes affect unit costs through the initial cost shares). In the following, we impose that $s_{i0}^R = s_0^R$ and $a_{i0,L}^M = a_{0,L}^M$ are independent of industry, which is realistic given the small robot cost share in all industries in the 1970s, the initial phase of robot adoption.[5]

Figure 1 visualizes the discussion so far. In both panels, the horizontal axis shows the task space $\Omega = [0, 1]$ and the vertical axis shows the unit cost of labor $w_t / a_{i,L}(\omega)$ and robots $p_{it}^R / a_{i,R}(\omega)$. The assumption in equation (5) is satisfied, so that the unit cost at the technological frontier $\bar{\omega}_{it}$ is higher for labor than for robots. A cost-minimizing producer chooses the threshold ω^* to allocate robots to tasks $\omega < \omega_{it}^* = \bar{\omega}_{it}$ and workers to tasks $\omega \geq \omega_{it}^* = \bar{\omega}_{it}$. The unit cost of production is the area under the unit cost line of a factor that is allocated to each task, and the cost saving is depicted in the shaded area. Panel 1a shows the effect of a reduction in robot prices, and we see that it does not induce a change in task allocation since the productivity of robots is zero above the technological frontier. However, the industry incurs cost savings from the decline in the unit cost of performing tasks that were already performed by robots. In contrast, Panel 1b shows the effect of automation, or a rightward shift of the technological frontier. In this case, the new tasks in which robots have become productive are now allocated to robots after the shock since the threshold was initially binding and allocating robots to the marginal task would have been more cost effective.

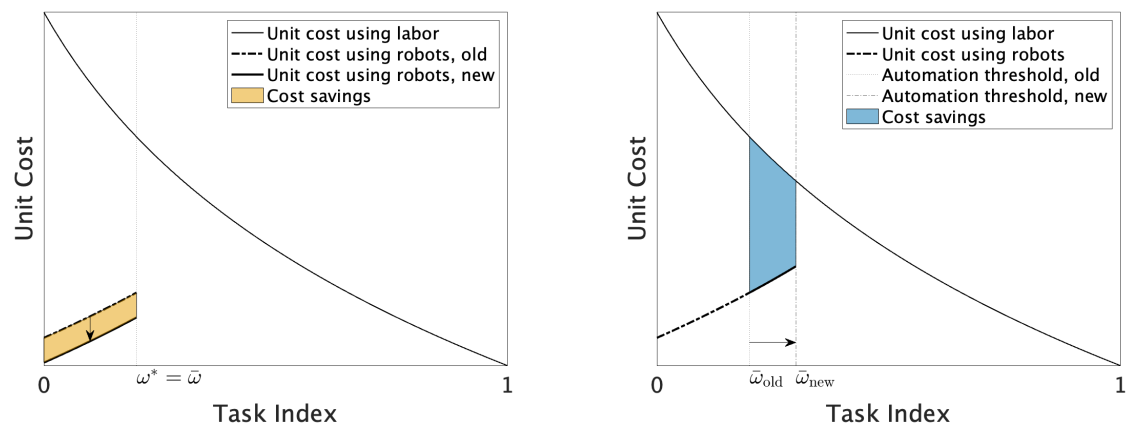
2.3 Regression Equation

When estimating equation (8), we encounter a problem in that we do not directly observe the change in the threshold $d\bar{\omega}_{it}$. To overcome this, we use the change in the price of robots ($d \ln p_{it}^R$) as a proxy for the change in the technological frontier ($d\bar{\omega}_{it}$) because technological progress in robot production induces both a price reduction and an expansion of the technological threshold. For this purpose, we describe the relationship between the change in the technological frontier and the

[5]Note that the infancy of robotics technology in the 1970s indicates $\omega_{i0} \to 0$. In this case, $a_{i0,L}^M \to a_{i,L}(0)$, and this term is independent of industries if $a_{i,L}(\cdot)$ does not depend on i at $\omega = 0$. In other words, the assumption $a_{i0,L}^M = a_{0,L}^M$ does not impose restrictions on other parts of the function $a_{i,L}(\cdot)$ across $\omega > 0$. Furthermore, the assumptions on s_{i0}^R and $a_{i0,L}^M$ are placed for simplicity and can be relaxed. When these assumptions are not imposed, the coefficient on robot prices in the regression equation becomes dependent on industry through these terms so that the regression coefficient would be a weighted average of the industry-specific effects.

Figure 1: Shocks and Cost Savings

(a) Robot Cost Reduction ($\omega^* = \bar{\omega}_{it}$) (b) Automation ($\omega^* = \bar{\omega}_{it}$)



Note: The diagrams show the allocation of robots and workers to tasks. The horizontal axis is the task space [0, 1], and the vertical axis shows the unit cost of performing each task by robots or workers. Under the assumption in equation (5), a cost-minimizing producer chooses the threshold $\omega^*_{it} = \bar{\omega}_{it}$ so that tasks $\omega < \omega^*$ are allocated to robots and tasks $\omega \geq \omega^*$ are allocated to workers. The two diagrams capture the different effects caused by the source of the increased availability of robots. Panel 1a shows the effect of a reduction in robot cost and Panel 1b demonstrates the impact of automation (a rightward shift of the technological frontier).

change in robot price using the following linear projection:

$$S_{i0} d\bar{\omega}_{it} = \rho d \ln p^R_{it} + \epsilon_{it}, \; \epsilon_{it} \perp d \ln p^R_{it}. \tag{11}$$

Note that the linear projection is adopted 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 in year t. This may be represented by a robot price reduction $-d \ln p^R_{it} > 0$ as well as an expansion of the robot tasks $d\bar{\omega}_{it} > 0$, or cost savings $-S_{i0} d\bar{\omega}_{it} > 0$, resulting in $\rho > 0$.[6] Note that ρ captures the correlation in a reduced form without any structural interpretation.

Combining equations (8), (9), (10) and (11), we can derive the following equation:

$$d \ln L_{it} = a^L_t + b^L d \ln p^R_{it} + e_{it}, \tag{12}$$

[6]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 robot producers, we omit the formal modeling of robot production and instead allow any correlation between the robotics automation shocks.

where $a_t^L \equiv d \ln w_t^{-\sigma} P_t^{\varepsilon} I_t$ is time fixed effects common across industries, $e_{it} \equiv \left(a_{0,L}^M + \sigma - \varepsilon\right) \epsilon_{it}$ is the idiosyncratic error term and b^L, our coefficient of interest, is the coefficient of the log price change, satisfying

$$b^L = (\sigma - \varepsilon)\, s_0^R + \left(-a_{0,L}^M + \sigma - \varepsilon\right) \rho. \tag{13}$$

This coefficient is composed of two terms. The first term represents the force that stems from standard factor demand theory; namely, the difference in the elasticity of task demand σ (driving the substitution effect) and of output demand ε (driving the scale effect) re-scaled by the robot share s_0^R which drives a change in the demand for labor. By contrast, the second term represents a new source of the labor demand effect; the reduced-form parameter ρ represents automation proxied by the change in the price of robots, which affects labor demand through a task shift (via $a_{0,L}^M$) and cost saving (via $\sigma - \varepsilon$).

These points have important implications for interpreting the regression coefficient in the empirical section below. First, consider the case when $\rho = 0$. In this case, the model reduces to the standard factor demand theory, as a large output elasticity relative to the substitution elasticity $\varepsilon - \sigma > 0$ would imply that the regression coefficient satisfies $b < 0$ as $s_0^R > 0$, so a decline in the robot price p_{it}^R increases employment. Second, our generalized model implies that coefficient b also depends on an additional element ρ. Therefore, if $\rho > 0$ as we argued above, coefficient b can be relatively large even when the initial robot cost share s_0^R is very small.

The interpretations of the remaining parameters are as follows. The time fixed effect a_t^L absorbs 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, so the OLS regression of equation (12) produces an unbiased and consistent estimator of b^L given equation (11). In addition to these regression variables, we also include industry fixed effects a_i^L in our empirical implementation to absorb any industry-specific time-invariant changes in labor demand.

Finally, as discussed above, the demand equation for robots, R_{it}, can be derived in a similar manner as equation (12) for labor, and the interpretation of the estimated coefficients are also similar. As our goal is to estimate the demand equations for robots and employment in terms of the robot price, we need to obtain measures of R_{it}, L_{it}, and p_{it}^R to implement our empirical analysis. The next section describes our data sources.

3 Data

In order to estimate factor demand as a function of robot price in equation (12), the required variables are the robot price, robot quantity, and employment by industry i in year t. We begin with a description of our unique robot data and its summary statistics, followed by data on employment and control variables.

3.1 Robot Data

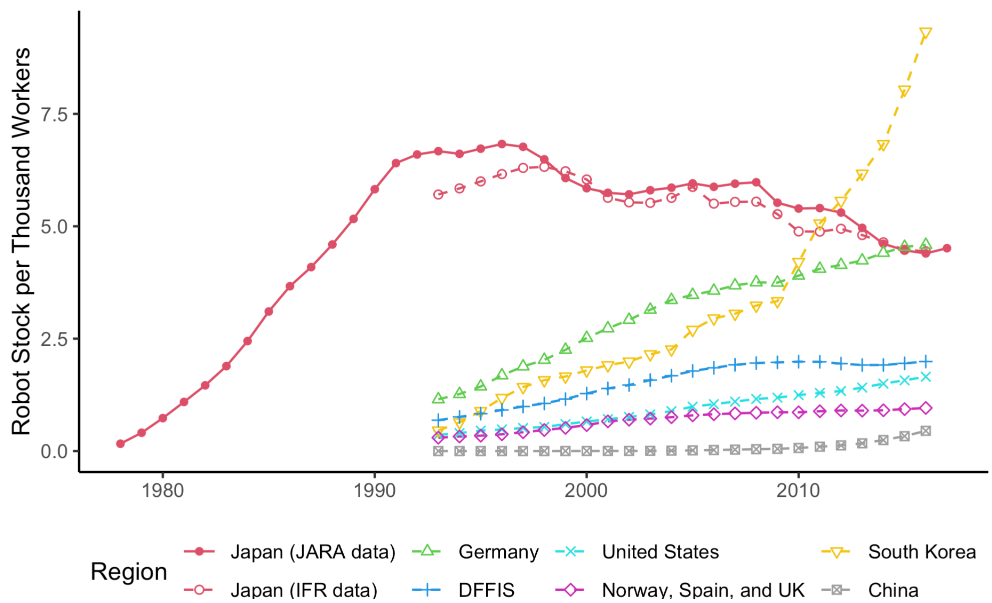
Our main dataset is derived from a *Japan Robot Association* (JARA) establishment-level survey of Japanese robot producers, the same Japanese data source as that used in the International Federation of Robotics (IFR) dataset, a leading information source in the robotics literature. For this study, we digitized the appendix tables of the *Survey Report on Company Conditions of Manipulators and Robots* (survey tables, henceforth) from the JARA annual survey.[7] Although the survey is available from 1974, we included only the years from 1978 in our main analysis because the shipment variable disaggregated by application only became available that year. The special feature of the JARA data is that it includes the monetary value of shipments as well as the units of robots by robot application, destination industry and year. The monetary value of each shipment allows us to calculate a time series of the unit value of robots by application, which will be the core of our identification strategy. As one would expect that there was a substantial upgrade in the quality of robots from 1978 to 2017, to address this concern, we implement quality adjustment according to Khandelwal et al. (2013) to confirm the robustness of our empirical results, as shown in Appendix C. In addition, in Appendix F.3, we also check the robustness of our key results without relying on the measurement of robot prices by application. Both of these robustness checks support our main results.

Figure 2 illustrates the trends in robot stock units per thousand workers for selected countries. Line colors and dot shapes indicate country groups, while line types indicate data sources (solid line for JARA, dashed line for IFR).[8] As mentioned above, Japan experienced a very different trajectory than that of other countries, with a rapid increase in the 1980s followed by a stable or

[7]The JARA is a non-profit organization of robot-producing member companies. As of October 2019, there were 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 provides the survey tables to its member companies.

[8]In calculating the robot stock in 1978, we assume that it was quantitatively smaller prior to 1978, which is warranted given the trends for 1974-1978, as shown in Figure E.3.

Figure 2: Trends of Robot Stock per Thousand Workers, by Country



Note: Authors' calculation based on data from JARA, IFR, OECD, and the National Bureau of Statistics of China (NBSC). The figure shows the trends of robot stock units for each country or region and, for Japan, each data source. The JARA data show the domestic 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 and regions reported in Acemoglu and Restrepo (2020a), as well as China, Japan, and South Korea. DFFIS stands for Denmark, Finland, France, Italy, and Sweden, as in Acemoglu and Restrepo (2020a). All values are normalized by country-level employment (thousand workers) taken from OECD statistics for all countries except for China, which is taken from the NBSC. A detailed description of these data is given in Section 3.

decreasing trend from the 1990s onward. In contrast, other large robot adopters such as Germany and other European countries, South Korea, and the USA saw a rapid increase in robot stock in the 1990s and 2000s. More recently, China has rapidly accelerated its robot adoption in the last decade, but the per-worker measure is still smaller than other country groups listed in the figure. Although there is no data available for any of these countries other than Japan before 1993, the novelty of robotics technology suggests that robot stocks in these countries before 1993 would have not been more than that of 1993. Therefore, Japan's trend in robot adoption is unique.[9]

In Appendix E.2, we confirm that the JARA series are broadly consistent with the IFR series,

[9]The decrease in the 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).

confirming the quality of the JARA data. We also describe a major classification difference between JARA and IFR, clean-room robots, which we will check does not affect our empirical results later.

3.2 Industrial Adoption, Application, and Price of Robots

In this section, we use the robot data described in Section 3.1 to provide descriptive statistics which not only increase our understanding of Japanese robot adoption but 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 annual volatility and focus on long-run structural changes, we created five-year average observations from the five years prior to and including the observation year (e.g., the observation for 1982 is the simple average of the data from 1978 to 1982). From this point, our discussion is of these five-year-average observations.

We begin the discussion by studying who purchases robots in Japan. Table 2 shows the decomposition of the sales of robots to destination industries in the "Total" column,[10] and we see that a substantial share of robot purchases are by the electric machine and transportation machine (including automobile) industries which together comprised 68.2 percent of all domestic absorption in 2017. Given this feature of the data, we focus on the application shares at the industry level, with an emphasis on these two industries. At the same time, this leads to a caution about our identification strategy in that these buyers are large, so their demand might affect observed unit values. We address this issue in depth in Section 4.3.

Robot Applications To construct a robot price measure for equation (12), we scrutinize robotics technology, studying the specific robot applications as the source of variation for our identification strategy. Note that the official 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 machines with different functionalities depending on the particular application. The mechanical distinction between robots that enables them to perform different applications is called the robot "type", which is one of the robot supply-side characteristics.

[10] In appendix E.7, we also show the decomposition into export and domestic sales.

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
	Other	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-rooms and the unclassified. "SAL control robot" stands for sensory-control, adaptive-control, and learning-control robot.

JARA's survey asks producers for the unit quantity and monetary value of industrial robots shipped by application, type, and destination industry. In our main analysis, we focus on the disaggregation by application, or the specific tasks each robot will perform.[11] The full list of the application and type categories is given in Table 1.

The specific mix of robot applications differs substantially across industries. For example, consider the tasks of spot welding (SW) and surface mounting (SM) which are important in the transportation and electronics industries, respectively. Spot welding (SW) attaches two or more metal sheets together by applying pressure and heat to a small weld area called a spot. While both humans and robots can perform this task, SW robots have become prevalent in the automobile industry in carrying out the critical task of welding numerous pieces of metal to produce a complex output such as a car body. Spot welding requires intensive repetitive movements in the assembly of large, heavy and complex automobile body shapes. Further, SW robots are a type of playback robot that can repeat the same complex process accurately after only being taught once, a considerable advantage over humans. Meanwhile, surface mounting (SM) is a robot application prevalent in the electronics industry which places surface-mounted devices (SMDs) onto a printed circuit board (PCB) quickly and with a high degree of precision on a horizontal trajectory. Since PCBs are primary inputs to a majority of electric machines, the electric machine industry uses SM robots intensively. Accordingly, when comparing the robots used in the two industries, the robots deployed

[11]In contrast, robot type is a categorization based on the mechanical way in which the robot works, while robot structure refers to the particular dimensions and directions along which each robot joint moves. Given the increasing sophistication of robotic technologies, the IFR and robot-producing companies agreed in 2004 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 E.4.

for surface mounting (SM) are substantially different in 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 in Japan for the large robot purchasers, electric and transportation machine industries, as well as the aggregate of all other industries. To illustrate the substantial difference in robotic applications in the two main industries, assembly robots and welding robots comprised 76.2 and 3.0 percent of total purchases in the electric machine industry in 1982 but 7.1 and 46.3 percent in the transportation machinery industry. Another takeaway from Table 2 is that the within-industry expenditure shares have been fairly constant over the years, even though there has been a significant change in prices and units of robot adoption.[12] These points suggest a stable industrial specificity regarding robot use for different tasks, meaning that robot applications are neither substitutes nor complements to each other.

Evolution of Robot Prices by Application The difference in the mechanical types of robots used for each robot application creates a variation in price by application. For example, technological progress in playback robots has reduced the price of welding robots relatively faster than that of assembly robots in recent decades. Our data allow us to measure such trends. Specifically, to compute the application-level robot price p^R_{at} from 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 3 shows the price trends for each application aggregated across industries. Robots for welding show a stable decline in the unit value, suggesting that the production technology for welding robots improved consistently over the sample period. As to the potential reasons why welding robots became cheaper, almost all welding robots are classified as playback robots which repeat the same sequence of motions in all their operations, and from 1982-1991, the unit value of playback robots declined.[13] Indeed, a review of articles in the

[12] An exception to this is the observed decrease in the share of assembly robots and increase in other robots shipped for the electric machinery industry. This is a spurious change, however, due to the change in classification when the JARA statistics began to include clean-room robots mentioned in Section 3.1. To study the robustness of our identification strategy to this classification change, we performed a sensitivity analysis by dropping the Other application in Section 4.3 and confirmed that this change does not pose an identification threat.

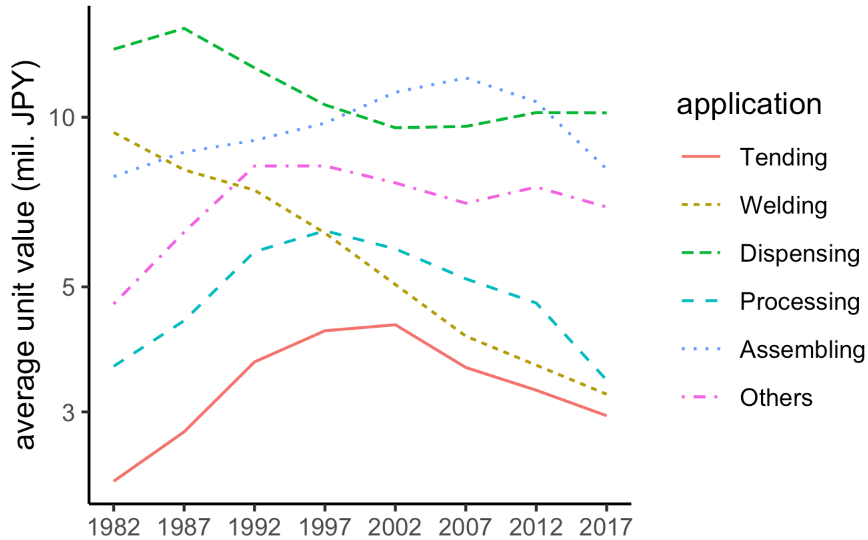
[13] See Figure E.4 and E.5 in Appendix E.6. The type-application cross-tabulation tables are only available between

Table 2: Total Robot Expenditure and Application Expenditure Share by Industry and Year

Industry		1982	1987	1992	1997	2002	2007	2012	2017
Electric	Total (Million JPY)	116.7	445.5	790.3	565.4	514.9	655.3	405.9	395.1
	(Application share %)								
	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
Transportation	Total (Million JPY)	117.7	241.1	468.0	244.3	285.6	423.0	243.0	270.9
	(Application share %)								
	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	Total (Million JPY)	120.7	330.3	594.9	439.0	437.6	311.4	204.3	310.3
	(Application share %)								
	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 machines (Electric), transportation machines (Transportation), and all other industries aggregated (Other). Sums over application within each industry and year equals 100 percent, up to a rounding error. The application list is discussed in the main text and shown in Table 1.

Figure 3: Unit-Value Robot Trends by Application



Note: Authors' calculation based on JARA data. The figure shows industry aggregated unit-value trends for each application. The y-axis is a natural logarithmic scale. The application list is discussed in the main text and shown in Table 1.

Nikkei database of newspaper and magazine articles 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 an electronic motor actuator (Nikkei, 1982, 1984), providing further confirmation that the price reduction in the welding application was caused by technological change.

3.3 Other Data

This section describes the sources for other data used in the study, which include labor-market outcome variables from the Employment Status Survey (ESS) and control variables from the Census of Manufacture (CoM), the Basic Survey on Overseas Business Activities (BSOBA), and the Japan Industrial Database (JIP). Each is described in more detail below.

Data for employment variables is taken from the ESS, a national survey administered by the Ministry of Internal Affairs and Communications (MIC) conducted first in October 1979 and then every five years since 1982 in years ending with a 2 or 7. In this study, we matched the final year of the 5-year bins of the JARA data with the relevant employment statistics by, for example,

1982 and 1991. Further details of the JARA dataset are discussed in the Online Data Appendix.

matching the average robot stock measure from 1978-1982 with employment in 1982. We regard this as naturally capturing the lagged impact of robot price reductions on employment (cf. Autor et al., 2020).[14] The ESS samples roughly one million people who live in Japan and are aged 15 or above, which is roughly one percent of the 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 more details on these variables, see Appendix E.10.

The CoM, which is conducted by Japan's Ministry of Economy, Trade and Industry (METI), is an annual survey of manufacturing establishments in Japan with more than three employees. The strength of the dataset is the fine industry coding employed, recording the 4-digit Japan Standard Industry Classification (JSIC) for each establishment. Additionally, the survey asks each respondent for its major products and product codes, which allows us to obtain a fairly accurate measure of employment in robot production. In Appendix E.11, we report some of our results using employment net of robot-producing workers, which helps to clarify the mechanism.

The BSOBA, which is also administered by METI, is an annual survey of the universe of Japanese multinational enterprises (MNEs). Since offshoring and multinational production are concurrent phenomena that change labor demand (e.g, Hummels et al., 2014), we control them with variables constructed from the BSOBA. The details are provided in Appendix E.12.

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 change. A detailed discussion of how these variables are constructed using the JIP data is provided in Appendix E.13.

Finally, throughout this paper, we work with 13 industry classifications (12 manufacturing and one "other" aggregate) that are consistent with the main datasets described above. The industries are: Steel; Non-ferrous metal; Metal products; General machine (including 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.

[14] Furthermore, this formulation leaves 1979 ESS employment data (introduced in Section 3.3) unused for the baseline analysis, which allows us to perform a pre-trend analysis in Appendix Table F.5.

4 Empirical Analysis

We implement our empirical analysis using the theoretically derived estimation equations from Section 2 and industry-year-level panel data described in Section 3. We first construct an industry-level robot measure by aggregating various robot applications. After reporting the main empirical results, we present the results of a validation test of our main identification assumption, followed by an exploration of potential mechanisms and the results of several robustness checks.

4.1 Estimation Strategy

First, we construct a robot stock measure following the standard immediate withdrawal method (IWM) employed by IFR (IFR, 2018).[15] Using this 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 robots are aggregated by a Cobb-Douglas function:

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

where a is a robot application and R_{ait} is the robot stock of application a in industry i in year t.[16] This robot aggregate measure can be understood as the service of robots in production. We use the initial-year expenditure share as the Cobb-Douglas weight 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 given in equation (14).

With these measures of robot stocks and robot prices, we estimate the equations for robot and labor demand. Based on the labor demand equation (12) and its robot counterpart, we specify the

[15]Recall that the JARA data have a flow shipment variable whereas we are concerned about the stock of robots that perform various tasks and its impact on employment. The IWM method constructs the robot stock at time t by adding the annual robot investment for the past 12 years, thereby assuming that the robot works immediately after installation for the first 12 years and then stops working completely in year 13. We discuss the robustness of our results to other potential stock measure construction choices in the robustness section below.

[16]This functional form is consistent with our model and can be derived from the task-based framework combined with a probabilistic formulation as described in Eaton and Kortum (2002). In Appendix A, we show that the task-based framework can imply the constant expenditure share of robot applications observed in the data.

estimation equations for robots and labor as

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

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

where L_{it} is employment in industry i in year t, and the vector X_{it} is the set of time-varying control variables in industry i in year t capturing three elements: (i) demographics, which may change the adoption incentive of robots and labor supply, (ii) globalization and (iii) technology, which can change production environments and thus concurrently change the motive for both robot adoption and employment. A detailed description of these variables is presented in Appendix B. ξ_i and τ_t are vectors of industry and year fixed effects. Note that equation (12) is the first difference equation but the current estimation equations are level equations, so the time fixed effects must be interpreted differently, i.e. $\tau_t^L = \sum_{h=1}^{t} a_h^L$. In all industry-level regressions, we cluster the standard error and estimate the cluster-robust standard errors using the cluster bootstrap method to account for the small number of clustering units, which is 13 industries.

Our coefficients of interest are β^R and β^L, and we focus our discussion here on β^L. As articulated in equation (13), β^L captures two effects; the gross own-price elasticity of robot demand with respect to robot price from standard factor demand theory and the effect of technological progress that expands the list of tasks that can be feasibly implemented by robots. Thus, the elasticity estimates in equations (17) and (18) capture the gross effects occurring through various mechanisms. Although it would be informative to separate these gross estimates into each specific mechanism, to do so, we would need an exogenous determinant of production scale apart from the exogenous source of robot price variation as well as a direct measurement of the list of tasks implementable by robots. Without this exogenous variation and additional information, we unfortunately are unable to separate the effects.[17] The gross effect, however, is still informative for policymakers, who are primarily concerned about the total labor-market effects of robot adoption, so we leave the derivation of individual effects to future work.

We assume that the variation in p_{at}^R is exogenous to demand industries, given that the price of a robot application is primarily driven by technological change, as discussed in the data section. However, we will test the robustness of this assumption in the next section by using several price measures that are presumably less endogenous to robot adopters such as leave-one-out and export

[17]Note, however, that 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.

robot prices. Further evidence of industrial price exogeneity, though, is that the i-level variation comes from the initial share s_{ai} across industries. In other words, the endogeneity of p^R_{at} does not give industry i-level variation, which alleviates concerns about using application prices as shifters of the IV.[18] 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).

4.2 Main Results

Panels A and B of Table 3 show the OLS estimates of robot demand equation (17) and labor demand equation (18). In both panels, column 1 controls only industry and year fixed effects, column 2 adds demographic controls, column 3 globalization controls, and column 4 technology controls. Our preferred specification is column 4, which includes all potential confounders discussed above. We consistently find significantly negative estimates for robot demand in all specifications (Panel A). Not surprisingly, a reduction in the robot price increases the quantity of robots demanded, with column 4 indicating that a one percent decline in robot prices drives a 1.54 percent increase in robot adoption.

We also consistently find significantly negative estimates for labor demand in all specifications (Panel B). To clarify, a negative coefficient implies that a decrease in the effective price of robots induces employment *growth*, not a reduction. Column 4 indicates that a one-percent decrease in the robot price raises employment by 0.44 percent. To interpret this result, recall that the coefficient β^L corresponds to the terms in equation (13). Therefore, a negative estimate of β^L implies two potential mechanisms: a larger demand elasticity ε than the substitution elasticity σ, or progress in automation (i.e. an expansion of the tasks implementable by robots) that reduces the cost of production. In sum, cheap robots and automation allows industries to produce goods at a lower cost, expand production subject to product demand, and hire more workers. We find that this effect dominates the substitution effect from labor to robots, making the overall relationship between robot price changes and employment negative. We will provide some evidence of the demand elasticities in Section 4.5.

One potential concern is the issue of upgrades in robot quality over the years, which is reasonable

[18] Recent studies in econometric theory such as Borusyak et al. (2022), for example, discuss the identification assumptions behind shift-share instrumental variables (SSIVs) based on the exogeneity of the "shift" component and show that the identification variation is at the industry level (and time level). Further, Adao et al. (2019) shows that the standard SSIV estimators over-reject the null hypothesis of no effects when cross-regional correlations are present.

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

	(1)	(2)	(3)	(4)	(5)	(6)
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^{***}	-0.525^{***}	-0.412^{***}
	(0.099)	(0.073)	(0.116)	(0.075)	(0.095)	(0.036)
R^2	0.975	0.984	0.985	0.987	0.987	0.987
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Demographic Controls		✓	✓	✓	✓	✓
Globalization Controls			✓	✓	✓	✓
Technology Controls				✓	✓	✓
Price Measure	Main	Main	Main	Main	Leave-one-out	Export
Observations	104	104	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 for industry and year fixed effects. All regressions are weighted by purchase values of robots in each year. Column 1 shows the result without other control variables. Column 2 includes demographic controls from ESS, including share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50. Column 3 includes log import values from JIP and log offshoring value from BSOBA. Column 4 includes log stock value measures for ICT capital, innovation capital, and competition capital from JIP. Column 5 and 6 are the same specifications as column 4 except for the use of alternative price measures (a leave-one-out price measure for column 5 and an export price measure for column 6) discussed in Section 4.3. The industry-level cluster-bootstrap standard errors are shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

given that our sample covers a long period from 1978-2017 when the technical capabilities of robots grew significantly. If an industry specializes in the application of robots whose quality grew rapidly, the efficiency-adjusted prices would drop even faster than raw robot prices. At the same time, employment growth in such an industry may have increased, causing our estimates to be biased. To alleviate this concern, we extend our robot aggregation function (15) to perform a quality adjustment, following the method developed by 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 in 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. The results of this exercise are presented in Appendix C and demonstrate that our results are qualitatively robust to this exercise.

4.3 Validating Identifying Assumptions

As one of the contributions of this paper is the new identification method based on the robot price index, expressed by the equation (16), in this section we conduct three robustness exercises to confirm that our choice of robot price index is an appropriate exogenous variable. Specifically, we consider alternative price measures to address potential reverse causality from growth in industrial employment to the robot price.

An endogeneity concern is that endogeneity of robot prices may possibly 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 alternative price measures that do not depend on the own industry robot price instead of the industry-aggregated price measure in equation (14) of our main analysis. The first measure is the leave-one-out price that omits the own industry when calculating robot prices for each application. We construct the industrial price index based on equation (16) but replacing p_{at}^{R} with a leave-one-industry-out price measure, which takes only the variation that is external to each industry.

Next, the leave-one-out price measure may still contain a feedback bias because the shock to one's own industry may propagate to the prices faced by the other industries. To address this, we consider the export price as our second alternative application-level robot price measure, which includes variation that is further external to each domestic industry. We again aggregate this export price measure to the industrial price index using equation (16).

In Table 3, columns 5 and 6 report the estimation results based on these alternative robot price measures. Column 1 shows the baseline estimates of our main analysis (thus the same as Table 3, Panel C, column 4) while columns 2 and 3 are based on leave-one-out prices and export prices, respectively. The estimates reveal that a one percent decrease in the leave-one-out and export prices increases employment by about 0.4 to 0.5%, which is broadly similar to the estimated coefficients of the main analysis.

We also perform two additional robustness checks in Online Appendix F.2. First, we drop large purchasers of robots from our main analysis sample to address potential price-setting effects these buyers may have. Second, we explore the role any specific application may play by iteratively calculating the robot price index (16) with one application removed. All of these exercises address the concern that the robot price (14) may be affected by robot and labor demand shocks, and the results show that our main empirical results are robust to these concerns.

4.4 Heterogeneity

The analysis thus far has found that a decline in robot prices has increased overall employment. However, this might not have been the case for all workers, so in this section we study potential heterogeneous impacts across demographic groups by estimating our main empirical specification (18) using the employment of several subgroups of workers as outcome variables. Table 4 shows the results, with column 1 our baseline estimate (from Table 3, Panel B, column 4) and columns 2-6 showing the impact of robots on the employment of high-school graduates, four-year university graduates, female workers, young workers aged 35 years or less, and older workers aged 50 years or more. Perhaps surprisingly, our main result that adopting robots increases employment is universally applicable to all of these subgroups as well. Moreover, the magnitude of the estimated coefficients does not differ substantially across demographic groups.[19] These findings suggest that the positive employment effects of robots have been driven by the output goods market which has benefited from robot adoption instead of from a particular labor market, and thus these benefits have been broadly shared within society.

[19]We also used our long sample period to investigate potential heterogeneity in the period of analysis, and found suggestive evidence that the positive impact on employment is found in the late period of our sample. See Appendix F.4 for details.

Table 4: 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^{***}
	(0.075)	(0.090)	(0.059)	(0.065)	(0.072)	(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, BSOBA 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 BSOBA, 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.

4.5 Mechanism: The Scale Effects

Our theoretical analysis suggests that a reduction in robot prices and automation induces producers to expand since they can reduce the cost of production and thus the output price. Here we present additional evidence that bolsters this interpretation of our main results reported in Table 3.

Output Volume First we examine if and how much a lower robot price changes output volume by analyzing four outcome measures: real output Y_{it} in year 2000 JPY, nominal output PY_{it}, nominal exports EX_{it}, and nominal domestic absorption AB_{it}, all at the sector level. The first three variables, Y_{it}, PY_{it} and EX_{it}, are taken from the JIP database and the fourth is defined by $AB_{it} \equiv PY_{it} - EX_{it}$. As mentioned in the Data Section, the JIP database only covers years 1978-2012, so in this section we drop 2017, the last year in the main analysis, leaving a sample size of 91, with 13 industries for 7 time periods.

Table 5 shows the regression results of the log of our four output measures on the log robot price p_{it}^R, and we find evidence that a decline in robot price induces an increase in real output, nominal output, and nominal domestic absorption at the industry-year level. This finding is robust to including the globalization and technology control variables. However, perhaps surprisingly, we do not find evidence that a lower robot price leads to export growth. However, as shown in Appendix E.15, although the export share of nominal output is not negligible in certain industries, the export elasticity with respect to the robot price is small. Therefore, this invariance in the export share with respect to the robot price does not affect our strong finding that lower robot prices lead to an increase in total demand for robots. Rather, 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 since Japan is a net exporter in robot-intensive industries such as automobiles and yet it is not exports but domestic absorption that expanded due to the availability of cheap robots. Therefore, other countries might also tap into their domestic demand by making industries more productive via robotization.

Output Price In this section, we analyze the output price since the scale effect works through the reduction in the sectoral output price. Unfortunately, the JIP database does not include a price deflator separated by industry, so for this analysis we instead draw on the price index assembled by the Bank of Japan (BOJ), though there are some complications in its use. First, the BOJ output price indices aggregate domestic and export destinations and data on some industries such as non-

Table 5: 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). The JIP database covers years 1978-2012, which results in the sample size of 91, with 13 industries for 7 time periods. The BOJ output price does not cover some industries such as non-manufacturing and other-manufacturing aggregates. We obtain 11 industries (10 if we exclude the reference Electric machine industry) for 8 time periods (1978-2017), totaling a sample size of 88 (or 80). *p<0.1; **p<0.05; ***p<0.01.

manufacturing and other-manufacturing aggregates are unavailable. Further, since the revision of industry codes makes the Electric machine industry incomparable across years, we use the BOJ "reference series" for the Electric machine industry which is less consistent across time than the series for other industries. As a result, for this analysis, we were able to obtain 11 industries (10 if we exclude the reference Electric machine industry) for 8 time periods, providing a sample size of 88. There is a further concern that the price series for the reference Electric machine industry shows a strikingly different trend that is likely to be unrelated to robotization, as discussed in Appendix E.16, so we report the results both with and without the Electric machine industry.

Columns 5 and 6 of Table 5 show the results of the regression analysis of log output prices. When we drop the reference Electric machine industry, we find a significantly positive effect of lower robot prices on lower output prices, as predicted by the scale effect mechanism. Quantitatively, a one-percent drop in 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.[20] As expected from the

[20]Note that like other studies in the literature, we observe only the price of a robot's main part (e.g., arms) but not the whole system including integration. Therefore, our quantitative interpretation is based on the assumption that prices of integration and peripheral equipment such as computing systems also declined at a similar pace as those

discussion above, including the Electric machine industry adds significant noise to the regression and the coefficients turn insignificant.

4.6 Further Robustness Checks

To round out our analysis, in this section we briefly report the results of additional robustness checks in which we netted out robot-producing workers and used alternative measures of the stock of robots. First, we dropped robot-producing workers from the employment variable to study the net effect of robotization on employment unrelated to the production of robots (Acemoglu and Restrepo, 2018). Appendix E.11 discusses in detail how to calculate robot-producing worker employment and the regression results when these robot producers are netted out of the outcome variable. We confirm that our main findings are qualitatively unchanged.

Next, we check alternative measures of the stock of robots. Recall that our main specification follows IFR and the literature by using the immediate withdrawal method (IWM), which aggregates the flows of robots for 12 years. As several authors argue, however, 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 conducted additional analyses using robot stock variables based on the IWM with varying withdrawal years and the PIM with several alternative depreciation rates. The regression results are reported in Appendix E.9. We confirm that changes in the definition of the robot stock variable did not meaningfully affect the regression results.

5 Local Labor Market Effects

To this point, we have shown that a decline in the price of robots increases employment at the industry level. In this section, we first compare our estimates with those in the literature such as AR and Dauth et al. (2021), and then provide evidence of some regional spillover effects not captured

of the main part. We believe that this is a reasonable assumption because the majority of the auxiliary equipment is comprised of computers such as sensors, controllers and, more recently, artificial intelligence. It is well-known that these equipment prices saw a dramatic decrease (e.g, Karabarbounis and Neiman, 2014). However, one could argue that if peripheral components did not see any price reduction during the sample period, then this would cause us to overestimate the robot price reduction. Since the best estimate suggests that the main part constitutes one-third of the cost of the complete robot system (Leigh and Kraft, 2018), this overestimation might be as great as three times the actual robot price reduction. Note, however, that since the robot price reduction is the regressor instead of the outcome variable, an overestimation of the decline in robot prices actually represents an *underestimation* of the effect of lower robot prices on lower output prices by up to a factor of three.

by an industry-level analysis. Two differences between the approach used in this study and others in the literature are that we use the industry as the unit of analysis and robot price as a measure of the effect on employment while others use the commuting zone and a quantity-based measure of robot exposure. Thus, in this section, we modify our unit of analysis and empirical specification to align our study with the literature so that we can compare the estimates and spillover effects.

First, we modify the unit of analysis from the industry to the local labor market, or more specifically, the Commuting Zone (CZ) delineated by Adachi et al. (2020). We then consider an empirical specification following AR in which employment is regressed on the quantity of robots:

$$\Delta Y_{ct} = \beta^{CZ} \Delta R_{ct} + X_{c,t-15} \gamma^{CZ} + \xi_i^{CZ} + \tau_t^{CZ} + u_{it}^{CZ}, \tag{19}$$

where Y_{ct} is a vector of 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 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 used in our industry-level analysis but prorated to each CZ according to its 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:

$$\Delta R_{ct} = \sum_i l_{cit} \frac{\Delta R_{it}}{L_{it}}, \tag{20}$$

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

A major concern regarding specification (19) 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 the change in the robot price, $\Delta \ln(r_{ct})$, as the instrumental variable because Japan is unique in its adoption of robots and so there is no comparable country as shown in Figure 2. To construct CZ-level IVs, we use $t_0 \equiv 1979$ as the base year and similarly generate shift-share measures but base them on price changes:

$$\Delta \ln(r_{ct}) = \sum_i l_{cit_0} \Delta \ln(r_{it}). \tag{21}$$

The introduction of this CZ-level analysis with a long-run difference specification has two advantages. First, the fixed effects in specification (19) control for different growth trends in each location. This is more flexible than controlling only for level differences and is preferable when studying regional differences, given that the various regions experience different trends in labor-market characteristics (Diamond, 2016). Second, it makes our specification more comparable with those in the literature such as AR. Note that our specification also allows differential trends across CZs, particularly the five first differences, as we assess many time periods.

The first-stage regression of the 2SLS estimator in equation (19) is highly significant (see Appendix F.5). The 2SLS results are shown in Table 6,[21] with all columns reporting our preferred specification with the full set of control variables.[22] First, column 1 shows that overall employment increased in CZs that were exposed to robots, confirming that our findings in Section 4 also hold at the regional level. 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, as reported by AR.

Next, column 2 shows that the regional population responded positively to robot exposure, so because both employment (column 1) and population (column 2) experience similarly positive effects, the effect on their ratio is mitigated because both the numerator and denominator have increased. This is confirmed by column 3, which shows that robot penetration does not affect the employment-population ratio in a statistically significant way. This finding is in contrast to the literature (the AR estimate, using a similar-country shift-share IV strategy, is -0.388 with a standard error of 0.091).

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

Additionally, the CZ-level analysis allows us to test the Moretti (2010) "local multiplier" hypothesis in which an increase in demand for manufacturing employment has a positive spillover to the labor demand in other industries within a locality. To study this, column 5 takes non-manufacturing employment ("L^{SER}", or service industry labor), defined as the total employment (column 1) minus manufacturing employment (column 4), as the outcome variable. The estimated coefficient is only imprecisely estimated and does not reject the null hypothesis, so we find little evidence of spillover effects to employment in the non-manufacturing sector. Finally, column 6

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

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

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

takes as its outcome variable the non-working population ("P^{DEP}", or dependents), defined as the total population (column 2) minus the employed population (column 1). As the estimated impact is not statistically significant, the robot impact does not spill over to the size of the dependent population.

Our findings show a sharp contrast between Japan and 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 early robot adoption in Japan, arguing that it was not likely due to the proximity to domestic robot producers but instead to unique Japanese employment practices such as long-term contracts, seniority-based wage setting, and company-level unions instead of occupation-level unions. These employment practices might have mitigated objections that workers under threat of automation might otherwise have felt about robot adoption, thus enabling firms to more easily increase the adoption of robots with their large productivity gains and thereby scale production.

5.1 Hours Worked and Wages

So far, our main outcome variables have been headcounts of people in terms of employment and population. Given that robot technology is characterized by the time-saving nature of routine tasks, it is possible that the impact on hours worked may be different from the headcount impact. Furthermore, such hour effects may have implications for hourly wages, which reflect the hourly productivity of workers. We explore these possibilities in Table 7, with column 1 showing the baseline result from column 1 of Table 6, which takes log employee headcounts as the outcome variable. Columns 2 and 3 take per-capita hours worked and hourly wages as the outcome variables, and column 2 shows that the adoption of robots caused average hours worked to decrease dramatically, with one robot per 1,000 employees reducing hours worked by 2 percent. Column 3 shows that robots increased hourly wages even more drastically, with one robot per 1,000 employees increasing hourly wages by 4 percent. These findings, combined with the positive impact on employment, suggest that robots enable work-sharing and time-saving technological changes which enhance the hourly productivity of employed workers.

At this point, it is important to consider local labor supply (migration) elasticity, since it affects how the local adoption of robots induces a 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 6 and 7 suggest that the local labor supply elasticity induced by robot adoption is 0.483

Table 7: 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, BSOBA and JIP data. The table presents estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and the log difference of outcome variables multiplied by 100 at the commuting zone (CZ) level. All regressions control for demographic variables, globalization controls, and technology controls as well as industry and year fixed effects. All regressions are weighted by initial-year population, and standard errors are shown in parentheses. The demographic variables include share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50 from ESS. The globalization controls contain the log import values from JIP and log offshoring values from BSOBA. The technology controls include log stock value measures for ICT capital, innovation capital, and competition capital from JIP. The outcome variables are total employment (baseline), average weekly hours, and average hourly wages in columns 1-3, respectively. *p<0.1; **p<0.05; ***p<0.01.

and thus significantly lower than 1.[23]

Finally, some studies in the literature (Autor et al., 2003; Webb, 2020) suggest that because some new technologies are skill-biased, their impact may differ across demographic backgrounds. To consider such potentially heterogeneous impacts, we examine the impact of robot adoption on employment, hours, and wages across different demographic groups of workers. Table 8 reports the results and, consistent with our main findings, we see that robot adoption increased employment significantly for everyone except older workers. Hours worked decreased significantly for everyone

[23]Column 1 of Table 6 shows that the employment elasticity with respect to robots is 1.943, while column 3 of Table 7 shows that the wage elasticity with respect to robots is 4.020, so the local labor supply elasticity induced by robot adoption is 1.943/4.020 = 0.483, which 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 8: CZ-level Regression By Demographic Group

	$\Delta\ln(L_{ct}^{HS})$	$\Delta\ln(L_{ct}^{CG})$	$\Delta\ln(L_{ct}^{Fem})$	$\Delta\ln(L_{ct}^{U35})$	$\Delta\ln(L_{ct}^{O50})$
	(1)	(2)	(3)	(4)	(5)
ΔR_{ct}	2.528**	2.616*	1.839*	2.184*	0.467
	(1.108)	(1.492)	(1.054)	(1.318)	(1.113)
	$\Delta\ln(h_{ct}^{HS})$	$\Delta\ln(h_{ct}^{CG})$	$\Delta\ln(h_{ct}^{Fem})$	$\Delta\ln(h_{ct}^{U35})$	$\Delta\ln(h_{ct}^{O50})$
	(1)	(2)	(3)	(4)	(5)
ΔR_{ct}	−2.038***	−1.080	−1.352*	−2.109***	−0.837
	(0.581)	(0.844)	(0.691)	(0.744)	(0.719)
	$\Delta\ln(w_{ct}^{HS})$	$\Delta\ln(w_{ct}^{CG})$	$\Delta\ln(w_{ct}^{Fem})$	$\Delta\ln(w_{ct}^{U35})$	$\Delta\ln(w_{ct}^{O50})$
	(1)	(2)	(3)	(4)	(5)
ΔR_{ct}	3.435***	4.274***	4.338***	4.997***	4.598***
	(0.869)	(1.336)	(1.027)	(1.011)	(1.291)
Group	High School	4-year Univ.	Female	Age ≤ 35	Age ≥ 50
Observations	1,265	1,265	1,265	1,265	1,265
R^2	0.853	0.767	0.820	0.826	0.889

Notes: Authors' calculation based on JARA, ESS, BSOBA and JIP data. The table presents the estimates of the relationship between shift-share measures of changes in robot stock per thousand workers and the log difference of employment (panel A), hours worked (panel B), and wages (panel C) multiplied by 100 for different demographic groups of workers at the commuting zone (CZ) level. All regressions control for demographic variables, globalization controls, and technology controls described in Section 4.1 as well as industry and year fixed effects. All regressions are weighted by initial-year population. *p<0.1; **p<0.05; ***p<0.01.

except four-year university graduates, and in terms of hourly wages, all groups of workers gained from the adoption of robots in the region. For example, an additional robot per 1,000 workers increased hourly wage growth by 3.4 percent among high school graduates and by 4.2 percent among 4-year university graduates, revealing that the return to robots is about 20 percent higher for 4-year university graduates than high-school graduates, which is consistent with the concept of skill-biased technical change.

6 Conclusion

This paper studies the effect of robotization on employment in Japan from 1978-2017, using a model that combines standard factor demand theory and a recently developed task-based framework to examine the role of declining robot prices on the demand for factors. We use newly digitized robot adoption data that has three unique features: (i) a long panel covering Japan, an early adopter of robotic technology, (ii) measures of both unit shipments and total value that allow a systematic calculation of robot unit costs, and (iii) disaggregation of these variables by robot application. Armed with these unique features, we exploit application share variations in each industry in the initial period of robot adoption as our source of identification. The estimates from our preferred specification show that a one-percent reduction in robot prices increased employment by 0.43 percent, a result that is robust to modifying price variables and the sources of identification such as the initial application shares. We also provide suggestive evidence of a significant scale effect of the decline in robot prices which supports our theoretical mechanism. The CZ-level shift-share analysis further shows a clear distinction of our findings from the findings in the literature.

Further, although this study is based on Japanese data, the identification strategy developed in this paper may be applicable to other contexts as well. Specifically, the effective robot price series by industry-year level developed for this study could serve as the explanatory variable for analyzing the effect of robot adoption in the other countries because Japanese manufacturers export robots worldwide. An examination of the effect of robot penetration on employment drawing on this new identification strategy could complement the existing evidence of the effects of robotization on the labor market.

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Appendix

A Microfoundation for Robot Aggregates

In this section, we provide the microfoundation for the task-based robot aggregate used in the main text whereby in the model section we treat robots R_{it} in aggregate and abstract away from specific applications but in our estimation equation (15) we aggregate robot applications with a Cobb-Douglas function. To show the connection between these two approaches, we illustrate that a key implication of the Cobb Douglas function, that the expenditure share is constant across prices, can be derived by our task-based framework. A key insight is drawn from the probabilistic space representation of tasks as shown in Eaton and Kortum (2002, EK) and a Fréchet distribution that implies a closed form CES-type aggregation that nests the Cobb-Douglas function.

Consider a set of tasks $\Omega_{it}^{R} \subset \Omega$ that are performed by robots in equilibrium as specified in the model section. Robot applications are indexed by $a = 1, \dots, \mathcal{A}$. Each task $\omega \in \Omega_{it}^{R}$ is small and fragmented so that one robot application can perform it. In each industry i, an application a has efficiency $z_{ia}(\omega)$ for performing task ω per unit of robot. The amount of task $\omega \in \Omega_{it}^{R}$ performed by robots is given by

$$y_{it}(\omega) = \sum_{a} a_{ia}^{R}(\omega) R_{iat}(\omega),$$

where $R_{iat}(\omega)$ is a unit of application-a robots deployed to perform task ω. A producer adopts robots for application a by paying rental rate p_{at}^{R}. The unit cost of adopting application a for task ω per efficiency is $c_{iat}(\omega) = r_{at}/z_{ia}(\omega)$. Due to the perfect substitutability within a task, the producer chooses to adopt application a for task ω if $c_{iat}(\omega) < \min_{a' \neq a} c_{ia't}(\omega)$.

Suppose that the efficiency distribution follows an i.i.d. Fréchet distribution F so that for each a,

$$F(z_{ia}(\omega) \leq z) = \exp\left(-T_{ia} z^{-\theta}\right),$$

where $T_{ia} > 0$ is the scale parameter representing application a's absolute level of efficiency in industry i, and $\theta > 0$ is the (constant) shape parameter representing the dispersion of efficiency across tasks. With this assumption, the distribution of the unit cost per efficiency is

$$\Pr(c_{iat}(\omega) \geq c) = \Pr\left(\frac{r_{at}}{c} \geq z_{ia}(\omega)\right) = \exp\left(-T_{ia}\left(p_{at}^{R}\right)^{-\theta} c^{\theta}\right)$$

and the minimum efficiency cost distribution is

$$\Pr\left(\min_a c_{iat}(\omega) \geq c\right) = \prod_a \Pr\left(c_{iat}(\omega) \geq c\right) = \exp\left(-\sum_a T_{ia}\left(p^R_{at}\right)^{-\theta} c^\theta\right).$$

We have used the i.i.d assumption in the first equality of the second expression. Hence, the probability of adopting application a can be shown as

$$\Pr\left(c_{iat}(\omega) < \min_{a' \neq a} c_{ia't}(\omega)\right) = \frac{T_{ia}\left(p^R_{at}\right)^{-\theta}}{\sum_{a'} T_{ia'}\left(p^R_{a't}\right)^{-\theta}}.$$

Due to the law of large numbers, the robot adoption probability is the adoption share of application a among all robots. Furthermore, following EK, the expenditure share is equal to the adoption share. Therefore, we have a CES demand function for robot application a:

$$\frac{p^R_{at} R_{iat}}{\sum_{a'} p^R_{a't} R_{ia't}} = \frac{T_{ia}\left(p^R_{at}\right)^{-\theta}}{\sum_{a'} T_{ia'}\left(p^R_{a't}\right)^{-\theta}}.$$

We consider the situation under which each robot application a is useful for performing only a certain set of tasks. Given the definition of θ, this situation corresponds to a low value of θ. Once we take the limit $\theta \to 0$, the robot expenditure share is a constant function of robot rental rate p^R_{at}, which is the property we find in the data section.[24] In this case, robot aggregation across applications can be modelled by a Cobb-Douglas aggregator with weight of relative efficiency parameter $s_{ai} \equiv T_{ia}/\sum_{a'} T_{ia'}$, where s_{ai} is the expenditure share in equation (15). The argument in this section shows that the Cobb-Douglas aggregator is a proper approximation if each robot application has a substantial comparative advantage for implementing a specific task over other robot applications, which is realistic given that each robot application (e.g., welding robots) is designed for a narrowly defined specific task (e.g., welding).

[24]One may be concerned that EK assumes $\theta > 1$, which prevents the average productivity to diverge to infinity. None of our derivations above, however, depend on this particular assumption, since our argument does not depend on the average productivity. Therefore, we do not need to impose this assumption. Our argument does depend, though, on the fact that the robot price index is well-defined, which is guaranteed by the parameter restriction $\theta > \sigma^T - 1$. Combining this assumption with the limit $\theta \searrow 0$, we have that $\sigma^T \searrow 1$.

B 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 both robot adoption incentives for producers and employment at the same time. In Japan, for example, the acute problems of labor shortages due to aging and low population growth rates have pushed firms to adopt robots (Acemoglu and Restrepo, 2022), so not including any demographic variables may bias the estimates. 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, globalization concurrently alters both labor demand and robot adoption, since given the complexity of modern manufacturing production, it is likely that easier access to foreign markets for 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 by taking the total import values of each sector from the JIP database which controls for the role of import competition (e.g., Autor et al., 2013) and outsourcing (e.g., Hummels et al., 2014). We also take the total gross sales value for each industry from the BSOBA database, which controls for 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 increased adoption of information and communications technologies or ICTs (Autor et al., 2003) may also simultaneously alter both labor demand and robot adoption. In fact, as robots need to be programmed rather than operated by humans, robots and ICT are complementary. However, since our interest is the direct impact of robot-based automation on employment, we control for other technological progress by using intangible capital stock values from the JIP database. We note that all explanatory variables (i.e., robot, globalization, and technology) are positively correlated, and are explained in detail in Section E.13.

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

Table B.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

C Robot Quality Adjustment

Since Cobb-Douglas aggregation (15) does not allow quality upgrading across applications, we modify our specification 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 that the demand for robot application a is

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

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

$$p_{it}^{R,QA} = \left(\sum_a \widetilde{s_{ai}} \left(p_{at}^{R} / \lambda_{ait} \right)^{1-\sigma} \right)^{1/(1-\sigma)} \tag{22}$$

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

$$\ln R_{ait} = -\sigma \ln p_{at}^{R} + \alpha_{ai} + \alpha_{it} + \eta_{ait}, \tag{23}$$

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

$$\widehat{\lambda_{ait}} = \exp\left(\widehat{\eta}_{ait} / (\widehat{\sigma} - 1)\right). \tag{24}$$

We now move to several discussions of our model. First, our extended specification nests the Cobb-Douglas case since 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, which we consider a natural interpretation in the case of robotics because robot quality may be conceptualized as the speed of task performance relative to that of older types of robots or human hands. Third, compared 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 report quality-adjusted prices but quality adjustment is not backed up based on a demand function in their data source. Instead, they use 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 (23), it is necessary to have an estimate for robot demand elasticity $\widehat{\sigma}$, which we obtain using two strategies. The first one is the fixed-effect regression as in equation (23), 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 bias the estimates of σ. Second, a remaining concern for endogeneity is that time t-varying application a-industry i-specific quality upgrading may still affect both the measured robot price and the measured quantity, thus 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 any 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 σ, the robot application elasticity of substitution, in Table C.2. Columns 1 and 2 report the results from the OLS regression of equation (23) and the IV of the leave-one-industry-out robot price. We find that robots are complementary to each other, with σ in the range of 0.3 to 0.5, which is broadly consistent with our idea of robot applications since different applications perform separate sets of tasks, which makes substitution across applications difficult.

Based on these results, we use $\sigma = 0.3$ and $\sigma = 0.5$ for our robustness analysis with the quality-adjusted price. Table C.3 shows the regression result of our main specification with the employment outcome variable, equation (18). Columns 1 and 2 show the results with $\sigma = 0.3$ and $\sigma = 0.5$, respectively. We confirm that quality adjustment does not affect our main conclusion that a reduction in robot prices increases employment, but the magnitude of the effect is smaller. Intuitively, a decline in the robot price of a given robot application, combined with our estimation

Table C.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 (23) 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, and 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 an a priori null hypothesis, we do not report significance against any values. *p<0.1; **p<0.05; ***p<0.01.

result of $\sigma < 1$ and roughly constant application expenditure share (Table 2), implies that the quality of robots must have been upgraded to keep the expenditure share constant. Therefore, part of the estimated positive impact on employment from a reduction in the price of robots in our 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 needed to maintain a constant expenditure share.

D Early Adoption of Robots in Japan

Industries in Japan began adopting robots at least 10 years earlier than in any other country (Figure 2), but while one might think that this early adoption is trivially explained by a greater availability of robot producers in Japan, the facts do not bear this out. Robot technology 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

Table C.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 for industry and year fixed effects, demography controls, globalization controls, and technology controls defined in Section 4.1. All regressions are weighted by the purchase values of robots in each year. The industry-level cluster-bootstrapped standard errors are shown in the parentheses. *p<0.1; **p<0.05.

US-based Unimation Inc, allegedly the first industrial robot producer in the world. Kawasaki signed a technical license agreement with Unimation in 1968 and sent its engineers to the United States to acquire technical knowledge and to import sample machines. Thus, the presence of domestic robot producers does not explain the early adoption of robots by Japanese industries, certainly compared to those in the US.

Instead, we argue that the Japanese employment practices of large manufacturing firms throughout the analysis period promoted the earlier adoption of robots at production sites in Japan compared with its Western counterparts. Standard textbooks of the Japanese economy list the features of Japanese employment practices as a combination of (i) long-term employment, (ii) seniority-based wages, (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-based wages, combined with a unique job rotation system of shop floor workers (Koike, 1988) which helps workers obtain an overview of the whole production process and knowledge about overall operation at plants, might have mitigated workers' concern about adopting robots and thus reduced the effective cost of their adoption.

In addition, enterprise-level labor unions tend to welcome the introduction of new technology that improves the work environment and labor productivity because workers who become redundant can be relocated to other worksites of the same firm while receiving a part of the productivity gain due to the profit-sharing nature of wages and bonus determinations (Freeman and Weitzman, 1987).[25] Without the fear of job loss, labor unions actually *welcomed* the introduction of robots at production sites because robots release union members from difficult tasks. For instance, KHI (2018) describes the impact of the *Kawasaki-Unimate 2000*, one of the first robot brands in Japan, as follows: "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." While the number of shop floor workers involved in spot welding tasks was reduced, these workers were released from the hardship associated with these tasks.

Our own interviews with high-ranking 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 Japanese employment practices, claiming that the adoption of robots did not lead to job loss.[26]

Further support of this argument is provided by an article in the early 1980s published in the Nikkei newspaper. In an interview with Nikkei reporter Tsuyoshi Higuchi, Teruyuki Yamasaki, the CEO of Yamazaki Iron Works (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.)

[25]Tachibanaki et al. (1996) and Jeong and Aguilera (2008) also document that Japanese employment practices allow workers to relocate within a company through retraining.

[26]Interviews with Mr. Tomonori Sanada and Mr. Seiji Amazawa of Kawasaki Heavy Industries, Ltd. were conducted on April 6, 2021; with Mr. Kazuyoshi Toyokawa of Yasukawa Electronic Corporation on April 9, 2021; and with Dr. Shinsuke Sakakibara of Fanuc Corporation on April 22, 2021.

Online Appendix

E Data Appendix

E.1 Coverage of JARA Data

JARA data covers most robot producers in Japan. In 1996, 445 of the 587 establishments asked to complete the survey responded, for a response rate of 76 percent. To show the trend in the JARA data coverage of 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 obtain the aggregated total sales of industrial robots each year, the construction of which is discussed in detail in Appendix E.11. Figure E.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, and in some years, the JARA data even surpass the total shipment values observed in the CoM/ECBA data. Therefore, we can conclude that the JARA covers most of the robot transactions measured in government statistics.

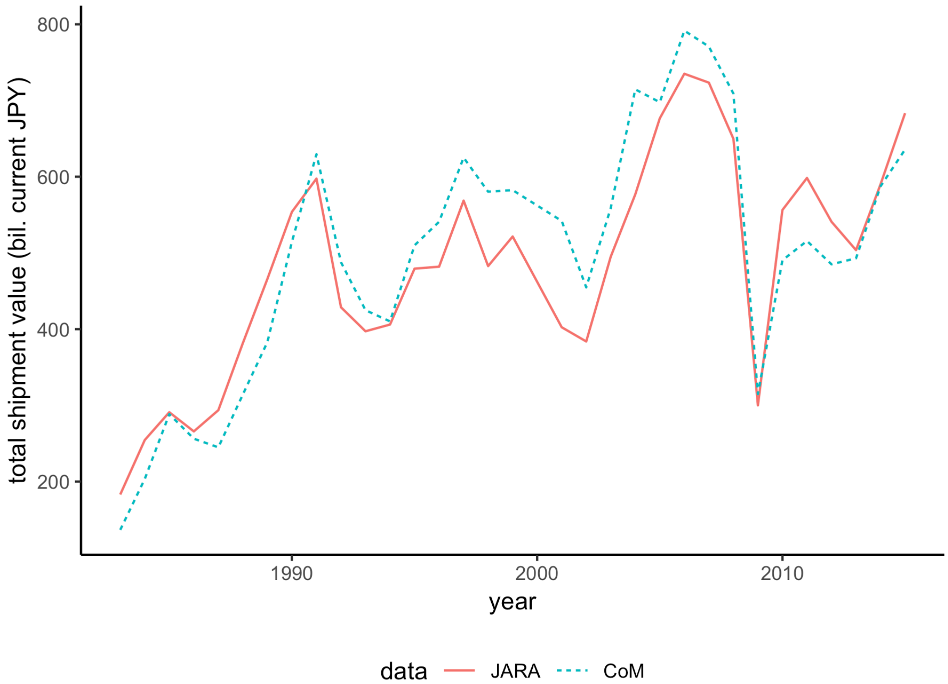
E.2 Comparison between JARA and IFR Datasets

The trends for Japan from the IFR and JARA datasets are broadly consistent, which is not surprising since the IFR creates its Japan series based on JARA data. The two series do not completely overlap, though, partly due to a robot category adjustment that is described below. Additionally, as the IFR series shows total adoption while the JARA series shows the adoption of robots shipped from Japan, Japan's small robot import share creates a small discrepancy between the two datasets,[27] which is addressed directly with import statistics in Appendix E.14.

One major discrepancy between the JARA and IFR data, however, is the classification of robots. Specifically, in the JARA data, robots used in "clean rooms" (or clean-room robots) are included in the "Other" category in Table 1. Clean rooms, which provide an environment that is free from dust and other contaminants, are mainly used in the electric and electronics industry, but there

[27]Any error caused by missing robot imports in the JARA data is quite small in the case of Japan, unlike other countries. 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.

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

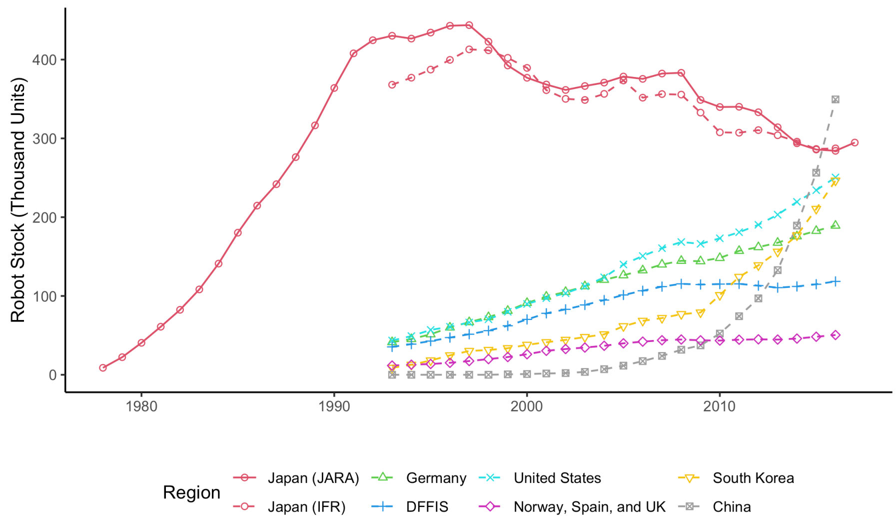


Note: Authors' calculation based on JARA and CoM/ECBA data. The trend for JARA is the sum of all shipment values of all robot applications to all industries. The trend for the CoM is the sum of shipment value (net of VAT) of all products categorized as industrial robots (available from 1983 to 2016).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

is a growing use of clean room machines to avoid contaminants brought by human labor. In an interview with a JARA official, we learned that JARA began covering clean-room robots in the electric machinery industry from the mid-1990s, and we indeed see a sharp increase in the "Other" application category shipped to the electric machinery industry in the JARA data. In contrast, IFR data does not count clean-room robots.

While some studies in the research literature have avoided using directly obtainable Japanese statistics, citing a classification issue (e.g., Graetz and Michaels, 2018 and AR), there are at least three reasons supporting the validity of the JARA robot data. First, as described above, we have identified the source of the classification difference (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 2. Third, our main results are robust to dropping the "Other" application category, as reported in Section 4.3.

Figure E.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. For Japan, we use both JARA and IFR data, as explained in the data section. The JARA data show the domestic 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 shown in AR.

E.3 Raw Trends of Robot Stock Units, by Country

Figure E.2 shows the raw trends in the number of robot units across the selected world regions that were shown adjusted by employment in Figure 2. Our main claims are unchanged; Japan shows a unique trend in robot stocks that emerged and grew quickly in the 1980s and plateaued and slightly declined afterward. In Figure E.2, China adopted robots very rapidly, and has been 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 E.2).

E.4 JARA Cross Tables

The cross tables we were able to access are as follows. The cross tables by application by buyer industry are available between 1978 and 2017 and are the data source for our primary analysis. The cross tables by robot type and buyer industry are also available, but only for the years between

1974 and 2000, after which cross tables of robot structures and buyer industries are available following the 2004 IFR statement that robot classifications should only be done in structures.[28] For 1982-1991, we can also access the cross tables by application and robot type.

In our study, we leverage the heterogeneity in these robot classifications. Robots may be categorized according to several dimensions, such as application, type, and structure. 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 used intensively in the automobile industry, and Assembling and disassembling (AD), which are used intensively 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 repeatedly, while numerical control robots receive the input by programs and move without memory based on the moves performed beforehand. Playback robots are used relatively intensively in the automobile industry, while numerical control robots tend to be used in the electric machine industry.

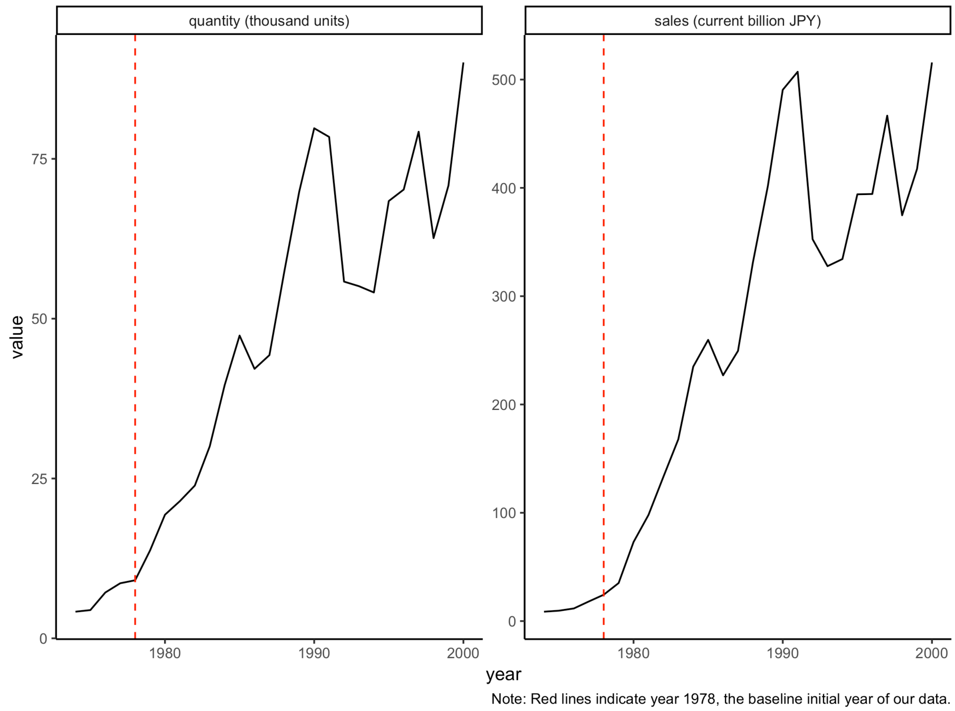
Starting in 2004, the IFR and major robot producers agreed that robots should not be classified according to the above types but instead by structures that represent the physical features of robots. In the JARA data, the type classification was discontinued in 2000 and the structure classification began 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.

E.5 Robot Trends in The Very Early Period

Figure E.3 shows the robot trends in Japan beginning 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 the years before 1978, the starting year of our sample period. Consistent with the fact that robot adoption in Japan expanded materially beginning in the late 1970s, 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 amounts are negligible compared to the observed application-level quantities and sales after 1982, this exercise does not

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

Figure E.3: Robot Trends Before and After 1978



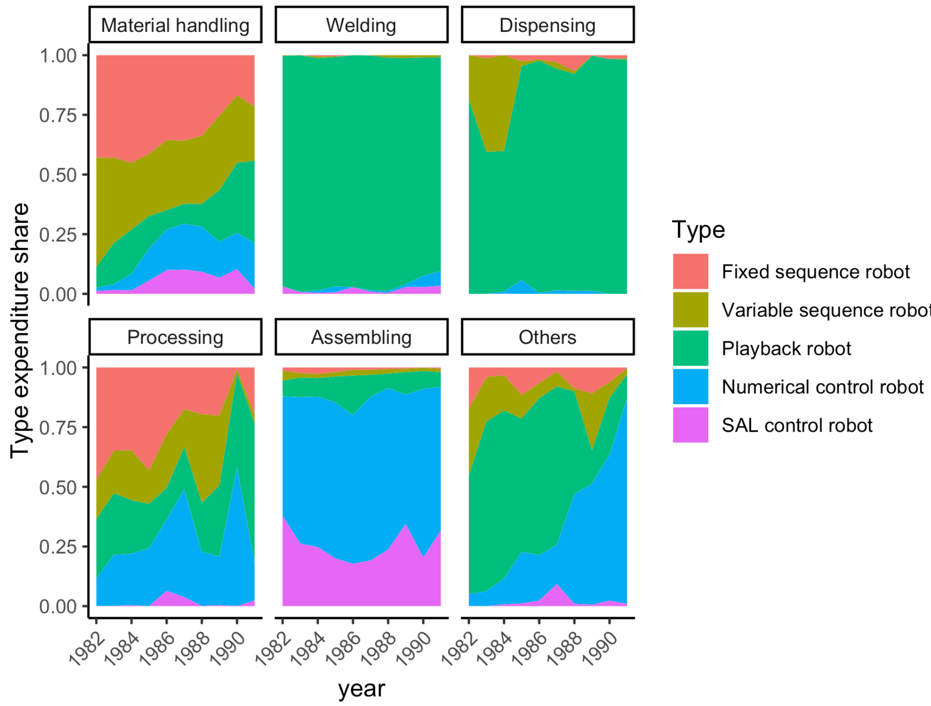
Note: Authors' calculation based on JARA data. The red dashed line indicates 1978, the initial year of our primary analysis. Trends before 1977 are taken by aggregating type-buyer industry across tables.

affect our empirical results, which are available upon request.

E.6 Robot Price Trend by Type

Figures E.4 and E.5 show the expenditure shares and unit value trends of each robot type, respectively. Figure E.4 reveals that, among others, the Welding application uses playback robots most intensively while Figure E.5 shows the secular declining trend in playback robots. This monotonic decline in the price of playback robots is in sharp contrast to the price trends of other robot types and caused the price decline in welding robots. These findings corroborate Table 2 and Figure 3, and support the idea that the price decline was caused by the mechanical specification of robots, classified by the type of robots.

Figure E.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.

E.7 Domestic Sales and Export of Japanese Robots

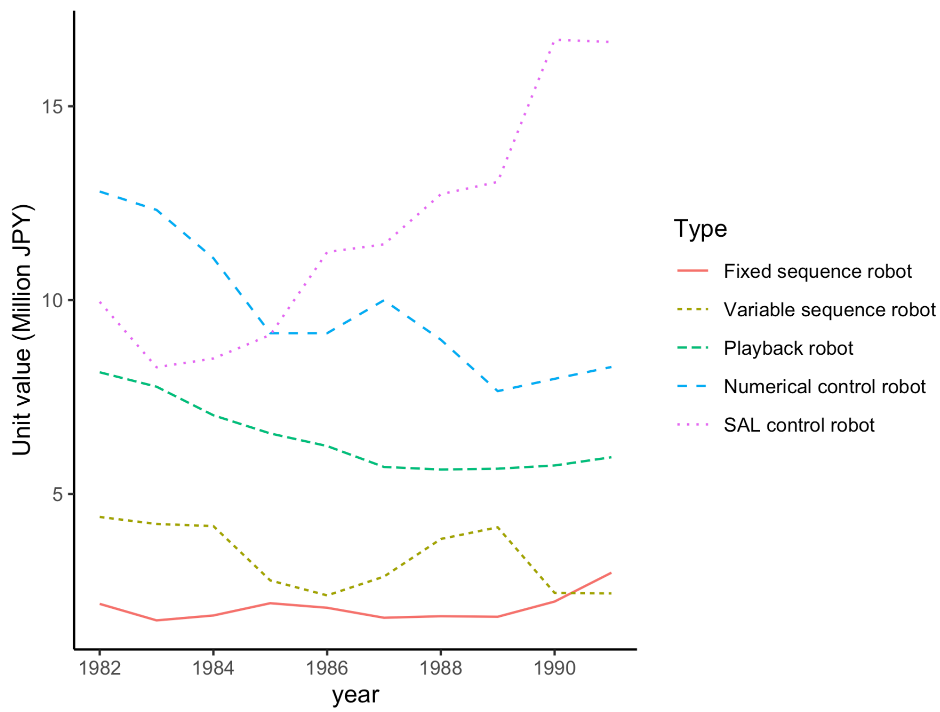
Figure E.6 reveals that the growth in robot adoption within Japan expanded during the 1980s but stagnated afterward, while the export trend grew rapidly starting around 1990. Although the structural break before and after 1990 is an interesting phenomenon in itself, we instead focus on the domestic adoption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

E.8 Technical Details of Robot Applications

Here we provide the technical details of robot applications to support our interpretation that the movement in robot prices is caused by technological change. 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

Figure E.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.

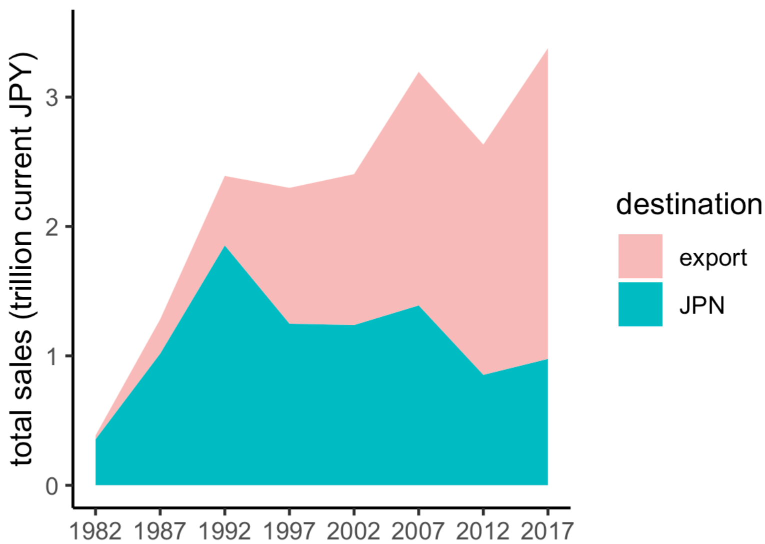
structured as articulated robots, which are equipped with multiple joints (typically six) that enable smooth movements in any direction. In contrast, SM requires quick and accurate movements along a horizontal dimension for mounting SMDs. For this purpose, a typical structure of SM robots is the Selective Compliance Assembly Robot Arm (SCARA), which is well suited to horizontal movements.[29]

E.9 Calculating Robot Stock

As we briefly discussed in Section 4.6, we have made alternative and flexible assumptions on the robot stock calculation to assess the robustness of our main findings. The first set of assumptions is based on the immediate withdrawal method (IWM), which assumes that shipped robots are in use immediately after purchase and not in use after a specified length of time (IFR follows this

[29] As is discussed in detail in Appendix E.4, robot structure is the mechanical aspect of robots.

Figure E.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).

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 a 12 year withdrawal. 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), which is a standard method used when calculating capital stocks adopted in National Accounts (OECD, 2009). A key parameter in this method is the depreciation rate, but there is no systematic empirical study of the appropriate value. Thus, following Artuc et al. (2020), we use an annual 10 percent depreciation rate as one measure and then for a more context-based estimate, we also employ the result from Nomura and Momose (2008). Based on disposable asset data in Japan (the Survey on

Table E.1: Industry-level Analysis with Different Stock Measures

	Dependent variable:			
	$\ln(L_{it})$			
	(1)	(2)	(3)	(4)
$\ln(p^R_{it})$	-0.386^{***}	-0.526^{***}	-0.525^{***}	-0.439^{***}
	(0.074)	(0.086)	(0.095)	(0.097)
Stock Measurement	10 Years IWM	15 Years IWM	$\delta = 0.10$	$\delta = 0.18$
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls	✓	✓	✓	✓
Globalization Controls	✓	✓	✓	✓
Technology Controls	✓	✓	✓	✓
Observations	104	104	104	104
R^2	0.987	0.987	0.987	0.987

Notes: Authors' calculation based on JARA, ESS, BSOBA and JIP data. The table presents estimates of the relationship between log robot price measure and log employment across industries and years with various robot stock measures. In Column 1, the stock measure is calculated by the immediate withdrawal method (IWM) after 10 years, or the assumption that robots are used for 10 years continuously after purchase and depreciated afterwards. Column 2 reports a 15-year IWM. Columns 4 and 5 suppose the exponential depreciation after purchase, with the annual depreciation rate of 10% and 18% ($\delta = 0.10, 0.18$). The employment measure includes the employment of robot-producing plants. All columns control for industry and year fixed effects. All regressions control the demography controls (explained in the main text), the log import values from JIP, log offshoring value from BSOBA, and log stock value measures for ICT capital, innovation capital, competition capital from JIP. All are weighted by purchase values of robots in each year. The industry-level cluster-bootstrapped standard errors are shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Capital Expenditures and Disposables), Nomura and Momose (2008) estimated the depreciation rate of machinery and equipment as 18 percent. While recognizing that machinery is a broader category than industrial robots, we nonetheless employ 18 percent as our larger alternative than 10 percent.

Table E.1 shows the baseline regression results for equation (18) with these alternative robot stock measures. Columns 1 and 2 show the 10 year and 15 year IWM, and columns 3 and 4 show the PIM results with depreciation rates of 10 and 18 percent. The results show that our main regression coefficients are robust to alternative choices of the stock measurement of robots.

E.10 Details of Japan's Employment Status Survey (ESS)

In the ESS, employment status is based on one's *usual* employment status (the "usual method"), and any of the following responses are recorded as employed: mostly worked, worked in addition to doing housework, worked in addition to attending school, and worked in addition to doing housework and attending school. 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).

E.11 Details of the Census of Manufacture

The Census of Manufacture (CoM) annually surveys manufacturing establishments in Japan,[30] asking each establishment for its product-level shipment values. The product code for industrial robots used in the CoM has existed since 1977, and we use the CoM data from 1983 to 2016. The CoM survey was not conducted in 2011 and 2015, because it was substituted by another government survey, the Economic Census of Business Activity (ECBA). We thus also use ECBA data to construct a complete set of observations of Japanese establishments that shipped robots in any year between 1983 and 2016.

The CoM and ECBA treat the VAT in the following way. For CoM, respondents were required to report the shipment value gross of VAT before 2014 but 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 subtracting the legislative VAT rate from the total sales value. The VAT rate was 0 before 1988, 0.03 between 1989 and 1996, 0.05 between 1997 and 2013, and 0.08 since 2014.

[30]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.

The primary purpose of using the CoM and ECBA is to obtain information on robot-producers' employment. For this purpose, we adopt the following steps. First, we calculate each establishment's intensity of robot production, defined as 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.

Table E.2 shows the estimation results for specification (18) with an outcome variable for employment that omits robot-producing workers. 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, which is due solely to the fact that the number of robot-producing workers is very small relative to the size of the Japanese manufacturing industry, ranging only 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).

E.12 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, any subsidiary including any subsidiary's subsidiaries must be reported, which we here collectively refer to as subsidiaries. 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 obtain offshoring intensity measures by aggregating operating revenues in foreign subsidiaries, using subsidiaries' industry codes when allocating revenues to each industry.

E.13 Details of the Japan Industrial Productivity Database

The Japan Industrial Productivity (JIP) database is a long-run industrial aggregate of several measures starting in 1970 and which includes industrial and trade data that are part of the global KLEMS

Table E.2: Industry-level Level Analysis After Removing Robot-Producing Workers

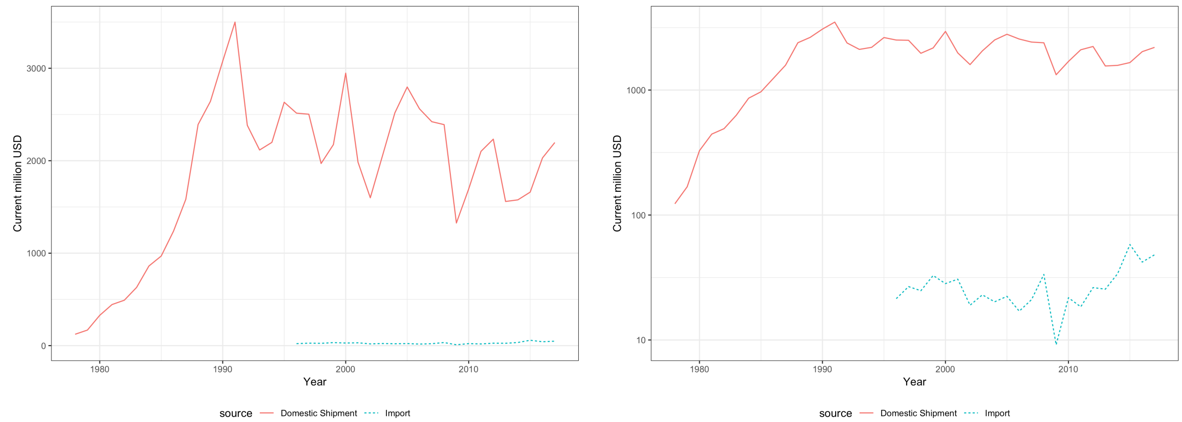
	Dependent variable:			
	$\ln(L_{it}^{NRP})$			
	(1)	(2)	(3)	(4)
$\ln(p_{it}^R)$	-0.841^{***}	-0.466^{***}	-0.274^{*}	-0.437^{***}
	(0.094)	(0.120)	(0.151)	(0.077)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
Observations	104	104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

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

data project. Among these variables, we use imports and intangible capital to control for recent developments regarding foreign competition and technologies, both of which are argued to be factors affecting 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, custom-developed software), innovative property (e.g., R and D expenditures, mineral exploration, copyright and trademark rights, other product/design/research development), and economic competencies (brand capital, firm-specific human capital, restructuring expenditures), and the basic concepts of these variables follow National Accounts. Further details are provided in Corrado et al. (2005) and Fukao et al. (2008).

Figure E.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.

E.14 Robot Imports in Japan

It is well known that Japan produces most of its robots domestically (Acemoglu and Restrepo, 2022, among others), but to confirm this, we compared imports (from the rest of the world to Japan) with domestic sales (from Japan to Japan) as measures of robots. In particular, we obtained Comtrade data on HS Code 847950 (Industrial Robots for Multiple Uses), and compared this to the domestic shipment trends from our main JARA data source. Trade data for that HS code are available only since 1996, while JARA data exist from 1978. Table E.7 shows the result. We also calculated the shipment share by domestic producers, which ranged from 97.9 percent to 99.3 percent between 1996 and 2017 depending on the year, which we interpret 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.

E.15 Industry Export Share

Table E.3 reports the export share of nominal output and since it is small relative to domestic absorption, the impact of robot prices on total output, if any, is likely to be observed in the domestic absorption component as opposed to the export component.

Table E.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

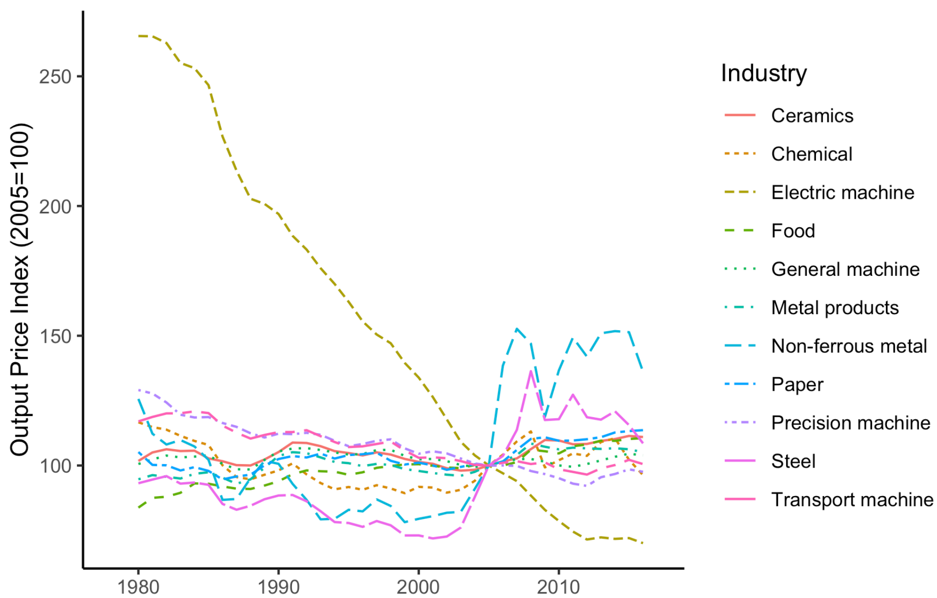
Note: The authors' calculation from the JIP database, sectoral growth accounting and export statistics. A value of 0 means all goods are absorbed in the domestic economy, while a value of 1 means all are exported.

E.16 Output Price Trends

In Figure E.8, we show the output price trends of several manufacturing sectors. In the 1980s and 90s, most industries experienced a modest reduction in the output price index, which is consistent with long-run technological growth, and this was followed by a slowdown and even a reversal in some industries.[31] Most notable in the figure is the very sharp and continuing reduction in output prices in the Electric machine industry during the period. Since the Electric machine industry includes ICT goods, this rapid drop in price is consistent with the large literature in macroeconomics 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 price of electric machines does not necessarily reflect robot penetration, however, including the electric machine industry 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 in Section 4.5.

[31]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.

Figure E.8: Output Price Trend



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

F Additional Empirical Results

F.1 Pretrend

To study if the pretrend drives our empirical results in Section 4, we ran the following regression:

$$L_{i,t-15} = \beta_0 + \beta_1 \ln p_{it}^R + u_{it}.$$

The estimation results are reported in Table F.1, and as none of the estimated coefficients are statistically positive and significant except for the first column in which we do not include any control variables. Furthermore, the point estimates shrink to zero as we include control variables, indicating that our choice of control variables is appropriate. Once controlled for the full set of control variables, the regression coefficient suggests that the effect of robot prices on lagged employment is both economically and statistically insignificant (column 4). Taken together, this suggests that there is no evidence of the pre-trend, suggesting that an industry that vigorously adopted robots in the subsequent period did not necessarily grow before the adoption of robots.

F.2 Further Validation Exercises of the Identifying Assumptions

Sensitivity to Industry Selection Next, we address potential endogeneity by dropping industries that are large purchasers of robots, as the demand from industries such as electric and transportation machinery may greatly affect robot prices. If the demand for their output surges, it may enhance the demand for both robots and labor, and the increase in robot demand would affect robot prices, creating a spurious relationship between robot prices and factor demand. While this concern is already partly addressed by using an arguably exogenous price series at the application level, we further address this concern in a more direct way by dropping the two large robot-purchasing industries in the analysis. The resulting sample consists entirely of smaller industries and so the resulting robot prices are less endogenous to robot demand-side shocks. Table F.2 shows the main specification (18) but varies the sample, with column 1 dropping electric machinery, column 2 transportation machinery, and column 3 both. In all columns, the coefficients are negative and significant, suggesting that we need not be concerned about endogeneity due to the demand for robots by large industries.

Table F.1: Pre-period Analysis at the Industry Level

	Dependent variable:			
	$\ln(L_{i,t-15})$			
	(1)	(2)	(3)	(4)
$\ln(p^R_{it})$	0.607***	0.289	0.224	0.033
	(0.198)	(0.239)	(0.236)	(0.326)
Industry FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Demographic Controls		✓	✓	✓
Globalization Controls			✓	✓
Technology Controls				✓
Observations	65	65	65	65
R^2	0.982	0.991	0.991	0.992

Notes: Authors' calculation based on JARA, ESS, BSOBA and JIP data. The table presents estimates of the relationship between log robot price and 15-year lagged log employment across industries and years. The employment measure includes the employment of robot-producing plants. All regressions are weighted by the purchase values of robots each year. All columns control for industry and year fixed effects, and column 1 shows the result without other control variables. Column 2 includes demographic controls from ESS, including share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50. Column 3 includes log import values from JIP and log offshoring value from BSOBA. Column 4 includes log stock value measures for ICT capital, innovation capital, competition capital from JIP. Standard errors are shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Role of Each Application Next, we check if changing the set of applications in the empirical specification affects our main results. To do so, we iteratively drop one application from Table 1 and perform our main regression of equation (18). Table F.3 reports the results, with column 1 showing the result with all applications (and thus repeats the result from column 4 of Panel C in Table 3) and columns 2-7 reporting the results with one application dropped, in the order of applications presented in Table 1. We see that our main empirical result is not qualitatively affected by dropping any specific application, which suggests that it is not a particular application but the application mix that drives our empirical results, and so our results are broadly applicable across all applications.

Also clear from column 7 of Table F.3 is that our findings are not driven by the "Other" application which, as discussed in Section 3.1, includes clean-room robots. This difference in robot

Table F.2: Dropping Major Industries

	Dependent variable:		
	$\ln(L_{it})$		
	(1)	(2)	(3)
$\ln(p_{it}^R)$	-0.650^{***}	-0.609^{***}	-0.834^{***}
	(0.073)	(0.099)	(0.224)
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, BSOBA and JIP data. The table presents estimates of the relationship between log robot price measure and log employment across industries and years. It shows the effect of dropping industries from the sample, with columns 1-3 showing the results after dropping the electronic machine industry, transportation machine industry, and both. All specifications control for industry and year fixed effects, demography controls, globalization controls, and technology controls defined in Section 4.1. All regressions are weighted by the purchase values of robots each year. The industry-level cluster-bootstrapped standard errors are shown in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table F.3: 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. The industry cluster-bootstrap 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.

categorization between our Japanese JARA data and the IFR data of other robot-adopting countries which does not count clean-room robots is relevant because the use of clean-room robots has surged in the electric machine industry, causing the application share to change since the initial years (cf. Figure 2). As the share component s_{ai} in this study is taken at the initial years, a potential concern is that robot measures in later periods might not capture the actual robot price and quantity in the industry. However, as our results are robust to the exclusion of the Other industry, this indicates that our findings are not driven by the varying application shares over time or the cross-country differences in robot definitions.

Furthermore, we apply the idea presented in Goldsmith-Pinkham et al. (2020) and 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. The detailed argument is presented in Appendix F.3, but the results confirm that our main findings are robust to a lack of exogeneity of the application-level robot prices in equation (16).

F.3 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, in this section, we provide further evidence that our results are not driven by this assumption by employing an 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, and to obtain an exogenous force that shifts the robot price measure but not employment directly, we take the initial application share and use it as an instrumental variable (IV). The premise is that, as we have discussed in Section 3.2, the initial application share is related to the perceived cost of adopting robots in each industry but does not directly affect future labor demand trends. This assumption is weaker than assuming our robot price measure (16) is exogenous, as it does not impose any restriction on the application-level price measure (14).

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

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

$$\hat{\beta} = \sum_a \hat{\alpha}_a^R \hat{\beta}_a^R, \tag{25}$$

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 results in Table F.4. For all robot applications, the Rotemberg weights are positive, with the Welding and soldering (WS) application showing the highest weights, followed by Assembling and disassembling (AD) and Handling operations/Machine tending (HM). As these patterns are consistent with the high adoption value of these applications, this shows that our empirical results are largely driven by these applications, and the large Rotemberg Weight for WS robots indicates that the substantial price variation of these robots plays a crucial role for our identification. This fact reflects the relevance of our results, as well as the sensitivity to misspecification, especially for these applications, which is examined further in Table F.3.

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

We examine if the employment pre-trend is associated with the initial application share to demonstrate the plausibility of the exogenous initial application share assumption. Table F.5 reports the regression results of 1979-1982 employment growth on the initial application shares.

Table F.4: 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: The table shows a 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 from Rotemberg (1983). Column "Coefficient" shows the IV regression coefficient for each regression.

Note that the employment data in our main analysis begins from 1982, as explained in footnote 14. We thus can use the 1979 ESS to perform an 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 conducted six such regressions. The results are shown in Table F.5, and we see 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.

F.4 Heterogeneity by Sample Periods

Using our long sample period, we also can study potential heterogeneity in the period of analysis. Recall that our data consists of eight points: 1978-1982, 1983-1987, 1988-1992, 1993-1997, 1998-2002, 2003-2007, 2008-2012, and 2013-2017. In this test, we experiment with how many data points we can drop while sustaining our current estimation results of equation (18). Table **??** shows the results, and we find suggestive evidence that the positive employment impact of robot price reduction is found in the later portion of our sample period. We find that the result does not change substantially when we drop one or two sample periods, 1978-1982 or 1983-1987, but dropping the other two sample periods makes the estimation results fragile, as indicated by the inflated standard

Table F.5: Application Shares and 1979-1982 Employment Growth

	Employment Growth					
	Tending	Welding	Dispensing	Processing	Assembling	Other
	(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 for demography control variables. Standard errors are shown in parentheses. All regressions are weighted by purchase values of robots in each year. *p<0.1; **p<0.05; ***p<0.01.

errors. Dropping three time periods renders very noisy results.[32] These results together suggest that drawing on a long-time period is indispensable to a stable estimate of the impact of robot adoption on employment, at least in the Japanese context.

F.5 The First Stage of the CZ-level specification

Table F.7 shows the first-stage results for CZ-level specification (19). Each column shows the results with a different set of control variables, with column 1 controlling only fixed effects, column 2 adding demographic controls, column 3 adding globalization, and column 4 adding technology. The results show a statistically significant and negative correlation between robot price changes and robot exposure, both with and without the covariates. The F test indicates that the use of our price measure passes the weak instrument test, and so, we focus on our preferred specification with full controls, the one in column 4.

[32]The results are available upon request.

Table F.6: Alternative Sample Periods

	Dependent variable:					
	$\ln(L_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(p^R_{it})$	-0.437^{***}	-0.221	-0.414^{*}	-0.108	0.002	-0.562^{*}
	(0.075)	(0.200)	(0.215)	(0.261)	(0.227)	(0.306)
Sample Period	1978-2017	1978-2012	1983-2017	1978-2007	1983-2012	1988-2017
Observations	104	91	91	78	78	78
R^2	0.987	0.989	0.989	0.991	0.992	0.989

Notes: Authors' calculation based on JARA, ESS, BSOBA and JIP data. The table presents estimates of the relationship between log robot prices and log employment across industries and years. The columns show results using different sample periods, with column 1 showing the benchmark case, 1978-2017 (8 sample periods), columns 2 and 3 dropping one sample year and keeping 1978-2012 for column 2 and 1983-2017 for column 3. Columns 4, 5, and 6 show the results from dropping two sample years, thus keeping 1978-2007, 1983-2012, and 1988-2017, respectively. The employment measure includes the employment of robot-producing plants. All regressions are weighted by purchase values of robots in each year. All columns control for industry and year fixed effects, demographic controls, the log import values from JIP and log offshoring value from BSOBA, and log stock value measures for ICT capital, innovation capital, and competition capital from JIP. The industry-level cluster-bootstrap standard errors are shown in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table F.7: CZ-level First Stage Regression

	Dependent variable:			
	ΔR_{ct}			
	(1)	(2)	(3)	(4)
Δp^R_{ct}	-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 log 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, and standard errors are shown in parentheses. Column 1 controls for industry and year fixed effects, column 2 controls for the following demographic variables from ESS: share of high school graduates, 4-year university graduates, female workers, workers under age 35, and workers above age 50. Column 3 controls for log import values from JIP and log offshoring value from SOBA in addition to the control variables in Column 2. Column 4 (baseline specification) controls log stock value measures for ICT capital, innovation capital, and competition capital from the JIP database in addition to the controls in column 3. *p<0.1; **p<0.05; ***p<0.01.