Robots and Wage Polarization: The Effects of Robot Capital by Occupation[1]

Daisuke Adachi[a,b]

[a] *Department of Economics and Business Economics, Aarhus University, Fuglesangs Alle 4, Aarhus, 8210, Denmark*
[b] *Research Institute of Economy, Industry and Trade, 1-3-1, Kasumigaseki, Chiyoda-ku, 100-8901, Tokyo, Japan*

Abstract

This paper examines the distributional impacts of increased utilization of industrial robots, emphasizing their roles in specific tasks and their international trade. To this end, the study constructs a novel dataset by tracking shocks to the cost of acquiring robots from Japan, termed the Japan Robot Shock (JRS), and analyzes these shocks across various occupations that have adopted robots. A general equilibrium model incorporating robot automation in a large open economy is developed, and a model-implied optimal instrumental variable is constructed from the JRS to address the identification challenges posed by the correlation between automation shocks and the JRS. The study finds that the elasticity of substitution (EoS) between robots and labor is heterogeneous across occupations, reaching up to 3 in production and material-moving jobs, significantly higher than the EoS between other capital goods and labor. The findings suggest that robots have significantly contributed to wage polarization in the US from 1990 to 2007.

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1. Introduction

Industrial robots have rapidly transformed factory production. Over the past three decades, the global robot market has grown by 12% annually (IFR, 2021). Robotics has heterogeneous impacts on workers across occupations, raising concerns about its distributional effects. Therefore, policymakers have proposed various countermeasures for the potential harms of robotization, such as taxes on robot adoption. Motivated by these observations, a growing body of literature has estimated the effects of robot penetration on human employment (e.g., Acemoglu and Restrepo, 2020) and the potential impact of robot taxes (e.g., Humlum, 2021). However, few studies have explored the effect of factors such as the substitutability of robots for workers in each occupation that also determine the impact of robotization.

In this paper, I analyze the role of robots in wage inequality between occupations and welfare in the US. In contrast to previous research that reveals the substitutability between professions, I estimate the substitutability between robots and workers within an occupation using a novel dataset that tracks the cost of adopting Japanese robots. For this purpose, I construct a model-implied optimal instrumental variable (MOIV) and estimate the elasticity of substitution (EoS) between robots and workers, which may be heterogeneous across occupations. Finally, I conduct counterfactual exercises to analyze the distributional effects of robotization in the US from 1990 to 2007.

I use information on shipments of Japanese robots, accounting for approximately one-third of the world's robot supply, from the Japan Robot Association (JARA). The critical feature of the JARA data is that sales quantity and total value are observed at the level of robot application or the specified task that robots perform. To obtain an occupation-level robot price measure, I combine the JARA data with the O*NET Code Connector match score. Ultimately, I extract a robot cost shock that controls for demand factors using leave-one-out regression, which I call the *Japan Robot Shock* (JRS).

I use an equilibrium model of robot automation in a large open economy. Occupations are bundles of tasks where tasks can be performed either by workers or robots (factors). I impose a Fréchet distribution for the task-specific productivity of each factor, enabling the aggregation of tasks to the occupational production function, featuring the constant EoS (CES) between robots and labor within each occupation. Using this formulation, I can interpret changes in robot quality in terms of changes in the robot expenditure share parameter, which I call the automation shock. In addition, I include the Armington-style robot trade to capture Japan's substantial robot exports.

An identification challenge in estimating robot–labor EoS is that the JRS may be correlated with the automation shock, which is unobserved. I overcome this challenge by using the general equilibrium restriction to obtain structural residuals of occupational wages, interpreted as the remaining variation in occupational wages after controlling for the effect of the automation shock. The identification assumption is that these structural residuals are not correlated with the JRS, implying a moment condition that provides consistent parameter estimates and an optimal instrumental variable to increase estimation precision.

Using this estimation method, I find that the average EoS between robots and workers is about 2. This estimate is higher than the typical values in the labor–capital EoS literature, highlighting a major difference between robots and other capital goods. Moreover, the EoS estimates are heterogeneous across occupations. In particular, for routine occupations that perform production tasks, the point estimates are as high as around 3, revealing the particular vulnerability of workers in these occupations to robots. These estimates are identified by a strong relationship between increased decline in robot price and lowered occupational wage growth rate in these occupations. In contrast, the estimates in other occupations are around 1, suggesting that robots and labor are less substitutable in such occupations.

The large EoS between robots and workers in occupations involving production and material moving implies that robotization significantly reduced the relative wage in these occupations over the sample period. In other words, the shock of robotization slowed the relative wage growth of occupations in the middle deciles, because robotized occupations tended to be in the middle of the occupational wage distribution in 1990. Moreover, the higher productivity in these occupations raised the marginal product of labor in other occupations, increasing labor demand. Quantitatively, these mechanisms explain a 6.4% increase in the 90-50 percentile wage ratio, a measure of wage inequality popularized by Goos and Manning (2007) and Autor et al. (2008).

This paper contributes to the literature on the economic impact of industrial robots by identifying the significant impact of robotization on wage polarization in the US. The closest papers to mine are Acemoglu and Restrepo (2020) and Humlum (2021). Acemoglu and Restrepo (2020) find that U.S. commuting zones with increased robot penetration in 1992–2007 experienced lower wage and employment growth.[2] Meanwhile, Humlum (2021) estimates a model of robot importers in a small open economy and the EoS between occupations using firm-level data on robot adoption, finding a positive average real wage effect with significant heterogeneity across occupations.[3] I complement the findings of these studies by providing a method to estimate the within-job EoS between robots and workers using occupation-level robot cost data. The estimations reveal the heterogeneous substitutability of robots and workers in the US.

Another strand of the literature focuses on occupations, aiming to clarify the potentially heterogeneous effects of automation (e.g., Cheng, 2018). In particular, Jaimovich et al. (2021) construct a general equilibrium model to study the impact of automation on the labor market of routine and nonroutine workers. I contribute to these efforts by providing a matching method for industrial robot applications and occupations that produces occupation-level

[2]Dauth et al. (2017) and Graetz and Michaels (2018) also use aggregate industry-level data on robot adoption to analyze its impact on labor markets. Galle and Lorentzen (2024) examine the interaction effects of trade and automation. In addition, Adachi et al. (2024) use JARA data to study the impact of robots on the Japanese labor market. In contrast, this paper studies the U.S. labor markets and examines the impact of robots on wage polarization by estimating the EoS between robots and workers.

[3]Like Humlum (2021), a growing number of studies (including Koch et al., 2021) use firm-level data to study robots and workers.

robot cost data, allowing me to estimate the robot–labor EoS.

In addition, this paper is related to the vast literature on estimating the EoS between capital and labor (e.g., Arrow et al., 1961; Oberfield and Raval, 2014).[4] Although the literature provides numerous estimates with a wide range, the upper limit appears to be around 1.5 (Karabarbounis and Neiman, 2014; Hubmer, 2023). By contrast, my EoS estimates of around 3 in occupations involving production and material moving are significantly higher than this upper limit. In this sense, the findings of this study highlight the particular vulnerability of workers to robots across occupations as one of the main differences between robots and other capital goods.

2. Model

The model adopts a task-based framework embedded in a multi-country Armington model. This framework has two main features: occupation-specific EoS between robots for workers and robot trade in a large open economy. In this study, I emphasize these features and discuss the other model elements based on later quantitative exercises in Appendix C.1.

2.1. Environment

Time is discrete and has an infinite horizon $t = 0, 1, \ldots$. There are N countries, O occupations, and two types of tradable goods (g): non-robot

[4] Caunedo et al. (2023) provide the EoS between labor and tools for each occupation by applying a natural language processing algorithm to tool descriptions, using data from the BEA fixed asset table. The exercise focuses on capital-embodied technological change (CETC), which is modeled as a reduction in tool prices. I treat the automation shock and robot price decline separately and address the resulting identification challenge.

goods $g = G$ and robots $g = R$. To clarify the country subscripts, whenever possible, I use l, i, and j to refer to robot-exporting, non-robot goods-exporting and robot-importing, and non-robot goods-importing countries, respectively. Each country has representative households and producers. As in the Armington model, non-robot goods are differentiated by country of origin while robots are differentiated by country of origin and occupation. non-robot goods can be consumed by households and invested to produce robots.[5]

In the main text, non-robot goods G are produced with two factors of production: labor $L_{(}i, o, t)$ and robot capital $K_{(}i, o, t)^R$ in each occupation o.[6] There is no international factor mobility. Producers own and accumulate robot capital. Households own the producers' shares in each country. All goods and factor markets are perfectly competitive. Workers are forward-looking, draw an idiosyncratic utility shock from a generalized extreme value distribution, pay a switching cost for changing occupations, and choose the occupation o that achieves the highest expected value $V_{(}i, o, t)$ among O occupations, following Caliendo et al. (2019). The discount rate is $\iota > 0$. The elasticity of the probability of changing occupation concerning the expected value is ϕ. The details of the worker problem are provided in Appendix C.1.

There are good-specific iceberg trade costs $\tau^g_{ij,t}$ for each $g = G, R$. There are no intra-country trade costs; therefore, $\tau^g_{ii,t} = 1$ for all i, g, and t. Due

[5] In the full model in Appendix C.1, non-robot goods are used as input for robot integration (Humlum, 2021).

[6] Appendix C.1 shows the model with intermediate goods and non-robot capital in the production function. The analytical results in our main analysis are unchanged.

to the iceberg costs, the bilateral price of good g that country j pays to i is $p^g_{ij,t} = p^g_{i,t}\tau^g_{ij,t}$.

Each country's government exogenously imposes a robot tax. Specifically, buyer i of robot o from country l in year t must pay an *ad valorem* robot tax $u_{li,t}$ on top of the producer price of robots $p^R_{li,o,t}$ to buy from l. The tax revenue is uniformly rebated to households in the country.

2.2. Production Function, Tasks, and Automation

Production of Non-Robot Goods. In country i and period t, the representative producer of non-robot good G uses the occupation-o service $T^O_{i,o,t}$ and produces with the following production function:

$$Y^G_{i,t} = A^G_{i,t}\left[\sum_o \left(b_{i,o,t}\right)^{\frac{1}{\beta}} \left(T^O_{i,o,t}\right)^{\frac{\beta-1}{\beta}}\right]^{\frac{\beta}{\beta-1}}, \tag{1}$$

where $A^G_{i,t}$ is a Hicks-neutral productivity, $b_{i,o,t}$ is the cost share parameter of each occupation o, and β is the EoS between each occupation in the production function. The parameters satisfy $b_{i,o,t} > 0$, $\sum_o b_{i,o,t} = 1$, and $\beta > 0$.

I adopt the canonical task-space framework at the occupation level (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020). The occupation service is a combination of tasks $\omega \in [0,1]$ with CES technology

$$T^O_{i,o,t} = \left[\int_0^1 \left(t_{i,o,t}\left(\omega\right)\right)^{\frac{\zeta-1}{\zeta}} d\omega\right]^{\frac{\zeta}{\zeta-1}}, \tag{2}$$

where $t_{i,o,t}(\omega)$ is the input of the task ω and $\zeta \geq 0$ is the EoS between tasks. A task is performed by robots or workers with perfect substitutability:

$$t_{i,o,t}\left(\omega\right) = Z^R_{i,o,t}\left(\omega\right) k^R_{i,o,t}\left(\omega\right) + Z^L_{i,o,t}\left(\omega\right) l_{i,o,t}\left(\omega\right)$$

where $Z^R_{i,o,t}(\omega)$ and $Z^L_{i,o,t}(\omega)$ are the task-specific productivity for robots and workers, respectively. Due to perfect competition, task prices are determined by marginal cost, the minimum of the efficiency prices of labor $w_{i,o,t}/Z^L_{i,o,t}(\omega)$ and robots $c^R_{i,o,t}/Z^R_{i,o,t}(\omega)$ for each task ω. The share of tasks performed by robots is denoted as $\xi_{i,o,t}$.

Following Artuc et al. (2023), I assume Fréchet-distributed productivity with scale parameter $a^s_{o,t}$ $(s = R, L)$ and shape parameter θ_o, with the restriction $\theta_o \geq \zeta$. I assume that robot productivity is a common technical characteristic for all countries; thus, $a^s_{o,t}$ does not vary across countries. I also normalize $a^R_{o,t}$ and $a^L_{o,t}$ so that they sum to one and write $a_{o,t}$ as the normalized parameter for robots to make it easier to interpret the share parameter in the robot task space. The maximum stability property of the Fréchet distribution implies that $\xi_{i,o,t}$ is equal to the fraction of spending on robots (Eaton and Kortum, 2002), and

$$\xi_{i,o,t} = \frac{c^R_{i,o,t} K^R_{i,o,t}}{P^O_{i,o,t} T^O_{i,o,t}} = a_{o,t} \left(\frac{c^R_{i,o,t}}{P^O_{i,o,t}} \right)^{1-\theta_o}, \tag{3}$$

$$\text{where} \qquad P^O_{i,o,t} = \left(a_{o,t} (c^R_{i,o,t})^{1-\theta_o} + (1 - a_{o,t})(w_{i,o,t})^{1-\theta_o} \right)^{1/(1-\theta_o)}, \tag{4}$$

where $c^R_{i,o,t}$ is the user cost of robot capital, formally given in Appendix C.2, and $P^O_{i,o,t}$ is the unit cost of occupation o. A key parameter is θ_o, which governs the EoS between labor and robots in each occupation o. Intuitively, the more dispersed the task productivities $Z^R_{i,o,t}(\omega)$ and $Z^L_{i,o,t}(\omega)$, the less sensitive the optimal allocation of labor and robots is to price changes because the unobserved productivity difference is more important.

Production of Robots. Robots for occupation o are produced by investing non-robot goods $I^R_{i,o,t}$ with productivity $A^R_{i,o,t}$ due to perfect competition:

$$Y^R_{i,o,t} = A^R_{i,o,t} I^R_{i,o,t}, \qquad \text{so} \qquad p^R_{i,o,t} = \frac{P^G_{i,t}}{A^R_{i,o,t}}, \tag{5}$$

where $P^G_{i,t}$ is the price index for non-robot goods, as given below in (6). The robot price is inversely proportional to the productivity term $A^R_{i,o,t}$. Therefore, I refer to the change in $A^R_{i,o,t}$ for $i = JPN$ as the JRS throughout.

Trade in Goods and Robots. The elasticity of trade in non-robot goods (or robots) is denoted as ε (or ε^R). The import shares of goods and robots in j from i and their price indices are provided by

$$x^G_{ij,t} = \left(\frac{p^G_{ij,t}}{P^G_{j,t}}\right)^{1-\varepsilon} \text{ and } x^R_{ij,o,t} = \left(\frac{p^R_{ij,o,t}}{P^R_{j,o,t}}\right)^{1-\varepsilon^R}$$
$$\text{where } P^G_{j,t} = \left[\sum_i \left(p^G_{ij,t}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \text{ and } P^R_{j,o,t} = \left[\sum_i \left(p^R_{ij,o,t}\right)^{1-\varepsilon^R}\right]^{\frac{1}{1-\varepsilon^R}}, \tag{6}$$

because of the Armington assumption.

2.3. Discussion of Model Assumptions

The robot technological efficiency parameter $a_{o,t}$ in (3) plays a central role in estimations and counterfactuals and is discussed in detail here. Because the task-based framework developed in Section 2.2 includes the allocation of factors to tasks, I can interpret $a_{o,t}$ as the shifter in the robots' share of tasks as opposed to labor by appropriately modifying the productivity term $b_{i,o,t}$, which is discussed in detail in Section 2.5. Thus, I call the change in $a_{o,t}$ the *automation shock*.

The robot cost share, $a_{o,t}$, can also represent robot quality, as it is a non-pecuniary attribute whose value all agents agree on (Khandelwal, 2010). As (3) states that the increase in $a_{o,t}$ implies an increase in the value of robots among production factors, the automation shock can be interpreted as a quality upgrade of robots relative to labor when combined with the productivity adjustment.

Therefore, my model does not distinguish between the automation shock and the quality upgrade: they have the same effect on equilibrium due to the restrictions of the Fréchet distribution assumption. To my knowledge, there has been no formal discussion of this point. Nevertheless, retaining this assumption is helpful to maintain complex technology improvements along with task automation and quality upgrades within a single parameter $a_{o,t}$.[7]

As comparative statics, I consider the JRS and the automation shock, which are together referred to as *robotization shocks*. It is likely that the JRS and the automation shocks are correlated with each other at the occupation level because innovations in robot technology improve the applicability of robots while reducing the cost of adoption.[8] This will be a source of the identification challenge discussed later.

2.4. Equilibrium

The rest of the model is standard in the dynamic general equilibrium literature and is presented in Appendix C.1. For the purpose of notation, I

[7]One of the reasons to impose this assumption is the lack of data on the set of tasks for each robot or the quality of the robots. Relaxing this assumption using rich data on this dimension will be addressed in future work.

[8]See Appendix A.1 for more concrete accounts of such a correlation.

summarize the solution of the workers' dynamic discrete choice problem of occupations given occupational wages by the labor supply function $L_{i,o,t}(\boldsymbol{w}_{i,t})$, suppressing its dependence on future values. The non-robot producer solves the dynamic robot capital investment problem under convex adjustment costs (Cooper and Haltiwanger, 2006).[9] The prices of goods, labor, and robots equilibrate the respective markets in general equilibrium.

2.5. Solving the Model

I apply the first-order approximation to the steady state (Blanchard and Kahn, 1980). I chose this strategy over the exact solution method like Caliendo et al. (2019) because the trade literature has shown that the errors of the first-order approximation with respect to (unilateral) productivity shocks are considerably smaller than those due to bilateral trade shocks (Kleinman et al., forthcoming). This paper considers a unilateral robotization shock. For example, my model assumes that Japanese robots have become accessible to all countries (not just the US). This subsection focuses on the steady-state change and drops the subscript t. The complete characterization of the approximation and transition dynamics is provided in Appendix C.3.

I describe the log total derivative using the hat notation. The exogenous shocks are the shocks to a_o, $A^R_{l,o}$, and the adjustment to the occupational productivity term $b_{i,o}$. Throughout the paper, I only consider a type of automation shock that does not change labor productivity, reflecting the rapid growth of robotic technology relative to that of human capital in recent

[9] de Souza and Li (2023) also apply the problem to the robot context.

decades. Mathematically, this is equivalent to

$$\widehat{b_{i,o}}^{\frac{1}{\beta-1}} \left(\widehat{1-a_o}\right)^{\frac{1}{\theta_o-1}} = 0, \tag{7}$$

for each automation shock $\widehat{a_o}$, such that the effect of the change in a_o on labor productivity is offset by a corresponding adjustment in $\widehat{b_{i,o}}$. This approach still captures overall productivity growth due to the change in $\widehat{a_o}$. This is the typical approach in the literature for controlling labor productivity growth when modeling robot shocks. For example, the canonical setup in Acemoglu and Restrepo (2020) model automation by increasing the robot availability threshold across tasks. This does not change labor productivity; however, the overall productivity increases due to the threshold increase.

I provide several approximation expressions useful in the following sections when defining the estimator. First, I combine (5) and (6) to get the change in the robot price index $P^R_{i,o}$ in country i due to the change in robot production technology $A^R_{l,o}$ in country l:

$$\widehat{P^R_{i,o}} = -x^R_{li,o}\widehat{A^R_{l,o}} + \sum_{l'} x^R_{l'i,o}\widehat{P^G_{l'}}, \tag{8}$$

where the first term reflects the direct effects of the change in robot productivity in l mediated by the import share of robots from l in i. The second term summarizes the general equilibrium effects due to changes in the production cost of robots in other countries on the robot price index.

Second, from (3) and (4), the labor demand in dollar units in (i, o) is given by $(1-\xi_{i,o})P^O_{i,o}T^O_{i,o}$. As a result, the approximated labor market equilibrium condition is as follows:

$$\widehat{w_{i,o}} + \sum_{o'} \frac{\partial \ln L_{i,o}}{\partial \ln w_{i,o'}}\widehat{w_{i,o'}} = \left(\widehat{1-a_o}\right) + (1-\theta_o)\left(\widehat{w_{i,o}} - \widehat{P^O_{i,o}}\right) + \widehat{P^O_{i,o}} + \widehat{T^O_{i,o}}, \tag{9}$$

where the LHS and RHS are the changes in supply and demand, respectively.

3. Estimation Strategy

Following Adao et al. (2023), I develop an estimation method using MOIV, which is applied to my novel measure of Japanese robot price reductions. Section 3.1 parameterizes the model and sets the stage for the estimation. I then introduce the data on robot prices in Japan in Section 3.2 and construct the JRS measure in 3.3. I define the MOIV estimator in Section 3.4 and provide the remaining discussion on identification assumptions in Section 3.5.

Throughout this section, I consider the following identification challenges; (i) Robot prices may be driven by demand rather than cost; (ii) There is a correlation between the automation shock and robot price; (iii) Unilateral technical changes may drive robot prices; and (iv) Non-Japanese robot prices also change.

3.1. Parameterization

First, I set the sample period to 1992-2007 (or 1990-2007 for the labor data) and, given the data availability, write $t_0 \equiv 1992$ and $t_1 \equiv 2007$. I will relate the long difference to the steady-state changes of the model.

I account for the heterogeneity of EoS between robots and labor across occupations while maintaining estimation power by defining the following occupational groups. First, occupations are divided into three broad occupational groups: Abstract, Service (Manual), and Routine, following Acemoglu and Autor (2011). Given the trend of intensive robot adoption in production and transportation (material moving) occupations over the sample period, I further divide routine occupations into three subcategories: Production (e.g., welders), Transportation (indicating transportation and material moving, e.g., laborers), and Other (e.g., repairers). This leads to five occupational groups, the full list of which is presented in Appendix A.2. Within each group, I assume a constant EoS between robots and workers. Each occupation group is denoted by the subscript g; thus, the robot-labor EoS for group g is written as θ_g.

As I use Japanese robot prices and study the US labor market, I set $N = 3$ and aggregate the country groups to the US (USA, country index 1), Japan (JPN, index 2), and the Rest of the World (ROW, index 3). The annual discount rate is $\iota = 0.05$. Following Graetz and Michaels (2018), the robot depreciation rate is 10%. I take the trade elasticity of $\varepsilon = 4$ from the literature on trade elasticity estimation (e.g., Simonovska and Waugh, 2014) and $\varepsilon^R = 1.2$ derived by applying the estimation method developed by Caliendo and Parro (2015) to the robot trade data, which is discussed in detail in Appendix D.1. The remaining parameters $\mathbf{\Theta} \equiv \{\theta_g, \beta\}$ are the target of the following structural estimation.

The first-order approximation requires different shares in the initial steady state, which are taken from the International Federation of Robotics (IFR), Integrated Public Use Microdata Series (IPUMS) USA, Current Population Survey (CPS), Database for International Trade Analysis (BACI), and the World Input-Output Table (WIOT). I set the initial robot share parameter a_{o,t_0} to the initial US occupation-specific expenditure share $c^R_{i,o,t_0} K^R_{i,o,t_0} / w_{i,o,t_0} L_{i,o,t_0}$ where $i = US$ and the initial robot tax is zero in all countries. The remaining labor market outcomes are measured as standard and mentioned in Appendix A.2.

3.2. Data Source on Robots

Industrial robots are formally defined as multi-axis manipulators and measured by the number of manipulators or robot arms.[10]. The main data source for robots by occupation is the JARA, a general incorporated association comprising Japanese robot manufacturing companies. In its "Export Statistics of Manipulators, Robots and Applied Systems by Country and Application", JARA annually surveys major robot manufacturers regarding the units and monetary values of robots sold for each destination country and robot application. Robot applications are defined as the specified tasks that robots perform and are discussed in detail in Section 3.3.

To convert robot applications to occupations, I use the Occupational Information Network Online (O*NET) Code Connector. The O*NET Code Connector is an online database of occupations sponsored by the US Department of Labor, Employment, and Training Administration and provides an occupational search service. The algorithm used in the search service provides a match score indicating the relevance of each occupation to the search term, as discussed by Morris (2019) and Appendix A.2.

To integrate Japanese robot data from JARA and international trade data from BACI, I use HS code 847950 ("Industrial robots for multiple uses") as the robot definition in the trade data. I match the BACI robot trade data to JARA robot exports by aggregating applications in the JARA data. As I do not observe the occupation-level disaggregation of robot trade in other countries, I impose $x^R_{ij,o} = x^R_{ij}$ for all o in the estimation. See Appendix A.4

[10]The full ISO-based definition is presented in Appendix A.1.

for the details of the robot measurement issues in JARA and BACI.

3.3. Data Construction

This subsection describes the construction of the robot price at the occupation level. Although Graetz and Michaels (2018) provide data on robot prices from IFR, their price data are aggregated but not distinguished by occupation. In contrast, I use variation at the occupation level to estimate substitutability between robots and workers.

Step 1. Application-Occupation Matching. The first step is to match robot applications and worker occupations. A heterogeneous mix of tasks in each occupation generates a difference in ease of automation across occupations, implying heterogeneous robot adoption across occupations (Manyika et al., 2017).[11] Formally, let a denote a robot application and o a labor occupation at the 4-digit level. The JARA data provide the number of robots sold and the total monetary transaction values for each application a. These robot measures are denoted as X_a^R, a generic notation indicating quantities and monetary values. The application-level robot measure X_a^R is converted to an occupation-level measure X_o^R using a weighted average. For this purpose, I search occupations in the O*NET Code Connector for the title of the robot application a and web-scrape the match score m_{oa} between a and o. Using

[11] Appendix A.1 provides further descriptions of robot applications and labor occupations using examples.

m_{oa} as the weight, I compute[12]

$$X_o^R = \sum_a \omega_{oa} X_a^R \text{ where } \omega_{oa} \equiv \frac{m_{oa}}{\sum_{o'} m_{o'a}}. \tag{10}$$

where $\sum_o \omega_{oa} X_a^R = X_a^R$ because $\sum_o \omega_{oa} = 1$.[13]

This matching method has low data requirements, which is useful given that I only observe the titles of robot applications, and not detailed descriptions such as patent texts. In this sense, this method complements the ones used in previous studies. For example, Webb (2019) provides a natural language processing method to match recent technological advances (e.g., robotics) embodied in patent titles and abstracts with occupations. Montobbio et al. (2020) extends this approach to analyzing full patent texts by applying the topic modeling method.

Step 2. Constructing JRS. Using the occupation-level robot quantity $q_{i,o,t}^R$ and sales $(pq)_{i,o,t}^R$ in destination country i, occupation o, and year t, the cost shocks to robot users are constructed in each occupation as follows. First, I take the average export price $p_{i,o,t}^R \equiv (pq)_{i,o,t}^R / q_{i,o,t}^R$.[14] One concern with using unit value data is simultaneity, i.e., demand shocks and not cost shocks drive prices, as in point (i) at the beginning of the section.[15] My measure of export

[12] More details on matching are described in Appendix A.5, including the use of hard-cut matching, which does not significantly affect the matching result.

[13] Appendix A.3 shows the robot trends based on the constructed occupation-level measures.

[14] I also compute the chain-weighted robot price index, which is commonly used to measure the price of capital goods. The results using this index are not qualitatively different from the main results.

[15] Another concern is robot quality upgrading; in my model, it is loaded on the automation shock term $a_{o,t}$, as discussed in section 2.3. A data-driven approach to this problem

prices is based on external robot sales; thus, I am less concerned with the endogeneity from the use of domestic robot prices. Nevertheless, I exclude US robot import prices from the sample to mitigate simultaneity concerns. Here, the argument is consistent with Hausman et al. (1994), who argued that changes in demand shocks are uncorrelated between the US and other countries, but that price variations are primarily driven by robot production costs in producer countries. This leave-one-out idea is widely used in the automation literature (e.g., Acemoglu and Restrepo, 2020).

To further address cross-country correlation in demand shocks, I exploit the fact that the data are from bilateral trade flows and control for the destination country-specific demand effect. Formally, I fit the fixed-effects regression as follows:

$$\ln\left(p^R_{i,o,t}\right) - \ln\left(p^R_{i,o,t_0}\right) = \psi^D_{i,t} + \psi^J_{o,t} + \epsilon_{i,o,t},\ i \neq USA \tag{11}$$

where t_0 is the initial year, $\psi^D_{i,t}$ is the destination-year fixed effect (FE), $\psi^J_{o,t}$ is the occupation-year FE, and $\epsilon_{i,o,t}$ is the residual. This regression controls for any country-year-specific effect $\psi^D_{i,t}$ that includes the demand shock of country i or the trade shock between Japan and country i. I use the remaining variation across occupations $\psi^J_{o,t}$ as the cost shock of robot adoption and define $\psi^J_o \equiv \psi^J_{o,t_1}$ as the measured JRS.

Finally, I relate JRS to the model's robot productivity using the perfect competition assumption and the robot production function (5):

$$\psi^J_o = -\widehat{A^R_{2,o}}. \tag{12}$$

is the hedonic and cost-estimation approaches, both of which are discussed in Appendix A.6.

Appendix B presents stylized facts and reduced-form evidence about robots and workers at the occupation level, suggesting strong substitutability between robots and workers.

3.4. Estimation Procedure

The constructed data provide information about the robot price shock, a critical input for estimating the elasticity parameter in (3). The next identification threat is the unobserved automation shock, $a_{o,t}$, as pointed out in (ii) at the beginning of this section. I develop a moment condition using the model's restriction to address this concern.

First, I decompose the automation shock $\widehat{a_o}$ into an "implied" component $\widehat{a_o^{\text{imp}}}$ and an "unobserved residual" component $\widehat{a_o^{\text{res}}}$ such that $\widehat{a_o} = \widehat{a_o^{\text{imp}}} + \widehat{a_o^{\text{res}}}$ for all o. The steady-state change in the relative demand for robots and labor implicitly defines the implied component. Using (3), (8), and (12),

$$\left(\frac{\widehat{c^R_{US,o}K^R_{US,o}}}{w_{US,o}L_{US,o}}\right) = (1-\theta_g)\left(x^R_{JP,US}\psi^J_o - \widehat{w_{US,o}}\right) + \frac{\widehat{a_o^{\text{imp}}}}{1-a_{o,t_0}} + D, \tag{13}$$

where $x^R_{JP,US}$ is the base-year import share of robots from Japan in the US, and $D \equiv (1-\theta_g)\sum_l x^R_{l,US}\widehat{P^G_l}$ is the international spillover term due to changes in price indices in other countries. That is, $\widehat{a_o^{\text{imp}}}$ is the automation shock component explaining the shift in the expenditure share of robots. In contrast, the unobserved residual component $\widehat{a_o^{\text{res}}}$ is the residual term, which I consider as the measurement error.

The identification challenge is that the JRS ψ^J_o is potentially correlated with the implied automation shock $\widehat{a_o^{\text{imp}}}$. The literature estimates the capital-labor elasticity of substitution using the CES demand function of the form

(3); however, this assumes that the technology shock is fixed or orthogonal to price changes.[16] As many task-based models provide a demand function where the technology shock (in my notation, $\hat{a}_{o,t}$) can be interpreted as the expansion of the task space for robots, the correlation of this shock with the decline in robot prices, another measure of technological progress, should be addressed formally.

A key observation is that the residual component $\widehat{a_o^{\text{res}}}$ can be inferred from the observed endogenous variables using the first-order solution and $\widehat{a_o^{\text{imp}}}$. Namely, the occupational labor market clearing condition (9) relates occupational wage changes and the automation shock. More specifically, combined with $\widehat{a_o^R} = \widehat{a_o^{R,\text{imp}}} + \widehat{a_o^{R,\text{res}}}$, I have

$$\widehat{a_o^{R,\text{res}}} = -\widehat{a_o^{R,\text{imp}}} - (1-a_o)\left[\widehat{w_{i,o}} + \sum_{o'} \frac{\ln L_{i,o}}{\ln w_{i,o'}} \widehat{w_{i,o'}} - (1-\theta_o)(\widehat{w_{i,o}} - \widehat{P_{i,o}^O}) - \widehat{P_{i,o}^O} - \widehat{T_{i,o}^O}\right] \tag{14}$$

where $\widehat{P_{i,o}^O}$ is implied by (4) and $\widehat{T_{i,o}^O}$ is given by (2). Equation (14) obtains a structural residual after controlling for the automation shock measured from the expenditure share expression in (13). Thus, the following moment condition is imposed on this structural residual and the JRS $\boldsymbol{\psi}^J \equiv \left\{\psi_o^J\right\}_o$.

Assumption 1. *(Moment Condition)*

$$\mathbb{E}\left[\widehat{a_o^{R,res}} | \boldsymbol{\psi}^J\right] = 0. \tag{15}$$

Given the moment condition (15), it is routine to construct the optimal GMM and implement it with the two-step estimator following Adao et al.

[16]See, for example, Herrendorf et al. (2015) and Eden and Gaggl (2018).

(2023). Therefore, I leave a detailed explanation in Appendix D.2. Instead, I end the section with a discussion of the identification assumption in the following subsection.

3.5. Discussion of the Identification Assumption

Assumption 1 restricts the structural residual $\widehat{a_o^{R,\text{res}}}$ such that it should not be predicted by the JRS. Note that it allows the automation shock $\widehat{a_o}$ to correlate with changes in robot producer productivity $\widehat{A_{2,o}^R}$. Intuitively, the structural residual $\widehat{a_o^{R,\text{res}}}$ refers to the remaining variation after controlling for the effects of the robotization shocks on wage changes, $\widehat{\boldsymbol{A}_2^R}$, and $\widehat{\boldsymbol{a}}$ (and the associated adjustment $\widehat{\boldsymbol{b}}$ in (7)). My restriction is that the remaining variation, as it is a measurement error, cannot be predicted by the JRS.

What breaks the measurement error assumption? First, it could be the correlation of the structural residuals with other shocks, such as trade shocks. In Section 4, a sensitivity analysis is performed by controlling for the China shock at the occupation level, demonstrating the robustness of the results. The robustness is further verified in Appendix B, which shows that the reduced-form linear regression coefficients do not change qualitatively after controlling for the China shocks.

The second threat is the directed technological changes raised in (iii) at the beginning of the section, where occupational labor demand drives changes in the cost of robots (e.g., Acemoglu and Restrepo, 2018). Specifically, suppose that a positive labor demand shock in occupation o induces research and development of robots in occupation o and drives down costs in the long run rather than exogenous technological change in the production function (5). In this case, the structural residual $\widehat{a_o^{R,\text{res}}}$ does not control for this effect and is negatively correlated with JRS ψ_o^J. Another possibility that fails Assumption 1 is increasing returns to robot producers, implying that the unobserved increase in robot demand reduces robot costs. However, my estimation relies on the *foreign* robot price data, mitigating this concern. Moreover, even though these concerns bias the estimates, they imply a negative bias in the elasticity estimates, thus preserving my qualitative results of strong substitutability.

Finally, the estimation procedure assumes that unobserved reductions in the cost of robots sourced from other countries are independent of the evolution of Japanese robot costs, as in (iv) at the beginning of the section. I discuss the plausibility of this assumption in Appendix B.4 by comparing the data from the JARA and the IFR, a widely used data source of robots worldwide.[17]

4. Results

Table 1 presents the estimates of the structural parameters. Column 1 shows the EoS parameter between robots and workers when constrained to be constant across occupation groups. The estimate of the within-occupation EoS between robots and labor θ is around 2, implying that robots and labor are substitutes within an occupation. The high estimate of EoS between labor and automation capital is also found in Eden and Gaggl (2018), who estimate the elasticity between ICT capital and labor. The point estimate of the EoS between occupations, β, is 0.83, indicating that the occupational

[17] Appendix A.4 shows the international robot flows, including Japan, the US, and the rest of the world.

Table 1: Parameter estimates

	(1)			(2)		(3)		(4)	
	Constant θ			Main		Past wage		China shock	
θ_g	2.05	(0.19)	Production	2.71	(0.32)	2.95	(0.42)	3.03	(0.60)
			Transportation	1.76	(0.15)	2.90	(0.48)	2.01	(0.16)
			Others	1.96	(0.17)	1.16	(0.32)	1.08	(0.28)
			Manual	1.01	(0.71)	1.23	(0.55)	1.16	(0.71)
			Abstract	1.01	(0.62)	0.64	(1.24)	1.00	(0.33)
β	0.83	(0.03)		0.73	(0.06)	0.73	(0.17)	1.18	(0.13)

Note: The structural parameter estimates are based on the moment condition (15) and the two-stage optimal GMM estimates, as described in Appendix D.2. The plug-in optimal standard errors are presented in parentheses. θ_g is the within-occupation elasticity of substitution (EoS) between robots and labor, while β is the EoS between occupations. Column (1) presents the results with the constraint that θ_g is constant across occupation groups. Column (2) presents the main results with θ_g allowed to be heterogeneous across five occupational groups. Column (3) presents the results of a sensitivity analysis using historical occupational wages. Column (4) presents the results of a sensitivity analysis using the China shock. Production, Transportation, and Other are the three subcategories of routine occupations.

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groups are complementary. This estimate is higher than the central estimate of 0.49 in Humlum (2021).

Column 2 presents the estimation result when heterogeneity is allowed across occupational groups. The EoS for routine-production occupations is 2.7. In contrast, those for other routine occupations (transportation and other routine) are close to 2, while those for other occupation groups are not significantly different from 1. Therefore, the routine-production occupation estimates indicate the particular vulnerability of workers in these occupations to robot capital. The estimate of EoS between occupations β does not change qualitatively between columns 1 and 2.

Consistent with the literature that estimates the capital-labor substitution elasticity, the source of identification of these large and heterogeneous EoS between robots and labor is the correlation between the JRS and the change in the labor market outcome. Intuitively, if θ_g is high, the steady-state relative demand for robots (or labor) responds strongly in the positive (or negative) direction to a unit decrease in the cost of using robots.[18]

Another potential cost shifter for occupational labor demand is the historical wage, which affects the contemporary incentive to adopt robots. To control for this effect, I consider an alternative measure of the JRS measured relative to the occupation wage in 1970. Column 3 of Table 1 shows the estimation result of this sensitivity analysis. In addition, I consider the role of the significant China trade shock during the sample period (Autor et al., 2013). To do so, I residualize the JRS by the measure of occupational exposure to Chinese imports before estimation.[19] The result is shown in Column 4. In both sensitivity analyses, the main message prevails: production workers are particularly vulnerable to robots. I find an even larger estimate of the EoS for transportation occupations in column 3.

A related concern is that as the US is a large economy, its demand shock

[18]This point is shown in a reduced-form analysis in Appendix B.2.

[19]Specifically, I take

$$IPW_{o,t} \equiv \sum_{s} l_{s,o,t_0} \Delta m^C_{s,t}, \tag{16}$$

where l_{s,o,t_0} is the sector-s share of employment in occupation o, and $\Delta m^C_{s,t}$ is the per-worker growth of Chinese exports to non-US developed countries. This method is in the spirit of Autor et al. (2013), whereas I measure the occupational variation in exposure.

may affect robot prices in the international market, simultaneously driving US labor demand. To address this concern, I check the data from the Netherlands, a small open economy, in Appendix B.3, showing a similar empirical pattern to the US data.

4.1. Decomposing the Source of Task Automation

The estimated model's task allocation (3) allows me to recover the automation shock. Specifically, I obtain the implied automation shock by inverting (13), using the observed change in relative robot demand, the EoS estimates θ_g, and the change in the relative price of robots $x^R_{JP,US}\psi^J_o - \widehat{w_{US,o}}$.[20]

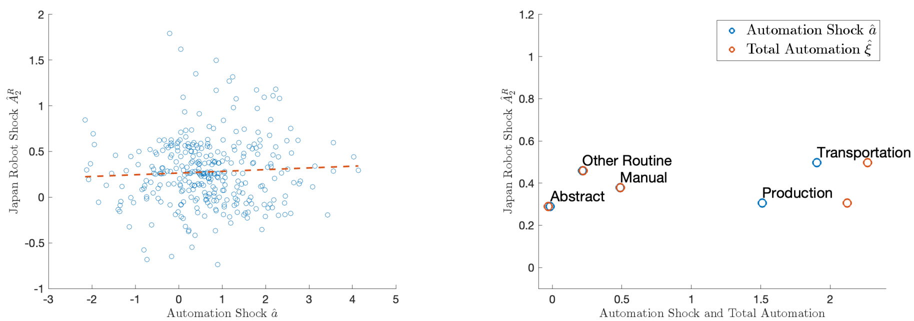
Figure 1a illustrates a scatterplot between the JRS and the automation shock, showing a slight positive relationship. This correlation is consistent with the example of robotic innovations discussed in Appendix A.1. Figure 1b summarizes the two shocks aggregated at the occupational group level. The figure shows 0.2-0.6 log points of the JRS, reflecting the decline in the price of robots from Japan. More importantly, the estimated automation shocks are positive and show greater variation across occupation groups. The two highly automated occupations, transportation and production, observe increases of 1.5-2 log points in robot task shares, whereas the other occupational groups experience a maximum of 0.5 log points.

Figure 1b also illustrates the total automation or change in the share of

[20] The international price spillover term D in (13) is excluded because it is quantitatively small, as the contribution of robots to the national price index is small. This can be confirmed by substituting the implied shock in the model-implied price index change. Note that including D does not change the main results on distributional effects, because D is constant across occupations.

Figure 1: The Automation Shock, Japan Robot Shock, and the Total Automation

(a) Calibrated Automation Shock (b) Aggregates and Total Automation



Note: The left panel shows the estimated automation shock (calibrated from Equation 13 and the estimated parameters in Table 1) on the horizontal axis and the Japan Robot Shock (obtained from the fixed effects in Equation 11) on the vertical axis. Each point is a 4-digit occupation, and the dashed line is the fitted line. The right panel adds total automation (implied by Equation 3) on the horizontal axis and shows the results at the occupation group level. Each occupation in the group is aggregated to the group level with the initial robot expenditure weight.

tasks performed by robots along the horizontal axis. Note that, according to (3), total automation can be driven by the exogenous change in the scale parameter of the Fréchet distribution $a_{o,t}$ (the automation shock) and the endogenous reallocation of tasks due to the cheap robots caused by the JRS, $A^R_{2,o,t}$. In the two heavily robotized occupation groups, transportation and production, the total automation experiences as large as a 200% increase in the share of robotized tasks. This is driven by the automation shock and endogenous task allocation, although the former plays a more important role. There is no evidence of task allocation toward robots in other occupations with less robotization.[21]

[21]Because the increase in robot penetration in production and transportation occupations is explained more by the automation shock than the JRS, as shown in Figure 1b, it

5. The Effect of Robotization on the Wage Polarization

I use the estimated model to quantify the distributional effects of robotization. As Heathcote et al. (2010) argues, wage inequality accounts for a significant portion of overall economic inequality in the US. I primarily use the wage inequality measure of the ratio of wages between the 90th percentile and the 50th percentile (90-50 ratio), following Autor et al. (2008) who show that this ratio has steadily increased since 1980. I examine how much of this increase can be explained by the growth in industrial robot use since 1990.

First, I show the pattern of robot accumulation across the occupational wage distribution. Figure 2a shows the distribution of estimated automation shocks across baseline wage deciles. There is a strikingly polarizing pattern– the automation shock hits the middle of the wage distribution harder compared with the bottom and top of the distribution.[22]

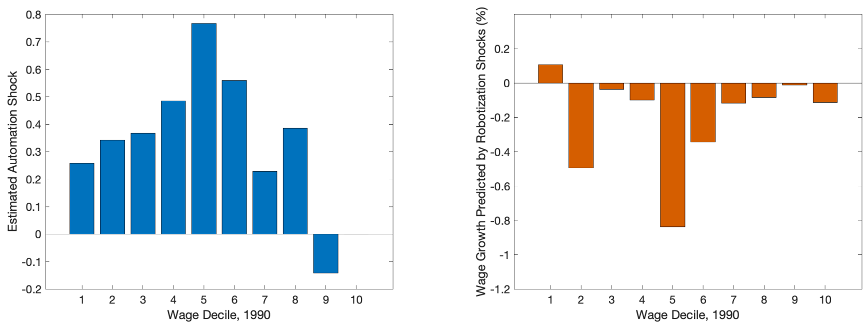
Figure 2b illustrates the predicted steady-state wage growth per year due to the robotization shocks and the estimated model with the first-order solution. Consistent with the high growth rate of robot stocks in the middle of the wage distribution and the strong substitutability between robots and labor, the counterfactual wage growth rate is more negative in the middle

is important for evaluating the performance of the model. Ignoring the automation shock can lead to a significant bias in interpreting the correlation between wage changes and the JRS. Appendix D.3 shows that it is critical to consider the automation shock when estimating the EoS between robots and labor.

[22]The Appendix figure Appendix B.2a shows no correlation between the baseline wage and the JRS, contrasting with the polarizing result for the automation shock. These results suggest that it was the automation shock, not the JRS, that caused the dynamics of the wage distribution in the 1990s and 2000s.

Figure 2: Robots, Wage Inequality, and Polarization

(a) Estimated Automation Shock (b) Effect of Robots on Wages



Note: The left panel shows the implied automation shock defined in Equation (13). The shocks are aggregated into 10 wage deciles in the base year 1990, weighted by initial employment levels. The right panel shows the annualized occupational wage growth rates for each wage decile predicted by the first-order approximated steady-state solution of the estimated model given in (C.32).

deciles of the initial wage distribution than in other parts of the wage distribution. Quantitatively, the 90-50 ratio observed in 1990 and 2007 is 1.588 and 1.668, respectively. In contrast, the 90-50 ratio predicted by the 1990 data and the first-order solution is 1.594. These numbers indicate that the robotization shock captured in this paper explains a 6.4% increase in the 90-50 ratio.

I also analyze the two robotization shocks (the automation shock $\widehat{\boldsymbol{a}}$ and the JRS $\widehat{\boldsymbol{A}}_2$) separately in another quantitative exercise. I find that the automation shock reduces labor demand by reallocating tasks from labor to robots, whereas the JRS increases the robot stock and the marginal product of labor. Appendix D.5 presents the detailed results.

Other Counterfactual Analysis. In addition, in response to fears of automation, policymakers have proposed to regulate industrial robots via robot taxes. The estimated model provides insight into the short- and long-term effects of taxing robot purchases on real wages across occupations and aggregate welfare losses. Appendix D.6 explores the implications of counterfactual policies regarding regulations of robot adoption.

6. Conclusion

This paper examines the distributional effects of the increased use of industrial robots, considering that robots perform specific tasks and are traded internationally. There are three contributions. First, I construct a measure of the cost reduction of buying robots from Japan (the JRS) across occupations in which robots are used. Second, I develop a general equilibrium model incorporating robot automation into a large open economy. Third, in estimating the occupation-specific EoS between robots and labor of the model, I construct a MOIV of the JRS to address the correlation between the automation shock and the JRS, the key identification challenge.

The estimates of the within-occupation EoS between robots and labor are heterogeneous and are as high as 3 in production and material-moving occupations. These estimates are significantly larger than corresponding estimates in capital goods and labor, revealing the particular vulnerability of workers in production and material-moving occupations to robots. The model also implies that robots contributed to wage polarization across occupations in the US from 1990 to 2007. These results can be an important reference for policy discussions about industrial robots.

Declaration of generative AI and AI-assisted technologies in the writing process. During the preparation of this work the author used ChatGPT-4o and

DeepL Pro in order to improve writing. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Online Appendix

Appendix A. Additional Background and Data

Appendix A.1. Details about Industrial Robots

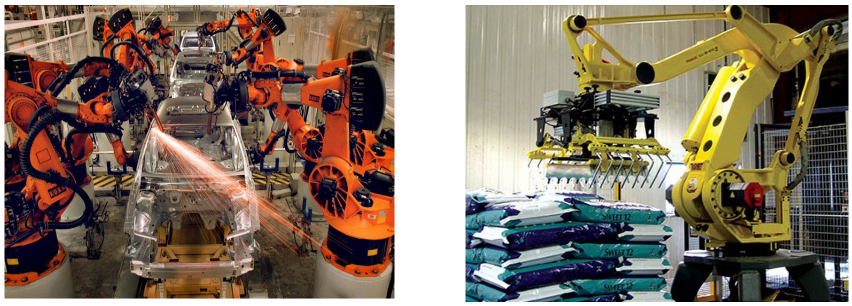
Industrial robots are defined as multiple-axes manipulators. Following the International Organization for Standardization (ISO), this paper defines robots as "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (ISO 8373:2012). This section provides a detailed discussion of such industrial robots. This definition precludes any automation equipment that does not have multiple axes out of the scope of the paper, even though some of them are often called "robots" (e.g., Roomba, an autonomous home vacuum cleaner made by iRobot Corporation). Figure Appendix A.1 provides examples of industrial robots that are intensively used in the production process and considered in this paper. Spot-welding and material-handling robots are depicted in the left and right panels, respectively.

Japan is a significant innovator, producer, and exporter of robots. As of 2017, the US had imported 5 billion dollars of Japanese robots, comprising roughly one-third of the robots used in the US. Thus, the cost reduction of Japanese robots significantly affects robot adoption in the US and the world.

JARA Robot Applications. The robot applications available in the JARA data comprise the following: Die casting; Forging; Resin molding; Pressing; Arc welding; Spot welding; Laser welding; Painting; Load/unload; Mechanical cutting; Polishing and deburring; Gas cutting; Laser cutting; Water jet

Figure Appendix A.1: Examples of Industrial Robots

(a) Spot Welding (b) Material Handling



Sources: Autobot Systems and Automation (https://www.autobotsystems.com) and PaR Systems (https://www.par.com)

cutting; General assembly; Inserting; Mounting; Bonding; Soldering; Sealing and gluing; Screw tightening; Picking alignment and packaging; Palletizing; Measurement/inspection/test; and Material handling.

Because robots are characterized by versatility as opposed to older specified industrial machinery, the question arises as to whether robots can be classified as one of these applications (Kawasaki Heavy Industry, 2018). Although a robot may be reprogrammed to perform more than one task, I claim that robots are well-classified to one of the applications listed above since the layer of dexterity is different. Robots might be able to adjust a model change of the products but are not designed to perform other tasks across the 4-digit occupation level. As small and medium enterprises are mostly high-mix and low-volume producers, robots are still too rigid to be transitioned from one occupation to another at a reasonable cost. Owing to this technological bottleneck, a versatile robot able to replace a wide range of workers at the 4-digit occupation level for the sample period of this study is not feasible.

The Cost of Using Robots and Robot Aggregation Function. The Cost of Using Robots and Robot Aggregation Function. A modern industrial robot typically does not have stand-alone hardware (e.g., robot joints and arms); instead, its ecosystem includes the hardware and control units operated by software (e.g., computers and robot programming language). Owing to its complexity, installing robots in the production environment usually requires hiring costly system integrators with the engineering knowledge necessary for integration. Therefore, the relevant costs of robots for adopters include hardware, software, and integration costs. The average price measure of robots used in this paper should be interpreted as reflecting part of overall robot costs. Following the literature's convention due to the data limitation about the robot software and integration, I address this point in the model section by separately defining the observable hardware cost using my data and the unobserved components of the cost. Namely, (C.7) explicitly includes software and integration, reflecting the modern industrial robot feature of not typically being stand-alone hardware but rather an ecosystem comprising control units operated by software requiring a significant amount of resources for integration.

Related to this, (C.7) follows the formulation of the trade of capital goods in the sense that the robots are traded because they are differentiated by origin country l. Note that (C.8) implies that the origin-differentiated investment good is aggregated at first and then added to the stock of capital following (C.7). This trick helps reduce the number of capital stock variables and is also used in the international macroeconomics literature.

Examples of Robotics Innovation. In Section 2.2, the automation shock is defined as the change in the robot task space $a_{o,t}$, and the cost shock to produce robots as the robot producer's total factor productivity (TFP) shock $A^R_{l,o,t}$. This section presents examples of changes in robot technology and new patents to facilitate understanding of these interpretations. An example of task space expansion is adopting the *Programmed Article Transfer* (PAT, Devol, 1961). The PAT is a machine that moves objects by the "teaching and playback" method, which requires one-time teaching of how to move, after which the machine repeatedly and automatically plays back the movement. This feature frees workers from performing repetitive tasks. The PAT was intensively introduced in spot welding tasks. Kawasaki Heavy Industry (2018) reports that among 4,000 spot welding points, 30% were previously performed by humans, which PAT then took over. Therefore, I interpret the adoption of PAT as an example of expanding the robot task space, increasing $a_{o,t}$.

An example of cost reduction is adopting the *Programmable Universal Manipulator for Assembly* (PUMA). The PUMA was designed to quickly and accurately transport, handle, and assemble automobile accessories. This was made possible by a new computer language, *Variable Assembly Language (VAL)*, which made the teaching process less complicated and more sophisticated. In other words, PUMA performed tasks previously performed by other robots but at a cheaper unit cost per task unit.

It is also worth mentioning that introducing a new robot brand typically contains both components of innovation (task space expansion and cost reduction). For example, PUMA also expanded the task space of robots because VAL allowed the use of sensors and "expanded the range of applications to include assembly, inspection, palletizing, resin casting, arc welding, sealing and research" (Kawasaki Heavy Industry, 2018).

Appendix A.2. More on Data Sources

*Details on the O*NET Code Connector Search.* From the O*NET Code Connector Search, we use the match score, which is generated by the *weighted search algorithm* used by the O*NET Code Connector. The weighted search algorithm is an internal search algorithm developed and employed by O*NET since September 2005. Since then, the O*NET has continually updated the algorithm and improved the quality of the search results. Morris (2019) reports that the latest weighted search algorithm scored 95.9% based on the position and score of the target best 4-digit occupation for a given query, a significant improvement from the previous search algorithm.

Additional Data Sources. In addition to the JARA and O*NET data, I use data from IFR, BACI, WIOT, IPUMS USA, and CPS. IFR is a standard data source of industrial robot adoption in several countries (e.g., Graetz and Michaels (2018); Acemoglu and Restrepo, 2020, AR hereafter), to which JARA contributes Japan's robot data.[23] I use IFR data to show the total robot adoption in each destination country. BACI provides disaggregated data on trade flows for more than 5000 products and 200 countries, from which the measures of international trade of industrial robots and baseline trade shares are obtained. I used data from WIOT from the year closest

[23] As of August 2020, JARA comprises 381 member companies, with 54 full members, 205 associate members, and 112 supporting members.

to the initial year, 1992, to obtain the intermediate input shares. IPUMS USA collects and harmonizes U.S. census microdata. I use Population Censuses (1970, 1980, 1990, and 2000) and American Community Surveys (ACS, 2006–2008 3-year sample and 2012–2016 5-year sample). Occupational wages, employment, and labor cost shares are obtained from these data sources.

I focus on occupation codes that existed between the 1970 Census and the 2007 ACS that cover the sample period and pre-trend analysis period to obtain consistent data across periods. Therefore, this paper focuses on the intensive-margin substitution in occupations as opposed to the extensive-margin effect of automation that creates new labor-intensive tasks and occupations, as in Acemoglu and Restrepo (2018). My dataset shows that 88.7% of workers in 2007 worked in the same occupations that existed in 1990. How to attribute the creation of new occupations to different types of automation goods, such as occupational robots in my case, remains an open question.

I follow Autor et al. (2013) for the Census/ACS data cleaning procedure. Namely, I extract the 1970, 1980, 1990, and 2000 Censuses, the 2006-2008 3-year ACS file, and the ACS 2012–2016 5-year file from Integrated Public Use Micro Samples. For each file, I select all workers with the OCC2010 occupation code between 16 and 64 years of age who are not institutionalized. I compute the education share for each occupation by the share of workers with more than “any year in college” and the foreign-born share by the share of workers whose birthplace is neither in the US nor in US outlying areas/territories. I compute hours worked by multiplying the usual weeks worked and hours worked per week. For 1970, I use the median values in each bin of the usual weeks worked variable and assume all workers worked

40 hours per week as the hour variable does not exist. I compute the hourly wage by first imputing each state-year's top-coded values by multiplying 1.5 and dividing by the hours worked. To remove outliers, I take wages below the first percentile of the distribution in each year and set the maximum wage as the top-coded earning divided by 1,500. I compute the real wage in 2000 dollars by multiplying the CPI99 variable prepared by IPUMS. The person weight variable is used to aggregate all these variables to the occupation level.

The occupation groups are formally defined as follows: Routine occupations encompass occupations such as production, transportation (material moving), sales, clerical, and administrative support. Abstract occupations are professional, managerial, and technical occupations. Service occupations comprise protective service, food preparation, cleaning, personal care, and personal services. The routine occupations are further separated into production, transportation, and others. Thus, the following five categories in terms of OCC2010 codes in the US Census are established: Routine-production occupations are in $[7700, 8965]$, Routine transportation occupations are in $[9000, 9750]$, Routine others are in $[4700, 6130]$, Service (manual) occupations are in $[3700, 4650]$, and Abstract occupations are in $[10, 3540]$.

I further use the bilateral occupation flow data following the idea of Caliendo et al. (2019) to estimate the model with workers' dynamic discrete choice of occupation. Specifically, I obtained the Annual Social and Economic Supplement (ASEC) of the CPS from 1976. For each year, I select all workers with the 2010 occupation code for the current (OCC2010) and prior year (OCC10LY) aged between 16 and 64 who are not institutionalized.

Table Appendix A.1: List of Data Sources

Variable	Description	blackSource
$\widetilde{y}^G_{ij,t_0}, \widetilde{x}^G_{ij,t_0}, \widetilde{y}^R_{ij,t_0}, \widetilde{x}^R_{ij,t_0}$	Trade shares of goods and robots	BACI, IFR
$\widetilde{x}^O_{i,o,t_0}$	Occupation cost shares	IPUMS
l_{i,o,t_0}	Labor shares within occupation	JARA, IFR, IPUMS
$s^G_{i,t_0}, s^V_{i,t_0}, s^R_{i,t_0}$	Robot expenditure shares	BACI, IFR, WIOT
$\alpha_{i,M}$	Intermediate input share	WIOT

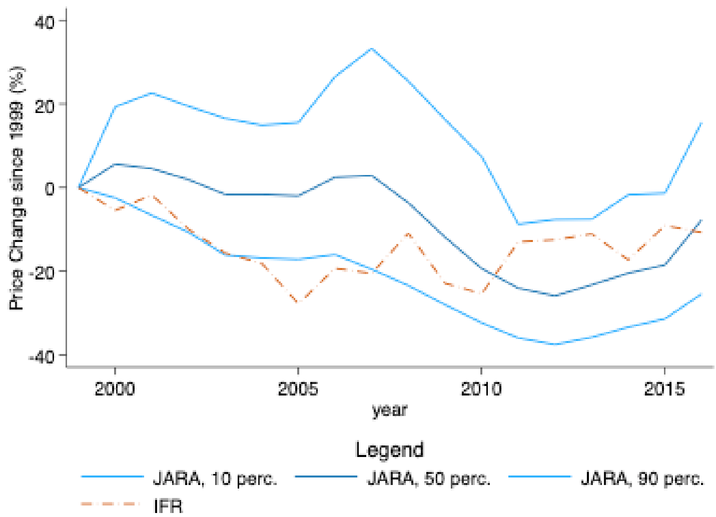
I then constructed variables using the same method used for the Census/ACS above. I assume that the workers do not flow between 4four-digit occupations within the 5 occupation groups defined in Section 3.2, but do flow between the 5 groups. I also assume that workers draw a destination 4-digit occupation from the initial-year occupational employment distribution within the destination group when switching occupations. I compute the occupation switching probability by year with these data.

Data on Initial Shares Used in Simulations. I need the data baseline share since the log-linearized sequential equilibrium solution depends on the initial steady-state shares. I define $t_0 = 1992$ and take data at the annual frequency. I consider the world that comprises three countries $\{USA, JPN, ROW\}$. Table Appendix A.1 summarizes the overview of the variable notations, descriptions, and data sources. I take the matrices of trade of goods and robots using BACI data. As in Acemoglu and Restrepo (2022), I measure robots by HS code 847950 ("Industrial Robots For Multiple Uses") and approximate the initial year value by year of 1998, in which the robot HS code is first available.

The domestic robot absorption data are obtained by taking the flow quantity variable and the aggregate price variable from IFR data for a selected set of countries. I then multiply these to obtain the US and Japanese robot adoption values. For robot prices in ROW, I take the simple average of the prices among the set of countries (France, Germany, Italy, South Korea, and the UK, as well as Japan and the US) for which the price is available in 1999, the earliest year when the price data are available. Graetz and Michaels (2018) discussed prices of robots with the same data source. Figure Appendix A.2 shows the comparison of the US price index measure available between JARA and IFR. The JARA measures are disaggregated by 4-digit occupations. The figure shows the 10th, 50th (median), and 90th percentiles each year, as in Figure Appendix B.1a. All measures are normalized in 1999, the year the first price measure is available in the IFR data. Overall, the JARA price trend variation tracks price evolution measured by IFR reasonably well: The long-run trends from 1999 to the late 2010s are similar between the JARA median price and the IFR price index. During the 2000s, the IFR price index dropped faster than the JARA data median price. It compares with the JARA 10th percentile price, possibly due to robotic technological changes in countries other than Japan in the corresponding period.

I construct occupation cost shares $\widetilde{x}^{O}_{i,o,t_0}$ and labor shares within occupation l_{i,o,t_0} as follows. To measure $\widetilde{x}^{O}_{i,o,t_0}$, I aggregate the total wage income of workers who primarily work in each occupation o in year 1990, the Census year closest to t_0. I then take the share of this total labor compensation measure for each occupation. The total labor compensation as the share of the total labor cost and the user cost of robots is then used to measure l_{i,o,t_0} for

Figure Appendix A.2: Comparison of US Price Indices between JARA and IFR



Note: The author's calculation of US robot price measures in JARA and IFR. The JARA measures are disaggregated by 4-digit occupations, and the figure shows the 10th, 50th (median), and 90th percentiles each year. All measures are normalized in 1999, the year the first price measure was available in the IFR data.

each occupation. The user cost of robots is calculated using the occupation-level robot price data available in IFR and the set of calibrated parameters in Section 3.1. Table Appendix A.2 summarizes these statistics for the aggregated 5 occupation groups in the US. The cost for production occupations and transportation occupations represent 18% and 8% of the US economy, respectively, which jointly comprise more than one-fourth. Furthermore, the share of robot cost in all occupations is still quite low, with the highest share of 0.19% in production occupations, revealing the US economy's overall small-scale adoption of robots.

To calculate the effect on total income, I must also compute the sales share of robots by occupations $y^R_{i,o,t_0} \equiv Y^R_{i,o,t_0} / \sum_o Y^R_{i,o,t_0}$ and absorption share

Table Appendix A.2: Baseline Shares by 5 Occupation Group

Occupation Group	$\widetilde{x}^O_{1,o,t_0}$	l^O_{1,o,t_0}	y^R_{2,o,t_0}	x^R_{1,o,t_0}	x^R_{2,o,t_0}	x^R_{3,o,t_0}
Routine, Production	17.58%	99.81%	64.59%	67.49%	62.45%	67.06%
Routine, Transportation	7.82%	99.93%	12.23%	11.17%	13.09%	11.04%
Routine, Others	28.78%	99.99%	10.88%	9.52%	11.68%	10.40%
Service	39.50%	99.99%	8.87%	8.58%	9.17%	8.32%
Abstract	6.32%	99.97%	3.43%	3.24%	3.60%	3.18%

Note: The author's calculation of initial-year share variables is shown based on the US Census, IFR, and JARA. As in the main text, country 1 indicates the US, country 2 Japan, and country 3 the rest of the world. See the main text for the construction of each variable.

$x^R_{i,o,t_0} \equiv X^R_{i,o,t_0}/\sum_o X^R_{i,o,t_0}$. To obtain y^R_{i,o,t_0}, I compute the share of robots by occupations produced in Japan $y^R_{2,o,t_0} = Y^R_{2,o,t_0}/\sum_o Y^R_{2,o,t_0}$ and assume the same distribution for other countries due to the data limitation: $y^R_{i,o,t_0} = y^R_{2,o,t_0}$ for all i. To obtain x^R_{i,o,t_0}, I compute the occupational robot adoption in each country by $X^R_{i,o,t_0} = P^R_{i,t_0} Q^R_{i,o,t_0}$, where Q^R_{i,o,t_0} is the occupation-level robot quantity obtained by the O*NET concordance generated in Section 3.3 applied to the IFR application classification. As mentioned above, the robot price index P^R_{i,t_0} is available for a selected set of countries. To compute the rest-of-the-world price index P^R_{3,t_0}, I use the average of all available countries weighted by the occupational robot values each year. The summary table for these variables y^R_{i,o,t_0} and x^R_{i,o,t_0} at 5 occupation groups are shown in Table Appendix A.2. All values in Table Appendix A.2 are obtained by aggregating 4-digit-level occupations.

I take the intermediate input share $\alpha_{i,M}$, from the WIOT. I combine the trade matrix generated above and the WIOT to construct the good and

Table Appendix A.3: 1990 Occupation Group Switching Probability

		Routine			Service	Abstract
		Production	Transportation	Others		
Routine	Production	0.961	0.011	0.010	0.006	0.012
	Transportation	0.020	0.926	0.020	0.008	0.025
	Others	0.005	0.006	0.955	0.020	0.014
Service		0.003	0.002	0.020	0.967	0.007
Abstract		0.014	0.014	0.036	0.015	0.922

Note: The table shows the between-occupation group transition rates calculated from the CPS-ASEC 1990 data. The probability is the switching probability to the column occupation group conditional on being in each row occupation.

robot expenditure shares s^G_{i,t_0}, s^V_{i,t_0}, and s^R_{i,t_0}. Specifically, with the robot trade matrix, I take the total sales value by summing across importers for each exporter and the total absorption value by summing across exporters for each importers. I also obtain the total good absorption by the WIOT. I compute expenditure shares from these total values.

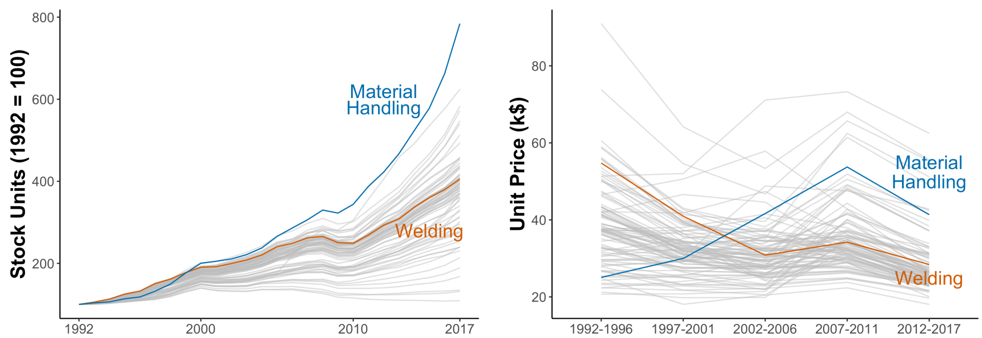
I take the 1990 flow Markov transition matrix from the cleaned CPS-ASEC data. Table Appendix A.3 shows this initial-year conditional switching probability. The matrix for the other years is available upon request. Because occupation employment data across the world are difficult to obtain, I assign the same flow probabilities for other countries in my estimation strategy.

Appendix A.3. Trends of Robot Stocks and Prices

Figure Appendix A.3 shows the US robot trends at the occupation level. The left panel shows the trend of raw stock, revealing that overall robot

Figure Appendix A.3: Trends of Japanese Robot Use at the US Occupation Level

(a) Stock (b) Prices



Note: The left panel shows the trend of stocks of robots in the US for each occupation, normalized at 100 in 1992. The right panel shows the trend of robot prices in the US for each occupation. Two occupations are highlighted in both panels: "Welding" corresponds to the occupation code in IPUMS USA, OCC2010 = 8140 "Welding, Soldering, and Brazing Workers." "Material Handling" corresponds to the occupation code OCC2010 = 9620 "Laborers and Freight, Stock, and Material Movers, Hand." Years are aggregated into five-year bins (with the last bin 2012-2017 being a six-year bin) to smooth out yearly noise.

stocks increased rapidly in the period, as found in the previous literature, and that the increase occurred at different speeds across occupations. To highlight such a difference, I plot the normalized trend at 100 in the initial year in the right panel. There is significant heterogeneity in the growth rates, ranging from a factor of one to eight. Next, Figure Appendix A.3b shows the trend of robot prices in the US for each occupation. In addition to the overall decreasing trend, there is significant heterogeneity in the pattern of price falls across occupations. The price patterns are strongly correlated across countries, with a correlation coefficient of 0.968 between the US and non-US prices at the occupation-year level. Motivated by this finding, I use the prices of non-US countries as the JRS to the US in the reduced-form analysis.

To further emphasize the trend heterogeneity, the following two occupations are colored: “Welding, Soldering, and Brazing Workers” (or “Welding”) and “Laborers and Freight, Stock, and Material Movers, Hand” (or “Material Handling”) in these two figures. A spot welding robot is used in routine-production occupations, while a material-handling robot is used in transportation (material-moving) occupations. On the one hand, the stock of welding robots grew throughout the period in the left panel, and their average price dropped during the 1990s. On the other hand, material handling robot stock grew rapidly, and the price increased over the sample period. These findings indicate the difference in automation shocks; Robots such as welding robots followed a standard pattern of expansion along the demand curve, whereas other robots such as material handling robots expanded their adoption even though the average price increased, indicating the impact of the automation shock described in the model section.

Figure Appendix A.3b suggests an anomaly in the increasing 2007-2011 trend. This pattern emerges because, during the Great Recession, the total number of units decreased more than the total sales. Following the Great Recession, the growth of values and quantities of robots accelerated. These observations suggest a structural break in the robot industry during the Great Recession, which is beyond the scope of the paper.

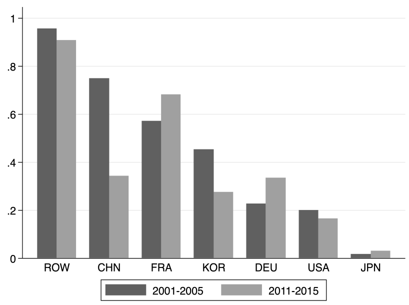
Appendix A.4. Trade of Industrial Robots

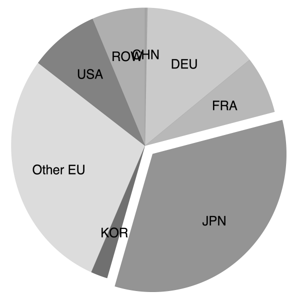
I combine BACI and IFR data to compute the trade shares of industrial robots. In particular, I use the HS code 847950 (“Industrial Robots For Multiple Uses”) to measure the robots, following (Humlum, 2021; Acemoglu and Restrepo, 2022), using 1998 as the initial year value, the first year when the HS code 847950 was available. To calculate the total absorption value of robots in each country, I use the IFR data's robot units (quantities), combined with the price indices of robots released by IFR annual reports for selected countries (Graetz and Michaels, 2018). Note that these price indices do not provide disaggregation by robot tasks or occupations, highlighting the JARA data's value added. Figure Appendix A.4 illustrates the international trade pattern of robots. In the left panel, I compute the import-absorption ratio. To remove the noise from yearly observations and focus on long-run trends, I aggregated the data by five-year bins: 2001-2005 and 2011-2015. The result indicates that many countries import robots instead of producing them. Japan's low import ratio is outstanding, revealing its comparative advantage in this area. Notably, China gradually domesticated the production of robots over the sample period. Another way to grasp the comparative advantage of the robot industry is to examine the share of exports as in the right panel of Figure Appendix A.4. The EU dominated half the world's robot market and one-third by Japan in 2001–2005. The remaining 20% is shared by the rest of the world, mostly the US and South Korea.

Figure Appendix A.5 shows the trend of robot export and import shares for the US, Japan, and the rest of the world (RoW). The trends are fairly stable for the three regions, except that the US import share declined relative to the RoW.

Robots from Japan in the US, Europe, and the Rest of the World. To compare the pattern of robot adoption internationally, I generate growth rates of stock of robots between 1992 and 2017 at the occupation level for each group of

Figure Appendix A.4: Trade of Industrial Robots



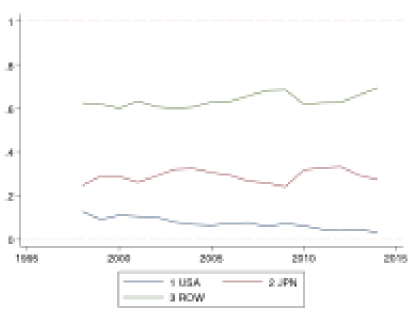


(a) Robot Import-Absorption Ratio (b) World Robot Export Share, 2001-2005

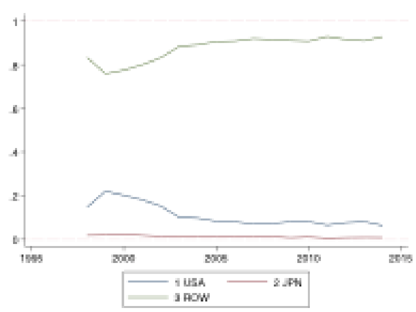
Note: The author's calculation from the IFR, and BACI data. The left panel shows the fraction of imports in the total absorption value. The import value is computed by aggregating trade values across the origin country in the BACI data (HS-1996 code 847950), and the absorption value is computed by the price index and the quantity variable available for selected countries in the IFR data. The data are aggregated by 5 years in 2001–2005 and 2011–2015, and countries are sorted according to the import shares during 2001–2005 in the descending order. The right panel shows the export share for 2001-2005 aggregates obtained from the BACI data.

Figure Appendix A.5: Robot Trade Share Trends

(a) Exports



(b) Imports



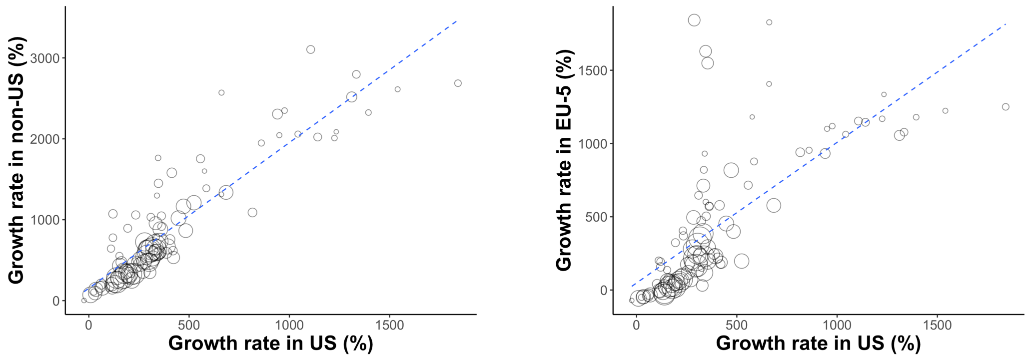
Note: The author's calculation of world trade shares is shown based on the BACI data. Industrial robots are measured by HS code 847950 (Industrial robots for multiple uses).

destination countries. The groups are the US, the non-US countries (all countries excluding the US and Japan), and the five European countries (or “EU5”) of Denmark, Finland, France, Italy, and Sweden used in AR. Following Graetz and Michaels (2018), the perpetual inventory method with a depreciation rate of $\delta = 0.1$ is used to calculate the stock of robots.

Figure Appendix A.6 shows scatter plots of the growth rates at the occupation level. The left panel shows the growth rates in the US on the horizontal axis while the vertical axis shows the non-US countries. The right panel shows the same measures on the horizontal axis, but the growth rates in the set of EU-5 countries on the vertical axis. These panels show that the stocks of robots at the occupation level grew (1992–2017) between the US and non-US proportionately relative to those between the US and EU-5. This finding contrasts with AR, who found that the US aggregate robot stocks grew at a roughly similar rate as those in EU-5. It also indicates that non-US growth patterns reflect growths of robotics technology at the occupation level available in the US. These patterns are used as the proxy for robotics technology available in the US. In the model section, I take a further step and solve for the robot adoption quantity and values in non-US countries in general equilibrium including the US and non-US countries.

A potential reason for the difference between my findings and AR’s is the difference in data sources. In contrast to the JARA data I use, AR use IFR data that include all robot seller countries. Because EU-5 is closer to major robot-producer countries other than Japan, including Germany, the robot adoption pattern across occupations may be influenced by their presence. If these close producers have a comparative advantage in producing robots for

Figure Appendix A.6: Growth Rates of Robots at the Occupation Level



(a) Comparison between the US and non-US

(b) Comparison between the US and EU-5

Note: The growth rates of robot stocks based on JARA, and O*NET are shown. The left panel shows the correlation between occupation-level growth rates of robot stock quantities from Japan to the US and the growth rates of quantities in non-US countries. The right side shows the correlation between the growth rates of the quantities in the US and EU-5 countries. Non-US are the aggregate of all countries excluding the US and Japan. EU-5 represents the aggregate of Denmark, France, Finland, Italy, and Sweden used in Acemoglu and Restrepo (2020). Each bubble shows an occupation. The bubble size reflects the stock of robots in the US in the baseline year, 1992.

a specific occupation, then EU-5 may adopt the robots for such occupations intensively from close producers. In contrast, non-EU-5 countries, including the US, may not benefit from proximity to these producers; thus they are more likely to purchase robots from producers located far from EU-5, such as Japan.

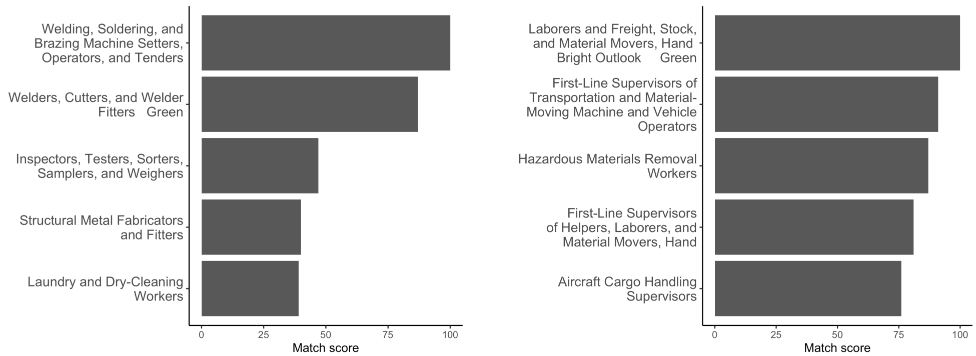
Appendix A.5. Details in Application-Occupation Matching

Details of the application-occupation matching are discussed. First, I access O*NET Code Connector (https://www.onetcodeconnector.org/) and web-scraped search results in the following way. For each robot application title listed in Section Appendix A.1, I search for matches on the webpage and record all occupation codes, names, and match scores. Then, I append the result files across all applications, which is called the match score file. At this stage, I drop the mounting and measurement/inspection/test robots from the data due to poor matching quality. Second, I merge the match score file and the JARA data at the application level and take the weighted average of robot sales values and quantities with the weight of the score, as in (10).

For example, consider spot-welding and material-handling robots. First, spot welding combines two or more metal sheets into one by applying heat and pressure to a small area called a spot. O*NET-SOC Code 51-4121.06 has the title "Welders, Cutters, and Welder Fitters" ("Welders" below). These suggest that spot-welding robots and welders perform the same welding task. Second, material handling involves moving heavy materials a short distance, another primary robot application. ONET-SOC Code 53-7062.00 has the title "Laborers and Freight, Stock, and Material Movers, Hand" ("Material Handler" below). Again, both material-handling robots and material handlers perform the material-handling task. Figure Appendix A.7 shows the top five match scores for spot welding and material handling, with these two occupations at the top of the match score ranking, respectively.

Hard-cut Matching of Applications and Occupations. Although matching between applications and occupations based on equation (10) is transparent and performed automatically, instead of using the researcher's judgment, there may be concern that such a matching method may potentially contain errors due to noise in the occupation dictionary's text descriptions. For exam-

Figure Appendix A.7: Examples of Match Scores



(a) Spot Welding (b) Material Handling

Note: The author's calculation from the search result of O*NET Code Connector. The bars indicate match scores for the search query term "Spot Welding" in panel (a) and "Material Handling" in panel (b). The occupations codes are 2010 O*NET-SOC codes. In each panel, occupations are sorted descendingly with the relative relevance scores, and the top five occupations are shown.

ple, Figure Appendix A.7 reveals a case in which spot-welding robots are matched to "Laundry and Dry-cleaning Workers" with a high score. This is primarily because the textual description for these workers includes "Apply bleaching powders to spots and spray them with steam to remove stains from fabrics...," which has a high matching score with the term "spot."

To mitigate this concern, I examine a manual hard-cut matching between applications and occupations by dropping potentially problematic application–occupation matches with a matching score of 75 or below while including enough data variation. I then construct the matching score following (10) conditional on remaining pairs and compute robot quantity and price variables. Figure Appendix A.8 shows the result of regression specification (B.1) using these measures. The estimated coefficients are somewhat larger than those with the preferred data matching procedure primarily because, in the

Figure Appendix A.8: Wage and Robot Prices with a Hard-cut Matching Method

Note: The figure shows the relationship between the Japan Robot Shock based on the application-level robot measures matched to occupations using the hard-cut method described in the main text (horizontal axis) and changes in the log wage (vertical axis). The sample includes all occupations that existed between 1970 and 2007. Bubble sizes reflect the employment in the baseline year, and the number of observations is 324. All variables are residualized by control variables (the occupational female share, college share, age distribution, foreign-born share, and the China shock in Equation 16).

hard-cut matching, erroneous matches that potentially contain noises are removed. Statistical significance remains in all columns.

Appendix A.6. Other Potential Methods for Adjusting the Robot Prices

In the paper, I use the general equilibrium model to control for the quality component of robot prices. However, other methods are proposed in the literature to measure the price of capital goods. In this subsection, I briefly describe these methods and their limitations.

The first approach is to control for quality change using the hedonic approach, which is used by, among others, Tambe et al. (2019), in their application to digital capital. The hedonic approach requires information about the detailed specifications of each robot. Unfortunately, it is difficult to keep track of the detailed specifications of commonly used robots as the robotics industry is rapidly changing.

The second method is more data-driven. The Bank of Japan (BoJ) provides the quality-controlled price index. Unfortunately, the method is not clearly declared in the BoJ technical documentation. It is claimed to be a "cost-evaluation method," in which the BoJ asks producer firms to measure the component of quality upgrading for price changes between periods. Obtaining the quality measures is challenging as I do not know the surveyed firms or quality components.

Appendix B. Reduced-form Analysis

With all the data in Appendix A combined, I show several facts and data patterns about the robots, JRS, and their relation to the labor market outcome in the US in this section.

Appendix B.1. The Japan Robot Shock Trends

Figure Appendix B.1a plots the distribution (10th, 50th, and 90th percentile) of the growth rates of the nominal price of Japanese robots in the US each year relative to the initial year. The figure shows two patterns: (i) the robot prices follow an overall decreasing trend, with a median growth rate of -17% from 1992 to 2007, or -1.1% annually, and (ii) there is significant heterogeneity in the rate of price decline across occupations. Specifically, the 10th percentile occupation experienced -34% growth (-2.8% per annum), while in the 90th percentile occupation, the price changed little in the sample period. This price drop is consistent with decreasing prices of general investment goods since 1980; Karabarbounis and Neiman (2014) report a 10% decrease per decade.

Figure Appendix B.1b shows the distribution of the long-run trend (1992–2007) for each occupation group: routine, service (or manual), and abstract. Routine is further divided into production, transportation, and others to reflect the rapid adoption of robots in production and transportation occupations. The figure confirms a significant price variation across occupations, which is observed even within occupation groups. Surprisingly, the average change in production robot prices is not as large as other robots although it is slightly positive. This indicates that the robotics technology change in production occupations is not reflected by the price decline but rather by the quality improvement; thus, the unit value rises.

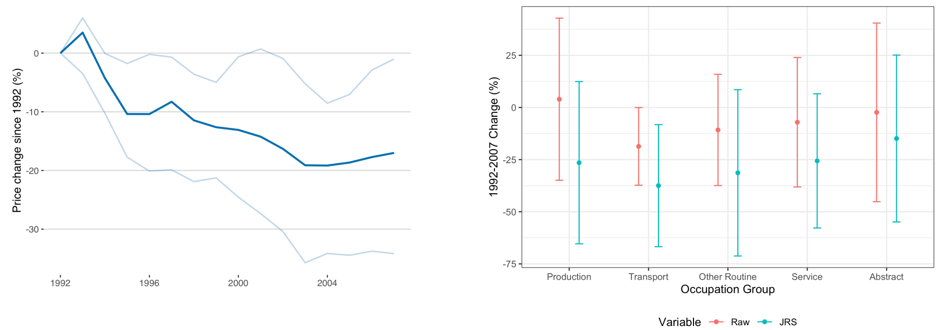
Furthermore, the figure shows the variation in JRS, or ψ^{J}_{i,t_1}, in (11). The large variation of the changes in prices by occupations persists even after controlling for the destination-year FE $\psi^{D}_{i,t}$. It also confirms that after controlling for US demand shocks, the Japanese robot cost significantly decreases, especially in the production occupation. I next use this cost variation to study the impact on the labor market and estimate the EoS between robots and workers.

Appendix B.2. The Effects of the Japan Robot Shock on US Occupations

Because labor demand may be affected by trade liberalization, notably the China shock in my sample period, I control for the occupational China shock by the method developed by Autor et al. (2013). Specifically, I compute the occupational China shock by (16). For the list of non-US countries, I follow Autor et al. (2013) and take eight countries: Australia, Denmark,

Figure Appendix B.1: Distribution of the Robot Prices and Japan Robot Shock

(a) Robot Prices in the US (b) Variation in the Japan Robot Shock



Note: The left panel shows the trend of nominal prices of robots in the US by occupations, $p^R_{USA,o,t}$. The bold and dark lines show the median price each year, and the two thin and light lines represent the 10th and 90th percentile. Three-year moving averages are taken to smooth out yearly noises. The right panel shows the mean and standard deviation of the long-run (1992–2007) raw price decline ("Raw") and the Japan Robot Shock measured by the fixed effect ψ^C_{o,t_1} in equation (11) ("JRS"). The occupation group is routine, service (manual), and abstract, where routine is further divided into production, transportation, and other.

Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Appendix A.2 shows the distribution of occupational employment l_{s,o,t_0} for each sector. Intuitively, an occupation receives a large trade shock if sectors that face increased import competition from China intensively employ the corresponding occupation. With this trade shock measure in the control variable, I run the following regression:

$$\Delta \ln \left(\ln w_o\right) = \alpha_0 + \alpha_1 \times \left(-\psi^J_o\right) + \alpha_2 \times IPW_{o,t_1} + \boldsymbol{X}_o \cdot \boldsymbol{\alpha} + \varepsilon_o, \tag{B.1}$$

where w_o is log hourly wage, and $\boldsymbol{X}_o$ is the vector of baseline demographic control variables. The controls are the female share, the college-graduate share, the age distribution, and the foreign-born share.

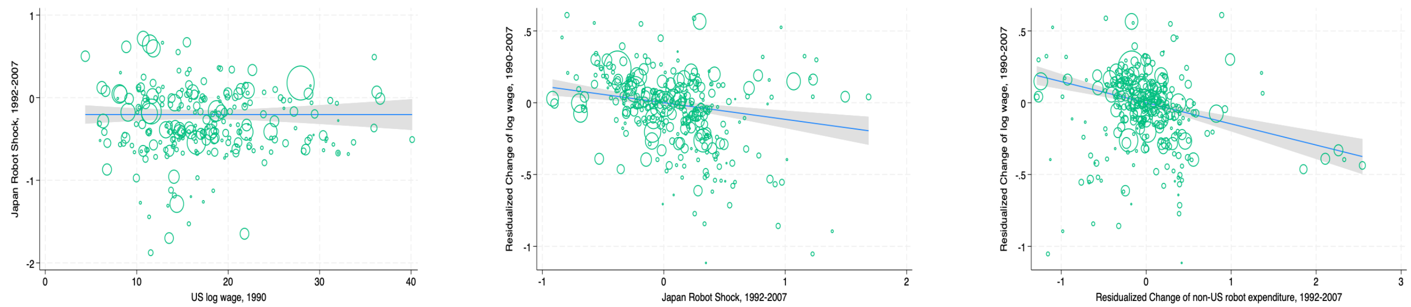
First, I check the correlation between various robot measures and wage

Figure Appendix B.2: The Japan Robot Shock and US Occupational Wages

(a) Japan Robot Shock and Baseline Wage

(b) Changes in Wage and Robot Prices

(c) Changes in Wage and Robot Expenditure



Note: The left panel shows the scatterplot, weighted fit line, and the 95% confidence interval of the baseline (1990) US log wage (horizontal axis) and the Japan Robot Shock (JRS) in Equation (11) (vertical axis) at the 4-digit occupation level. The middle panel shows the relationship between the JRS (horizontal axis) and changes in log wage (vertical axis). The right panel shows the relationship between the log total expenditure on Japanese robots in non-US countries (horizontal axis) and changes in log wage (vertical axis). In all panels, the sample comprises all occupations between 1970 and 2007, bubble sizes reflect the employment in the baseline year, and the number of observations equals 324. In the middle and right panels, the variables are residualized by control variables (the occupational female share, college share, age distribution, foreign-born share, and the China shock in Equation 16).

measures. In Figure Appendix B.2a, the left panel shows the correlation between the JRS and US baseline wages in 1990 at the occupation level. No systematic relationships between these variables are found, indicating that the JRS did not necessarily trigger wage inequality expansion during the 1990s and 2000s. Next, the middle panel shows the result of estimation (B.1) in a scatterplot, revealing that a 10% reduction in Japanese robot prices decreases US occupational wages by 1.2%. Therefore, the JRS adversely affected US occupations, suggesting substituting labor for robots. Finally, total expenditures on robots quantitatively affect the demand for labor in each occupation, conditional on robot prices. The right panel shows the relationship between the change in robot expenditures and wages, suggesting negative impacts on wages also operate through the expenditure margin, indicating the substitutability of labor due to robot penetration at the occupation level.

Next, Table Appendix B.1 shows the result of regression (B.1) to vary across occupation groups defined above. I find the negative effects in routine-production and routine-transportation occupations, demonstrating the heterogeneity in the impact across occupation groups. This finding motivates me to consider the group-specific EoS between robots and workers in the model section.

Again, the novelty of these findings lies in using robot cost reductions at the occupation level. Therefore, I will show additional results that complement the findings. Table Appendix B.2 shows the results of regression (B.1) using several alternative outcome periods and robot measures on the right-hand side. Panel A takes the wage change between 1990 and 2007, the main period, while Panel B takes the change between 1970 and 1990, the

Table Appendix B.1: The heterogeneous effects of the Japan robot shock on US occupations

	(1)
VARIABLES	$\Delta \ln(wage)$
$(-\psi^J) \times$ Routine, production	-0.627***
	(0.112)
$(-\psi^J) \times$ Routine, transportation	-0.738***
	(0.0624)
$(-\psi^J) \times$ Routine, others	0.00770
	(0.0536)
$(-\psi^J) \times$ Service	-0.0639
	(0.107)
$(-\psi^J) \times$ Abstract	0.00693
	(0.0789)
Observations	324
R-squared	0.462

Note: The table shows the coefficients in regression (B.1) allowing the coefficient α_1 to vary across occupation groups. Observations are 4-digit level occupations, and the sample comprises all occupation codes that consistently existed between 1970 and 2007. ψ^J stands for the Japan Robot Shock from Equation (11). Control variables of the female share, the college-graduate share, the age distribution (shares of age 16-34, 35-49, and 50-64 among workers aged 16-64), the foreign-born share as of 1990, and the China shock in Equation (16), are included. Standard errors are clustered at the 2-digit occupation level. *** p<0.01, ** p<0.05, * p<0.1.

Table Appendix B.2: Regression of Wages on Robot Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	dln_wage	dln_wage	dln_wage	dln_wage	dln_wage	dln_wage	dln_wage	dln_wage
					A. 1990-2007			
Robot Measure	-0.169***	-0.196***	-0.180***	-0.171***	-0.0399	-0.0798**	-0.210***	-0.206***
	(0.0395)	(0.0398)	(0.0460)	(0.0463)	(0.0399)	(0.0346)	(0.0601)	(0.0458)
R-squared	0.066	0.283	0.055	0.245	0.005	0.214	0.093	0.284
					B. 1970-1990			
Robot Measure	0.00691	0.00772	-0.00388	0.00142	0.00699	-0.00480	0.00866	0.0189
	(0.0262)	(0.0233)	(0.0306)	(0.0269)	(0.0236)	(0.0244)	(0.0286)	(0.0240)
R-squared	0.000	0.079	0.000	0.079	0.000	0.079	0.000	0.081
Robot Measure	US Stock	US Stock	- US Price	- US Price	Non-US Stock	Non-US Stock	- Non-US Price	- Non-US Price
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	324	324	324	324	324	324	324	324

Note: The author's calculation based on JARA, O*NET, and US Census/ACS. Observations are 4-digit level occupations, and the sample comprises all occupations that existed between 1970 and 2007. Panel A takes the wage change between 1990 and 2007, the main period, while Panel B takes the change between 1970 and 1990, the pre-sample period. The regressors are robot stock in the US (Columns 1 and 2), robot stock in non-US countries (Columns 3 and 4), robot price in the US (Columns 5 and 6), or robot price in non-US countries (Columns 7 and 8). Control variables are demographic variables (the female share, the college-graduate share, the share of age 16–34, 35–49, and 50–64 among workers aged 16-–64, and the foreign-born share as of 1990), and the China trade shock defined in Equation (16). Bootstrapped standard errors are reported in parentheses.

trade shock.

Table Appendix B.3 shows the regression result of B.1 with the outcome variable of employment. A qualitatively similar pattern is found in the sense that employment in a subset of the routine occupation group (production workers) is reduced in the occupations that experienced the JRS; in contrast, there is no statistically significant point estimate for transportation workers.

Furthermore, to address a concern that the US is a large country that affects robot prices more directly, I confirm that the effect of the robot price reduction on labor demand is also observed in a small open economy as well in Appendix B.3.

Although these data patterns and regressions are informative regarding the substitutability of robots, they do not provide definitive answers about the value of the substitution parameter or the distributional and aggregate effect of robotization. First, the observed JRS may reflect the quality upgrading of robots, meaning the quality-adjusted robot cost reduction might be even greater. Second, changes in labor demand for one occupation following the shock can impact wages and employment in other occupations by changing their marginal products. Third, coefficients in (B.1) reveal the relative effect of the JRS but not the real wage impact. I develop and estimate a general equilibrium model to overcome these issues in the main text.

Appendix B.3. Validation Exercise in a Small Country

One concern of my reduced-form analysis is that as a large buyer of robots, US demand may influence the price. To mitigate this, I conduct a robustness exercise using data from a small country unlikely to affect the

Table Appendix B.3: The heterogeneous effects of the Japan Robot Shock on US occupations

	(1)
VARIABLES	$\Delta \ln(emp)$
$(-\psi^J)$ × Routine, others	-0.657***
	(0.229)
$(-\psi^J)$ × Routine, transportation	-0.258
	(0.180)
$(-\psi^J)$ × Routine, production	-0.0651
	(0.143)
$(-\psi^J)$ × Service	-0.126
	(0.227)
$(-\psi^J)$ × Abstract	-0.342
	(0.256)
Observations	324
R-squared	0.126

Note: The table shows the coefficients in regression (B.1) allowing the coefficient α_1 to vary across occupation groups, with the outcome variable of the long difference of log employment from 1990 to 2007. Observations are 4-digit level occupations, and the sample comprises all occupation codes that consistently existed between 1970 and 2007. ψ^J stands for the Japan Robot Shock from Equation (11). Control variables of the female share, the college-graduate share, the age distribution (shares of age 16-34, 35-49, and 50-64 among workers aged 16-64), the foreign-born share as of 1990, and the China shock in Equation (16), are included. Standard errors are clustered at the 2-digit occupation level. *** p<0.01, ** p<0.05, * p<0.1.

world price of robots. I use data from the Netherlands since it is the largest exporting destination of Japanese robots in Europe, following Germany, the UK, Italy, and France, and a small open economy. The data are taken from the IPUMS international and provide the ISCO 1-digit level occupation in-

Figure Appendix B.3: The Effect of Japan Robot Shock in the Netherlands

Note: The bubble plot and fitted line between the Netherlands occupational growth and the Japan Robot Shock are shown. The period is from 2001 to 2011. The size of the bubble reflects the initial period size of employment. The occupations are aggregated to the ISCO 1-digit level. The shade indicates the 95% confidence interval.

dicator for 2001 and 2011. Occupational robot prices are aggregated at the same level and the relationship between the JRS and occupational employment growth is examined. Because the wage variable is not available in the IPUMS international, I use the employment variable to proxy labor demand changes. Figure Appendix B.3 summarizes the results. Despite a significant difference in context and the level of data aggregation, I find a significant negative relationship between these two variables. This exercise suggests that reducing the price of Japanese robots, which is likely to hit small open economies exogenously, reduces labor demand in the Netherlands.

Appendix B.4. The Effect of Robots from Japan and Other Countries

A potential concern in my empirical setting is the selection issue regarding the robot source country. Specifically, because robots from Japan may differ from those from other countries, the labor market implications may also vary. Unfortunately, it is difficult to directly compare the effects of these two different groups of robots due to the data limitation; thus, I focus on the best comparable measures of robotization between Japan-sourced robots and those from all countries, which is the quantity of robot stock. I take the total stock of robots in the US from the IFR data. The IFR data only has the total number and do not specify the source country. I then convert the IFR application codes to the JARA application codes to use the allocation rule to match the JARA application codes and the occupation codes. As a result, I obtained the robots used in the US that are sourced from any country at the occupation level. I then run the following regression using the obtained robot measures and my preferred measure from the JARA:

$$\Delta Y_o = \beta^Q \Delta K_o^{R,Q} + X_o \gamma^Q + \varepsilon_o^Q, \tag{B.2}$$

where ΔY_o is the changes in wages at the occupation-o level, ΔK_o^Q is the measure of the number of robots taken either from JARA (i.e., robots from Japan) or IFR (i.e., robots from the world), and ε_o^Q is the error term. The coefficient of interest is β^Q, which provides insight into the correlation between the changes in labor market outcomes and in robot quantity, depending on whether the robots are sourced from Japan. Specifically, if robots from Japan substitute workers stronger than robots from the other countries, coefficient β^Q is expected to be larger when I use the JARA robot measure than IFR.

Table Appendix B.4: Regression Results of Labor Market Outcome on JARA and IFR Robot Stocks

VARIABLES	(1) $\Delta \ln(w)$	(2) $\Delta \ln(w)$	(3) $\Delta \ln(w)$	(4) $\Delta \ln(w)$
$\Delta \ln(K^{R,Q}_{JPN \to USA})$	-0.372		-0.271	
	(0.0466)		(0.0304)	
$\Delta \ln(K^{R,Q}_{USA})$		-0.144		-0.111
		(0.0300)		(0.0185)
Observations	324	324	324	324
R-squared	0.307	0.200	0.349	0.262
Controls			✓	✓

Note: Regression results of the changes in occupational wage are shown. Observations are 4-digit level occupations, and the regression is between 1990 and 2007 with the sample of all occupations that existed between 1970 and 2007. Columns 1 and 3 take robot measures from Japan from JARA data, while Columns 2 and 4 take robot measures from the world using IFR data as explained in the main text. Columns 1 and 2 do not include the control variables of demographic variables (female share, age distribution, college-graduate share, and foreign-born share) and China trade shock in (16), while Columns 3 and 4 do. Heteroskedasticity-robust standard errors are reported in the parenthesis.

Table Appendix B.4 shows the regression result of (B.2). The IFR data result aligns with the previous findings by Acemoglu and Restrepo (2020). Table Appendix B.4 reveals that both the JARA- and IFR-based robot measures capture the substitution of workers with robots, although the coefficient is somewhat larger for JARA robot measures than for IFR.

Appendix C. Theory Appendix

Appendix C.1. The Full Model

The full model used for structural estimation extends that in the model section with worker dynamics, intermediate goods, and non-robot capital.

Workers' Problem. I formalize the assumptions behind the derivation and show (C.3) and (C.4). Workers are immobile across countries but choose occupations by solving a dynamic discrete choice problem (Humlum, 2021). Specifically, workers choose occupations that maximize the lifetime utility based on switching costs and the draw of an idiosyncratic shock. The problem has a closed-form solution when the shock follows an extreme value distribution, which is the property used by the previous literature (e.g., Caliendo et al. (2019)).

Fix country i and period t. There is a mass $\overline{L}_{i,t}$ of workers. At the beginning of each period, worker $\omega \in \left[0, \overline{L}_{i,t}\right]$ draws a multiplicative idiosyncratic preference shock $\left\{Z_{i,o,t}\left(\omega\right)\right\}_o$ that follows an independent Fréchet distribution with scale parameter $A^V_{i,o,t}$ and shape parameter $1/\phi$. To keep the expression simple, I focus on the case of independent distribution. A worker ω works in the current occupation, earns income, consumes and derives logarithmic utility, and then chooses the next period's occupation with the discount rate ι. When selecting the next period occupation o', she pays an ad-valorem switching cost $\chi_{i,oo',t}$ in terms of consumption unit that depends on current occupation o. She consumes her income in each period. Thus, worker ω who currently works in occupation o_t maximizes the following objective function over the future stream of utilities by choosing occupations $\{o_s\}_{s=t+1}^{\infty}$:

$$E_t \sum_{s=t}^{\infty} \left(\frac{1}{1+\iota}\right)^{s-t} \left[\ln\left(C_{i,o_s,s}\right) + \ln\left(1 - \chi_{i,o_s o_{s+1},s}\right) + \ln\left(Z_{i,o_{s+1},s}\left(\omega\right)\right)\right] \quad \text{(C.1)}$$

where $C_{i,o,s}$ is a consumption bundle when working in occupation o in period $s \geq t$, and E_t is the expectation conditional on the value of $Z_{i,o_t,t}(\omega)$. Each worker owns occupation-specific labor endowment $l_{i,o,t}$. Her income comprises labor income $w_{i,o,t}$ and an occupation-specific ad-valorem government transfer with the rate $T_{i,o,t}$. Given the consumption price $P_{i,t}^G$, the budget constraint is

$$P_{i,t}^G C_{i,o,t} = w_{i,o,t} l_{i,o,t} \left(1 + T_{i,o,t}\right) \quad \text{(C.2)}$$

for any worker, with $P_{i,t}^G$ denoting the price index of the non-robot good G.

Following a similar derivation as Caliendo et al. (2019), (C.1) and (C.2) imply worker's optimization conditions characterized by, for each country i and period t, the transition probability $\mu_{i,oo',t}$ from occupation o in period t to occupation o' in period $t+1$, and the exponential expected value $V_{i,o,t}$ for occupation o that satisfy

$$\mu_{i,oo',t} = \frac{\left(\left(1 - \chi_{i,oo',t}\right)\left(V_{i,o',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}}{\sum_{o''}\left(\left(1 - \chi_{i,oo'',t}\right)\left(V_{i,o'',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}}, \quad \text{(C.3)}$$

$$V_{i,o,t} = \widetilde{\Gamma} C_{i,o,t} \left[\sum_{o'}\left(\left(1 - \chi_{i,oo',t}\right)\left(V_{i,o',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}\right]^{\frac{1}{\phi}}, \quad \text{(C.4)}$$

respectively, where $C_{i,o,t+1}$ is the real consumption, $\chi_{i,oo',t}$ is an ad-valorem switching cost from occupation o to o', ϕ is the occupation-switch elasticity, and $\widetilde{\Gamma} \equiv \Gamma\left(1 - 1/\phi\right)$ is a constant that depends on the Gamma function $\Gamma\left(\cdot\right)$.

For each i and t, the employment level satisfies the law of motion

$$L_{i,o,t+1} = \sum_{o'} \mu_{i,o'o,t} L_{i,o',t}. \tag{C.5}$$

Non-robot Good Producers' Problem. The producer's problem is made of two tiers–static optimization of labor input in each occupation and dynamic optimization of robot investment. The static part chooses employment conditional on market prices and the current stock of robot capital. Namely, for each i and t, conditional on the o-vector of the stock of robot capital $\left\{K^R_{i,o,t}\right\}_o$, producers solve

$$\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) \equiv \max_{\left\{L_{i,o,t}\right\}_o} p^G_{i,t} Y^G_{i,t} - \sum_o w_{i,o,t} L_{i,o,t}, \tag{C.6}$$

where $Y^G_{i,t}$ is presented by the production function (1).

The dynamic optimization problem involves choosing the size of the robot investment, given the current stock of robot capital. It is derived from the following three assumptions. First, for each i, o, and t, robot capital $K^R_{i,o,t}$ accumulates according to

$$K^R_{i,o,t+1} = (1-\delta) K^R_{i,o,t} + Q^R_{i,o,t}, \tag{C.7}$$

where $Q^R_{i,o,t}$ is the amount of new robot investment and δ is the depreciation rate of robots. Second, the new investment is presented by a CES aggregation of robot hardware from country l, $Q^R_{li,o,t}$, and non-robot good input $I^{int}_{i,o,t}$ that represents the input of software and integration or

$$Q^R_{i,o,t} = \left[\sum_l \left(Q^R_{li,o,t}\right)^{\frac{\varepsilon^R-1}{\varepsilon^R}}\right]^{\frac{\varepsilon^R}{\varepsilon^R-1}\alpha^R} \left(I^{int}_{i,o,t}\right)^{1-\alpha^R} \tag{C.8}$$

where l denotes the origin of the newly purchased robots, and α^R is the expenditure share of robot arms in the cost of investment. Discussions about the functional form choice of (C.8) are made in Appendix A.1. Third, installing robots is costly and requires a per-unit convex adjustment cost $\gamma Q^R_{i,o,t}/K^R_{i,o,t}$ measured in units of robots, where γ governs the size of the adjustment cost (e.g., Cooper and Haltiwanger, 2006), reflecting the sluggishness of robot adoption.

Given these assumptions, a producer of non-robot good G in a country i solves the dynamic optimization problem

$$\begin{aligned}\max_{\left\{\left\{Q^R_{li,o,t}\right\}_l, I^{int}_{i,o,t}\right\}_o} \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota}\right)^t \Bigg[\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) \\ - \sum_o \left(\sum_l p^R_{li,o,t}\left(1+u_{li,t}\right) Q^R_{li,o,t} + P^G_{i,t} I^{int}_{i,o,t} + \gamma P^R_{i,o,t} Q^R_{i,o,t} \frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\Bigg],\end{aligned} \tag{C.9}$$

subject to accumulation (C.7) and (C.8), and given $\left\{K^R_{i,o,0}\right\}_o$. A standard Lagrangian multiplier method yields Euler equations for investment, which are derived in Appendix C.2. Note that the Lagrange multiplier $\lambda^R_{i,o,t}$ represents the equilibrium marginal value of robot capital.

Intermediate Good Producers' Problem. The intermediate goods are the same goods as the non-robot goods but are an input to the production function. The stock of non-robot capital is exogenously given in each period for each country, and producers rent non-robot capital from the rental market. The non-robot good production function is presented by

$$Y^G_{i,t} = A^G_{i,t}\left\{\alpha_{i,L}\left(T^O_{i,t}\right)^{\frac{\vartheta-1}{\vartheta}} + \alpha_{i,M}\left(M_{i,t}\right)^{\frac{\vartheta-1}{\vartheta}} + \alpha_{i,K}\left(K_{i,t}\right)^{\frac{\vartheta-1}{\vartheta}}\right\}^{\frac{\vartheta}{\vartheta-1}},$$

where ϑ is the EoS between occupation aggregates, intermediates goods, and non-robot capital, and $\alpha_{i,L}$, $\alpha_{i,M}$, and $\alpha_{i,K} \equiv 1-\alpha_{i,L}-\alpha_{i,M}$ are cost share parameters for the occupation aggregates, intermediates, and non-robot capital, respectively. Parameters satisfy $\vartheta > 0$ and $\alpha_{i,L}, \alpha_{i,M}, \alpha_{i,K} > 0$, and in the structural estimation, I set $\vartheta = 1$ and compute each country's cost share parameters from the data. Intermediate goods are aggregated by

$$M_{i,t} = \left[\sum_{l} \left(M_{li,t} \right)^{\frac{\varepsilon - 1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon - 1}}, \tag{C.10}$$

where $\varepsilon > 0$ is the EoS between source countries. Since intermediate goods are traded across countries and aggregated by (C.10), the elasticity parameter ε plays the role of trade elasticity. The static decision of the producers now includes the rental amount of non-robot capital and the purchase of intermediate goods from each source country.

Equilibrium. To close the model, the employment level must satisfy an adding-up constraint

$$\sum_{o} L_{i,o,t} = \overline{L}_{i,t}, \tag{C.11}$$

and market clearing conditions for robots and non-robot goods must hold. There is one numeraire good to pin down the price system. In the following, a temporary equilibrium in each period is first defined, followed by a sequential equilibrium, leading to the definition of a steady state. The full expressions are provided in Appendix C.2.

I define the bold symbols as column vectors of robot capital $\boldsymbol{K}_t^R \equiv \left[K_{i,o,t}^R \right]_{i,o}$, marginal values of robot capital $\boldsymbol{\lambda}_t^R \equiv \left[\lambda_{i,o,t}^R \right]_{i,o}$, employment $\boldsymbol{L}_t \equiv \left[L_{i,o,t} \right]_{i,o}$, workers' value functions $\boldsymbol{V}_t \equiv \left[V_{i,o,t} \right]_{i,o}$, non-robot goods prices $\boldsymbol{p}_t^G \equiv \left[p_{i,t}^G \right]_i$, robot prices $\boldsymbol{p}_t^R \equiv \left[p_{i,o,t}^R \right]_{i,o}$, wages, $\boldsymbol{w}_t \equiv \left[w_{i,o,t} \right]_{i,o}$, bilateral non-robot goods trade levels $\boldsymbol{Q}_t^G \equiv \left[Q_{ij,t}^G \right]_{i,j}$, bilateral non-robot goods trade levels $\boldsymbol{Q}_t^R \equiv \left[Q_{ij,o,t}^R\right]_{i,j,o}$, and occupation transition shares $\boldsymbol{\mu}_t \equiv [\mu_{i,oo',t}]_{i,oo'}$, where $\boldsymbol{V}_t$ and $\boldsymbol{\mu}_t$ are explained in detail in Appendix C.1. I write $\boldsymbol{S}_t \equiv \left[\boldsymbol{K}_t^{R\prime}, \boldsymbol{\lambda}_t^{R\prime}, \boldsymbol{L}_t', \boldsymbol{V}_t'\right]'$ as state variables.

Definition 1. In each period t, given state variables $\boldsymbol{S}_t$, a *temporary equilibrium* (TE) $\boldsymbol{x}_t$ is the set of prices $\boldsymbol{p}_t \equiv \left[\boldsymbol{p}_t^{G\prime}, \boldsymbol{p}_t^{R\prime}, \boldsymbol{w}_t'\right]'$ and flow quantities $\boldsymbol{Q}_t \equiv \left[\boldsymbol{Q}_t^{G\prime}, \boldsymbol{Q}_t^{R\prime}, \boldsymbol{\mu}_t'\right]$ that satisfy: (i) given $\boldsymbol{p}_t$, workers choose occupations optimally by (C.3), (ii) given $\boldsymbol{p}_t$, producers maximize flow profit by (C.6) and demand robots by (C.17), and (iii) markets clear: Labor adds up as in (C.11), and goods markets clear with trade balances as in (C.25) and (C.27).

In other words, the inputs of the TE are all state variables, while the outputs are all endogenous variables determined in each period. Adding the conditions about state variable transitions, a sequential equilibrium determines all state variables given initial conditions as follows.

Definition 2. Given initial robot capital stocks and employment $\left[\boldsymbol{K}_0^{R\prime}, \boldsymbol{L}_0'\right]'$, a *sequential equilibrium* (SE) is a sequence of vectors $\boldsymbol{y}_t \equiv [\boldsymbol{x}_t', \boldsymbol{S}_t']_t'$ that satisfies the TE conditions and employment law of motion (C.5), the value function condition (C.4), capital accumulation (C.7), producer's dynamic optimization (C.21) and (C.20).

Finally, I define the steady state as a SE $\boldsymbol{y}$ that does not change over time.

Appendix C.2. Equilibrium Characterization

To characterize the producer problem, I show the static optimization conditions and then the dynamic ones. For simplicity, I focus on the case with

$\vartheta = 1$, or Cobb-Douglas in the mix of occupation aggregates, intermediates, and non-robot capital. To solve for the static problem of labor, intermediate goods, and non-robot capital, consider the first-order conditions (FOCs) of (C.6)

$$p_{i,t}^{G}\alpha_{i,L}\frac{Y_{i,t}^{G}}{T_{i,t}^{O}}\left(b_{i,o,t}\frac{T_{i,t}^{O}}{T_{i,o,t}^{O}}\right)^{\frac{1}{\beta}}\left(\left(1-a_{o,t}\right)\frac{T_{i,o,t}^{O}}{L_{i,o,t}}\right)^{\frac{1}{\theta_o}} = w_{i,o,t}, \tag{C.12}$$

where $T_{i,t}^{O}$ is the aggregated occupations $T_{i,t}^{O} \equiv \left[\sum_o \left(T_{i,o,t}^{O}\right)^{(\beta-1)/\beta}\right]^{\beta/(\beta-1)}$,

$$p_{i,t}^{G}\alpha_{i,M}\frac{Y_{i,t}^{G}}{M_{i,t}}\left(\frac{M_{i,t}}{M_{li,t}}\right)^{\frac{1}{\varepsilon}} = p_{li,t}^{G}, \tag{C.13}$$

and

$$p_{i,t}^{G}\alpha_{i,K}\frac{Y_{i,t}^{G}}{K_{i,t}} = r_{i,t}, \tag{C.14}$$

where $\alpha_{i,K} \equiv 1 - \alpha_{i,L} - \alpha_{i,M}$. Note also that by the envelope theorem,

$$\frac{\partial \pi_{i,t}\left(\left\{K_{i,o,t}^{R}\right\}\right)}{\partial K_{i,o,t}^{R}} = p_{i,t}^{G}\frac{\partial Y_{i,t}}{\partial K_{i,o,t}^{R}} = p_{i,t}^{G}\left(\alpha_L\frac{Y_{i,t}^{G}}{T_{i,t}^{O}}\left(b_{i,o,t}\frac{T_{i,t}^{O}}{T_{i,o,t}^{O}}\right)^{\frac{1}{\beta}}\left(a_{o,t}\frac{T_{i,o,t}^{O}}{K_{i,o,t}^{R}}\right)^{\frac{1}{\theta}}\right). \tag{C.15}$$

Another static problem for producers is robot purchase. Define the "before-integration" robot aggregate $Q_{i,o,t}^{R,BI} \equiv \left[\sum_l \left(Q_{li,o,t}^{R}\right)^{\frac{\varepsilon^R-1}{\varepsilon^R}}\right]^{\frac{\varepsilon^R}{\varepsilon^R-1}}$ and the corresponding price index $P_{i,o,t}^{R,BI}$. By the first order condition with respect to $Q_{li,o,t}^{R}$ for (C.8), I have $p_{li,o,t}^{R}Q_{li,o,t}^{R} = \left(\frac{p_{li,o,t}^{R}}{P_{i,o,t}^{R,BI}}\right)^{1-\varepsilon^R} P_{i,o,t}^{R,BI}Q_{i,o,t}^{R,BI}$, and $P_{i,o,t}^{R,BI}Q_{i,o,t}^{R,BI} = \alpha P_{i,o,t}^{R}Q_{i,o,t}^{R}$. Thus $p_{li,o,t}^{R}Q_{li,o,t}^{R} = \alpha\left(\frac{p_{li,o,t}^{R}}{P_{i,o,t}^{R,BI}}\right)^{1-\varepsilon^R} P_{i,o,t}^{R}Q_{i,o,t}^{R}$. Hence

$$Q_{li,o,t}^{R} = \alpha\left(p_{li,o,t}^{R}\right)^{-\varepsilon^R}\left(P_{i,o,t}^{R,BI}\right)^{\varepsilon^R-1}P_{i,o,t}^{R}Q_{i,o,t}^{R}.$$

Writing $P^R_{i,o,t} = \left(P^{R,BI}_{i,o,t}\right)^{\alpha^R} \left(P_{i,t}\right)^{1-\alpha^R}$, I have

$$Q^R_{li,o,t} = \alpha \left(\frac{p^R_{li,o,t}}{P^{R,BI}_{i,o,t}}\right)^{-\varepsilon^R} \left(\frac{P^{R,BI}_{i,o,t}}{P_{i,t}}\right)^{-\left(1-\alpha^R\right)} Q^R_{i,o,t}.$$

Alternatively, one can define the robot price index by $\widetilde{P}^R_{i,o,t} = \alpha^{\frac{1}{\varepsilon^R}} \left(P^{R,BI}_{i,o,t}\right)^{\frac{\varepsilon^R - \left(1-\alpha^R\right)}{\varepsilon^R}} P_{i,t}^{\frac{1-\alpha^R}{\varepsilon^R}}$ and show

$$Q^R_{li,o,t} = \left(\frac{p^R_{li,o,t}}{\widetilde{P}^R_{i,o,t}}\right)^{-\varepsilon^R} Q^R_{i,o,t}, \tag{C.16}$$

which is a standard gravity representation of robot trade.

To solve the dynamic problem, set up the (current-value) Lagrangian function for non-robot goods producers

$$\mathcal{L}_{i,t} = \sum_{t=0}^{\infty} \left\{ \left(\frac{1}{1+\iota}\right)^t \left[\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) - \sum_{l,o}\left(p^R_{li,o,t}\left(1+u_{li,t}\right) Q^R_{li,o,t} + P^G_{i,t} I^{int}_{i,o,t} + \gamma P^R_{i,o,t} Q^R_{i,o,t} \frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\right]\right.$$
$$\left. - \lambda^R_{i,o,t}\left\{K^R_{i,o,t+1} - (1-\delta) K^R_{i,o,t} - Q^R_{i,o,t}\right\}\right\}$$

Taking the FOC with respect to the hardware from country l, $Q^R_{li,o,t}$, I have

$$p^R_{li,o,t}\left(1+u_{li,t}\right) + 2\gamma P^R_{i,o,t}\left(\frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\frac{\partial Q^R_{i,o,t}}{\partial Q^R_{li,o,t}} = \lambda^R_{i,o,t}\frac{\partial Q^R_{i,o,t}}{\partial Q^R_{li,o,t}}. \tag{C.17}$$

Taking the FOC with respect to the integration input $I^{int}_{i,o,t}$, I have

$$P^G_{i,t} + 2\gamma P^R_{i,o,t}\left(\frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\frac{\partial Q^R_{i,o,t}}{\partial I^{int}_{i,o,t}} = \lambda^R_{i,o,t}\frac{\partial Q^R_{i,o,t}}{\partial I^{int}_{i,o,t}}, \tag{C.18}$$

Taking the FOC with respect to $K^R_{i,o,t+1}$, I have

$$\left(\frac{1}{1+\iota}\right)^{t+1}\left[\frac{\partial \pi_{i,t+1}\left(\left\{K^R_{i,o,t+1}\right\}_o\right)}{\partial K^R_{i,o,t+1}} + \gamma P^R_{i,o,t+1}\left(\frac{Q^R_{i,o,t+1}}{K^R_{i,o,t+1}}\right)^2 + (1-\delta)\lambda^R_{i,o,t+1}\right] - \left(\frac{1}{1+\iota}\right)^t \lambda^R_{i,o,t} = 0, \tag{C.19}$$

and the transversality condition: for any j and o,

$$\lim_{t\to\infty} e^{-\iota t}\lambda^R_{j,o,t}K^R_{j,o,t+1} = 0. \tag{C.20}$$

Rearranging equation (C.19), I obtain the following Euler equation.

$$\lambda^R_{i,o,t} = \frac{1}{1+\iota}\left[\left(1-\delta\right)\lambda^R_{i,o,t+1} + \frac{\partial}{\partial K^R_{i,o,t+1}}\pi_{i,t+1}\left(\left\{K^R_{i,o,t+1}\right\}\right) + \gamma p^R_{i,o,t+1}\left(\frac{Q^R_{i,o,t+1}}{K^R_{i,o,t+1}}\right)^2\right]. \tag{C.21}$$

Turning to the demand for non-robot goods, in the following, I characterize bilateral intermediate goods trade demand and total expenditure. Write $X^G_{j,t}$ the total purchase quantity (but not value) of good G in country j in period t. By (C.10), the bilateral trade demand is given by

$$p^G_{ij,t}Q^G_{ij,t} = \left(\frac{p^G_{ij,t}}{P^G_{j,t}}\right)^{1-\varepsilon} P^G_{j,t}X^G_{j,t}, \tag{C.22}$$

for any i, j, and t. In this equation, $P^G_{j,t}X^G_{j,t}$ is the total expenditures on non-robot goods. The total expenditure is the sum of final consumption $I_{j,t}$, payment to intermediate goods $\alpha_M p^G_{j,t}Y^G_{j,t}$, input to robot productions $\sum_o P^G_{j,t}I^R_{j,o,t} = \sum_{o,k} p^R_{jk,o,t}Q^R_{jk,o,t}$, and payment to robot integration $\sum_o P^G_{j,t}I^{int}_{j,o,t} = \left(1-\alpha^R\right)\sum_o P^R_{j,o,t}Q^R_{j,o,t}$. Hence

$$P^G_{j,t}X^G_{j,t} = I_{j,t} + \alpha_M p^G_{j,t}Y^G_{j,t} + \sum_{o,k} p^R_{jk,o,t}Q^R_{jk,o,t} + \left(1-\alpha^R\right)\sum_o P^R_{j,o,t}Q^R_{j,o,t}.$$

For country j and period t, by substituting into income $I_{j,t}$ the period cash flow of non-robot goods producer that satisfies

$$\Pi_{j,t} \equiv \pi_{j,t}\left(\left\{K^R_{j,o,t}\right\}_o\right) - \sum_{i,o}\left(p^R_{ij,o,t}\left(1+u_{ij,t}\right)Q^R_{ij,o,t} + \sum_o P^G_{j,t}I^{int}_{j,o,t} + \gamma P^R_{j,o,t}Q^R_{j,o,t}\left(\frac{Q^R_{j,o,t}}{K^R_{j,o,t}}\right)\right)$$

and robot tax revenue $T_{j,t} = \sum_{i,o} u_{ij,t} p^R_{ij,o,t} Q^R_{ij,o,t}$, I have

$$I_{j,t} = (1-\alpha_M) \sum_k p^G_{jk,t} Q^G_{jk,t} - \left(\sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} + \left(1-\alpha^R\right) \sum_o P^R_{j,o,t} Q^R_{j,o,t} \right), \tag{C.23}$$

or in terms of variables in the definition of equilibrium,

$$I_{j,t} = (1-\alpha_M) \sum_k p^G_{jk,t} Q^G_{jk,t} - \frac{1}{\alpha^R} \sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t}.$$

Hence, the total expenditure measured in terms of the production side, as opposed to the income side, is

$$P^G_{j,t} X^G_{j,t} = \sum_k p^G_{jk,t} Q^G_{jk,t} - \sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} \left(1 + \gamma \frac{Q^R_{ij,o,t}}{K^R_{j,o,t}} \right). \tag{C.24}$$

Note that this equation embeds the balanced trade condition. By substituting (C.24) into the (C.22), I have

$$p^G_{ij,t} Q^G_{ij,t} = \left(\frac{p^G_{ij,t}}{P^G_{j,t}} \right)^{1-\varepsilon^G} \left(\sum_k p^G_{jk,t} Q^G_{jk,t} + \sum_{k,o} p^R_{jk,o,t} Q^R_{jk,o,t} - \sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} \right). \tag{C.25}$$

The good and robot-o market-clearing conditions are given by,

$$Y^R_{i,t} = \sum_j Q^G_{ij,t} \tau^G_{ij,t}, \tag{C.26}$$

for all i and t, and

$$p^R_{i,o,t} = \frac{P^G_{i,t}}{A^R_{i,o,t}} \tag{C.27}$$

for all i, o, and t, respectively.

Conditional on state variables $\boldsymbol{S}_t = \left\{ \boldsymbol{K}^R_t, \boldsymbol{\lambda}^R_t, \boldsymbol{L}_t, \boldsymbol{V}_t \right\}$, (C.3), (C.12), (C.17), (C.25), (C.26), and (C.27) characterize the TE $\left\{ \boldsymbol{p}^G_t, \boldsymbol{p}^R_t, \boldsymbol{w}_t, \boldsymbol{Q}^G_t, \boldsymbol{Q}^R_t, \boldsymbol{L}_t \right\}$.

In addition, conditional on initial conditions $\left\{\boldsymbol{K}_0^R, \boldsymbol{L}_0\right\}$, (C.7), (C.21), and (C.20) characterize the SE.

Finally, the steady-state conditions are provided by imposing the time-invariance condition to (C.7) and (C.21):

$$Q_{i,o}^R = \delta K_{i,o}^R, \tag{C.28}$$

$$\frac{\partial}{\partial K_{i,o}^R} \pi_i \left(\left\{ K_{i,o}^R \right\} \right) = \left(\iota + \delta \right) \lambda_{i,o}^R - \sum_l \gamma p_{li,o}^R \left(\frac{Q_{li,o}^R}{K_{i,o}^R} \right)^2 \equiv c_{i,o}^R. \tag{C.29}$$

Note that (C.29) can be interpreted as equalizing the flow marginal profit of capital to the marginal cost. Thus, I define the steady-state marginal cost of robot capital $c_{i,o}^R$ from the right-hand side of (C.29). Note that if there is no adjustment cost $\gamma = 0$, the steady state Euler equation (C.29) implies

$$\frac{\partial}{\partial K_{i,o}^R} \pi_i \left(\left\{ K_{i,o}^R \right\} \right) = c_{i,o}^R = \left(\iota + \delta \right) \lambda_{i,o}^R,$$

which states that the marginal profit of capital is equal to the user cost of robots in the steady state.

Appendix C.3. The First-Order Approximation of the General Equilibrium

Because the GE system is highly nonlinear and does not have a closed-form solution due to flexible robot-labor substitution, the equilibrium system of equations is log-linearized around the initial steady state. Consider the increases in the robot task space $a_{o,t}$ and in the productivity of the robot production $A_{i,o,t}^R$ in baseline period t_0, and combine all these changes into a column vector $\boldsymbol{\Delta}$. Write state variables $\boldsymbol{S}_t = \left[\boldsymbol{K}_t^{R\prime}, \boldsymbol{\lambda}_t^{R\prime}, \boldsymbol{L}_t^\prime, \boldsymbol{V}_t^\prime \right]^\prime$, and use "hat" notation to denote changes from t_0, or $\widehat{z}_t \equiv \ln\left(z_t\right) - \ln\left(z_{t_0}\right)$ for any variable z_t,. I take the following three steps to solve the model.

Step 1. In given period t, I combine the vector of shocks $\boldsymbol{\Delta}$ and (given) changes in state variables $\widehat{\boldsymbol{S}_t}$ into a column vector $\widehat{\boldsymbol{A}_t} = \left[\boldsymbol{\Delta}', \widehat{\boldsymbol{S}_t}'\right]'$. Log-linearizing the TE conditions, I solve for matrices $\overline{\boldsymbol{D}^x}$ and $\overline{\boldsymbol{D}^A}$ such that the log-difference of the TE $\widehat{\boldsymbol{x}}_t$ satisfies

$$\overline{\boldsymbol{D}^x}\widehat{\boldsymbol{x}}_t = \overline{\boldsymbol{D}^A}\widehat{\boldsymbol{A}_t}. \tag{C.30}$$

In this equation, $\overline{\boldsymbol{D}^x}$ is a substitution matrix, and $\overline{\boldsymbol{D}^A}\widehat{\boldsymbol{A}_t}$ is a vector of partial equilibrium shifts in period t Adao et al. (2023).[24]

Step 2. Log-linearizing the laws of motion and Euler equations around the initial steady state, I solve for matrices $\overline{\boldsymbol{D}^{y,SS}}$ and $\overline{\boldsymbol{D}^{\Delta,SS}}$ such that $\overline{\boldsymbol{D}^{y,SS}}\widehat{\boldsymbol{y}} = \overline{\boldsymbol{D}^{\Delta,SS}}\boldsymbol{\Delta}$, where superscript SS denotes the steady state. Note that there exists a block separation $\overline{\boldsymbol{D}^A} = \left[\overline{\boldsymbol{D}^{A,\Delta}} | \overline{\boldsymbol{D}^{A,S}}\right]$ such that equation (C.30) can be written as

$$\overline{\boldsymbol{D}^x}\widehat{\boldsymbol{x}}_t - \overline{\boldsymbol{D}^{A,S}}\widehat{\boldsymbol{S}_t} = \overline{\boldsymbol{D}^{A,\Delta}}\boldsymbol{\Delta}. \tag{C.31}$$

Combined with this equation evaluated at the steady state, I have

$$\overline{\boldsymbol{E}^y}\widehat{\boldsymbol{y}} = \overline{\boldsymbol{E}^\Delta}\boldsymbol{\Delta}, \tag{C.32}$$

where

$$\overline{\boldsymbol{E}^y} \equiv \left[\begin{array}{cc} \overline{\boldsymbol{D}^x} & -\overline{\boldsymbol{D}^{A,T}} \\ \multicolumn{2}{c}{\overline{\boldsymbol{D}^{y,SS}}} \end{array}\right], \text{ and } \overline{\boldsymbol{E}^\Delta} \equiv \left[\begin{array}{c} \overline{\boldsymbol{D}^{A,\Delta}} \\ \overline{\boldsymbol{D}^{\Delta,SS}} \end{array}\right],$$

[24] Because the TE vector $\widehat{\boldsymbol{x}_t}$ includes wages $\widehat{\boldsymbol{w}_t}$, (C.30) generalizes the general equilibrium comparative statics formulation in Adao et al. (2023), who consider the variant of (C.30) with $\widehat{\boldsymbol{x}_t} = \widehat{\boldsymbol{w}_t}$.

which implies $\widehat{\boldsymbol{y}} = \overline{\boldsymbol{E}}\boldsymbol{\Delta}$, where matrix $\overline{\boldsymbol{E}} = \left(\overline{\boldsymbol{E}^{y}}\right)^{-1}\overline{\boldsymbol{E}^{\Delta}}$ represents the first-order approximated steady-state impact of the shock $\boldsymbol{\Delta}$. This steady-state matrix $\overline{\boldsymbol{E}}$ will be a key object in estimating the model in Section 3.2.

Step 3. Log-linearizing the laws of motion and Euler equations around the new steady state, I solve for matrices $\overline{\boldsymbol{D}_{t+1}^{y,TD}}$ and $\overline{\boldsymbol{D}_{t}^{y,TD}}$ such that $\overline{\boldsymbol{D}_{t+1}^{y,TD}}\check{\boldsymbol{y}}_{t+1} = \overline{\boldsymbol{D}_{t}^{y,TD}}\check{\boldsymbol{y}}_{t}$, where the superscript TD stands for transition dynamics, and $\check{z}_{t+1} \equiv \ln z_{t+1} - \ln z'$ and z' is the new steady state value for any variable z. Log-linearized SE satisfies the following first-order difference equation

$$\overline{\boldsymbol{F}_{t+1}^{y}}\widehat{\boldsymbol{y}_{t+1}} = \overline{\boldsymbol{F}_{t}^{y}}\widehat{\boldsymbol{y}}_{t} + \overline{\boldsymbol{F}_{t+1}^{\Delta}}\boldsymbol{\Delta}. \tag{C.33}$$

Following the insights in Blanchard and Kahn (1980), there is a converging matrix representing the first-order transitional dynamics $\overline{\boldsymbol{F}_{t}}$ such that

$$\widehat{\boldsymbol{y}}_{t} = \overline{\boldsymbol{F}_{t}}\boldsymbol{\Delta} \text{ and } \overline{\boldsymbol{F}_{t}} \to \overline{\boldsymbol{E}}. \tag{C.34}$$

The matrix $\overline{\boldsymbol{F}_{t}}$ characterizes the transition dynamics after robotization shocks and is used to study the effect of policy changes in counterfactual analyses.

Appendix D. Additional Results on Estimation and Simulation

Following the convention in the literature, I assume $\alpha^{R} = 2/3$, meaning that the share of robot integration cost is two-thirds of the total robot-related expenditure. As in Cooper and Haltiwanger (2006), the parameter of adjustment cost is set at $\gamma = 0.295$. The estimates from the literature on the dynamic discrete choice of occupations are used and the occupation switching elasticity is set as $\phi = 1.4$.

Appendix D.1. Robot Trade Elasticity

To estimate robot trade elasticity ε^R, I apply and extend the trilateral method of Caliendo and Parro (2015). First, decompose the robot trade cost $\tau^R_{li,t}$ into $\ln \tau^R_{li,t} = \ln \tau^{R,T}_{li,t} + \ln \tau^{R,D}_{li,t}$, where $\tau^{R,T}_{li,t}$ is the tariff on robots taken from the UNCTAD-TRAINS database and $\tau^{R,D}_{li,t}$ is the asymmetric non-tariff trade cost. The latter term is assumed to be $\ln \tau^{R,D}_{li,t} = \ln \tau^{R,D,S}_{li,t} + \ln \tau^{R,D,O}_{l,t} + \ln \tau^{R,D,D}_{i,t} + \ln \tau^{R,D,E}_{li,t}$, where $\tau^{R,D,S}_{li,t}$ captures symmetric bilateral trade costs such as distance, common border, language, and free-trade agreement (FTA) belonging status and satisfies $\tau^{R,D,S}_{li,t} = \tau^{R,D,S}_{il,t}$, $\tau^{R,D,O}_{l,t}$ and $\tau^{R,D,D}_{i,t}$ are the origin and destination FEs such as non-tariff barriers respectively, and $\tau^{R,D,E}_{li,t}$ is the random error that is orthogonal to tariffs. By (C.16), I have

$$\ln\left(\frac{X^R_{li,t}X^R_{ij,t}X^R_{jl,t}}{X^R_{lj,t}X^R_{ji,t}X^R_{il,t}}\right) = \left(1-\varepsilon^R\right)\ln\left(\frac{\tau^{R,T}_{li,t}\tau^{R,T}_{ij,t}\tau^{R,T}_{jl,t}}{\tau^{R,T}_{lj,t}\tau^{R,T}_{ji,t}\tau^{R,T}_{il,t}}\right) + e_{lij,t}, \tag{D.1}$$

where $X^R_{li,t}$ is the bilateral sales of robots from l to i in year t and $e_{lij,t} \equiv \ln \tau^{R,D,E}_{li,t} + \ln \tau^{R,D,E}_{ij,t} + \ln \tau^{R,D,E}_{jl,t} - \ln \tau^{R,D,E}_{lj,t} - \ln \tau^{R,D,E}_{ji,t} - \ln \tau^{R,D,E}_{il,t}$. The benefit of this approach is that it does not require symmetry for non-tariff trade cost $\tau^{R,D}_{li}$, but only the orthogonality condition for the asymmetric component of the trade cost. My method also extends Caliendo and Parro (2015) in using the time-series variation as well as trilateral country-level variation to complement the relatively small number of observations in robot trade data.

When regressing (D.1), I further consider controlling for two separate sets of FEs. The first is the unilateral FE indicating if a country is included in the trilateral pair of countries, and the second is the bilateral FE for the pair of countries. These FEs are relevant in my setting as only a few countries export robots, and controlling for these exporters' unobserved characteristics is critical.

Table Appendix D.1 shows the result of the regression of (D.1). The first two columns show the result for the HS code 847950 ("Industrial robots for multiple uses", the definition of robots used in, among others, Acemoglu and Restrepo, 2022), and the last two columns HS code 8479 ("Machines and mechanical appliances having individual functions, not specified or included elsewhere in this chapter," used by Humlum, 2021). The first and third columns control for the unilateral FE, while the second and fourth control the bilateral FE. The implied trade elasticity of robots ε^R is fairly tightly estimated and ranges between 1.13 and 1.34. Given these estimation results, I use $\varepsilon^R = 1.2$ in the estimation and counterfactuals.

To put my estimation result in context, note that Caliendo and Parro (2015) showed in Table 1 that the regression coefficient of equation (D.1) is 1.52, with the standard error of 1.81, for "Machinery n.e.c", corresponding to HS 84. Therefore, my estimate for industrial robots falls in the one-standard-deviation range of their estimate for a broader category of goods.

Note that the average trade elasticity across sectors is estimated to be significantly higher than these values, such as 4 in Simonovska and Waugh (2014). The low trade elasticity for robots ε^R reflects that robots are highly heterogeneous and hardly substitutable. This low elasticity implies small gains from robot taxes, with the robot tax incidence almost on the US (robot buyer) side rather than that of the robot-selling country.

Appendix D.2. Detailed Discussion of the Estimator

Using Assumption 1, I develop a consistent and asymptotically efficient two-step estimator. Specifically, I follow the method developed by Adao

Table Appendix D.1: Coefficient of equation (D.1)

	(1) HS 847950	(2) HS 847950	(3) HS 8479	(4) HS 8479
Tariff	-0.272	-0.236	-0.146	-0.157
	(0.0718)	(0.0807)	(0.0127)	(0.0131)
Constant	-0.917	-0.893	-1.170	-1.170
	(0.0415)	(0.0381)	(0.00905)	(0.00853)
FEs	h-i-j-t	ht-it-jt	h-i-j-t	ht-it-jt
N	4610	4521	88520	88441
r2	0.494	0.662	0.602	0.658

Note: The author's calculation, based on BACI data from 1996 to 2018 and equation (D.1), is shown. The first two columns show the result for HS code 847950 ("Industrial robots for multiple uses"), while the last two columns show HS code 8479 ("Machines and mechanical appliances having individual functions, not specified or included elsewhere in this chapter"). The first and third columns control the unilateral fixed effect, while the second and fourth control the bilateral FE.

et al. (2023), who extended the classical two-stage GMM estimator to the general equilibrium environment and defined the MOIV. The key idea is that the optimal GMM estimator is based on the instrumental variable that depends on unknown structural parameters. The two-step estimator solves this unknown-dependence problem and achieves consistency and asymptotic efficiency. Specifically, I define IVs $Z_{o,n}$ where $n = 0, 1$ as follows:

$$Z_{o,n} \equiv H_{o,n}\left(\boldsymbol{\psi}^{J}\right) = \mathbb{E}\left[\nabla_{\boldsymbol{\Theta}}\nu_{o}\left(\boldsymbol{\Theta}_{n}\right)|\boldsymbol{\psi}^{J}\right]\mathbb{E}\left[\nu_{o}\left(\boldsymbol{\Theta}_{n}\right)\left(\nu_{o}\left(\boldsymbol{\Theta}_{n}\right)\right)^{\top}|\boldsymbol{\psi}^{J}\right]^{-1}, \tag{D.2}$$

where ν_o is the function of the structural residual satisfying

$$\boldsymbol{\nu_w} = \boldsymbol{\nu_w}(\Theta) = \widehat{\boldsymbol{w}} - \bar{\boldsymbol{E}}_{\boldsymbol{w}_1,\boldsymbol{a}}\widehat{\boldsymbol{a}^{\text{obs}}} - \bar{\boldsymbol{E}}_{\boldsymbol{w}_1,\boldsymbol{A}_2^R}\widehat{\boldsymbol{A}_2^R} - \bar{\boldsymbol{E}}_{\boldsymbol{w}_1,\boldsymbol{b}}\widehat{\boldsymbol{b}},$$

in a matrix notation. For the formal statement, the following additional assumption is needed.

Assumption 2. *(i) A function of* $\widetilde{\boldsymbol{\Theta}}$, $\mathbb{E}\left[H_o\left(\boldsymbol{\psi}_{t_1}^J\right)\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\right] \neq 0$ *for any* $\widetilde{\boldsymbol{\Theta}} \neq \boldsymbol{\Theta}$. *(ii)* $\underline{\theta} \leq \theta_o \leq \overline{\theta}$ *for any* o, $\underline{\beta} \leq \beta \leq \overline{\beta}$, $\underline{\gamma} \leq \gamma \leq \overline{\gamma}$, *and* $\underline{\phi} \leq \phi \leq \overline{\phi}$ *for some positive values* $\underline{\theta}, \underline{\beta}, \underline{\gamma}, \underline{\phi}, \overline{\theta}, \overline{\beta}, \overline{\gamma}, \overline{\phi}$. *(iii)* $\mathbb{E}\left[\sup_{\boldsymbol{\Theta}} \parallel H_o\left(\boldsymbol{\psi}_{t_1}^J\right)\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\parallel\right] < \infty$. *(iv)* $\mathbb{E}\left[\parallel H_o\left(\boldsymbol{\psi}_{t_1}^J\right)\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\parallel^2\right] < \infty$ *(v)* $\mathbb{E}\left[\sup_{\boldsymbol{\Theta}} \parallel H_o\left(\boldsymbol{\psi}_{t_1}^J\right)\nabla_{\widetilde{\boldsymbol{\Theta}}}\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\parallel\right] < \infty$.

Under Assumptions 1 and 2, Adao et al. (2023) showed that the estimator $\boldsymbol{\Theta}_2$ obtained in the following procedure is consistent, asymptotically normal, and optimal: Step 1: With a guess $\boldsymbol{\Theta}_0$, estimate $\boldsymbol{\Theta}_1 = \boldsymbol{\Theta}_{\boldsymbol{H}_0}$ using $Z_{o,0}$ defined in (D.2); and Step 2: With $\boldsymbol{\Theta}_1$, estimate $\boldsymbol{\Theta}_2$ by $\boldsymbol{\Theta}_2 = \boldsymbol{\Theta}_{\boldsymbol{H}_1}$ using $Z_{o,1}$ defined in (D.2).

Appendix D.3. Model Fit

I apply the simulated data to the linear regression model (B.1). First, I apply the JRS and the implied automation shock, calling this counterfactual wage change a "targeted change." The predicted wage changes are consistent with the moment condition (15), and, thus, the linear regression coefficient α_1 of (B.1) is expected to be matched with that obtained from the data. Second, I apply only the JRS but not the automation shock, calling this counterfactual wage change an "untargeted change." In this case, the moment condition (15) is violated since the structural residual does not incorporate the unobserved automation shock, causing a bias in the regression. The difference in estimates from the one using the targeted wage change reveals the size of this bias. Therefore, this exercise demonstrates the importance

Table Appendix D.2: Model Fit: Linear Regression with Observed and Simulated Data

	(1)	(2)	(3)
VARIABLES	$\widehat{\boldsymbol{w}}_{data}$	$\widehat{\boldsymbol{w}}_{\psi^J \widehat{\boldsymbol{a}^{imp}}}$	$\widehat{\boldsymbol{w}}_{\psi^J}$
$-\psi^J$	-0.118	-0.107	-0.536
	(0.0569)	(0.0711)	(0.175)
Observations	324	324	324

Note: Model fit exercises using various simulations based on the estimated model is shown. Column (1) is the coefficient of the JRS ψ^J in the reduced-form regression with the China shock control. Column (2) takes the change in US wages predicted by the model with ψ^J and the implied automation shock $\widehat{\boldsymbol{a}^{\text{imp}}}$. Column (3) takes the US wage change predicted by the model with only the JRS (but not the automation shock). Heteroskedasticity-robust standard errors are in parentheses.

of considering the automation shock in the estimation. The details of the method for simulating the data are provided in Appendix D.4.

Table Appendix D.2 shows the result of these exercises. The first column shows the estimates of (B.1) using the data, the second column is the estimate based on the targeted wage change, and the third column is the estimate based on the untargeted wage change. As expected, comparing the first and second columns confirms that the targeted moments match. Furthermore, comparing the third column with these two columns reveals a stronger negative correlation between the simulated wage and the JRS. This is due to the positive correlation between the JRS $-\psi_o^J$ and the implied automation shock $\widehat{a_o^{\text{imp}}}$, which is consistent with the fact that robotic innovations that save costs (thus $\widehat{A_{2,o}^R} > 0$ or $-\widehat{\psi_o^J} > 0$) and that upgrades in quality (thus $\widehat{a_o^{\text{imp}}} > 0$) are likely to happen at the same time. More specifically, with the real data, the regression specification (B.1) contains a positive bias due to this positive correlation. In contrast, the untargeted wage is free from this bias since its data-generating process only contains the JRS, not the automation shock. Thus, the linear regression coefficient α_1 is higher than that obtained from the real data. In other words, if I had mistakenly assumed that the economy did not experience the automation shock and if I had believed that the coefficient obtained in Figure Appendix B.2 was bias-free, I would have estimated a higher EoS by ignoring the actual positive correlation between $-\psi_o^J$ and $\widehat{a_o^{\text{imp}}}$. This thought experiment reveals that it is critical to consider the automation shock in estimating the EoS between robots and labor using the JRS and that the large EoS in my structural estimates is robust even after taking this point into account.

Appendix D.4. Details in the Simulation Method

The simulation for the counterfactual analysis comprises three steps. First, the observed shocks are backed out from the estimated model for each year between 1992 and 2007. Namely, I obtain the efficiency increase of Japanese robots $\widehat{A_{2,o,t}^R}$ using (12). With the point estimates in Table 1, the implied automation shock $\widehat{a_{o,t}^{\text{imp}}}$ using (13). To back out the efficiency shock of robots in the other countries, I assume that $\widehat{A_{i,o,t}^R} = \widehat{A_{i,t}^R}$ for $i = 1, 3$. Then by the robot trade prices $p_{ij,t}^R$ from BACI, I fit a fixed-effect regression $\Delta \ln \left(p_{ij,t}^R\right) = \widetilde{\psi}_{j,t}^D + \widetilde{\psi}_{i,t}^C + \widetilde{e}_{ij,t}$, and use $\widehat{A_{i,t}^R} = -\widetilde{\psi}_{i,t_1}^C$. The idea to back out the negative efficiency shock $\widetilde{\psi}_{i,t_1}^C$ is similar to the fixed-effect regression in Section 3.2, but without the occupational variation that is not observed in the BACI data. Second, applying the backed-out shocks $\widehat{A_{i,o,t}^R}$ and $\widehat{a_{o,t}^{\text{imp}}}$ to the first-order solution of the GE in (C.34) obtains the prediction of changes in endogenous variables to these shocks to the first-order. Finally, the predicted level of endogenous variables is obtained by applying the predicted changes to the initial data in $t_0 = 1992$.

Appendix D.5. The Effect of Robotization and the Sources of Shocks

Figure 2b shows the effect of two robotization shocks in a sum: the automation shock $\widehat{\boldsymbol{a}}$ and the JRS $\widehat{\boldsymbol{A}}_2$. Although both are relevant shocks to robotics technology during the sample period, the result on the wage distribution combines these two effects, making it difficult to assess the contribution of each shock. To address this concern, Figure Appendix D.1 shows the decomposition of the main exercise. The left panel has the same result as Figure 2b. In contrast, the center panel shows the predicted wage changes with only the automation shock and the right only the JRS. Notably, the automation shock reduces the labor demand and, thus, the wage across many occupations. By contrast, the JRS decreased the price of robots and increased the marginal product of labor, increasing occupational wages.

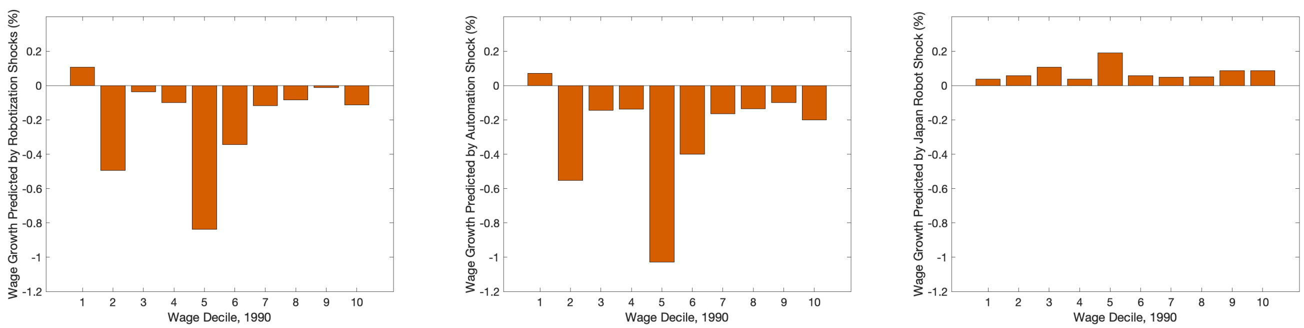
Appendix D.6. Counterfactual Analysis on Robot Taxes

The Effect of Robot Tax on Occupations. To study the effect of counterfactually introducing a robot tax, consider an unexpected, unilateral, and permanent increase in the robot tax by 6% in the US, which is called the general tax scenario. I also consider the 33.6% tax only on imported robots, and call it the import tax scenario, which implies the same amount of tax revenue as in the general tax scenario and makes the comparison of the two scenarios straightforward.[25] I first examine the effect of the general robot tax on occupational inequality.

[25]The 6% rate of the general tax is more modest than the 30% rate considered by Humlum (2021) for the Danish case.

Figure Appendix D.1: The Effect on Occupational Wages by Sources of Shocks

(a) Both Shocks (b) Automation Shock (c) Japan Robot Shock



Note: The left panel shows the annualized occupational wage growth rates for each wage decile, predicted by the first-order solution of the estimated model in the steady state, given in Equation (C.32), for each of the ten deciles of the occupational wage distribution in 1990. This left panel is equivalent to Figure 2b. The center and right panels distinguish the effect of the automation shock (center) and the Japan Robot Shock (right).

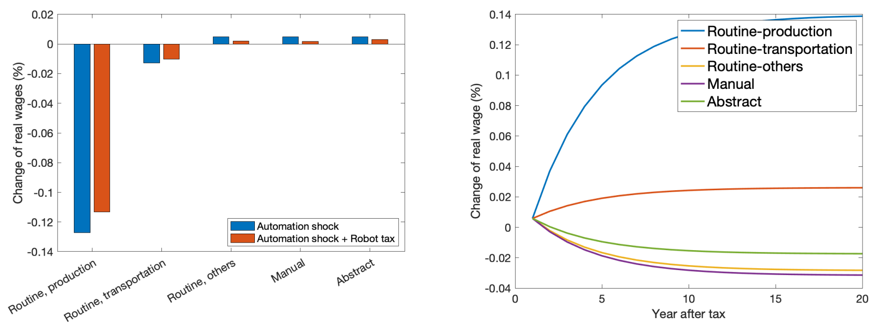
Figure Appendix D.2a shows two scenarios of the steady-state changes in real occupational wages. In one scenario, the economy is hit only by the automation shock. In the other scenario, the economy is hit by both the automation shock and the robot tax. The result shows heterogeneous effects of the robot tax on real occupational wages. The tax mitigates the negative effect of automation on routine-production and routine-transportation workers, while the tax also decreases the small gains that workers in the other occupations would have enjoyed. Overall, the robot tax mitigates the large heterogeneous effects of the automation shock, which could go in negative and positive directions depending on occupation groups, and compresses the effects toward zero.

Figure Appendix D.2b illustrates the dynamics of the effects of only the robot tax. Although the steady-state effects of robot tax were heterogeneous, as shown in Figure Appendix D.2a, the effect is not immediate but materializes after around 10 years, due to the sluggish adjustment in the accumulation of the robot capital stock. Overall, I find that the robot tax rolls back the real wage effect of automation because the robot tax hinders the adoption of robots. In other words, workers in occupations that negatively experienced significant automation shock (e.g., production and transportation in the routine occupation groups) benefit from the tax, while the others lose. Appendix D.7 discusses the effect of robot taxes on worker welfare in each occupation.

Robot Tax and Aggregate Income. Next, I study how the two robot tax schemes affect the US real income. In Figure Appendix D.3a, the solid line tracks the real-income effect of the general robot tax over a 20-year time

Figure Appendix D.2: The Effects of the Robot Tax on Real Occupational Wages

(a) Steady-state Comparison (b) Transitional Effect of Tax



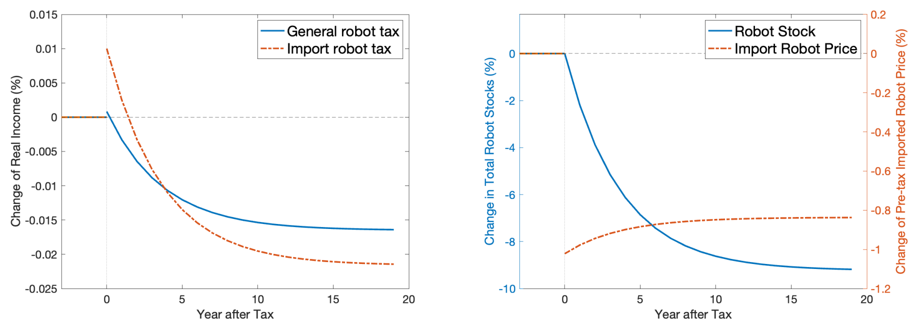
horizon after the tax introduction. First, the magnitude of the effect is small because the cost of buying robots compared to the aggregate production cost is small. Second, there is a positive effect in the short run, but this effect turns negative quickly and remains negative in the long run.

To understand why there is a short-run positive effect on real income, it is useful to distinguish the source of national income in the model. A country's total income comprises workers' wage income, non-robot goods producers' profit, and the tax revenue rebate. Because robots are traded, and the US is a large economy that can affect the price of robots produced in other countries, there is a terms-of-trade effect of robot tax in the US. Namely, the robot tax reduces the demand for robots traded in the global market and lets the equilibrium robot price go down along the supply curve. This reduction in the robot price compresses the cost of the robot investment, increasing the firm's profit and raising the real income. This positive effect is stronger in the import robot tax scenario because the higher tax rate induces a more substantial drop in the import robot price.

Figure Appendix D.3: Effects of the Robot Tax

(a) US Real Income

(b) US Robot Stock and Import Robot Price



Note: The left panel shows the counterfactual effect on the US real income of the two robot tax scenarios described in the main text over a 20-year time horizon. The right panel shows that of the import robot tax on the US total robot stocks (solid line) and the pre-tax robot price from Japan (dash-dot line) over the same time horizon.

The reason for the different effects on real income, in the long run, is as follows. The solid line in Figure Appendix D.3b shows the dynamic impact of the import robot tax on the accumulation of robot stock. The robot tax significantly slows accumulating robot stocks and decreases the steady-state stock of robots by 9.7% compared to the no-tax case. The small robot stock reduces firm profits, which contributes to low real income.[26] These results highlight the role that costly robot capital (de-)accumulation plays in the effect of the robot tax on aggregate income. Figure Appendix D.3b also illustrates the dynamic effect on import robot prices in the dash-dot line.

[26]For each occupation, the counterfactual evolution of robot stocks is similar to each other in percentage and, thus, similar to the aggregate trend in percentage. This is not surprising because the robot tax is ad-valorem and uniform across occupations.

In the short run, the price decreases due to the decreased demand from the US, as explained above. As the SE reaches the new steady state where the US stock of robots is lower, the marginal value of the robots is higher. The effect of this increased marginal value partially more than offsets the short-run effect of reduced price of robots in the long run.

Appendix D.7. Robot Tax and Workers' Welfare

To examine how the robot tax affects workers in different occupations, I define the equivalent variation (EV) as follows. Consider the US unilateral (not inducing a reaction in other countries), unexpected, and permanent tax on robot purchases as in Section Appendix D.6. Write $C'_{i,o,t}$ as the consumption stream under the robotized economy with tax and $C_{i,o,t}$ as that under the robotized but not taxed economy, where the robotization shock is backed out in Appendix D.3. For each country i and occupation o, $EV_{i,o}$ is implicitly defined as follows:

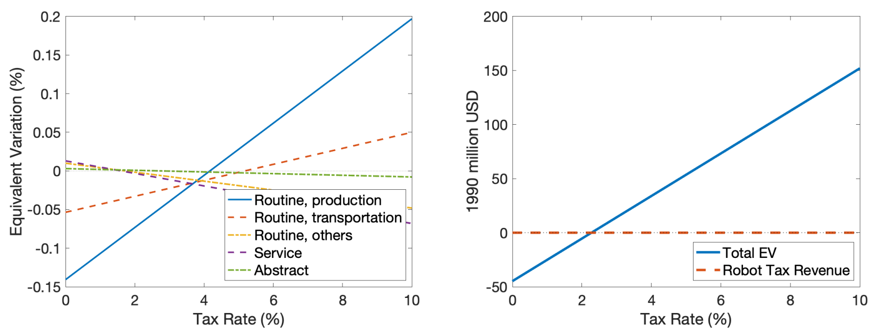
$$\sum_{t=t_0}^{\infty}\left(\frac{1}{1+\iota}\right)^t \ln\left(\left[C'_{i,o,t}\right]\right) = \sum_{t=t_0}^{\infty}\left(\frac{1}{1+\iota}\right)^t \ln\left(C_{i,o,t}\left[1+EV_{i,o}\right]\right). \qquad \text{(D.3)}$$

Namely, the EV is the fraction of the occupation-specific subsidy that would make the present discounted value (PDV) of the utility in the robotized and taxed economy equal to the PDV of the utility if the occupation-specific subsidy were exogenously given every period in a non-taxed economy. Workers in country i and occupation o prefer the economy with tax if and only if $EV_{i,o}$ is positive.

Figure Appendix D.4a shows this occupation-specific EV as a function of the tax rate. The far-left side of the figure is the case of zero robot tax, thus a case of only the robotization shock. Consistent with the occupational wage

Figure Appendix D.4: Robot Tax and Workers' Welfare

(a) Occupational Equivalent Variation (b) Total EV and Revenue



Note: The left panel shows the US workers' equivalent variation defined in Equation (D.3) as a function of the US robot tax rate. The right panel shows the monetary values of equivalent variations aggregated across workers and robot tax revenue as a function of the robot tax rate, measured in 1990 million USD.

effects (cf. Figure Appendix D.2a), workers in production and transportation occupations lose significantly due to robotization. In contrast, other workers are roughly indifferent between the robotized world and the non-robotized initial steady state or slightly prefer the former world. Going right through the figure, the production and transportation workers' EV improves as the robot tax reduces the adoption of robots that substitute their jobs. The EV of production workers turns positive when the tax rate is approximately 6%, and that of transportation workers is positive when the rate is about 7%. However, these tax rates are too high and would negatively affect EVs in other occupations. This is because, with such a high tax rate, robot accumulation in production and transportation occupations was significantly reduced, adversely affecting labor demand in other occupations.

To study if the reallocation policy by robot tax may work, I also compute the equivalent variation in terms of monetary value aggregated by occupation groups (total EV) and compare it with the robot tax revenue, both as a function of robot tax. Figure Appendix D.4b shows the result. One can confirm that the marginal robot tax revenue is far from enough to compensate for workers' loss that concentrates on production and transportation workers at the initial steady state with zero robot tax rate. The robot tax revenue is negligible at this margin compared with the workers' loss due to robotization. As the robot tax rate increases, the total EV rises: When the rate is as large as 2-3%, the sum of the total EV and the robot tax revenue is positive.