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Robots and Wage Polarization: The effects of robot capital by occupation [*]

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Abstract

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

Keywords: Industrial Robots, Robot Prices, Elasticity of Factor Substitution, Wage Polarization

JEL classification: J23, J24, J62, E24, F16, F66, O33

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1 Introduction

Industrial robots have been changing factory production rapidly. In the last three decades, the size of the global robot market has grown by 12% per year (IFR, 2021). Robotization has heterogeneous effects on workers across occupations, raising concern about its distributional effects. Policymakers have proposed various countermeasures to the potential harms of robotization, such as introducing taxation on robot adoption. Motivated by these observations, a growing literature has estimated the effects of robot penetration on employment (e.g., Acemoglu and Restrepo, 2020) and the potential impact of robot taxes (e.g., Humlum, 2021). However, the effects of robotization also depend on under-explored factors, such as the substitutability of robots for workers in each occupation.

In this paper, I study the effect of the increased availability of robots on the wage inequality between occupations and welfare in the US. Using a new dataset on the cost of adopting Japanese robots, I estimate the substitutability between robots and workers within an occupation, unlike the previous research that reveals the substitutability between occupations. I construct a model-implied optimal instrumental variable and estimate the elasticity of substitution (EoS) between robots and workers that can be heterogeneous across occupations. Finally, I perform counterfactual exercises to study the distributional effect of robotization in the US since 1990.

A unique feature of my dataset is the robot price measure for each 4-digit occupation in which robots replace labor. To obtain the dataset, I use the information about the shipment of Japanese robots, which comprise about one-third of the world's robot supply, from the Japan Robot Association (JARA). JARA's key feature is that the data are disaggregated at the level of robot application or the specified task that robots perform. I combine JARA data with O*NET Code Connector's match score to get an occupation-level robot price measure. Finally, I extract a robot cost shock that controls for the demand factors using leave-one-out regression, which I call the *Japan robot shock* (JRS).

I employ an equilibrium model of robotics automation and quality changes. Occupations are bundles of tasks where tasks can be performed by either labor or robots (factors). I impose Fréchet distribution for the task-specific productivity of each factor, allowing aggregation of tasks to the occupational production function that features the constant elasticity of substitution (CES) between robots and labor within each occupation. This formulation allows me to interpret the robot quality change in terms of the change in the robot expenditure share parameter, which I call the automation shock. Furthermore, I incorporate the Armington-style trade of robots to capture Japan's sizable robot export in my dataset.

The identification challenge in estimating the robot-labor EoS is that the JRS can be correlated with the automation shock, which is unobserved. To overcome this, I use the general equilibrium restriction to obtain structural residuals of occupational wages, which controls for the effect of the automation shock. The structural residuals are interpreted as the remaining variations of occupational wages after controlling for the impact of automation shock. The identification assumption is that these structural residuals are uncorrelated with the JRS. This assumption implies a moment condition, which provides me with consistent parameter estimates and an optimal instrumental variable to increase estimation precision.

Applying this estimation method, I find that the EoS between robots and workers is around 2 when estimated with a restricted constant across occupations. This estimate is higher than the typical values reported in the literature on the EoS between labor and general capital, such as structure and equipment, highlighting one of the main differences between robots and other capital goods. Moreover, the EoS estimates are heterogeneous when allowed to vary across occupations. Specifically, for routine occupations that perform production and material moving, the point estimates are as high as around 3, revealing the special susceptibility of workers to robots in these occupations. These estimates are identified from the strong relationship between a larger robot price drop and a lower occupational wage growth rate in these occupations. In contrast, the estimates in the other occupations are close to 1, indicating that robots and labor are neither substitutes nor complements in the other occupations.

The large EoS between robots and workers in production and material moving occupations implies that the robotization in the sample period significantly decreased relative wage in these occupations. This implies that the robotization shock slowed the relative wage growth of occupations in the middle deciles since robotized occupations tended to be in the middle of the occupational wage distribution in 1990. Moreover, the higher productivity in these occupations raises the marginal product of labor in other occupations, raising labor demand. Quantitatively, these mechanisms explain a 6.4% increase in the 90-50th 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 impacts of industrial robots by finding a sizable impact of robots on US wage polarization. The closest papers to mine are Acemoglu and Restrepo (2020) and Humlum (2021). Acemoglu and Restrepo (2020) establish that the US commuting zones that experienced a greater penetration of robots in 1992-2007 saw lower growth in wages and employment.[1] Humlum's (2019) contribution is to estimate a model of robot importers in a small open economy and an EoS between occupations using firm-level data on robot adoption to find a positive real-wage effect on average with significant heterogeneity across occupations.[2] I complement these studies by providing a method of estimating the within-occupation EoS between robots and labor using data on occupation-level robot costs. The estimation result reveals the heterogeneous substitutability of robots and workers in the US. I also consider large open countries' trade of robots, which introduces the terms-of-trade effect when considering robot taxes.

Another strand of the literature studies pays attention to occupations to learn about the potentially heterogeneous impacts of automation (e.g., Cheng, 2018). Among others, Jaimovich et al. (2021) construct a general equilibrium model to study the effect of automation on the labor market of routine and non-routine workers in a steady state. In a contribution to this literature, I provide a matching method for industrial robot applications and occupations, which produces the occupation-level data of robot costs.

This paper is also related to the vast literature on estimating the EoS between capital and labor since robots are one type of capital goods (e.g., Arrow et al., 1961; Oberfield and Raval, 2014). Although the literature yields a set of estimates with a wide range, the upper limit of the range appears to be around 1.5 (Karabarbounis and Neiman, 2014; Hubmer, 2023). Therefore, my EoS estimates around 3 in production and material-moving occupations are significantly higher than this upper limit. In this sense, they highlight one of the main differences between robots and other capital goods: the special

[1]Dauth et al. (2017) and Graetz and Michaels (2018) also use the industry-level aggregate data of robot adoption to analyze its impact on labor markets. Galle and Lorentzen (2024) studies the interaction effects of trade and automation. Furthermore, Adachi et al. (2024) also use the JARA data to study the Japanese labor market implications of robots. By contrast, this paper studies the US labor markets and explores robots' impact on US wage polarization by estimating the elasticity of substitution between robots and workers.

[2]There is also a growing body of studies (among others, Acemoglu et al., 2020; Koch et al., 2021) that use the firm-level data to study the impact on workers.

susceptibility of workers to robots across different occupations.

Caunedo et al. (2023) provides the elasticity of substitution across occupations by applying an NLP algorithm to the description of the set of tools used in each occupation using BEA fixed asset table data. The exercise is concerned with capital-embodied technological change (CETC), which is modeled by the reduction in the price of various tools. In contrast, this paper's strategy for measuring robot variables differs in that I use the O*NET Code Connector match score to compute the assignment weight. Theoretically, I treat the automation shock and the capital price decline (the JRS, in my terminology) separately, which is a natural concern of much of the automation literature.

2 Model

The basis of the model is a task-based framework embedded in a multi-country Armington model. It has two main features: occupation-specific elasticities of substitution (EoS) between robots for workers and robot trade in a large open economy. I emphasize these features and relegate other model elements to C.1, on which later quantitative exercises are based.

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 goods $g = G$, and robots $g = R$. To clarify country subscripts, I use l, i, and j, where l is a robot-exporting country, i is a non-robot good-exporting and robot-importing country, and j is a non-robot good-importing country, whenever I can. There are representative households and producers in each country. As in the Armington model, both goods are differentiated by country of origin and occupation. Non-robot goods can be consumed by households and invested to produce robots.[3]

In the main text, non-robot goods G are produced with two factors of production: labor $L_{i,o,t}$ and robot capital $K^R_{i,o,t}$ in each occupation o.[4] There

[3] In the full model in C.1, non-robot goods are also used as input for robot integration (Graetz and Michaels, 2018; Humlum, 2021).

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

is no international movement of factors. Producers own and accumulate robot capital. Households own the producers' share in each country. All good and factor markets are perfectly competitive. Workers are forward-looking, draw an idiosyncratic utility shock from a generalized extreme value (GEV) distribution, pay a switching cost for changing occupation, and choose the occupation o that achieves the highest expected value $V_{i,o,t}$ among O occupations as in Caliendo et al. (2019). The discount factor $\iota > 0$ is shared between all agents. The elasticity of occupation switch probability with respect to the expected value is ϕ. The detail of the worker's problem is discussed in C.1.

There are bilateral and good-specific iceberg trade costs $\tau^{g}_{ij,t}$ for each $g = G, R$. There is no within-country trade cost, so $\tau^{g}_{ii,t} = 1$ for all i, g and t. Due to the iceberg cost, the bilateral price of good g that country j pays to i is $p^{g}_{ij,t} = p^{g}_{i,t}\tau^{g}_{ij,t}$.

The government in each country exogenously sets the robot tax. Specifically, buyer i of robot o from country l in year t has to pay ad-valorem robot tax $u_{li,t}$ on top of the robot producer price $p^{R}_{li,o,t}$ 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 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 elasticity of substitution 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 follow 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 the CES technology

$$T^{O}_{i,o,t} = \left[\int_{0}^{1}\left(t_{i,o,t}\left(\omega\right)\right)^{\frac{\zeta-1}{\zeta}} d\omega\right]^{\frac{\zeta}{\zeta-1}},$$

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

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

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

Following Artuc et al. (2023), I assume that these productivity is Fréchet-distributed 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 technical feature that all countries share, and thus $a^s_{o,t}$ does not vary by country. As popularized by Eaton and Kortum (2002), the maximum stability property of the Fréchet distribution implies that $\xi_{i,o,t}$ is equal to the expenditure share on robots and that

$$\xi_{i,o,t} = \frac{c^R_{i,o,t} K^R_{i,o,t}}{P^O_{i,o,t} T^O_{i,o,t}} = a^R_{o,t} \left(\frac{c^R_{i,o,t}}{P^O_{i,o,t}} \right)^{1-\theta_o}, \tag{2}$$

$$\text{where} \qquad P^O_{i,o,t} = \left(a^R_{o,t} (c^R_{i,o,t})^{1-\theta_o} + (1 - a^R_{o,t})(w_{i,o,t})^{1-\theta_o} \right)^{1/(1-\theta_o)}, \tag{3}$$

and $c^R_{i,o,t}$ is the user cost of robot capital formally defined in C.2, and $P^O_{i,o,t}$ is the unit cost of performing occupation o. A key parameter is θ_o, which governs the elasticity of substitution 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 with respect to the price changes since the unobserved productivity difference matters more.

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

$$Y^R_{i,o,t} = A^R_{i,o,t} I^R_{i,o,t}, \qquad \text{so} \qquad p^R_{i,o,t} = \frac{P^G_{i,t}}{A^R_{i,o,t}} \tag{4}$$

due to the perfect competition, where $P^G_{i,t}$ is the non-robot goods price index given below in (5). The robot price is inversely proportional to the productivity term $A^R_{i,o,t}$. Therefore, I call the change in $A^R_{i,o,t}$ for i being Japan as *Japan robot shock* (JRS) throughout the paper.

Trade in Goods and Robots Write non-robot goods (resp. robots) trade elasticity as ε (resp. ε^R). The Armington assumption implies that the trade of goods and robots and their price indices are given by

$$x^G_{ij,t} = \left(\frac{p^G_{ij,t}}{P^G_{j,t}}\right)^{(1-\varepsilon)} \text{ and } x^R_{ij,o,t} = \left(\frac{p^R_{ij,o,t}}{P^R_{j,o,t}}\right)^{(1-\varepsilon^R)}$$
$$\text{where } P^G_{j,t} = \left[\sum_i \left(p^G_{ij,t}\right)^{1-\varepsilon}\right]^{1/(1-\varepsilon)} \text{ and } P^R_{j,o,t} = \left[\sum_i \left(p^R_{ij,o,t}\right)^{1-\varepsilon^R}\right]^{1/\left(1-\varepsilon^R\right)}. \tag{5}$$

Here, $p^R_{ij,o,t} = p^R_{i,o,t}\tau^R_{ij,o}$ is the price of robots used in occupation o traded from i to j, and the producer price of robots $p^R_{i,o,t}$ is given in the production structure (4).

2.3 Discussion of the Model Assumptions

As comparative statics and dynamics, I consider the change in the robots' technological efficiency parameter $a^R_{o,t}$ in (2), but also the shock to the productivity to produce robots in (4). Collectively, I call these two shocks *robotization shocks*. The two robotization shocks are likely to be correlated with each other at the occupation level since innovation in robot technology improves the applicability of robots and the cost efficiency of production at the same time.[5] This will be the source of the identification challenge, discussed further in the next section.

The robots' technological efficiency parameter $a^R_{o,t}$ plays a central role in estimation and counterfactuals and is discussed in detail here. Since the task-based framework developed in Section 2.2 contains the allocation of factors to tasks, I can interpret $a^R_{o,t}$ as the shifter of the share of tasks performed by robots as opposed to labor with a proper modification to the productivity term $b_{i,o,t}$, which is discussed in detail in Section 2.5. Thus, I call the change in $a^R_{o,t}$ the *automation shock*.

[5]See A.1 for more concrete narratives of such a correlation.

In contrast, the robot cost share $a_{o,t}$ also represents the quality of the robots. Specifically, the quality of goods can be regarded as a non-pecuniary attribute that all consumers agree upon in terms of its value (Khandelwal, 2010). As (2) states that the increase in $a_{o,t}$ implies the rise in the value of the robots among factors, the automation shock can also be interpreted as quality upgrading of robots relative to labor when combined with a suitable adjustment in the TFP term.

Therefore, my model does not distinguish between automation shock and quality upgrade but has the same implication for equilibrium. This is the restriction of the Fréchet distribution assumption. To the best of my knowledge, there has been no formal discussion on this point. Nonetheless, it is useful to maintain this assumption since I can keep complex technology improvements along with task automation and quality upgrades in a single parameter $a_{o,t}$.[6]

We do not explicitly consider the industrial heterogeneity in this paper. The heterogeneous impact on workers is captured through the rich occupational heterogeneity. Nonetheless, it is well-known that heterogeneous robotization across industries creates varying competitive advantages due to robot-driven productivity boosts and input-output linkages (Caliendo and Parro, 2015). We proxy the latter effect by introducing the input-output linkages in the roundabout production in the production function in the full quantitative model. See C.1 for details.[7]

2.4 Equilibrium

The remaining part of the model is standard in the literature on dynamic general equilibrium and given in C.1. For the sake of notation, I summarize the solution to the workers' dynamic discrete choice problem of occupations by labor supply function $L_{i,o,t}(\boldsymbol{w}_{i,t})$. The non-robot producer solves dynamic robot capital investment problem under convex adjustment cost (Cooper and

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

[7] In a similar vein, regional variation is not introduced in the model (Caliendo et al., 2019; Acemoglu and Restrepo, 2020). Such an additional consideration yields rich implications about regional heterogeneity and inequality with the cost of significantly complicating the model. Analyzing the heterogeneous robot price effects across regions is beyond the scope of this paper.

Haltiwanger, 2006; recent application to the robot context is by de Souza and Li, 2023). 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 have chosen this strategy over the exact solution method like Caliendo et al. (2019) because the trade literature has shown that the approximation errors with respect to (unilateral) productivity shocks are considerably smaller than those due to bilateral trade shocks (Kleinman et al., forthcoming). The robotization shock considered in this paper is unilateral. For example, my model assumes that Japanese robots have become accessible to all countries (not only in the US). Since I focus on the steady-state change, I drop subscript t in this subsection. I relegate the full characterization of the approximation, including that of the transition dynamics, in C.3.

I use the hat notation to describe the log total derivative. The exogenous shocks are the shocks to $a_{o,t}^R$, $A_{l,o}^R$, and the adjustment to the occupational productivity term $b_{i,o}$. Specifically, I only consider the automation shock that does not change labor productivity throughout the paper, reflecting on the rapid growth in robot technology in the past few decades relative to human capital growth. Mathematically, this is equivalent to imposing

$$\hat{b}_{i,o}^{\frac{1}{\beta-1}} (1 \hat{-} a_o^R)^{\frac{1}{\theta_o - 1}} = 0, \tag{6}$$

for any automation shock $\widehat{a_o}$ so that the effect of the change in a_o on labor productivity is undone by appropriate adjustment in $\hat{b}_{i,o}$. Moreover, this approach still captures the overall productivity growth due to change in $\widehat{a_o}$. It is the typical approach to control labor productivity growth when modeling robot shocks in the literature. For instance, the canonical setup in Acemoglu and Restrepo (2020) models the automation by the increased threshold for robot availability across tasks, which does not change the labor productivity, but the overall productivity increases because of the threshold increase.

I provide several approximation expressions that are useful in the following sections when defining the estimator. First, combining (5) and (4), I have the the change in the robot price index $P_{i,o}^R$ in the country i due to the change in the robot production technology $A^R_{l,o}$ in the country l:

$$\hat{P^R_{i,o}} = -x^R_{li,o}\hat{A^R_{l,o}} + \sum_{l'} x^R_{l'i,o}\hat{P^G_{l'}}, \tag{7}$$

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

Second, from (2) and (3), the labor demand in the dollar unit in (i, o) is given by $(1 - \xi_{i,o})P^O_{i,o}T^O_{i,o}$. Using this, the approximated labor market equilibrium condition is:

$$\hat{w_{i,o}} + \sum_{o'} \frac{\ln L_{i,o}}{\ln w_{i,o'}}\hat{w_{i,o'}} = (1 \hat{-} a_o) + (1 - \theta_o)(\hat{w_{i,o}} - \hat{P^O_{i,o}}) + \hat{P^O_{i,o}} + \hat{T^O_{i,o}}, \tag{8}$$

where the LHS is the supply change and the RHS is the demand change.

3 Estimation Strategy

I develop an estimation method using the model-implied optimal instrumental variable (MOIV) following Adao et al. (2023). First, Section 3.1 parameterizes the model. I then introduce the data on robot prices in Japan in Section 3.2. Finally, I define the MOIV estimator in Section 3.4. I set the sample period to 1992-2007 (or 1990-2007 for the labor data) and write $t_0 \equiv 1992$ and $t_1 \equiv 2007$ given the data availability, and I will relate the long difference to the model's steady state changes.

3.1 Parametrization

To allow the heterogeneity of the EoS between robots and labor across occupations and maintain the estimation power at the same time, I define the occupation groups as follows. First, occupations are separated into three broad occupation groups: Abstract, Service (Manual), and Routine, following Acemoglu and Autor (2011) and described in A.2. Given the trend that robots are introduced intensively in production and transportation (material-moving) occupations in the sample period, I further divide routine occupations into three sub-categories: Production (e.g., welders), Transportation (indicating transportation and material-moving, e.g., hand laborer), and Others (e.g., repairer). As a result, I obtain five occupation groups shown in A.2. Within each group, I assume a constant EoS between robots and labor. Each occupation group is denoted by subscript g, and thus, the robot-labor EoS for group g is written as θ_g.

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

The first-order solution matrix needs various shares in the initial steady state. I take these shares from IFR, IPUMS USA/CPS, BACI, and the World Input-Output Table (WIOT). I set the initial robotization share $a_{o,0}$ to be the initial US occupation-specific expenditure share $c^R_{i,o,t_0} K^R_{i,o,t_0} / w_{i,o,t_0} L_{i,o,t_0}$ for $i = US$ and the initial robot tax to be zero in all countries. The remaining measurement of labor market outcomes is standard and relegated to A.2.

3.2 Data Source

Industrial robots are defined as multiple-axe manipulators and are measured by the number of such manipulators or robot arms.[8] The main data source for robots by occupation is the Japan Robot Association (JARA). JARA is a General Incorporated Association composed of Japanese robot-producing companies. In its "Export Statistics of Manipulators, Robots and Applied Systems by Country and Application," JARA annually surveys major robot producers about the units and monetary values of robots sold for each destination country and robot application.[9] Robot application is defined as the specified task that robots perform, which is discussed in detail in Section 3.3.

[8] A more formal definition from ISO is provided in A.1.

[9] Adopting a modern robot system is more complicated than just buying the hardware. It requires tailored integration and configuration, up-to-date tuning via robot programming, and fine maintenance. Although the data only contains the price of the hardware, the full model considers the integration costs using the estimates of Leigh and Kraft (2018).

I use digitized summary cross tables from JARA's annual publications.

I use the Occupational Information Network Online (O*NET) Code Connector to convert robot applications to labor occupations. 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 search algorithm provides a match score that shows the relevance of each occupation to the search word, discussed in Morris (2019) and 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 definition of robots in the trade data. I match the BACI robot trade data to JARA's Japanese robot exports by aggregating across applications in the JARA data. Since I do not observe the occupation-level disaggregate of the robot trade in other countries, I impose $x_{ij,o}^R = x_{ij}^R$ for all o in the estimation. See A.4 for the details of robot measurement issues in JARA and BACI.

3.3 Data Construction

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

Step 1. Application-Occupation Match The first task is matching robot applications and labor occupations. A heterogeneous mix of tasks in each occupation generates a difference in the ease of automation across occupations, implying the heterogeneous adoption level of robots (Manyika et al., 2017).[10] Formally, let a denote robot application, and o denote labor occupation at the 4 digit level. The JARA data give me the number of robots sold and total monetary transaction values for each application a. I write these as robot measures X_a^R, a generic notation that can mean quantity and monetary values. I convert an application-level robot measure X_a^R to an occupation-level measure X_o^R using a weighted average. For this purpose, I search occupations in the O*NET Code Connector by the title of robot

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

application a and web-scrape the match score m_{oa} between a and o. Using m_{oa} as the weight, I compute[11]

$$X_o^R = \sum_a \omega_{oa} X_a^R \text{ where } \omega_{oa} \equiv \frac{m_{oa}}{\sum_{o'} m_{o'a}}. \tag{9}$$

where $\sum_o \omega_{oa} X_a^R = X_a^R$ since $\sum_o \omega_{oa} = 1$. Robot trends based on the constructed occupation-level measures are shown in A.3.

This matching method complements these studies by matching the data of robot quantities with lower data requirements, as I only observe the title of robot applications but not detailed descriptions as those in patent texts. For example, Webb (2019) provides a natural-language-processing method to match technological advances (e.g., robots, software, and artificial intelligence) embodied in the patent title and abstract to occupations. Furthermore, Montobbio et al. (2020) extend this approach to analyzing full patent texts by applying the topic modeling method of machine learning.

Step 2. Japan Robot Shock (JRS) The second task is to define the measure of the JRS. Using the occupation-level robot quantity $q^R_{i,o,t}$ and sales $(pq)^R_{i,o,t}$ in destination country i, occupation o, and year t, I construct the cost shocks to robot users in each occupation in the following steps. First, I take the average export price $p^R_{i,o,t} \equiv (pq)^R_{i,o,t} / q^R_{i,o,t}$.[12] A concern when using the unit value data is the simultaneity–Demand shocks, not cost shocks, drive prices. My export price measure is based on external robot sales, and thus, I have less concern than domestic robot prices. Nonetheless, I exclude the US's robot import prices from the sample to mitigate the simultaneity concern further. Here, the argument is close to the one in Hausman et al. (1994), that the changes in demand shocks are uncorrelated between the US and other countries, but the price variations are primarily driven by the robot production costs in Japan. This leave-one-out idea is used intensively in the automation literature (e.g., Acemoglu and Restrepo, 2020).[13]

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

[12] I have also computed the chain-weighted robot price index, which is commonly used when measuring the capital good price. The results using this index are not qualitatively different from the main findings.

[13] A related but distinct concern is that since the US is a large economy, their demand shock may affect robot prices in the international market, which at the same time drives

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

$$\ln\left(p^R_{i,o,t}\right) - \ln\left(p^R_{i,o,t_0}\right) = \psi^D_{i,t} + \psi^J_{o,t} + \epsilon_{i,o,t},\ i \neq USA \tag{10}$$

where t_0 is the initial year, $\psi^D_{i,t}$ is the destination-year fixed effect, $\psi^J_{o,t}$ is the occupation-year fixed effect, and $\epsilon_{i,o,t}$ is the residual. This regression controls for any country-year specific effect $\psi^D_{i,t}$, which includes country i's demand shock or trade shock between Japan and i that are constant across occupations. I use the remaining variation across occupations $\psi^J_{o,t}$ as a cost shock of robot adoption and specifically define $\psi^J_o \equiv \psi^J_{o,t_1}$ as the measured JRS.

Using the perfect competition assumption and robot production function (4), I relate the JRS and the robot productivity in the model by

$$\psi^J_o = -\widehat{A^R_{2,o}}. \tag{11}$$

I show stylized facts and reduced-form evidence about robots and workers at the occupation level that suggest strong substitutability between robots and labor to motivate the model and estimation in B. As addressed in Section 2.3, my model loads the robot quality component on the automation shock term $a^R_{o,t}$. Other possible approaches include the hedonic and cost evaluation approach, both of which are discussed in A.6.

3.4 Estimation Procedure

The JARA data provides information about the robot price, a critical input to estimate the elasticity parameter that shows up in (2). However, I still have an unobserved automation shock element, $a_{o,t}$, that potentially causes an identification threat. To deal with this concern, I will develop a moment condition using the model restriction.

First, I decompose the automation shock $\widehat{a_o}$ into an "implied" component $\widehat{a_o^{\text{imp}}}$ and "unobserved error" component $\widehat{a_o^{\text{err}}}$ such that $\widehat{a_o} = \widehat{a_o^{\text{imp}}} + \widehat{a_o^{\text{err}}}$ for all

the US labor demand. To address this concern, I will perform the same exercise as in Section B using data from the small-open economy in B.3, showing a similar empirical pattern to the US data.

o. The implied component is implicitly defined by the steady-state change of relative demand for robots and labor, combining (2), (7), and (11),

$$\left(\frac{\widehat{c^R_{US,o}K^R_{US,o}}}{w_{US,o}L_{US,o}}\right) = (1-\theta_g)\left(x^R_{JP,US}\psi^J_o - \hat{w}_{US,o}\right) + \frac{\widehat{a^{\text{imp}}_o}}{1-a_{o,t_0}} + D, \tag{12}$$

where $x^R_{JP,US}$ is the baseline import share of robots from Japan in the US, and $D \equiv (1-\theta_g)\sum_l x^R_{l,US}\hat{P^G}_l$ is the international spillover term due to the changes in price indices in other countries. In other words, $\widehat{a^{\text{imp}}_o}$ is the component of the automation shock that explains the shift in the task automation and expenditure share of robots. In contrast, the unobserved error component $\widehat{a^{\text{err}}_o}$ is the remaining term, which I view as the measurement error.

The identification challenge is that the JRS ψ^J_o may have a potential correlation with the implied automation shock $\widehat{a^{\text{imp}}_o}$. To my knowledge, no studies in the literature address this identification challenge in the literature. The previous literature estimates the elasticity of substitution between capital and labor using the CES demand function of the form (2), but assumes that the technology shock is fixed or orthogonal to the price changes.[14] Since much of the automation literature provides the demand function and price index where one can interpret the technology shock $a_{o,t}$ as the expansion of the task space due to automation, it seems that addressing the correlation of this shock with another measure of technological progress, the decline in robot prices, needs to be addressed formally.

A key observation to address this identification challenge is that the error component $\widehat{a^{\text{err}}_o}$ can be inferred from the observed endogenous variables using the first-order approximation to the model solution and $\widehat{a^{\text{imp}}_o}$. Namely, the occupational labor market clearing condition (8) gives a restriction between the occupational wage and the automation shock. More specifically, combined with $\hat{a^R_o} = \hat{a}^{R,\text{imp}}_o + \hat{a}^{R,\text{err}}_o$, I have

$$\hat{a}^{R,\text{err}}_o = -\hat{a}^{R,\text{imp}}_o - (1-a_o)\left[\hat{w_{i,o}} + \sum_{o'}\frac{\ln L_{i,o}}{\ln w_{i,o'}}\hat{w_{i,o'}} - (1-\theta_o)(\hat{w_{i,o}} - \hat{P^O_{i,o}}) - \hat{P^O_{i,o}} - \hat{T^O_{i,o}}\right] \tag{13}$$

where $\hat{P^O_{i,o}}$ is implied by the zero-profit condition and $\hat{T^O_{i,o}}$ is given by production function, as detailed in C.1.

[14]See, for instance, Antras (2004); Herrendorf et al. (2015); Eden and Gaggl (2018).

Thus, (13) gives me the structural residual after controlling for the automation shock, which I measure from the expenditure share expression in (12). I then impose the following moment condition regarding this structural residual and the JRS $\boldsymbol{\psi}^J \equiv \left\{\psi_o^J\right\}_o$.

Assumption 1. *(Moment Condition)*

$$\mathbb{E}\left[\hat{a}_o^{R,err}|\boldsymbol{\psi}^J\right] = 0. \tag{14}$$

Assumption 1 restricts that the structural residual $\hat{a}_o^{R,\text{err}}$ should not be predicted by the JRS. Note that it allows that the automation shock $\widehat{a_o}$ correlates with the change in the robot producer productivity $\widehat{A_{2,o}^R}$. The structural residual $\nu_{\boldsymbol{w},o}$ purges out the first-order effects of all shocks, $\widehat{\boldsymbol{A}_2^R}$ and $\widehat{\boldsymbol{a}}$ (and accompanying adjustment $\widehat{\boldsymbol{b}}$ according to (6)), on wage changes. I then put the restriction that the remaining variation should not be predicted by the JRS from the data. This is justified by the fact that the structural residual $\boldsymbol{\nu}_{\boldsymbol{w}}$, and measurement error $\widehat{a_o^{\text{err}}}$.[15]

Given the moment condition (14), it is straightforward to construct the optimal instrument and implement it with the two-step estimator Adao et al. (2023). Therefore, I relegate the detailed explanation to D.2. The estimation section is closed with the remaining discussion on the identification assumption in the following.

3.5 Discussion of the Identification Assumption

In the moment condition (14), I treat unobserved reductions in robot costs sourced from other countries as independent from the evolution of Japanese robot costs and discuss the plausibility of this assumption in B.4 by comparing the JARA data and the data from the International Federation of Robotics (IFR), a widely-used data source of robots in the world. Furthermore, A.4 shows the international robot flows, including Japan, the US, and the rest of the world.

When does Assumption 1 break down? One such threat is a directed technological change, in which the occupational labor demand drives the changes

[15]The correlation of the structural residuals with other shocks, such as trade shocks, is unlikely to break Assumption 1 as I have confirmed that controlling for such shocks does not qualitatively change the reduced-form findings in B.

in the cost of robots (e.g., (Acemoglu and Restrepo, 2018)). Specifically, suppose that a positive labor demand shock in occupation o induces the research and development of robots in occupation o and drives costs down in the long run instead of exogenous technological change in production function (4). The structural residual ν_o does not control for this effect and is negatively correlated with JRS ψ_o^J. Another possibility that fails Assumption 1 is the increasing returns for robot producers, which would also imply that the unobserved robot demand increase drives a reduction of robot costs. However, these concerns imply a negative bias to the elasticity estimates, and thus, my qualitative results about strong substitutability are maintained.

Note that the measure of the JRS (11) does not contain the price shock of the robots brought to the US from countries other than Japan. Since I do not have high-quality data on robots from other countries, I simply take the robot shocks from Japan. I mainly use this shock for identification and estimation. Price shocks of robots from other countries are therefore included in the implied automation shock (12).

4 Results

Table 1 gives the estimates of the structural parameters. The Case 1 column shows the EoS parameter between robots and labor when restricted to be constant across occupation groups. The estimate of the within-occupation EoS between robots and labor θ is around 2 and implies that robots and labor are substitutes within an occupation and rejects the Cobb-Douglas case $\theta_g = 1$ at the conventional significance levels. The high estimate of the EoS between labor and automation capital is also found in Eden and Gaggl (2018), where they estimate the elasticity between ICT capital and workers. The point estimate of the EoS between occupations, β, is 0.83, implying that occupation groups are complementary. The estimate is slightly higher than Humlum's (2019) central estimate of 0.49.

The second column shows the estimation result when I allow the heterogeneity across occupation groups (Case 2). I find that the EoS for routine production occupations is 2.7. In contrast, those for other routine occupations (transportation and other routine) are close to 2, and those for other occupation groups are not significantly different from 1. Therefore, the estimates for routine production occupations indicate the special susceptibility of workers in these occupations to robot capital. The estimate of the EoS

Table 1: Parameter Estimates

	Case 1: Homogeneous $\theta_g = \theta$	Case 2: Heterogeneous θ_g	
θ_g	2.05 (0.19)	Routine, Production	2.71 (0.32)
		Routine, Transportation	1.76 (0.15)
		Routine, Others	1.96 (0.17)
		Manual	1.01 (0.71)
		Abstract	1.01 (0.62)
β	0.83 (0.03)		0.73 (0.06)

Note: The estimates of the structural parameters based on the estimator described in Section A.1. Standard errors are in parentheses. Parameter θ is the within-occupation elasticity of substitution between robots and labor. Parameter β is the elasticity of substitution between occupations. The column "Case 1: $\theta_g = \theta$" shows the result with the restriction that θ_o is constant across occupation groups. The column "Case 2: Free θ_g" shows the result with θ_g allowed to be heterogeneous across five occupation groups. Transportation indicates "Transportation and Material Moving" occupations in the Census 4-digit occupation codes (OCC2010 from 9000 to 9750).

between occupations β does not change qualitatively between Case 1 and Case 2.

As in the literature on estimating the capital-labor substitution elasticity, the source of identification of these large and heterogeneous EoS between robots and labor is the negative correlation between the JRS and the change in the labor market outcome. Intuitively, if θ_g is large, then the steady-state relative robot (resp. labor) demand responds strongly in the positive (resp. negative) direction conditional on a unit decrease in the cost of using robots, as is shown in B.2. However, my model features the automation shock $a_{o,t}$ and endogenous task automation (cf. (2)) as well as the price reduction. I discuss the relationship between these model elements and the estimates in the following subsections.

4.1 Decomposing the Source of Task Automation

The estimated model's task allocation (2) allows me to back out of the automation shock. Specifically, I obtain the implied automation shock in (12) using the observed change in the relative robot demand (the LHS of equation 12), the EoS estimates θ_g, and the change in the relative price of robots $x^R_{JP,US}\psi^J_o - \hat{w}_{US,o}$. The international price spillover term D in (12) is quantitatively small as the robots' contribution to the national price index is small. This can be confirmed by substituting the implied shock in the model-implied price index change. The main results on distributional impacts are unchanged in the inclusion of D, which is constant across occupations, and the appendix results are robust in inclusion due to the small size.

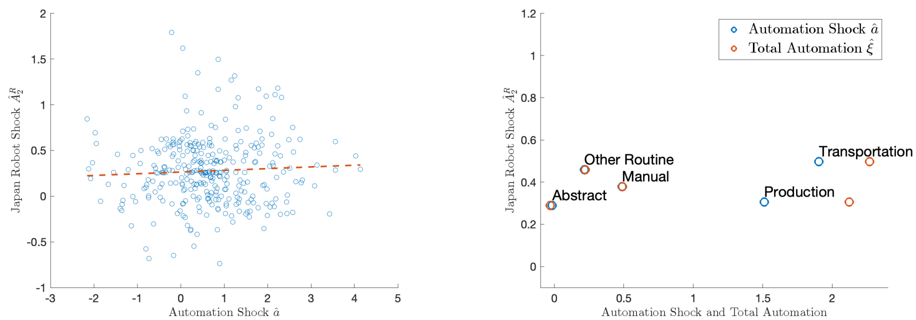
Figure 1a shows a scatter plot between the JRS and automation shock, revealing a mild positive relationship between them. This correlation is consistent with the robotic innovations example discussed in A.1. In turn, Figure 1b summarizes the two shocks aggregated at the occupation group level. The figure reveals 0.2-0.6 log points of the JRS, reflecting the observed reduction in the price of robots from Japan. More importantly, estimated automation shocks are positive and reveal greater variation between occupation groups. The two highly automated occupations, transportation and production, see 1.5-2 log points increase in the task shares of robots, while the other occupation groups have 0.5 log points at the maximum.

Figure 1b also shows the total automation or the change in the share of tasks performed by the robots along the horizontal axis. Note that, according to (2), total automation can be driven both by the exogenous change in the scale parameter of the Fréchet distribution $a_{o,t}$ (the automation shock) and the endogenous assignment of tasks due to the cheap robots caused by the JRS $A^R_{2,o,t}$. I find that in the two heavily robotized occupation groups, transportation and production, the total automation is as large as a 200 percent increase in the share of robotized tasks. This is driven by both the automation shock and the endogenous task allocation, but the former plays a more important role. In other occupations with less robotization, such as the abstract and manual occupations, I do not find evidence for the task allocations toward robots. In the counterfactual analysis, I will analyze the role of each of these robotization mechanisms on wage polarization.

The fact that the greater increase in the penetration of robots in production and transportation occupations is explained more by automation shocks than by the JRS, revealed in Figure 1b, is also important for evaluating the

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 12 and the estimated parameters in Table 1) on the horizontal axis and the Japan robot shock (measured by equation 11 and regression 10) on the vertical axis. Each point is a 4-digit occupation, and the dashed line is the fitted line. The right panel adds the total automation (implied by 2) 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.

model performance. Ignoring the automation shock could lead to significant bias in interpreting the correlation between wage changes and the JRS. In D.3, I show that it is critical to take into account the automation shock in estimating the EoS between robots and labor and that the large EoS in my structural estimates is robust even after taking this point into account.

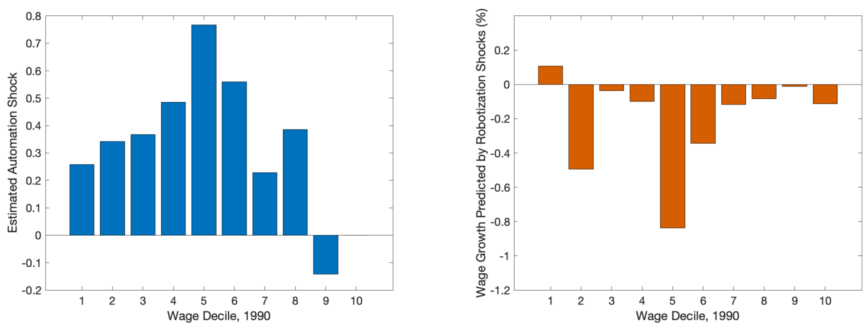
5 The Effect of Robotization on the Wage Polarization

I use the estimated model to answer the question about the distributional effects of robotization. As Heathcote et al. (2010) argues, wage inequality comprises a significant part of overall economic inequality in the US. I primarily use the wage inequality measure of the wage ratio between the 90th percentile and the 50th percentile (90-50 ratio), following Autor et al. (2008) who showed that the 90-50 ratio has steadily increased since 1980. I study how much such an increase can be explained by the increased use of industrial robots from 1990.

First, I show the pattern of robot accumulations across the occupational

Figure 2: Robots, Wage Inequality, and Polarization

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



Note: The left panel shows the implied automation shocks defined in equation (12). The shocks are aggregated into 10 wage deciles in the baseline year, 1990, weighted by the initial employment level. 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 equation (48).

wage distribution. Figure 2a shows the distribution of estimated automation shocks across baseline wage deciles. The figure shows a strikingly polarizing pattern: the automation shock hits the middle of the wage distribution more severely than at the bottom and top of the distribution. Note that this contrasts well with the no correlation result in Figure 12a. These findings indicate that it was the automation shock, not the JRS, that caused the wage distribution dynamics during the 1990s and 2000s.

In contrast, Figure 2b shows the predicted steady-state wage growths per year due to the robotization shocks and the estimated model with the first-order solution given in equation (50). Consistent with the high growth rate of robot stocks in the middle of the wage distribution and the strong substitutability between robots and labor, I find that the counterfactual wage growth rate in the middle deciles of the initial wage distribution is more negative than that in the other part of the wage distribution. Quantitatively, the 90-50 ratio observed in 1990 and 2007 is, respectively, 1.588 and 1.668. On the other hand, the 90-50 ratio predicted by the initial 1990 data and the first-order solution (50) is 1.594. These numbers imply that the robotization shock captured in this paper can explain an increase of 6. 4% in the 90-50 ratio.

It is worth emphasizing that I consider two shocks in this main exercise, the automation shock $\widehat{\boldsymbol{a}}$ and the JRS $\widehat{\boldsymbol{A}}_2$. When these two shocks are distinguished in the quantitative exercise, the automation shock reduces the labor demand due to task reallocation from labor to robots. In contrast, the JRS increased the stock of robots and the marginal product of labor.

Other Counterfactual Analysis In addition, due to the fear of automation, policymakers have proposed regulating industrial robots using robot taxes. The estimated model provides an answer to the short- and long-term effects of taxing robot purchases on real wages across occupations and aggregate welfare losses. In D.5, I also study the implications of counterfactual policies regarding the regulation of robot adoption.

6 Conclusion

In this paper, I study the distributional effects of the increased use of industrial robots, with the emphasis that robots perform specified tasks and are internationally traded. I make three contributions. First, I construct a dataset that tracks shocks to the cost of buying robots from Japan (the Japan robot shock, JRS) across occupations in which robots are adopted. Second, I developed a general equilibrium model that features robot automation in a large open economy. Third, when estimating the occupation-specific EoS between robots and labor of the model, I construct a model-implied optimal instrumental variable from the JRS to address the identification challenge of the correlation between the automation shock and the JRS.

The estimates of within-occupation EoS between robots and labor are heterogeneous and as high as 3 in production and material-moving occupations. These estimates are significantly larger than estimates of the EoS of capital goods and workers, with a maximum of about 1.5, revealing the special susceptibility of workers in these occupations to robot adaptation. The estimated model also implies that robots contributed to wage polarization across occupations in the US from 1990-2007. These results inform the policy discussions of industrial robots.

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Online Appendix

A Background and Data

A.1 Details about Industrial Robots

Industrial robots are defined as multiple-axe manipulators. More formally, 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 gives 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 3 shows the pictures of examples of industrial robots that are intensively used in the production process and considered in this paper. The left panel shows spot-welding robots, while the right panel shows the material-handling robots.

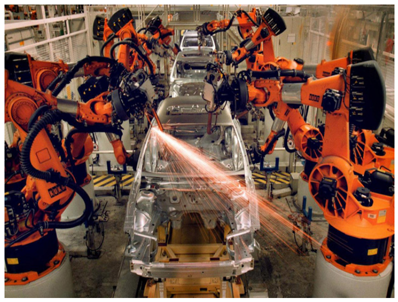
Japan is a significant innovator, producer, and exporter of robots. For example, as of 2017, the US had imported 5 billion dollars worth of Japanese robots, which comprise roughly one-third of the robots used in the US. Therefore, the cost reduction of Japanese robots significantly affects robot adoption in the US and the world.

JARA Robot Applications The full list of robot applications available in JARA data is: 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 cutting; General assembly; Inserting; Mounting; Bonding; Soldering; Sealing and gluing; Screw tightening; Picking alignment and packaging; Palletizing; Measurement/inspection/test; and Material handling.

One might wonder if robots can be classified as one of these applications since robots are characterized by versatility as opposed to older specified industrial machinery (Kawasaki Heavy Industry, 2018). Although a robot may indeed 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

Figure 3: 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)

of dexterity is different. Robots might be able to adjust a model change of the products but are not supposed to perform other tasks across the 4-digit occupation level. As SMEs are mostly high-mix and low-volume producers, robots are still too rigid to be transitioned from one occupation to another occupation at a reasonable cost. Due to this technological bottleneck, it is still infeasible to have such a versatile robot that can replace a wide range of workers at the 4-digit occupation level for the sample period of my study.

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) but an ecosystem that includes the hardware and control units operated by software (e.g., computers and robot programming language). Due to its complexity, installing robots in the production environment often requires hiring costly system integrators who offer engineering knowledge for integration. Therefore, the relevant costs of robots for adopters include hardware, software, and integration costs.[16] The average price measure of robots used in this paper should be interpreted as reflecting part of overall robot costs. Even though this follows the literature's convention due

[16]The current industry and occupation classifications do not allow separating system integrators, making it difficult to estimate the cost from these classifications. In addition, relevant costs associated with the robot still remain, e.g., maintenance fees, of which I also lack quantitative evidence. Although understanding these components of the costs is of first-order importance, this paper follows the literature convention and measures robots from the market transaction of hardware.

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, equation (23) explicitly includes the software and integration, reflecting a feature of modern industrial robots being typically not stand-alone hardware but an ecosystem that includes control units operated by software requiring a significant amount of resources for integration.

Related to this, equation (23) 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 equation (24) implies that the origin-differentiated investment good is aggregated at first and then added to the stock of capital following equation (23). This trick helps reduce the number of capital stock variables and is also used in the literature of international macroeconomics.

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

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

It is also worth mentioning that the introduction of 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. Since 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).

A.2 More on Data Sources

Details on the O*NET Code Connector Search In the O*NET Code Connector Search, the match score is the result of the *weighted search algorithm* used by the O*NET Code Connector, which is the 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 updated weighted search algorithm scored 95.9% based on the position and score of a best 4-digit occupation for a given query.

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 provides the robot data of Japan.[17] 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, which is used to obtain the measure of international trade of industrial robots and baseline trade shares. To obtain the intermediate input shares, I took data from the World Input-Output Table (WIOT) from the year closest to the initial year, 1992. IPUMS USA collects and harmonizes US census micro-data. 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). I obtain occupational wages, employment, and labor cost shares from these data sources.

I focus on occupation codes that existed between the 1970 Census and

[17] As of August 2020, the JARA association consists of 381 member companies, with the number of full members being 54, associate members being 205, and supporting members being 112.

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 Acemoglu and Restrepo (2018). My dataset shows that 88.7 percent of workers in 2007 worked in the occupations that existed in 1990. It is an open question of how to attribute the creation of new occupations to different types of automation goods, like occupational robots in my case.

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 file of American Community Survey (ACS), and the 2012-2016 5-year file of ACS from Integrated Public Use Micro Samples. For each file, I select all workers with the OCC2010 occupation code whose age is between 16 and 64 and who are not institutionalized. I compute education share in each occupation by the share of workers with more than "any year in college," and 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 used the median values in each bin of the usual weeks worked variable and assumed all workers worked for 40 hours a week since the hour variable does not exist. To compute hourly wage, I first impute 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. I use the person weight variable to aggregate all of these variables to the occupation level.

The occupation groups are formally defined as follows: Routine occupations include occupations such as production, transportation (material moving), sales, clerical, and administrative support. Abstract occupations are professional, managerial, and technical occupations. Service occupations are protective service, food preparation, cleaning, personal care, and personal services. The routine occupations are further separated into production, transportation, and others. Thus, I have the following five categories in terms of OCC2010 codes in the US Census: 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 $[10, 3540]$.

Table 2: List of Data Sources

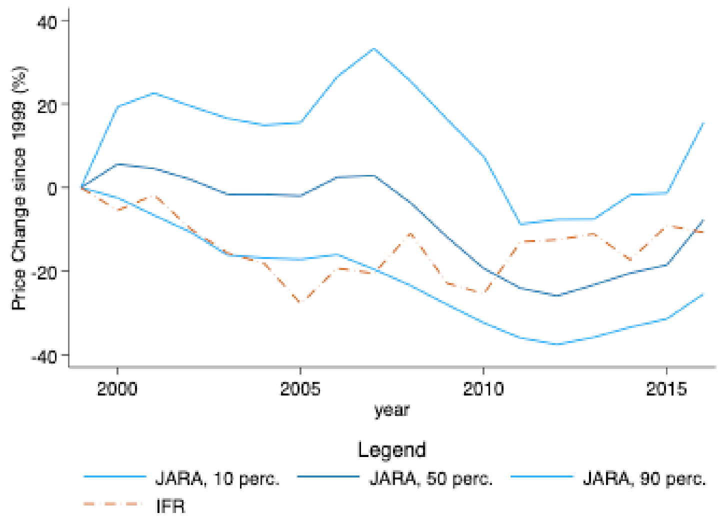
Variable	Description	blackSource
$\widetilde{y}^G_{ij,t_0}, \widetilde{x}^G_{ij,t_0}, \widetilde{y}^R_{ij,t_0}, \widetilde{x}^R_{ij,t_0}$	Trade shares of goods and robots	BACI, IFR
$\widetilde{x}^O_{i,o,t_0}$	Occupation cost shares	IPUMS
l_{i,o,t_0}	Labor shares within occupation	JARA, IFR, IPUMS
$s^G_{i,t_0},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

To estimate the model with workers' dynamic discrete choice of occupation, I further use the bilateral occupation flow data following the idea of Caliendo et al. (2019). Specifically, I have obtained the Annual Social and Economic Supplement (ASEC) of the CPS since 1976. For each year, I select all workers with the 2010 occupation code for the current year (OCC2010) and the last year (OCC10LY) whose age is between 16 and 64 and who are not institutionalized. I then constructed variables using the same method as the one used for the Census/ACS above. I assume that the workers do not flow between 4-digit occupations within the 5 occupation groups defined in Section 3.2, but do 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. With these data and assumptions, I compute the occupation switching probability by year.

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 consists of three countries $\{USA, JPN, ROW\}$. Table 2 summarizes overview of the variable notations, descriptions, and data sources. I take matrices of trade of goods and robots by 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.

To obtain the domestic robot absorption data, I take from IFR data the flow quantity variable and the aggregate price variable for a selected set of countries. I then multiply these to obtain the USA and JPN robot adoption values. For robot prices in ROW, I take the simple average of the prices

Figure 4: 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 in which the first price measure is available in the IFR data.

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 in which the price data are available. Graetz and Michaels (2018) discuss prices of robots with the same data source. Figure 4 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 11a. All measures are normalized in 1999, the year in which the first price measure is available in the IFR data. Overall, the JARA price trend variation tracks the overall 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

Table 3: 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.

workers that primarily work in each occupation o in year 1990, the Census year closest to t_0. I then take the share of this total compensation measure for each occupation. To measure l_{i,o,t_0}, I take the total compensation as the total labor cost and a measure of the user cost of robots for each occupation. The user cost of robots is calculated with the occupation-level robot price data available in IFR and the set of calibrated parameters in Section 3.1. Table 3 summarizes these statistics for the aggregated 5 occupation groups in the US. The cost for production occupations and transportation occupations comprise 18% and 8% of the US economy, respectively, totaling 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 still small-scale adoption of robots from the overall US economy.

To calculate the effect on total income, I also need to 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 the absorption share $x^R_{i,o,t_0} \equiv X^R_{i,o,t_0}/\sum_o X^R_{i,o,t_0}$. 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 have 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 take 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 3. All values in Table 3 are obtained by aggregating 4-digit-level

Table 4: 1990 Occupation Group Switching Probability

		Production	Routine Transportation	Others	Service	Abstract
	Production	0.961	0.011	0.010	0.006	0.012
Routine	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 author's calculation from the CPS-ASEC 1990 data is shown. The conditional switching probability to the column occupation group is conditional on being in each row occupation.

occupations.

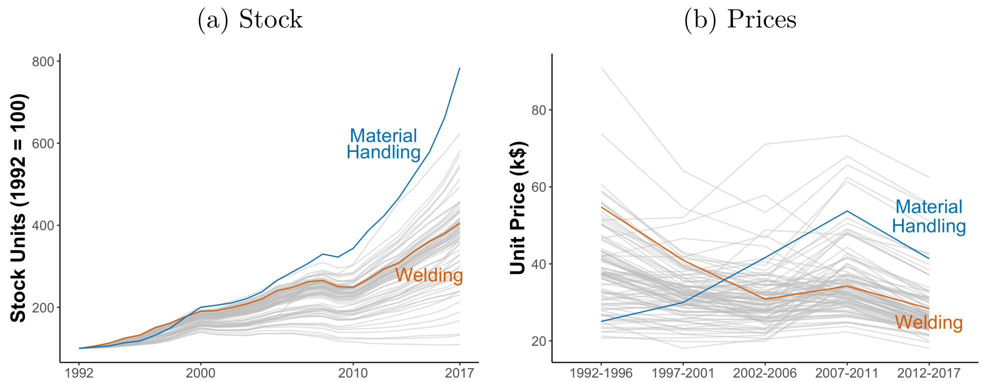
I take the intermediate input share $\alpha_{i,M}$, from World Input-Output Tables (WIOT). I combine the trade matrix generated above and WIOT to construct the good and robot expenditure shares s^G_{i,t_0}, s^V_{i,t_0}, and s^R_{i,t_0}. Specifically, with the robot trade matrix, I take the total sales 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 WIOT. From these total values, I compute expenditure shares.

As initial year occupation switching probabilities μ_{i,oo',t_0}, I take the 1990 flow Markov transition matrix from the cleaned CPS-ASEC data created in A.2. Table 4 shows this initial-year conditional switching probability. The matrix for the other years is available upon request. occupation employment data across the world are hard to obtain. Therefore, I assign the same flow probabilities for other countries in my estimation strategy.

A.3 Trends of Robot Stocks and Prices

Figure 5 shows the US robot trends at the occupation level. In the left panel, I show the trend of raw stock, which reveals the following two facts. Firstly, it shows that the overall robot stocks increased rapidly in the period, as found in the previous literature. Second, the panel also depicts 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 5b shows the trend of prices of robots in the US for each occupation. In addition to the overall decreasing trend, there

Figure 5: Trends of Japanese Robot Use at the US Occupation Level



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. In both panels, I highlight two occupations. "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 one) to smooth out yearly noises.

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 Japan robot shock (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 an example of a robot in routine-production occupations, while a material-handling robot is 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 its price increased over the sample period in the sample period. These findings indicate the difference in automation shock realization; Robots like welding robots followed a standard pattern of demand quantity expansion along the demand curve, while other robots like material handling robots expanded their adoption even though the average price increased, indicating the role of the automation shock in the model section.

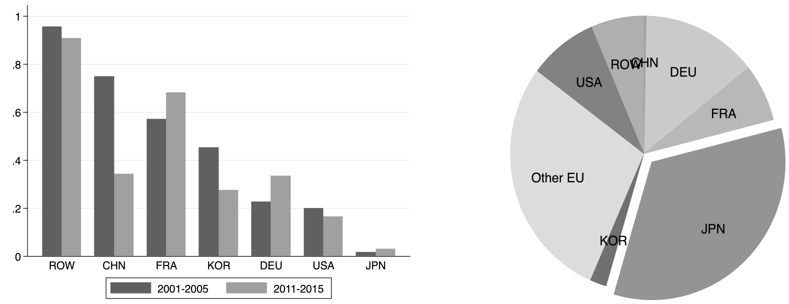
In Figure 5b, one might find an anomaly increasing trend during 2007-2011. This pattern emerges because, during the Great Recession period, the total units decreased more than the total sales. After the Great Recession, both the growth of sales and units of robots accelerated. These observations suggest a structural break in the robot industry during the Great Recession, which is out of the scope of the paper.

A.4 Trade of Industrial Robots

To compute the trade shares of industrial robots, I combine BACI and IFR data. In particular, I use the HS code 847950 ("Industrial Robots For Multiple Uses") to measure the robots, following (Humlum, 2021; Acemoglu and Restrepo, 2022). I use 1998 as the initial year value, as 1998 is the first year when the HS code 847950 is 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's annual reports for selected countries (Graetz and Michaels, 2018). Note that these price indices do not give disaggregation by robot tasks or occupations, highlighting the value added made by the JARA data. Figure 6 the pattern of international trade of international robots. In the left panel, I compute the import-absorption ratio. To remove the noise due to yearly observations and focus on a long-run trend, I aggregated the data by five-year bins: 2001-2005 and 2011-2015. The result indicates that many countries import robots as opposed to producing them in their own countries. Japan's low import ratio is outstanding, revealing that its comparative advantage in this area. It is noteworthy that 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 6. Half of the world's robot market was dominated by the EU and one-third by Japan in 2001-2005. The rest 20% is shared by the rest of the world, mostly by the US and South Korea.

Figure 7 shows the trend of export and import shares of robots for the US, Japan, and the Rest Of the World. The trends are fairly stable for the three regions of the world, except that the import share of the US has declined relative to the ROW.

Figure 6: Trade of Industrial Robots

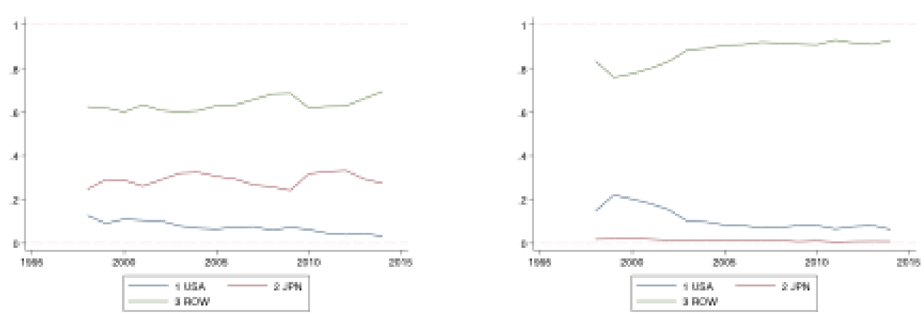


(a) Robot Import-Absorption Ratio (b) World Robot Export Share, 2001-2005

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 five-year aggregated in 2001-2005 and 2011-2015, and countries are sorted according to the import shares in 2001-2005 in descending order. The right panel shows the export share for 2001-2005 aggregates obtained from the BACI data.

Figure 7: Robot Trade Share Trends

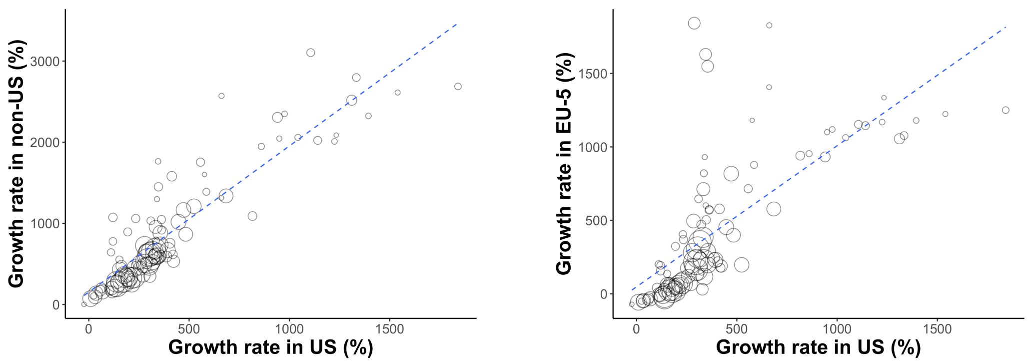
(a) Exports (b) Imports



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).

Robots from Japan in the US, Europe, and the Rest of the World To compare the pattern of robot adoption internationally, I generate the growth rates of stock of robots between 1992 and 2017 at the occupation level for each group of destination countries. The groups are the US, the non-US (all countries excluding the US and Japan), and five European countries (or "EU-

Figure 8: 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 author's calculation based on JARA, and O*NET. 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 the quantities to the non-US countries. The right one shows the correlation between growth rates of the quantities to the US and EU-5 countries. Non-US are the aggregate of all countries excluding the US and Japan. EU-5 are 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 robot in the US in the baseline year, 1992. See the main text for the detail of the method to create the variables.

5"), Denmark, Finland, France, Italy, and Sweden used in AR. The perpetual inventory method with depreciation rate of $\delta = 0.1$ is used to calculate the stock of robots, following Graetz and Michaels (2018).

Figure 8 shows scatterplots of the growth rates at the occupation level. The left panel shows the growth rates in the US on the horizontal axis and the ones in non-US countries on the vertical axis. 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 grow (1992-2017) between the US and non-US proportionately relative to those between the US and EU-5. This finding is in contrast to AR, who find that the US aggregate robot stocks grew at a roughly similar rate as those did in EU-5. It also indicates that non-US growth patterns reflect growths of robotics technology at the occupation level available in the US. I will use these patterns as the proxy for robotics technology available in the US. In Section 2 and on, 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 finding 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. Since 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 a specific occupation, then EU-5 may adopt the robots for such occupations intensively from close producers. In contrast, countries out of EU-5, including the US, may not benefit the closeness to these producers. Thus they are more likely to purchase robots from far producers from EU-5, such as Japan.

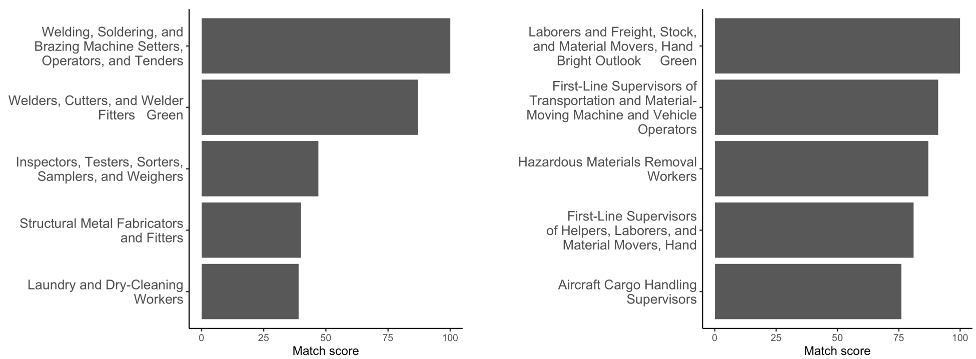
A.5 Details in Application-Occupation Matching

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 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, since the mounting and measurement/inspection/test robots have overall poor matching quality, I dropped them from the data. 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 equation (9).

For example, consider spot welding and material handling robots. First, spot welding is the task of combining 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 is a short-distance movement of heavy materials, 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 9 shows the top-5 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 (9) is transpar-

Figure 9: Examples of Match Scores



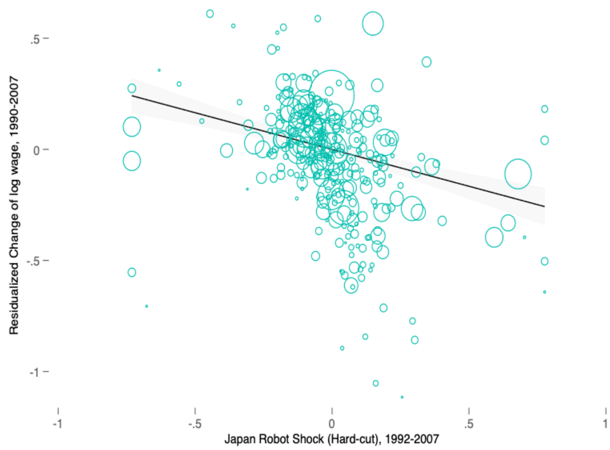
(a) Spot Welding (b) Material Handling

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 the left panel and "Material Handling" in the right panel. Occupations codes are 2010 O*NET SOC codes. In each panel, occupations are sorted in a descending way with the relative relevance scores, and the top 5 occupations are shown.

ent in a completely automatic way instead of using the researcher's judgment, one may be concerned that such a matching method may potentially contain erroneous matching due to noise in the text description in occupation dictionary. For example, Figure 9 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."

In order to mitigate this concern, I examine a manual hard-cut matching between applications and occupations. To be more specific, I drop all application-occupation matching with a matching score of 75 or below to exclude problematic matches while including enough data variation. I then construct the matching score following equation (9) conditional on remaining pairs and compute robot quantity and price variables. Figure 10 shows the result of regression specification (53) using these measures. The estimated coefficients are somewhat larger than the ones with the preferred data matching procedure primarily because, in the hard-cut matching, erroneous matches that potentially contain noises are removed. The statistical significance remains in all columns.

Figure 10: 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 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 partialled out by control variables (the occupational female share, college share, age distribution, foreign born share, and the China shock in equation (15)).

A.6 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, there are other methods proposed in the literature involving the measurement of the price of capital goods. In this subsection, I briefly describe these methods and their limitations.

The first approach is to control for the quality change by the hedonic approach used in, among others, the application to digital capital in Tambe et al. (2019). The hedonic approach requires detailed 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 a more data-driven one. Specifically, 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. As I do not know the surveyed firms and quality components, obtaining the quality measures is challenging for me.

B Reduced-form Analysis

First, I convert the JRS variable at the O*NET-SOC 4-digit occupation level to the ones at the OCC2010 occupation level to match the labor market measures from the US Census, American Community Survey (ACS), retrieved from the Integrated Public Use Microdata Series (IPUMS) USA. These labor data are standard in the literature, and their description is relegated to Appendix A.2. With all these data combined, I show stylized facts about the JRS and its relation to the labor market outcome in the US.

B.1 Trends of the Japan Robot Shock

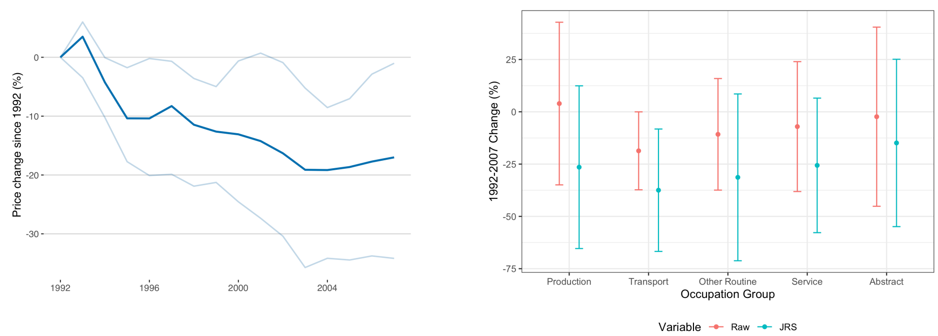
Figure 11a plots the distribution (10th, 50th, and 90th percentile) of the growth rates of the nominal price of Japanese robots in the US each year relative to the initial year. The figure shows two patterns: (i) the robot prices follow an overall decreasing trend, with a median growth rate of -17% from 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 the trend of decreasing prices of general investment goods since 1980; Karabarbounis and Neiman (2014) report a 10% decrease per decade.

Figure 11b 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, and that variation is observed even within occupation groups. Perhaps surprisingly, the average change in production robot prices is not as large as other robots but is slightly positive. This indicates that the robotics technology change in production occupations is not reflected by the price decline but by the quality improvement, so the unit value rises. Furthermore, the figure also shows the variation in JRS, or ψ^{J}_{i,t_1}, in equation (10). The large variation of the changes in prices by occupations persists even after controlling for

Figure 11: 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 line shows the median price in each year, and the two thin and light lines are 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 long-run (1992-2007) raw price decline ("Raw") and Japan Robot Shock measured by the fixed effect ψ^C_{o,t_1} in equation (10) ("JRS"). The occupation group is routine, service (manual), and abstract, where routine is further divided into production, transportation, and other.

the destination-year fixed effect $\psi^D_{i,t}$. It also confirms that after controlling for US demand shocks, the cost of Japanese robots is strongly decreasing, especially in the production occupation. In the following, I will use this cost variation to study the impact on the labor market and estimate the elasticity of substitution between robots and workers.

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

Since the 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). Namely, I compute

$$IPW_{o,t} \equiv \sum_s l_{s,o,t_0} \Delta m^C_{s,t}, \tag{15}$$

where l_{s,o,t_0} is sector-s share of employment for occupation o, and $\Delta m^C_{s,t}$ is the per-worker Chinese export growth to non-US developed countries.[18]

[18] Specifically, following Autor et al. (2013), I take eight countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Appendix A.2 shows

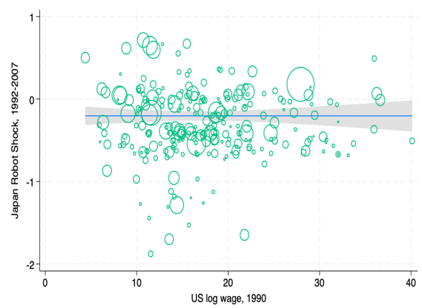
Intuitively, an occupation receives a large trade shock if sectors that face increased import competition from China intensively employ the corresponding occupation. With this trade shock measure in the control variable, I run regression (53).

In Figure 12a, the left panel shows the correlation between the JRS and US baseline wages in 1990 at the occupation level. I find that there are no systematic relationships between these variables. This indicates that the JRS did not necessarily trigger wage inequality expansion during the 1990s and 2000s. Next, the middle panel shows the result of estimation equation (53) in a scatterplot. It reveals that a 10% reduction of Japanese robot prices decreases US occupational wages by 1.2%. Therefore, the JRS did have an adverse effect on 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. This result also indicates the substitutability of labor due to robot penetration at the occupation level.

the distribution of occupational employment l_{s,o,t_0} for each sector.

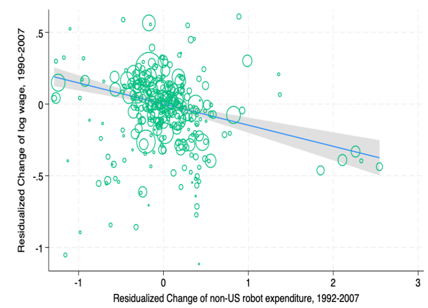
Figure 12: The Japan Robot Shock and US Occupational Wages

(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 percent confidence interval of the baseline (1990) US log wage (horizontal axis) and the Japan Robot Shock in equation (10) (vertical axis) at the 4-digit occupation level. The middle panel shows the relationship between the Japan Robot Shock (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 is all occupations that existed between 1970 and 2007, bubble sizes reflect the employment in the baseline year, and the number of observations is 324. In the middle and right panel, variables are residualized by control variables (the occupational female share, college share, age distribution, foreign-born share, and the China shock in equation (15)).

Table 5: The heterogeneous effects of the Japan robot shock on US occupations

VARIABLES	(1) $\Delta \ln(wage)$
$(-\psi^J) \times$ 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 (53) with allowing the coefficient α_1 to vary across occupation groups. Observations are 4-digit level occupations, and the sample includes all occupations that existed between 1970 and 2007. ψ^J stands for the JRS from equation (10). 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 (15), are included. Standard errors are clustered at the 2-digit occupation level. *** p<0.01, ** p<0.05, * p<0.1.

Next, Table 5 shows the result of regression (53) with allowing the coefficient α_1 to vary across occupation groups defined above. I find the negative effects in routine production and routine transportation occupations. Therefore, it demonstrates the heterogeneity in the impact across occupation groups. This finding motivates me to consider the group-specific elasticity of substitution between robots and workers.

Again, the novelty of these findings lies in the use of robot cost reduction at the occupation level. Therefore, I will show additional results that complement the findings. Table 6 shows the results of regression (53) using several alternative outcome periods and robot measures on the right-hand side. Panel A takes the wage change between 1990-2007, the main period, while Panel B takes the change between 1970-1990, the pre-sample period. In each panel, columns differ by two dimensions: (i) the robot measure, out of the robot stock in the US and other countries (non-US) and the robot price in the US and other countries, and (ii) whether the regressions include control variables of demographic variables and the China trade shock.

Table 6: 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 is all occupations that existed between 1970 and 2007. Panel A takes the wage change between 1990-2007, the main period, while Panel B takes the change between 1970-1990, 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 (15). Bootstrapped standard errors are reported in parentheses.

Table 7: The heterogeneous effects of the Japan robot shock on US occupations

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

Note: The table shows the coefficients in regression (53) with 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 includes all occupations that existed throughout 1970 and 2007. ψ^J stands for the Japan robot shock from equation (10). 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 (15), are included. Standard errors are clustered at the 2-digit occupation level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 shows the regression result of 53 with the outcome variable of employment. I find a qualitatively similar pattern 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, I do not find a 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 about the substitutability of robots, they do not definitively give answers to 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 more drastic. Second, changes in labor demand for one occupation following the shock can have a bearing on wages and employment in other occupations by changing their marginal products. Third, coefficients in equation (53) 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.

B.3 Validation Exercise in a Small Country

One concern of my reduced-form analysis is that the US is a large buyer of robots, and thus, its demand may influence the price. To mitigate this, I will conduct a robustness exercise using data from a small country that is unlikely to affect the world price of robots. Specifically, I use data from the Netherlands as a case since it is the largest exporting destination of Japanese robots in Europe, following Germany, the UK, Italy, and France, and yet a small-open economy at the same time. The data are taken from the IPUMS international and provide the ISCO 1-digit level occupation indicator in the years 2001 and 2011. I aggregate the occupational robot prices at the same level and examine the relationship between the JRS and occupational employment growth. Since the wage variable is not available in the IPUMS international, I use the employment variable to proxy the labor demand changes. Figure 13 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 the reduction of the price of Japanese robots, which is likely to hit small-open economies exogenously, reduces the labor demand in the Netherlands.

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

A potential concern for my empirical setting is a selection issue regarding the robot source country. Specifically, robots from Japan may differ from those from other countries, so the labor market implications may also differ between them. Unfortunately, it is hard to directly compare the effects of these two different groups of robots due to the data limitation, so I will focus on the best comparable measures of robotization between Japan-sourced robots and robots from all countries, which is the quantity of robot stock. Namely, I take the total stock of robot quantity in the US from the IFR data. The IFR data only has the total number, and they do not specify the source country. I

Figure 13: 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.

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:

$$\Delta Y_o = \beta^Q \Delta K_o^{R,Q} + X_o \gamma^Q + \varepsilon_o^Q, \tag{16}$$

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 gives me an insight into the correlation between the changes in labor market outcomes and the changes in robot quantity, depending on whether the robots are sourced from Japan. Specifically, if robots from Japan may 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 8 shows the regression result of equation (16). The IFR data result aligns with the previous findings by Acemoglu and Restrepo (2020). Table

Table 8: Regression Result 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 from 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 equation (15), while columns 3 and 4 do. Heteroskedasticity-robust standard errors are reported in the parenthesis.

8 reveals that both the JARA- and IFR-based robot measures capture the substitution of workers with robots, although the coefficient is somewhat stronger for JARA robot measures than for IFR.

C Theory Appendix

C.1 The Full Model

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

Workers' Problem I formalize the assumptions behind the derivation and show equations (19) and (20). Workers are immobile across countries but choose an occupation by solving a dynamic discrete choice problem (Humlum, 2021). Specifically, workers choose the 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 that the previous literature utilized (e.g., Caliendo et al. (2019)).

Fix country i and period t. There is a mass $\overline{L}_{i,t}$ of workers. In the beginning of each period, worker $\omega \in \left[0, \overline{L}_{i,t}\right]$ draws a multiplicative idiosyncratic preference shock $\left\{Z_{i,o,t}(\omega)\right\}_o$ 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 then 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 choosing 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 $\{o_s\}_{s=t+1}^{\infty}$:

$$E_t \sum_{s=t}^{\infty} \left(\frac{1}{1+\iota}\right)^{s-t} \left[\ln\left(C_{i,o_s,s}\right) + \ln\left(1-\chi_{i,o_s o_{s+1},s}\right) + \ln\left(Z_{i,o_{s+1},s}(\omega)\right)\right] \quad (17)$$

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 $l_{i,o,t}$. I assume that her income is comprised of labor income $w_{i,o,t}$ and occupation-specific ad-valorem government transfer with the rate $T_{i,o,t}$. Given the consumption price $P^G_{i,t}$, the budget constraint is

$$P^G_{i,t} C_{i,o,t} = w_{i,o,t} l_{i,o,t} \left(1 + T_{i,o,t}\right) \quad (18)$$

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

Following the similar derivation as Caliendo et al. (2019), equations (17) and (18) imply worker's optimization conditions that can be 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

$$\mu_{i,oo',t} = \frac{\left(\left(1-\chi_{i,oo',t}\right)\left(V_{i,o',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}}{\sum_{o''}\left(\left(1-\chi_{i,oo'',t}\right)\left(V_{i,o'',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}}, \quad (19)$$

$$V_{i,o,t} = \widetilde{\Gamma} C_{i,o,t} \left[\sum_{o'} \left(\left(1 - \chi_{i,oo',t}\right) \left(V_{i,o',t+1}\right)^{\frac{1}{1+\iota}} \right)^{\phi} \right]^{\frac{1}{\phi}}, \tag{20}$$

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, $\widetilde{\Gamma} \equiv \Gamma\left(1 - 1/\phi\right)$ is a constant that depends on the Gamma function $\Gamma(\cdot)$. For each i and t, employment level satisfies the law of motion

$$L_{i,o,t+1} = \sum_{o'} \mu_{i,o'o,t} L_{i,o',t}. \tag{21}$$

Non-robot Good Producers' Problem The producer's problem is made of two tiers–static optimization about labor input in each occupation and dynamic optimization about robot investment. The static part is to choose 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

$$\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) \equiv \max_{\left\{L_{i,o,t}\right\}_o} p^G_{i,t} Y^G_{i,t} - \sum_o w_{i,o,t} L_{i,o,t}, \tag{22}$$

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

The dynamic optimization problem is about choosing the quantity of new robots to purchase or 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

$$K^R_{i,o,t+1} = (1 - \delta) K^R_{i,o,t} + Q^R_{i,o,t}, \tag{23}$$

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

$$Q^R_{i,o,t} = \left[\sum_l \left(Q^R_{li,o,t}\right)^{\frac{\varepsilon^R - 1}{\varepsilon^R}} \right]^{\frac{\varepsilon^R}{\varepsilon^R - 1}\alpha^R} \left(I^{int}_{i,o,t}\right)^{1-\alpha^R} \tag{24}$$

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 equation (24) 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), which reflects the complexity and sluggishness of robot adoption.

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

$$\begin{aligned}\max_{\left\{\left\{Q^R_{li,o,t}\right\}_l, I^{int}_{i,o,t}\right\}_o} \sum_{t=0}^{\infty}\left(\frac{1}{1+\iota}\right)^t \Big[\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) \\ -\sum_o\left(\sum_l p^R_{li,o,t}\left(1+u_{li,t}\right)Q^R_{li,o,t} + P^G_{i,t} I^{int}_{i,o,t} + \gamma P^R_{i,o,t} Q^R_{i,o,t}\frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\Big],\end{aligned} \tag{25}$$

subject to accumulation equations (23) and (24), and given $\left\{K^R_{i,o,0}\right\}_o$. A standard Lagrangian multiplier method yields Euler equations for investment, which I derive 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 given 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 elasticity of substitution 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

$$M_{i,t} = \left[\sum_l \left(M_{li,t}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{26}$$

where $\varepsilon > 0$ is the elasticity of substitution. Since intermediate goods are traded across countries and aggregated by equation (26), the elasticity parameter ε plays the role of the 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

$$\sum_{o} L_{i,o,t} = \overline{L}_{i,t}, \tag{27}$$

and market clearing conditions for robots and non-robot goods must hold. There is one numeraire good to pin down the price system. I first define a temporary equilibrium in each period and then a sequential equilibrium, which leads to the definition of a steady state. The detailed expressions are 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 $\boldsymbol{\mu}_t \equiv \left[\mu_{i,oo',t}\right]_{i,oo'}$, where $\boldsymbol{V}_t$ and $\boldsymbol{\mu}_t$ are explained in detail in Appendix C.1. I write $\boldsymbol{S}_t \equiv \left[\boldsymbol{K}_t^{R'}, \boldsymbol{\lambda}_t^{R'}, \boldsymbol{L}_t', \boldsymbol{V}_t'\right]'$ 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 $\boldsymbol{p}_t \equiv \left[\boldsymbol{p}_t^{G'}, \boldsymbol{p}_t^{R'}, \boldsymbol{w}_t'\right]'$ and flow quantities $\boldsymbol{Q}_t \equiv \left[\boldsymbol{Q}_t^{G'}, \boldsymbol{Q}_t^{R'}, \boldsymbol{\mu}_t'\right]$ that satisfy: (i) given $\boldsymbol{p}_t$, workers choose occupation optimally by equation (19), (ii) given $\boldsymbol{p}_t$, producers maximize flow profit by equation (22) and demand robots by equation (33), and (iii) markets clear: Labor adds up as in equation (27), and goods markets clear with trade balances as in equations (41) and (43).

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

Definition 2. Given initial robot capital stocks and employment $\left[\boldsymbol{K}_0^{R'}, \boldsymbol{L}_0'\right]'$, a *sequential equilibrium* (SE) is a sequence of vectors $\boldsymbol{y}_t \equiv \left[\boldsymbol{x}_t', \boldsymbol{S}_t'\right]_t'$ that satisfies the TE conditions and employment law of motion (21), value function condition (20), capital accumulation equation (23), producer's dynamic optimization (37) and (36).

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

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 FOCs of equation (22)

$$p_{i,t}^{G}\alpha_{i,L}\frac{Y_{i,t}^{G}}{T_{i,t}^{O}}\left(b_{i,o,t}\frac{T_{i,t}^{O}}{T_{i,o,t}^{O}}\right)^{\frac{1}{\beta}}\left(\left(1-a_{o,t}\right)\frac{T_{i,o,t}^{O}}{L_{i,o,t}}\right)^{\frac{1}{\theta_{o}}}=w_{i,o,t}, \tag{28}$$

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

$$p_{i,t}^{G}\alpha_{i,M}\frac{Y_{i,t}^{G}}{M_{i,t}}\left(\frac{M_{i,t}}{M_{li,t}}\right)^{\frac{1}{\varepsilon}}=p_{li,t}^{G}, \tag{29}$$

and

$$p_{i,t}^{G}\alpha_{i,K}\frac{Y_{i,t}^{G}}{K_{i,t}}=r_{i,t}, \tag{30}$$

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

$$\frac{\partial\pi_{i,t}\left(\left\{K_{i,o,t}^{R}\right\}\right)}{\partial K_{i,o,t}^{R}}=p_{i,t}^{G}\frac{\partial Y_{i,t}}{\partial K_{i,o,t}^{R}}=p_{i,t}^{G}\left(\alpha_{L}\frac{Y_{i,t}^{G}}{T_{i,t}^{O}}\left(b_{i,o,t}\frac{T_{i,t}^{O}}{T_{i,o,t}^{O}}\right)^{\frac{1}{\beta}}\left(a_{o,t}\frac{T_{i,o,t}^{O}}{K_{i,o,t}^{R}}\right)^{\frac{1}{\theta}}\right). \tag{31}$$

Another static problem of 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 $Q^R_{li,o,t}$ for equation (24), I have $p^R_{li,o,t}Q^R_{li,o,t} = \left(\frac{p^R_{li,o,t}}{P^{R,BI}_{i,o,t}}\right)^{1-\varepsilon^R} P^{R,BI}_{i,o,t}Q^{R,BI}_{i,o,t}$, and $P^{R,BI}_{i,o,t}Q^{R,BI}_{i,o,t} = \alpha P^R_{i,o,t}Q^R_{i,o,t}$. Thus $p^R_{li,o,t}Q^R_{li,o,t} = \alpha \left(\frac{p^R_{li,o,t}}{P^{R,BI}_{i,o,t}}\right)^{1-\varepsilon^R} P^R_{i,o,t}Q^R_{i,o,t}$. Hence

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

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

$$Q^R_{li,o,t} = \left(\frac{p^R_{li,o,t}}{\widetilde{P}^R_{i,o,t}}\right)^{-\varepsilon^R} Q^R_{i,o,t}, \tag{32}$$

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

$$p^R_{li,o,t}\left(1+u_{li,t}\right) + 2\gamma P^R_{i,o,t}\left(\frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\frac{\partial Q^R_{i,o,t}}{\partial Q^R_{li,o,t}} = \lambda^R_{i,o,t}\frac{\partial Q^R_{i,o,t}}{\partial Q^R_{li,o,t}}. \tag{33}$$

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

$$P^G_{i,t} + 2\gamma P^R_{i,o,t}\left(\frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\frac{\partial Q^R_{i,o,t}}{\partial I^{int}_{i,o,t}} = \lambda^R_{i,o,t}\frac{\partial Q^R_{i,o,t}}{\partial I^{int}_{i,o,t}}, \tag{34}$$

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

$$\left(\frac{1}{1+\iota}\right)^{t+1}\left[\frac{\partial\pi_{i,t+1}\left(\left\{K^R_{i,o,t+1}\right\}_o\right)}{\partial K^R_{i,o,t+1}}+\gamma P^R_{i,o,t+1}\left(\frac{Q^R_{i,o,t+1}}{K^R_{i,o,t+1}}\right)^2+(1-\delta)\,\lambda^R_{i,o,t+1}\right]-\left(\frac{1}{1+\iota}\right)^t\lambda^R_{i,o,t}=0, \tag{35}$$

and the transversality condition: for any j and o,

$$\lim_{t\to\infty} e^{-\iota t}\lambda^R_{j,o,t}K^R_{j,o,t+1}=0. \tag{36}$$

Rearranging equation (35), I obtain the following Euler equation.

$$\lambda^R_{i,o,t}=\frac{1}{1+\iota}\left[(1-\delta)\,\lambda^R_{i,o,t+1}+\frac{\partial}{\partial K^R_{i,o,t+1}}\pi_{i,t+1}\left(\left\{K^R_{i,o,t+1}\right\}\right)+\gamma p^R_{i,o,t+1}\left(\frac{Q^R_{i,o,t+1}}{K^R_{i,o,t+1}}\right)^2\right]. \tag{37}$$

Turning to the demand for non-robot good, I will characterize bilateral intermediate good 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 equation (26), the bilateral trade demand is given by

$$p^G_{ij,t}Q^G_{ij,t}=\left(\frac{p^G_{ij,t}}{P^G_{j,t}}\right)^{1-\varepsilon}P^G_{j,t}X^G_{j,t}, \tag{38}$$

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 good 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

$$I_{j,t} = (1-\alpha_M) \sum_k p^G_{jk,t} Q^G_{jk,t} - \left(\sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} + \left(1-\alpha^R\right) \sum_o P^R_{j,o,t} Q^R_{j,o,t} \right), \tag{39}$$

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 income side is

$$P^G_{j,t} X^G_{j,t} = \sum_k p^G_{jk,t} Q^G_{jk,t} - \sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} \left(1 + \gamma \frac{Q^R_{ij,o,t}}{K^R_{j,o,t}} \right). \tag{40}$$

Note that this equation embeds the balanced trade condition. By substituting equation (40) into the equation (38), I have

$$p^G_{ij,t} Q^G_{ij,t} = \left(\frac{p^G_{ij,t}}{P^G_{j,t}} \right)^{1-\varepsilon^G} \left(\sum_k p^G_{jk,t} Q^G_{jk,t} + \sum_{k,o} p^R_{jk,o,t} Q^R_{jk,o,t} - \sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} \right). \tag{41}$$

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

$$Y^R_{i,t} = \sum_j Q^G_{ij,t} \tau^G_{ij,t}, \tag{42}$$

for all i and t, and

$$p^R_{i,o,t} = \frac{P^G_{i,t}}{A^R_{i,o,t}} \tag{43}$$

for all i, o, and t, respectively.

Conditional on state variables $\boldsymbol{S}_t = \left\{ \boldsymbol{K}^R_t, \boldsymbol{\lambda}^R_t, \boldsymbol{L}_t, \boldsymbol{V}_t \right\}$, equations (19), (28), (33), (41), (42), and (43) characterize the temporary equilibrium $\left\{ \boldsymbol{p}^G_t, \boldsymbol{p}^R_t, \boldsymbol{w}_t, \boldsymbol{Q}^G_t, \boldsymbol{Q}^R_t, \boldsymbol{L}_t \right\}$. In addition, conditional on initial conditions $\left\{ \boldsymbol{K}^R_0, \boldsymbol{L}_0 \right\}$, equations (23), (37), and (36) characterize the sequential equilibrium.

Finally, the steady-state conditions are given by imposing the time-invariance condition to equations (23) and (37):

$$Q^R_{i,o} = \delta K^R_{i,o}, \tag{44}$$

$$\frac{\partial}{\partial K_{i,o}^{R}}\pi_i\left(\left\{K_{i,o}^{R}\right\}\right)=\left(\iota+\delta\right)\lambda_{i,o}^{R}-\sum_{l}\gamma p_{li,o}^{R}\left(\frac{Q_{li,o}^{R}}{K_{i,o}^{R}}\right)^{2}\equiv c_{i,o}^{R}. \tag{45}$$

Note that equation (45) can be interpreted as the flow marginal profit of capital must be equalized to the marginal cost term. Thus, I define the steady-state marginal cost of robot capital $c_{i,o}^{R}$ from the right-hand side of equation (45). Note that if there is no adjustment cost $\gamma=0$, the steady state Euler equation (45) 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 the user cost of robots in the steady state.

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

Since the GE system is highly nonlinear and does not have a closed-form solution due to flexible robot-labor substitution, I log-linearize the system around the initial steady state. Consider increases of the robot task space $a_{o,t}$ and of 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 $\boldsymbol{S}_t=\left[\boldsymbol{K}_t^{R'},\boldsymbol{\lambda}_t^{R'},\boldsymbol{L}_t',\boldsymbol{V}_t'\right]'$, 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

$$\overline{\boldsymbol{D}^x}\widehat{\boldsymbol{x}}_t=\overline{\boldsymbol{D}^A}\widehat{\boldsymbol{A}_t}. \tag{46}$$

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).[19]

[19]Since the temporary equilibrium vector $\widehat{\boldsymbol{x}_t}$ includes wages $\widehat{\boldsymbol{w}_t}$, equation (46) generalizes the general equilibrium comparative statics formulation in Adao et al. (2023), who consider

Step 2 Log-linearizing 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 (46) can be written as

$$\overline{\boldsymbol{D}^{x}}\widehat{\boldsymbol{x}_t} - \overline{\boldsymbol{D}^{A,S}}\widehat{\boldsymbol{S}_t} = \overline{\boldsymbol{D}^{A,\Delta}}\boldsymbol{\Delta}. \tag{47}$$

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

$$\overline{\boldsymbol{E}^{y}}\widehat{\boldsymbol{y}} = \overline{\boldsymbol{E}^{\Delta}}\boldsymbol{\Delta}, \tag{48}$$

where

$$\overline{\boldsymbol{E}^{y}} \equiv \begin{bmatrix} \overline{\boldsymbol{D}^{x}} \quad -\overline{\boldsymbol{D}^{A,T}} \\ \overline{\boldsymbol{D}^{y,SS}} \end{bmatrix}, \text{ and } \overline{\boldsymbol{E}^{\Delta}} \equiv \begin{bmatrix} \overline{\boldsymbol{D}^{A,\Delta}} \\ \overline{\boldsymbol{D}^{\Delta,SS}} \end{bmatrix},$$

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 laws of motion and Euler equations around the new steady state, I solve for matrices $\overline{\boldsymbol{D}^{y,TD}_{t+1}}$ and $\overline{\boldsymbol{D}^{y,TD}_{t}}$ such that $\overline{\boldsymbol{D}^{y,TD}_{t+1}}\check{\boldsymbol{y}}_{t+1} = \overline{\boldsymbol{D}^{y,TD}_{t}}\check{\boldsymbol{y}}_{t}$, 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 sequential equilibrium satisfies the following first-order difference equation

$$\overline{\boldsymbol{F}^{y}_{t+1}}\widehat{\boldsymbol{y}_{t+1}} = \overline{\boldsymbol{F}^{y}_{t}}\widehat{\boldsymbol{y}}_t + \overline{\boldsymbol{F}^{\Delta}_{t+1}}\boldsymbol{\Delta}. \tag{49}$$

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

$$\widehat{\boldsymbol{y}}_t = \overline{\boldsymbol{F}_t}\boldsymbol{\Delta} \text{ and } \overline{\boldsymbol{F}_t} \to \overline{\boldsymbol{E}}. \tag{50}$$

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

the variant of equation (46) with $\widehat{\boldsymbol{x}_t} = \widehat{\boldsymbol{w}_t}$.

D Additional Results on Estimation and Simulation

I assume $\alpha^R = 2/3$ following the convention in the literature. By Cooper and Haltiwanger (2006), I set the parameter of adjustment cost at $\gamma = 0.295$. I use the estimates from the literature on the dynamic discrete choice of occupations and set the occupation switching elasticity as $\phi = 1.4$.

D.1 Robot Trade Elasticity

To estimate robot trade elasticity ε^R, I apply and extend the trilateral method of Caliendo and Parro (2015). Namely, 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 tariff on robots taken from the UNCTAD-TRAINS database and $\tau^{R,D}_{li,t}$ is 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 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 fixed effects (FEs) such as non-tariff barriers respectively, and $\tau^{R,D,E}_{li,t}$ is the random error that is orthogonal to tariffs. By equation (32), I have

$$\ln\left(\frac{X^R_{li,t}X^R_{ij,t}X^R_{jl,t}}{X^R_{lj,t}X^R_{ji,t}X^R_{il,t}}\right) = \left(1-\varepsilon^R\right)\ln\left(\frac{\tau^{R,T}_{li,t}\,\tau^{R,T}_{ij,t}\,\tau^{R,T}_{jl,t}}{\tau^{R,T}_{lj,t}\,\tau^{R,T}_{ji,t}\,\tau^{R,T}_{il,t}}\right) + e_{lij,t}, \tag{51}$$

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 requires the orthogonality 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 implementing regression of equation (51), I further consider controlling for two separate sets of FEs. The first set is the unilateral FE indicating if a country is included in the trilateral pair of countries, and the second set is the bilateral FE for the twin of countries is included in the trilateral pair. These FEs are relevant in my setting as a few number of countries ex-

Table 9: Coefficient of equation (51)

	(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 (51), 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 (FE), while the second and fourth the bilateral FE.

port robots, and controlling for these exporters' unobserved characteristics is critical.

Table 9 shows the result of regression of equation (51). 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, and the second and fourth 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) show in Table 1 that the regression coefficient of equation (51) is 1.52, with the standard error of 1.81, for "Machinery n.e.c", which roughly corresponds 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 significantly higher than these values, such as 4 in Simonovska and Waugh (2014). The low trade elasticity for robots ε^R reflects the fact 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 the robot-selling country.

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 et al. (2023), who extend the classical two-stage GMM estimator to the general equilibrium environment and define the model-implied optimal instrumental variable (MOIV). The key idea is that the optimal GMM estimator is based on the instrumental variable that depends on unknown structural parameters. Therefore, the two-step estimator solves this unknown-dependent problem and achieves desirable properties of consistency and asymptotic efficiency. As a result, I define IVs $Z_{o,n}$ where $n = 0, 1$ as follows:

$$Z_{o,n} \equiv H_{o,n}\left(\boldsymbol{\psi}^J\right) = \mathbb{E}\left[\nabla_{\boldsymbol{\Theta}}\nu_o\left(\boldsymbol{\Theta}_n\right)|\boldsymbol{\psi}^J\right]\mathbb{E}\left[\nu_o\left(\boldsymbol{\Theta}_n\right)\left(\nu_o\left(\boldsymbol{\Theta}_n\right)\right)^\top|\boldsymbol{\psi}^J\right]^{-1}. \quad (52)$$

For the formal statement, I need the following additional assumption.

Assumption 2. *(i) A function of* $\widetilde{\boldsymbol{\Theta}}$*,* $\mathbb{E}\left[H_o\left(\boldsymbol{\psi}^J_{t_1}\right)\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\right] \neq 0$ *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)* $\mathbb{E}\left[\sup_{\boldsymbol{\Theta}} \parallel H_o\left(\boldsymbol{\psi}^J_{t_1}\right)\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\parallel\right] < \infty$*. (iv)* $\mathbb{E}\left[\parallel H_o\left(\boldsymbol{\psi}^J_{t_1}\right)\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\parallel^2\right] < \infty$ *(v)* $\mathbb{E}\left[\sup_{\boldsymbol{\Theta}} \parallel H_o\left(\boldsymbol{\psi}^J_{t_1}\right)\nabla_{\widetilde{\boldsymbol{\Theta}}}\nu_o\left(\widetilde{\boldsymbol{\Theta}}\right)\parallel\right] < \infty$*.*

Under Assumptions 1 and 2, Adao et al. (2023) shows 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 equation (52). 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 equation (52).

D.3 Model Fit

I apply the simulated data to the linear regression model:

$$\Delta \ln\left(\ln w_o\right) = \alpha_0 + \alpha_1 \times \left(-\psi^J_o\right) + \alpha_2 \times IPW_{o,t_1} + \boldsymbol{X}_o \cdot \boldsymbol{\alpha} + \varepsilon_o, \quad (53)$$

where w_o is log hourly wage, and $\boldsymbol{X}_o$ is the vector of baseline demographic control variables.[20]

Consider the following two simulations. First, I apply the JRS and the implied automation shock, and I call this counterfactual wage change "targeted." The predicted wage changes are consistent with the moment condition (14), and thus the linear regression coefficient α_1 of equation (53) is expected to be close to the one obtained from the data. Second, I apply only the JRS but not the automation shock, and I call this counterfactual wage change "untargeted." In this case, the moment condition (14) is violated since the structural residual does not incorporate the unobserved automation shock, which causes 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 of considering the automation shock in the estimation. The details of the method for simulating the data are explained in D.4.

Table 10 shows the result of these exercises. The first column shows the estimates of equation (53) 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. Comparing the first and second columns confirms that the targeted moments match as expected. Furthermore, examining the third column compared to these two columns, one can see 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 upgrade 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 (53) contains a positive bias due to this positive correlation. In contrast, the untargeted wage is free from this bias since its data-generating process does not contain the automation shock but only the JRS. Thus, the linear regression coefficient α_1 is higher than the one 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 12 is bias-free, I would have estimated a higher EoS by ignoring the actual positive correlation be-

[20]The controls are the female share, the college-graduate share, the age distribution, and the foreign-born share. B.2 provides a thorough discussion on these reduced-form regressions.

Table 10: Model Fit: Linear Regression with Observed and Simulated Data

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

Note: The author's calculation is shown based on the dataset generated by JARA, O*NET, and the US Census. 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 $\widehat{\boldsymbol{a}^{\mathrm{imp}}}$. Column (3) takes the US wage change predicted by the model with only the JRS (but not the automation shock). Heteroskedasticity-robust standard errors in parentheses.

tween $-\psi_o^J$ and $\widehat{a_o^{\mathrm{imp}}}$. This thought experiment reveals that it is critical to take into account 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.

D.4 Details in the Simulation Method

The simulation for the counterfactual analysis comprises three steps. First, I back out the observed shocks 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 equation (11). With the point estimates in Table 1, the implied automation shock $\widehat{a_{o,t}^{\mathrm{imp}}}$ using (12). 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 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 BACI data. Second, applying the backed-out shocks $\widehat{A_{i,o,t}^R}$ and $\widehat{a_{o,t}^{\mathrm{imp}}}$ to the first-order solution of the GE in equation (50), I obtain the prediction of changes in endogenous variables to these shocks to the first-order. Finally, I obtain the predicted level of endogenous variables by applying the predicted changes to the initial data in $t_0 = 1992$.

D.5 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 I call the general tax scenario. I also consider the tax on only imported robots by 33.6%, 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 straightforward between the two scenarios.[21] First, I examine the effect of the general robot tax on occupational inequality.

In Figure 14a, I show two scenarios of the steady-state changes in real occupational wages. In one scenario, I shock the economy only with the automation shocks. In the other scenario, I shock the economy with both the automation shocks and the robot tax. The result shows heterogeneous effects on real occupational wages of the robot tax. The tax mitigates the negative effect of automation on routine production workers and routine transportation workers, while the tax marginally 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 shocks, which could go in negative and positive directions depending on occupation groups, and compresses the effects towards zero. Figure 14b shows the dynamics of the effects of only the robot tax. Although the steady-state effects of robot tax were heterogeneous, as shown in Figure 14a, 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 since the robot tax slows down the adoption of robots, it rolls back the real wage effect of automation–workers in occupations that experienced significant automation shocks (e.g., production and transportation in the routine occupation groups) benefit from the tax, while the others lose. Appendix D.6 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 15a, the solid line tracks the real-income effect of the general robot tax over a 20-year time 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.

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

Figure 14: The Effects of the Robot Tax on Real Occupational Wages

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

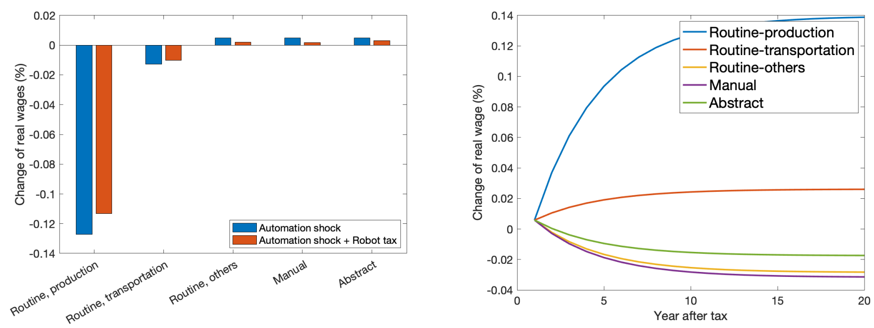
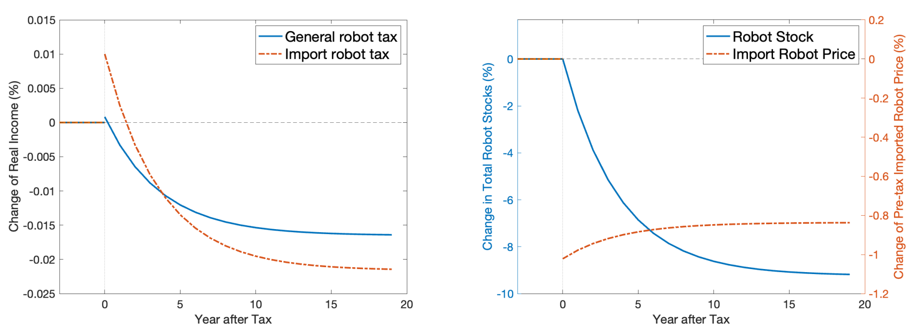


Figure 15: Effects of the Robot Tax

(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.

Second, there is a positive effect in the short run, but this effect turns negative quickly and continues to be 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. Since robots are traded, and the US is a large economy that can affect the robot price 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 world market and lets the equilibrium robot price go down along the supply curve. This reduction in the robot price contributes to compressing the cost of robot investment thus to increasing the firm's profit, 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. While this terms-of-trade manipulation is well-studied in the trade policy literature, my setting is novel since it implies the upward-sloping export supply curve from the GE.

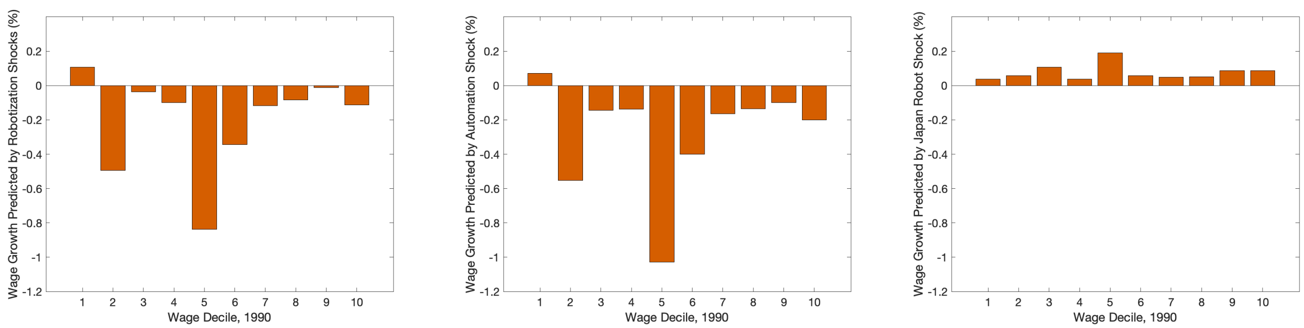
The reason for the different effects on real income, in the long run, is as follows. The solid line in Figure 15b shows the dynamic impact of the import robot tax on the accumulation of robot stock. The robot tax significantly slows the accumulation of robot stocks and decreases the steady-state stock of robots by 9.7% compared to the no-tax case. The small robot stock reduces the firm profit, which contributes to low real income.[22] These results highlight the role that costly robot capital (de-)accumulation plays in the effect of the robot tax on aggregate income. Figure 15b also shows the dynamic effect on import robot prices in the dash-dot line. In the short run, the price decreases due to the decreased demand from the US, as explained above. As the sequential equilibrium reaches the new steady state where the US stock of robots decreases, the marginal value of the robots is higher. This increased marginal value partially offsets the reduced price of robots in the short run.

The Effect of Robotization and the Sources of Shocks In Figure 2b, I show the effect of two robotization shocks: the automation shock $\widehat{\boldsymbol{a}}$ and the JRS $\widehat{\boldsymbol{A}}_2$. Although both are relevant shocks to the robotics technology during the sample period, the result is a mixture of these two effects, making it hard to assess the contribution of each shock. To address this concern, Figure 16 shows the decomposition of the main exercise. The left panel shows 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, and therefore occupational wages

[22]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 since the robot tax is ad-valorem and uniform across occupations.

Figure 16: 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 approximated steady-state solution of the estimated model given in equation (48), for each of ten deciles of the occupational wage distribution in 1990, and is equivalent to Figure 2b. The center and right panels distinguish the effect of the automation shock (center) and the Japan robot shock (right).

increased.

D.6 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 D.5. 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 D.3. For each country i and occupation o, $EV_{i,o}$ is implicitly defined as

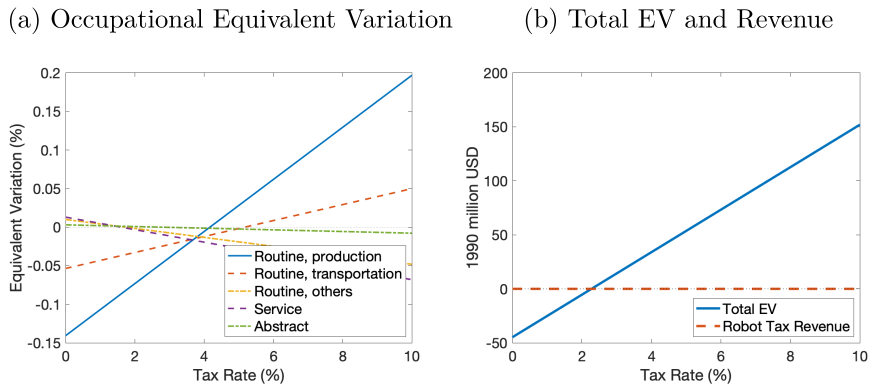
$$\sum_{t=t_0}^{\infty}\left(\frac{1}{1+\iota}\right)^t \ln\left(\left[C'_{i,o,t}\right]\right) = \sum_{t=t_0}^{\infty}\left(\frac{1}{1+\iota}\right)^t \ln\left(C_{i,o,t}\left[1+EV_{i,o}\right]\right). \tag{54}$$

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 17a 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 effects (cf. Figure 14a), 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 around 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, which adversely affects 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

Figure 17: Robot Tax and Workers' Welfare



Note: The left panel shows the US workers' equivalent variation defined in equation (54) 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.

groups (total EV) and compare it with the robot tax revenue, both as a function of robot tax. Figure 17b 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.