Robots and Wage Polarization: The Effects of Robot Capital by Occupations*

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Abstract

Robotization has been substituting or complementing workers in a wide range of occupations. To study the strength of this substitutability and the distributional impacts of robotization, I match unique data on imported robot prices with the occupational task information to measure the cost of using robots by occupation. The data reveal that a 10% cost reduction induces a 1.2% drop in wages of production and transportation occupations in the US, suggesting strong substitutability. This finding motivates developing a model in which robots are traded and can substitute for labor with different elasticities of substitution across occupations. Using a model-implied optimal instrumental variable, I estimate higher elasticity of substitution between robots and workers than that of general capital goods in production and transportation occupations. These estimates imply that the adoption of industrial robots significantly affects the wage polarization in the US.

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1 Introduction

The adoption of industrial robots has been changing factory production rapidly.[1] In the last three decades, the size of the global robot market has grown by 12% per year. The robotization has heterogeneous effects on workers across occupations, raising a concern about the distributional effects of robot adoption. Policymakers have proposed various countermeasures to the potential harms of robotization, such as introducing taxation on robot adoption.[2] Motivated by these observations, an emerging literature has estimated the relative effects of robot penetration on employment and the potential impact of robot taxes (e.g., Acemoglu and Restrepo 2020; Humlum 2019). 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 show that the robot cost reduction affects the US wage and employment adversely. This suggests a substitutability between robots and workers within an occupation, which is unlike the previous research that reveals the substitutability between occupations. Building on this fact, I develop an equilibrium model in which robots substitute for labor within each occupation. Using these data and model, 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, based on this estimated model, I perform counterfactual exercises to study the distributional effect of robotization in the US since 1990 as well as the welfare impact

[1] Throughout the paper, industrial robots (or robots) are defined as multiple-axes manipulators and are measured by the number of such manipulators, or robot arms, following a standard in the literature. A more formal definition given by ISO is provided in Appendix E.2. Such a definition implies that any automation equipment that does not have multiple axes is 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).

[2] The European Parliament proposed a robot tax on robot owners in 2015, although it eventually rejected the proposal (Delvaux et al. 2016). South Korea revised the corporate tax laws that downsize the "Tax Credit for Investment in Facilities for Productivity Enhancement" for enterprises investing in automation equipment (MOEF 2018).

of robot taxes.

A unique feature of my dataset is in the robot price measure for each 4-digit occupation in which robots replace labor. To obtain such a dataset, I use the information about the shipment of Japanese robots, which comprises about one-third of the world 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 the JARA data with the O*NET Code Connector's match score to get an occupation-level robot price measure. Finally, I use the fixed effect regression on the unit robot price to get the robot cost shock that controls for the demand factors, which I call "the Japan robot shock".

The dataset reveals two stylized facts. First, from 1990-2007, there is a sizable and heterogeneous reduction in the average cost of Japanese robots, ranging from -150% to 0% across occupations.[3] Second, there is a negative relationship between the Japan robot shock and the US wage growth, or a 1.2% decline in occupational wage growths per year associated with a 10% decrease in the cost of using Japanese robots. This finding is robust to controlling for other occupational demand shocks, such as the China trade shock, and suggests that the relative demand for labor is responsive to the robot cost reduction due to the strong substitutability of robots for labor.

However, the Japan robot shock measure may be affected by the robot quality change instead of the change in the cost of robots, and thus the reduced-form relationship does not reveal the elasticity of substitution parameters. To address this concern and derive the distributional effects of robotization, I employ an equilibrium model of robotics automation and quality changes with the following three key features. First, I incorporate the trade of robots following Armington (1969) to capture the sizable robot export by Japan in my dataset. Furthermore, this large-open economy setting implies that a robot tax would affect the world price of robots, allowing a country to potentially improve the welfare by manipulating the terms-of-trade. Second, the model describes the endogenous

[3] I focus on this sample period and omit data after the Great Recession since the aggregate data about robots show a strikingly different trend than before, and capturing it is out of the scope of this paper.

investment in robots with a convex adjustment cost, which controls for the speed of robot accumulation. Therefore, compared to static models, the aggregate income implication of the robot tax is nuanced and different over the time horizon. Finally, the production function is characterized by EoS between robots and labor that varies across occupations as well as EoS between occupations. I show that this production function can be micro-founded by the task-based framework à la Acemoglu and Autor (2011), and that it yields rich predictions about the real-wage effect of robot capital accumulation.

To estimate these robot-labor EoS, however, I confront the identification challenge that the Japan robot shock can be correlated with the unobserved automation shock, and these shocks affect the labor market outcomes simultaneously. To overcome this challenge, I use the model solution and obtain the structural residual of the labor market outcomes, which controls for the effect of the automation shock. I then impose a moment condition in which this structural residual is orthogonal to the Japan robot shock. This moment condition does not only provide me with the consistent parameter estimates but also with an optimal instrumental variable to increase estimation precision significantly.

Applying this estimation method, I find that the EoS between robots and workers is around 2 when estimated with a restricted constant across occupation. This estimate is higher than the typical values reported in the literature of the EoS between labor and general capital like 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 occupation. 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. I then validate the estimated model by checking that the predicted occupational US wage changes from 1990-2007 fit well with the observed ones.

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 finding indicates that the robotization shock slowed the wage growth of occupations in the middle deciles since these occupations tend to be in the middle of the occupational wage distribution in 1990. Quantitatively, it explains a 6.4% increase of the 90th-50th percentile wage ratio, a measure of wage inequality popularized by Goos and Manning (2007) and Autor, Katz, and Kearney (2008). The robotization also explains a 0.2 percentage point increase of the US real income, mostly accounted for by the rise in the producers' profit due to the accumulation of robots.

Finally, I examine the counterfactual effect of introducing a tax on robot purchases. As mentioned above, such a robot tax could potentially increase the aggregate income of a country through the change in robot prices. By contrast, the robot tax also disincentivizes the accumulation of robots in the steady state, potentially reducing aggregate income. Quantitatively, the net positive effect by terms-of-trade effect quickly disappears in 2-3 years as the effect of robot distortion starts to dominate. As a result, the robot tax decreases the real income in the long run. Therefore, this finding provides a caution to policy measures proposed to slow down the adoption of industrial robots even when the country can strategically tap into the opportunity of terms-of-trade manipulation.

This paper contributes to the literature of the economic impacts of industrial robots by finding a sizable impact of robots on US wage polarization and a short-run positive aggregate effect of a robot tax. The closest papers to mine are Acemoglu and Restrepo (2020) and Humlum (2019). Acemoglu and Restrepo (2020) establish that the US commuting zones that experienced a greater penetration of robots in 1992-2007 saw lower growths of wage and employment.[4] To examine robot taxes, Humlum (2019) uses firm-level data on robot adoption and estimates a model that incorporates robot importers in a small-

[4]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.

open country, a binary decision of robot adoption, and an EoS between occupations.[5] In contrast, I use the data on the robot cost by occupation, which empirically reveal the substitutability of robots in US occupations. I also consider large open countries' trade of robots, which introduces terms-of-trade manipulation when considering robot taxes.

An increasing number of studies pay attention to occupations to learn potentially heterogeneous impacts of automation. While Jäger, Moll, and Lerch (2016) find no association between industrial robot adoptions and total employment at the firm level, Dinlersoz, Wolf, et al. (2018) report the cost share of workers in the production occupation decreased after the adoption of robots within a firm. In contrast, Cheng (2018) studies the heterogeneous capital price decrease and its implication for job polarization. Jaimovich et al. (2020) construct a general equilibrium model to study the effect of automation on the labor market of routine and non-routine workers in the steady state. Compared to these papers, I provide the method of estimating the within-occupation EoS between robots and labor with the occupation-level data of robot costs and labor market outcomes, as well as incorporating the endogenous trade of robots and characterizing the transition dynamics of the effect of robot tax.

My paper is also related to the vast literature of estimating the EoS between capital and labor, as robots are one type of capital goods (to name a few, Arrow et al. 1961; Chirinko 2008; Oberfield and Raval 2014). Although the literature yields a set of estimates with a wide range, the upper limit of the range appears around 1.5 (Karabarbounis and Neiman 2014; Hubmer 2018). Therefore, my EoS estimates around 3 in production and material-moving occupations are significantly higher than this upper limit. In this sense, my estimates highlight one of the main differences between robots and other capital goods: the occupational workers' vulnerability to robots.

[5] There is also a growing body of studies that use the firm- and plant-level microdata to study the impact on workers in Canada (Dixon, Hong, and Wu 2019), France (Acemoglu, Manera, and Restrepo 2020; Bonfiglioli et al. 2020), the Netherlands (Bessen et al. 2019), Spain (Koch, Manuylov, and Smolka 2019), and the US (Dinlersoz, Wolf, et al. 2018).

2 Data and Stylized Facts

To approach the substitutability of robots for workers, the measures for the cost of using robots are needed. For this purpose, I provide key data sources, the Japan Robot Association survey. I combine this data source with the O*NET Code Connector for matching robot application codes to labor occupation codes at the 4-digit level. Using these data, I propose a method for matching robot applications and occupations, and measuring the cost of using robots. I then present stylized facts about robots and workers at the occupation level that suggest a strong substitutability between robots and labor to motivate the model and estimation in later sections. Throughout the paper, I set the sample period to 1992-2007 (or 1990-2007 for the labor data) and write $t_0 \equiv 1992$ and $t_1 \equiv 2007$.

2.1 Data Sources

The robot measures of my dataset are sourced from the Japan Robot Association (JARA), a general incorporated association composed of Japanese robot-producing companies. As of August 2020, the association counts 381 member companies. JARA annually surveys all these member companies about the units and monetary values of robots sold for each destination country and robot application. Here, robot application is defined as the specified task that robots perform, which is discussed in detail in Section 2.2 and in Appendix E.2 with examples. I digitize JARA's annual publication of the summary cross tables starting from 1978.

Japan is a major robot innovator, producer, and exporter. For example, as of 2017, the US had imported 5 billion dollars' worth of Japanese robots, which comprises roughly one-third of the robots used in the US.[6] Therefore, the cost reduction of Japanese robots significantly affects robot adoption in the US and the world. In this paper, I use the cost drop of Japanese robots as one of the sources of robotization shocks and treat the unobserved reduction of the cost of robots from other countries as independent from the evo-

[6] Appendix E.3 shows the international robot flows, including Japan, the US, and the rest of the world.

lution of Japanese robot costs. I will clarify the source of the shocks in detail in Section 3 and discuss the plausibility of this assumption in Appendix H.6 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.

I also 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 the definitions of occupations sponsored by the US Department of Labor, Employment, and Training Administration, and provides an occupational search service that helps workforce professionals determine relevant 4-digit level O*NET-SOC Occupation Codes. Using this service, one can provide any words in search query and get occupations that are close to the search words. Furthermore, the search algorithm provides a match score that shows the relevance of each occupation to the search term.[7] I use this match score to match robot applications and labor occupations. The set of occupations consists of all of the 324 four-digit-level occupations that exist throughout my sample period and pre-period, which is discussed in detail in Appendix E.1.

2.2 Constructing the Dataset

To construct the dataset, I first describe the matching process between robot applications and labor occupations. Second, I describe the measurement method of robot costs, which is novel compared to the past literature which only focuses on the quantity of robots (e.g., Acemoglu and Restrepo 2020; Humlum 2019).[8]

[7]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 and 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 target best 4-digit occupation for a given query.

[8]While Graetz and Michaels (2018) provide data about robot prices from IFR, the price data is aggregated but not distinguished by occupations. By contrast, I will use the variation at the occupation level to estimate the substitutability between robots and workers.

Matching Robot Applications and Labor Occupations Robot applications and labor occupations are close concepts, although there has not been formal concordance between application and occupation codes. On the one hand, a robot application is the task to which the robot is applied, and each task has different technological requirements for robotics automation. On the other hand, an occupation also requires multiple types of tasks. Therefore, 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). To further facilitate the understanding, I show examples of robot applications and labor occupations in Appendix E.2.

Specifically, let a denote robot application and o denote labor occupation. The JARA data measure the quantity 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 means both quantity and monetary values. The goal is to convert an application-level robot measure X_a^R to an occupation-level measure X_o^R. First, I search occupations in the O*NET Code Connector by the title of robot application a. Second, I web scrape the match score m_{oa} between a and o. Finally, I allocate X_a^R to each occupation o according to m_{oa}-weight by

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

As a result, X_o^R is the robot measure at the occupation level. Note that $\sum_o \omega_{oa} X_a^R = X_a^R$ since $\sum_o \omega_{oa} = 1$, which is a desired property of allocation that occupation-level robot values get back to the application level when summed across occupations. Further details of matching are described using examples in Appendix E.5.

It is relevant to comment on recent literature that studies the task contents of recent technological development. 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. My matching method between robot application and occupation complements these studies by matching the data of robot quantities and prices but requiring lower data inputs, as I only observe the title of robot applications but not the detailed descriptions such as those in patent texts.

The Japan Robot Shock The above matching method provides the robot quantity $q^R_{i,o,t}$ and sales $(pq)^R_{i,o,t}$ in destination country i, occupation o, and year t. Using them, I construct the cost shocks to the users of robots in each occupation. Specifically, I start with the average price $p^R_{i,o,t} \equiv (pq)^R_{i,o,t} / q^R_{i,o,t}$.[9] Since this measure may be affected by the demand shock in country i, it is not suitable as a cost shock. To mitigate this concern, I exclude the US prices from the sample following the automation literature that treats the demand shock (Acemoglu and Restrepo 2020). Formally, I fit the fixed-effect regression

$$\ln\left(p^R_{i,o,t}\right) - \ln\left(p^R_{i,o,t_0}\right) = \psi^D_{i,t} + \psi^J_{o,t} + \epsilon_{i,o,t},\ i \neq USA \tag{1}$$

where t_0 is the initial year, $\psi^D_{i,t}$ is destination-year fixed effect, $\psi^J_{o,t}$ is 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 "Japan robot shock."

Another issue with the average price approach is that it includes the component of robot quality upgrading. Namely, a rapid innovation in robotics technology could entail both a quality upgrading that makes robots perform more tasks at a greater efficiency as well as the cost saving of producing robots that perform the same task as before. The inseparability of these two components makes it hard to compare prices over time, which poses an identification threat described in a later section. To work around this issue, I will use the general equilibrium model to predict the labor market effects of quality upgrading in Section 3. Other possible approaches and their limitations are discussed in Appendix

[9] I have also computed the chain-weighted robot price index as it is used commonly when measuring the capital good price. The results using this index are not qualitatively different from the main findings and are available upon requests.

H.2. Furthermore, the robot cost in this paper only measures that of robot hardware, not software or integration. A detailed discussion about this point is relegated to Appendix A.

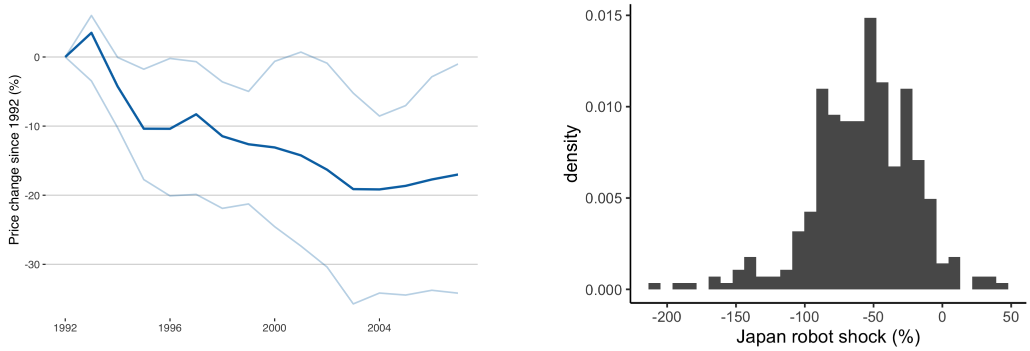
2.3 Stylized Facts

I convert the Japan robot shock data 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 (Ruggles et al. 2018). These labor data are standard in the literature, and their description is relegated to Appendix E.1. Using the resulting dataset, I show stylized facts about the Japan robot shock and its relation to the labor market outcome in the US.

Fact 1: Trends of the Japan Robot Shock I start with the patterns of average prices of robots across occupations. Figure 1a plots the distribution (10th, 50th, and 90th percentile) of the growth rates of the price of Japanese robots in the US relative to the initial year. The figure shows two patterns: (i) the robot prices follow an overall decreasing trend, with the median growth rate of -17% from 1992 to 2007, or -1.1% annually, and (ii) there is a 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. Two notable observations follow. First, the 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. Second, the large variation of the changes in prices by occupations persists even after controlling for the destination-year fixed effect $\psi^D_{i,t}$; Figure 1b shows the distribution of the Japan robot shock in the long run (1992-2007), or ψ^J_{i,t_1} in equation (1).

Figure 1: Distribution of the Cost of Robots

(a) US Robot Price by Occupations (b) Histogram of the Japan Robot Shock



Note: The author's calculation based on JARA and O*NET. The left panel shows the trend of prices of robots in the US by occupations, $p^R_{USA,o,t}$. The thick and dark line shows the median price in each year, and 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 histogram of long-run (1992-2007) cost shock of robots measured by the fixed effect ψ^C_{o,t_1} in equation (1).

Fact 2: Effects of the Japan robot shock on US occupations Using the variation of the Japan robot shock, I study the relative effect on US labor market outcomes. 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, Dorn, and Hanson (2013). Namely, I compute

$$IPW_{o,t} \equiv \sum_s l_{s,o,t_0} \Delta m^C_{s,t}, \tag{2}$$

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.[10] Intuitively, an occupation receives a large trade shock if sectors that faced increased import competition from China intensively employ the corresponding occupation. With this measure of the trade shock, I run the following regression

$$\Delta \ln (Y_o) = \alpha_0 + \alpha_1 \times \left(-\psi^J_o\right) + \alpha_2 \times IPW_{o,t_1} + \boldsymbol{X}_o \cdot \boldsymbol{\alpha} + \varepsilon_o, \tag{3}$$

[10] Specifically, following Autor, Dorn, and Hanson (2013), I take eight countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Appendix E.1 shows the distribution of occupational employment l_{s,o,t_0} for each sector.

Table 1: Effects of the Japan robot shock on US occupations

VARIABLES	(1) $\Delta \ln(w)$	(2) $\Delta \ln(w)$	(3) $\Delta \ln(L)$	(4) $\Delta \ln(L)$
Japan Robot Shock, $-\psi^J$	-0.116**	-0.118**	-0.358**	-0.371***
	(0.0570)	(0.0569)	(0.148)	(0.142)
Exposure to China Trade		-0.582		-3.868**
		(0.763)		(1.495)
Observations	324	324	324	324
R-squared	0.275	0.279	0.074	0.096
Demographic controls	✓	✓	✓	✓

Note: The table shows the coefficients in regression (3), based on the dataset constructed from JARA, O*NET, and the US Census/ACS. Observations are 4-digit level occupations, and the sample includes all occupations that existed throughout 1970 and 2007. ψ^C stands for the Japan robot shock from equation (1) and IPW stands for the occupation-level import penetration measure (in thousand USD) in equation (2). Demographic control variables are 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), and the foreign-born share as of 1990. All time differences, Δ, are taken with a long difference between 1990 and 2007. All regressions are weighted by the employment in the initial year (1990, which is the closest Census year to the initial year that I observe the robot adoption, 1992). Robust standard errors are reported in the parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

where Y_o is a labor market outcome by occupations such as hourly wage and employment, $\boldsymbol{X}_o$ is the vector of baseline demographic control variables which are the female share, the college-graduate share, the age distribution, and the foreign-born share, and Δ is the long-run difference between 1990 and 2007.

Table 1 shows the result of regression (3). The first two columns take hourly wages as the outcome, while the last two columns take employment. Columns 2 and 4 are the main specifications that include both the Japan robot shock and the China shock, in which I find that the negative Japan robot shock (the reduction in the cost of Japanese robots) drives the reduced growth rate of the labor market outcomes by occupation. Quantitatively, a 10% decrease of the robot cost implies a fall in the occupational wage growth rate by 1.2%. This finding suggests the substitutability between robots and workers; when the cost of robots falls in an occupation, the relative demand for robots (resp. labor) increases (resp. decreases) in the same occupation.

Again, these findings are unique in the use of the robot cost reduction at the occupation level. By contrast, in Appendix E.6, I complement the findings in Table 1 by taking similar approaches as in the literature, such as Acemoglu and Restrepo (2020), and confirm past findings. The Appendix also shows a number of robustness checks such as measuring robot stocks by quantity, using quality-adjusted robot measures following the method of Khandelwal, Schott, and Wei (2013), and the pre-trend analysis showing no systematic relation between the wage growth rates in 1970-1990 and the Japan robot shock in 1992-2007.

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. Namely, the observed Japan robot shock may reflect the quality upgrading of robots, meaning the quality-adjusted robot cost reduction might be even more drastic. Furthermore, the relative effect of the Japan robot shock on the growth of occupational labor market outcomes does not reveal the real wage impact per se. To overcome these issues, I will develop and estimate a general equilibrium model in the following sections.

3 Model

The basis of the model is a multi-country multi-factor Armington model. It has the following three features: (i) occupation-specific elasticities of substitution (EoS) of robots for workers, (ii) robot trade in a large open economy, and (iii) endogenous investment in robots with an adjustment cost. I emphasize these features, while other standard points are relegated to the Appendix. Section 3.1 states the setup, including assumptions, agents' optimization problems, and the equilibrium definition. After showing the solution method in Section 3.2, I discuss the key analytical result that the wage implication of automation depends on the occupation-specific EoS, which underscores the relevance of the parameter in Section 3.3.

3.1 Setup

Environment Time is discrete and has 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 means a non-robot good-exporting and robot-importing country, and j indicates a non-robot good-importing country, whenever I can. There is a representative household and producer in each country. The non-robot goods are differentiated by origin countries and can be consumed by households, invested to produce robots, and used as an input for robot integration. Robots are differentiated by country of origin and occupation. There are bilateral and good-specific iceberg trade costs $\tau^g_{ij,t}$ for each $g = G, R$. I use notation Y for the total production, Q for the quantity arrived at the destination. There is no intra-country trade cost, so $\tau^g_{ii,t} = 1$ for all i, g and t. Due to the iceberg cost, the bilateral price of non-robot goods (resp. robots) that country j pays to i is $p^G_{ij,t} = p^G_{i,t}\tau^G_{ij,t}$ (resp., $p^R_{ij,o,t} = p^R_{i,o,t}\tau^R_{ij,t}$). The non-robot goods (resp. robots) demand elasticity is ε (resp. ε^R), so that the price indices in country j are

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

respectively.

There are two factors for production of non-robot goods G: labor $L_{i,o,t}$ and robot capital $K^R_{i,o,t}$ in each occupation o.[11] There 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 (Caliendo, Dvorkin, and Parro 2019). The elasticity of occupation switch probability with respect to the expected value is ϕ. The detail of the worker's problem is discussed in Appendix B.

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

[11] Appendix (B) shows the model with intermediate goods and non-robot capital. The main analytical results are unchanged.

producer price $p^R_{li,o,t}$ to buy from l. The tax revenue is uniformly rebated to destination country i's workers.

Production Functions In country i and period t, the producer of non-robot good G inputs the occupation-o service $T^O_{i,o,t}$ and produces with the production function[12]

$$Y^G_{i,t} = A^G_{i,t} \left[\sum_o (b_{i,o,t})^{\frac{1}{\beta}} \left(T^O_{i,o,t} \right)^{\frac{\beta-1}{\beta}} \right]^{\frac{\beta}{\beta-1}}, \tag{4}$$

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 from the production side. Parameters satisfy $b_{i,o,t} > 0$, $\sum_o b_{i,o,t} = 1$, and $\beta > 0$. Each occupation o is performed by labor $L_{i,o,t}$ and robot capital $K^R_{i,o,t}$ by the following "occupation performance function:"

$$T^O_{i,o,t} = \left[(1 - a_{o,t})^{\frac{1}{\theta_O}} (L_{i,o,t})^{\frac{\theta_O - 1}{\theta_O}} + (a_{o,t})^{\frac{1}{\theta_O}} \left(K^R_{i,o,t} \right)^{\frac{\theta_O - 1}{\theta_O}} \right]^{\frac{\theta_O}{\theta_O - 1}}, \tag{5}$$

where $\theta_o > 0$ is the elasticity of substitution between robots and labor within occupation o that affects the changes in real wages due to adopting robots, and $a_{o,t}$ is the cost share of robot capital in tasks performed by occupation o. Equation (5) is key to understanding the automation and is discussed in detail in the next paragraph.

For simplicity, robots R for occupation o are produced by investing non-robot goods $I^R_{i,o,t}$ with productivity $A^R_{i,o,t}$:[13]

$$Y^R_{i,o,t} = A^R_{i,o,t} I^R_{i,o,t}. \tag{6}$$

Note that the change in the productivity of robot production in Japan captures the Japan robot shock in my data since the robot price is inversely proportional to the productivity

[12]Appendix B considers an extension to the version with intermediate goods and non-robot capital.

[13]The assumption simplifies the solution of the model because occupation services, intermediate goods, and non-robot capital are used only to produce non-robot goods, but not robots. To conduct the estimation and counterfactual exercises without this simplification, one would need to observe the cost shares of intermediate goods and non-robot capital for robot producers, which is hard to measure.

term in the competitive market.

Discussion–The Occupation Performance Function and Automation It is worth mentioning the relationship between the occupation performance function (5) and the way automation is treated in the literature. A standard modeling of the robot adoption in the literature, called the task-based approach, sets up a producer's allocation problem of factors (e.g., robots, labor) to a set of tasks. It then solves the allocation problem using an assumption on the efficiency structure of performing tasks for each factor. In Appendix F, I show that this task-based approach implies an occupation production function (5) with the Fréchet distribution assumption on the task-efficiency structure. Intuitively, one can regard the occupation service as the aggregate of robot capital and labor inputs, after optimally allocating robots and workers to each task.

Since this task-based approach consists of the allocation of factors to tasks, the cost-share parameter $a_{o,t}$ of equation (5) has an additional interpretation of the share of the space of tasks performed by robot capital as opposed to labor. Following Acemoglu and Restrepo (2020), who defined automation as the expansion of the space of tasks that robots perform, I call the change in $a_{o,t}$ the *automation shock*. I discuss some real-world examples of the automation shock and its relationship to the models in the literature in Appendix F.1.

By contrast, the robot cost share $a_{o,t}$ also represents the quality of robots. Specifically, the quality of goods can be regarded as a non-pecuniary "attribute whose valuation is agreed upon by all consumers" (Khandelwal 2010). Since the increase in the cost-share parameter $a_{o,t}$ implies the rise in the value of the robot input among robots and labor, it can also be interpreted as quality upgrading of robots relative to labor when combined with a suitable adjustment in the TFP term I discuss in Section 3.3. In particular, equation (5) implies that in the long run (hence dropping the time subscript), the demand for robot capital is

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

where $c^R_{i,o,t}$ is the user cost of robot capital formally defined in Appendix I.3, and $P^O_{i,o}$ is the unit cost of performing occupation o. In this equation, a_o is the quality term as defined above.

These considerations imply that the automation shock and the quality upgrading are not distinguished in my model but have the same implication to the economy. This is the implication of the Fréchet distribution assumption. It is useful to maintain this assumption since I can keep complex technology improvement in a single exogenous variable $a_{o,t}$. One of the reasons for the need to impose this assumption is the lack of data on the set of tasks for each robots or the quality of robots. Relaxing this assumption using rich data on this dimension would be a future work in this field.

In this paper, I consider not only the automation shock, but also the shock to the price of adopting robots. I call these two shocks "robotization shocks" collectively. The robotization shocks are likely to be correlated at the occupation level since an innovation in the robot technology improves the applicability of robots and the cost efficiency of production at the same time. An example of such a correlation is provided in Appendix E.2.

To the best of my knowledge, equation (5) is the most flexible formulation of substitution between robots and labor in the literature. Specifically, I show that the industry-level unit cost function of Acemoglu and Restrepo (2020) can be obtained by $\theta_o \to 0$ for any o in Lemma F.1 in Appendix F.2. I also show that my model can imply the production structure of Humlum (2019) in Lemma F.2 in the same Appendix.

The Producer's Problem The producer's problem comprises two tiers–static optimization about labor input in each occupation and dynamic optimization about robot investment. The static part is to choose the employment conditional on market prices and 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

$$\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) \equiv \max_{\left\{L_{i,o,t}\right\}_o} p^G_{i,t} Y^G_{i,t} - \sum_o w_{i,o,t} L_{i,o,t}, \tag{7}$$

where $Y^G_{i,t}$ is given by production function (4).

The dynamic optimization 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

$$K^R_{i,o,t+1} = (1-\delta) K^R_{i,o,t} + Q^R_{i,o,t}, \tag{8}$$

where $Q^R_{i,o,t}$ is the amount of new robot investments 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 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

$$Q^R_{i,o,t} = \left[\sum_l \left(Q^R_{li,o,t}\right)^{\frac{\varepsilon^R - 1}{\varepsilon^R}}\right]^{\frac{\varepsilon^R}{\varepsilon^R - 1}\alpha^R} \left(I^{int}_{i,o,t}\right)^{1-\alpha^R} \tag{9}$$

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.[14] 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., Holt 1960; Cooper and Haltiwanger 2006), which reflects the technological difficulty and sluggishness of robot adoption, as reviewed in Autor, Mindell, and Reynolds (2020) and discussed in detail in Appendix I.1.

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

[14]Equation (8) follows the formulation of the trade of capital goods in Anderson, Larch, and Yotov (2019) in the sense that the robots are traded because they are differentiated by origin country l. Note that equation (9) implies that the origin-differentiated investment good is aggregated at first and then added to the stock of capital following equation (8). This trick helps reduce the number of capital stock variables and is also used in Engel and Wang (2011).

namic optimization problem

$$\begin{aligned}\max_{\left\{\left\{Q^R_{li,o,t}\right\}_l, I^{int}_{i,o,t}\right\}_o} \sum_{t=0}^{\infty}\left(\frac{1}{1+\iota}\right)^t \Big[\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) \\ -\sum_{l,o}\left(p^R_{li,o,t}\left(1+u_{li,t}\right)Q^R_{li,o,t}+P^G_{i,t}I^{int}_{i,o,t}+\gamma P^R_{i,o,t}Q^R_{i,o,t}\frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\Big],\end{aligned} \tag{10}$$

subject to accumulation equation (8) and (9), and given $\left\{K^R_{i,o,0}\right\}_o$. A standard Lagrangian multiplier method yields the Euler equations for investment, which I derive in Appendix I.3. Note that the Lagrange multiplier $\lambda^R_{i,o,t}$ represents the equilibrium marginal value of robot capital.

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

$$\sum_o L_{i,o,t} = \overline{L}_{i,t}, \tag{11}$$

and robot and non-robot goods markets clear. 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 steady state. To save space, detailed expressions are relegated in Appendix I.3.

I define the bold symbols as column vectors of robot capital $\boldsymbol{K}^R_t \equiv \left[K^R_{i,o,t}\right]_{i,o}$, marginal values of robot capital $\boldsymbol{\lambda}^R_t \equiv \left[\lambda^R_{i,o,t}\right]_{i,o}$, 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 $\boldsymbol{p}^G_t \equiv \left[p^G_{i,t}\right]_i$ robot prices $\boldsymbol{p}^R_t \equiv \left[p^R_{i,o,t}\right]_{i,o}$, wages, $\boldsymbol{w}_t \equiv \left[w_{i,o,t}\right]_{i,o}$, bilateral non-robot goods trade levels $\boldsymbol{Q}^G_t \equiv \left[Q^G_{ij,t}\right]_{i,j}$, bilateral non-robot goods trade levels $\boldsymbol{Q}^R_t \equiv \left[Q^R_{ij,o,t}\right]_{i,j,o}$, 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 B. I write $\boldsymbol{S}_t \equiv \left[\boldsymbol{K}^{R'}_t, \boldsymbol{\lambda}^{R'}_t, \boldsymbol{L}'_t, \boldsymbol{V}'_t\right]'$ 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 $\boldsymbol{p}_t \equiv \left[\boldsymbol{p}^{G'}_t, \boldsymbol{p}^{R'}_t, \boldsymbol{w}'_t\right]'$ and flow quantities $\boldsymbol{Q}_t \equiv \left[\boldsymbol{Q}^{G'}_t, \boldsymbol{Q}^{R'}_t, \boldsymbol{\mu}'_t\right]$ that satisfy: (i) given $\boldsymbol{p}_t$, workers choose occupation optimally by equation (B.2), (ii) given $\boldsymbol{p}_t$, producers maximize flow profit by equation (7) and demand robots by equation (I.7), and (iii) markets clear: Labor adds up as in equation (11), and goods markets clear with trade balances as in equations (I.15) and (I.17).

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 $\left[\boldsymbol{K}_0^{R\prime}, \boldsymbol{L}_0'\right]'$, 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 (B.4), value function condition (B.3), capital accumulation equation (8), producer's dynamic optimization (I.11) and (I.10).

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

3.2 Approximated Solution

I log-linearize the system around the initial equilibrium to solve the above equilibrium to the first order. I choose this strategy because it is well-known that the errors due to first-order approximation with respect to productivity shocks are considerably small (cf. Kleinman, Liu, and Redding 2020). 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 $\boldsymbol{S}_t = \left[\boldsymbol{K}_t^{R\prime}, \boldsymbol{\lambda}_t^{R\prime}, \boldsymbol{L}_t', \boldsymbol{V}_t'\right]'$, and use "hat" notation to denote changes from t_0, or $\widehat{z_t} \equiv \ln(z_t) - \ln(z_{t_0})$ 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

$$\overline{\boldsymbol{D}^x}\widehat{\boldsymbol{x}_t} = \overline{\boldsymbol{D}^A}\widehat{\boldsymbol{A}_t}. \tag{12}$$

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, Arkolakis, and Esposito 2019). [15]

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 (12) can be written as

$$\overline{\boldsymbol{D}^{x}}\widehat{\boldsymbol{x}_t} - \overline{\boldsymbol{D}^{A,S}}\widehat{\boldsymbol{S}_t} = \overline{\boldsymbol{D}^{A,\Delta}}\boldsymbol{\Delta}. \tag{13}$$

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

$$\overline{\boldsymbol{E}^{y}}\widehat{\boldsymbol{y}} = \overline{\boldsymbol{E}^{\Delta}}\boldsymbol{\Delta}, \tag{14}$$

where

$$\overline{\boldsymbol{E}^{y}} \equiv \begin{bmatrix} \overline{\boldsymbol{D}^{x}} & -\overline{\boldsymbol{D}^{A,T}} \\ \multicolumn{2}{c}{\overline{\boldsymbol{D}^{y,SS}}} \end{bmatrix}, \text{ and } \overline{\boldsymbol{E}^{\Delta}} \equiv \begin{bmatrix} \overline{\boldsymbol{D}^{A,\Delta}} \\ \overline{\boldsymbol{D}^{\Delta,SS}} \end{bmatrix},$$

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 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 4.

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

[15] Since the temporary equilibrium vector $\widehat{\boldsymbol{x}_t}$ includes wages $\widehat{\boldsymbol{w}_t}$, equation (12) generalizes the general equilibrium comparative statics formulation in Adao, Arkolakis, and Esposito (2019), who consider the variant of equation (12) with $\widehat{\boldsymbol{x}_t} = \widehat{\boldsymbol{w}_t}$.

following first-order difference equation

$$\overline{\boldsymbol{F}_{t+1}^{y}}\widehat{\boldsymbol{y}_{t+1}} = \overline{\boldsymbol{F}_{t}^{y}}\widehat{\boldsymbol{y}}_{t} + \overline{\boldsymbol{F}_{t+1}^{\Delta}}\boldsymbol{\Delta}. \tag{15}$$

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

$$\widehat{\boldsymbol{y}}_t = \overline{\boldsymbol{F}_t}\boldsymbol{\Delta} \text{ and } \overline{\boldsymbol{F}_t} \to \overline{\boldsymbol{E}}. \tag{16}$$

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. Appendix K gives the details of the derivation of these matrices.

3.3 The Real-Wage Effect of Automation

Before moving on to the estimation, I demonstrate the analytical result that the effect of automation on real wages depends negatively on substitution elasticity parameters θ_o and β conditional on the changes in input and trade shares. The key insight is that real wages are the relative price of labor to the consumer price index that reflects a price bundle of other factors, and the relative price changes are related to changes in the corresponding input shares and trade shares via the demand elasticities of factors and goods.

For this purpose, I modify notations in equation (5) to express the result in a concise way. Namely, define

$$A_{i,o,t}^{K} \equiv \left(A_{i,t}^{G}\right)^{\theta-1} a_{o,t},\ A_{i,o,t}^{L} \equiv \left(A_{i,t}^{G}\right)^{\theta-1} \left(1 - a_{o,t}\right). \tag{17}$$

Substituting these into production functions (4) and (5), I have

$$Y_{i,t}^{G} = \left[\sum_{o} \left(b_{i,o,t}\right)^{\frac{1}{\beta}} \left(\widetilde{T}_{i,o,t}^{O}\right)^{\frac{\beta-1}{\beta}}\right]^{\frac{\beta}{\beta-1}},$$

where

$$\widetilde{T}^{O}_{i,o,t} \equiv \left[\left(A^{L}_{i,o,t} \right)^{\frac{1}{\theta_o}} \left(L_{i,o,t} \right)^{\frac{\theta_o - 1}{\theta_o}} + \left(A^{K}_{i,o,t} \right)^{\frac{1}{\theta_o}} \left(K^{R}_{i,o,t} \right)^{\frac{\theta_o - 1}{\theta_o}} \right]^{\frac{\theta_o}{\theta_o - 1}}.$$

Therefore, one can interpret the new terms $A^{K}_{i,o,t}$ and $A^{L}_{i,o,t}$ as the productivity shock on robots and labor, respectively.[16] Furthermore, define the labor share of producer of non-robot good G within occupation o by $\widetilde{x}^{L}_{i,o,t}$, occupation o's cost share among the occupation aggregate by $\widetilde{x}^{O}_{i,o,t}$, and trade share by $\widetilde{x}^{G}_{ij,t}$. Formally, these terms are defined as:

$$\widetilde{x}^{L}_{i,o,t} \equiv \frac{w_{i,o,t} L_{i,o,t}}{P^{O}_{i,o,t} T^{O}_{i,o,t}}, \; \widetilde{x}^{O}_{i,o,t} \equiv \frac{P^{O}_{i,o,t} T^{O}_{i,o,t}}{p^{G}_{i,t} Q^{G}_{i,t}}, \; \widetilde{x}^{G}_{ij,t} \equiv \frac{p^{G}_{i,t} Q^{G}_{ij,t}}{P^{G}_{i,t} Q^{G}_{i,t}}, \tag{18}$$

where $P^{O}_{i,o,t}$ is the price index of occupation o. The following proposition characterizes the real-wage changes in the steady state.

Proposition 1. *Suppose robot productivity grows $\widehat{A^{K}_{i,o}} > 0$. For each country i and occupation o,*

$$\widehat{\left(\frac{w_{i,o}}{P^{G}_{i}} \right)} = \frac{\widehat{\widetilde{x}^{L}_{i,o}}}{1 - \theta_o} + \frac{\widehat{\widetilde{x}^{O}_{i,o}}}{1 - \beta} + \frac{\widehat{\widetilde{x}^{G}_{ii}}}{1 - \varepsilon}. \tag{19}$$

Proposition 1 clarifies how the elasticity parameters and change of shares of input and trade affect real wages at the occupation level. For example, one can observe that if $\theta_o > 1$, then (i) the larger the fall of the labor share within occupation $\widehat{\widetilde{x}^{L}_{i,o}}$, the larger the real wage gains, and (ii) pattern (i) is stronger if θ_o is small and close to 1. Therefore, conditional on other terms, the steady state changes of occupational real wages depend on the elasticity of substitution between robots and labor θ_o.

The intuition of Proposition 1 comes from a series of revealed cost reductions, $\widehat{\widetilde{x}^{L}_{i,o}}$, $\widehat{\widetilde{x}^{O}_{i,o}}$, and $\widehat{\widetilde{x}^{G}_{ii}}$. The first term reveals the robot cost reduction relative to the labor cost. If $\theta_o >$

[16] By equation (17), robot productivity change $\widehat{A^{K}_{i,o,t}}$ and automation shock $\widehat{a_{o,t}}$ satisfy that $\widehat{A^{K}_{i,o,t}} = \frac{\theta - 1}{\alpha_{i,L}} \widehat{A^{G}_{i,t}} + \widehat{a_{o,t}}$. Namely, robot productivity change is the sum of total factor productivity change caused by robotics and the automation shock. I choose to use the automation shock in my main specification in equations (4) and (5) since it has a tight connection to the task-based approach, a common approach in the automation literature (e.g., Acemoglu and Restrepo 2020), as discussed in Section 3.1.

1, then the reduction in the price index or cost savings induced by robotization shocks dominate the drop in nominal wage, increasing the real wage. Similarly, the second term reflects the reduction of the relative cost of the occupation, and the last term represents the decrease in the production cost relative to other countries.

Proposition 1 also extends the result of the welfare sufficient statistic in the trade literature. In particular, Arkolakis, Costinot, and Rodriguez-Clare (2012, ACR) showed that under a large class of trade models, the welfare effect of the reduction in trade costs can be characterized by the well-known ACR formula, or log-difference of the trade shares times the negative inverse of the trade elasticity. Specifically, suppose I drop robots and non-robot capital from the model and aggregate all occupations into one factor (labor). Then, one can prove that the shocks to the productivity $\left\{A_{i,t}^{G}\right\}$ implies

$$\widehat{\left(\frac{w_i}{P_i^G}\right)} = \frac{1}{1-\varepsilon}\widehat{\widetilde{x}_{ii}^{G}},$$

which is the ACR formula. In the next section, motivated by Proposition 1, I estimate the model and back out the automation shock to study the impact of robotization on the occupational wage.

4 Estimation

Using the Japan robot shock described in Section 2 and the solution to the general equilibrium model in Section 3, I develop an estimation method using the model-implied optimal instrumental variable (MOIV) from Adao, Arkolakis, and Esposito (2019). First, Section 4.1 sets the stage by providing the implementation detail of the model. I then formalize the MOIV estimator in Section 4.2, which provides the parameter estimates shown in Section 4.3. Section 4.4 discusses the performance of my estimates.

4.1 Bringing the Model to the Data

Since I observe 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). 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. I first separate occupations into three broad occupation groups, Abstract, Service (Manual), and Routine following Acemoglu and Autor (2011).[17] 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.[18] Within each group, I assume a constant EoS between robots and labor. Each occupation group is denoted by subscript g, and the robot-labor EoS for group g is denoted by θ_g.

I fix some parameters of the model at conventional values as follows. The annual discount rate is $\iota = 0.05$ and the robot depreciation rate is 10% following Graetz and Michaels (2018).[19] I take the trade elasticity of $\varepsilon = 4$ from the large 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, discussed in detail in Appendix G.1. Following Leigh and Kraft (2018), I assume $\alpha^R = 2/3$. By Cooper and Haltiwanger (2006), I set the parameter of adjustment cost at $\gamma = 0.295$. I use the estimates from Traiberman (2019) and set the dynamic occupation switching elasticity as $\phi = 0.8$. With these parametrizations, structural parameters to be

[17] Routine occupations include occupations such as production, transportation and 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.

[18] In terms of OCC2010 codes in the US Census, Routine production occupations are ones in [7700, 8965], Routine transportation are in [9000, 9750], Routine others are in [4700, 6130], Service are in [3700, 4650], and Abstract are in [10, 3540].

[19] For example, see King and Rebelo (1999) for the source of the conventional value of ι who matches the discount rate to the average real return on capital.

estimated are $\mathbf{\Theta} \equiv \{\theta_g, \beta\}$.

Finally, since I use the first-order approximated solution, I need to measure the initial equilibrium $\boldsymbol{y}_{t_0}$, which is an input to the solution matrix $\overline{\boldsymbol{E}}$ in equation (14). I take these data from JARA, IFR, IPUMS USA and CPS, BACI, and World Input-Output Data (WIOD). The measurement of labor market outcomes is standard and relegated to Appendix H.7. I set the initial period robot tax to be zero in all countries.

In the estimation, I use the changes in US occupational wages $\widehat{\boldsymbol{w}_1}$ between 1992 and 2007 as the target variables. I use the steady-state changes from the model to match these 15-year changes in the data. Recall that the robot production function (6) implies that $\widehat{A^R_{2,o}}$ is equal to the negative cost shock to produce robots in Japan, so that I measure the robot efficiency gain by

$$\widehat{A^R_{2,o}} = -\psi^J_o, \tag{20}$$

where ψ^J_o is the Japan robot shock defined in equation (1) and observed using my dataset.

4.2 Estimation Method

I begin with discussing the identification challenge that the Japan robot shock is correlated with the unobserved automation shock. For this purpose, I decompose the automation shock $\widehat{a_o}$ into the component $\widehat{a_o^{\text{imp}}}$ implied from the relative demand function 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 o. Implied component $\widehat{a_o^{\text{imp}}}$ satisfies the steady-state change of relative demand of robots and labor

$$\left(\frac{\widehat{c^R_{i,o} K^R_{i,o}}}{w_{i,o} L_{i,o}}\right) = \frac{\widehat{a_o^{\text{imp}}}}{1 - a_{o,t_0}} + \left(1 - \theta_g\right) x^R_{12} \psi^J_o + \epsilon_o, \tag{21}$$

where x^R_{12} is the import share of robots from Japan in the US, and ϵ_o is the error term that depends on the changes in wages and robot costs in the other countries. The identification challenge is that the Japan robot shock ψ^J_o does not work as an instrumental variable (IV) in equation (21) because of a potential correlation between ψ^J_o and an observed task-space expansion shock $\widehat{a_o^{\text{imp}}}$ as mentioned in Section 3.1.

To overcome this identification issue, I employ a method based on the model solution. A key observation is that conditional on $\widehat{a_o^{\text{imp}}}$, and using the solution of the wage change, the error component $\widehat{a_o^{\text{err}}}$ can be inferred from the observed endogenous variables. Specifically, from the steady-state solution matrix $\overline{\boldsymbol{E}}$, I obtain $O \times O$ sub-matrices $\overline{\boldsymbol{E}}_{w_1,\boldsymbol{a}}$ and $\overline{\boldsymbol{E}}_{w_1,\boldsymbol{A}_2^R}$ such that[20]

$$\widehat{\boldsymbol{w}} = \overline{\boldsymbol{E}}_{w_1,\boldsymbol{a}} \widehat{\boldsymbol{a}} + \overline{\boldsymbol{E}}_{w_1,\boldsymbol{A}_2^R} \widehat{\boldsymbol{A}_2^R}. \tag{22}$$

Using $\widehat{\boldsymbol{a}} = \widehat{\boldsymbol{a}^{\text{obs}}} + \widehat{\boldsymbol{a}^{\text{err}}}$, I derive the structural residual $\boldsymbol{\nu}_w \equiv \overline{\boldsymbol{E}}_{w_1,\boldsymbol{a}} \widehat{\boldsymbol{a}^{\text{err}}} \equiv [\nu_{w,o}]_o$, which is a vector of length O generated from the linear combination of the unobserved component of the automation shocks:

$$\boldsymbol{\nu}_w = \boldsymbol{\nu}_w(\boldsymbol{\Theta}) = \widehat{\boldsymbol{w}} - \overline{\boldsymbol{E}}_{w_1,\boldsymbol{a}} \widehat{\boldsymbol{a}^{\text{obs}}} - \overline{\boldsymbol{E}}_{w_1,\boldsymbol{A}_2^R} \widehat{\boldsymbol{A}_2^R}.$$

I assume the following moment condition regarding this structural residual and the Japan robot shock $\boldsymbol{\psi}^J \equiv \left\{\psi_o^J\right\}_o$.

Assumption 1. *(Moment Condition)*

$$\mathbb{E}\left[\nu_{w,o} | \boldsymbol{\psi}^J\right] = 0. \tag{23}$$

Given this moment condition, it is relatively standard to construct the optimal instrument and implement it with the two-step estimator (Adao, Arkolakis, and Esposito 2019). Therefore, I relegate the detailed explanation to Appendix C and instead discuss the interpretation of Assumption 1 and a case in which it may not hold. Assumption 1 restricts that the structural residual $\boldsymbol{\nu}$ should not be predicted by the Japan robot shock. Note that it allows that the automation shock $\widehat{a}_o$ may correlate with the change in the robot producer productivity $\widehat{A_{2,o}^R}$. The structural residual $\nu_{w,o}$ purges out all the predictions of the impacts of shocks $\widehat{\boldsymbol{a}}$ and $\widehat{\boldsymbol{A}_2^R}$ on endogenous variables. I then place the assumption that

[20] Appendix I.5 explains the technical reason for the choice of the steady-state matrix in equation (22).

the remaining variation should not be predicted by the Japan robot shock from the data. Furthermore, note that the correlation of the structural residuals with other shocks such as trade shocks is not likely to break Assumption 1; I have confirmed controlling for such shocks does not qualitatively change the reduced-form findings in Section 2.3.

To further clarify the role of Assumption 1, consider the circumstances under which Assumption 1 breaks. One such threat is a directed technological change, in which the occupational labor demand drives the changes in the cost of robots. Specifically, suppose a positive labor demand shock in an occupation o induces the research and development of robots in occupation o and drives costs down in the long run instead of simply assuming my production function (6) with exogenous technological change. In this case, the structural residual ν_o does not remove this effect and is negatively correlated with Japan robot shock ψ_o^J. Another possibility that breaks 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, even if this is the case, the positive impact of Japan robot costs found in Section 2.3 shows the lower limit, and thus my qualitative results about strong substitutability are maintained.

4.3 Estimation Results

Table 2 gives the estimates of the structural parameters. The first column shows the estimation result when I restrict the EoS between robots and labor to be constant across occupation groups (Case 1). 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 a conventional significance level. 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 and

Table 2: Parameter Estimates

	Case 1: $\theta_g = \theta$	Case 2: Free θ_g	
θ	2.05 (0.19)	Routine, Production	2.95 (0.42)
		Routine, Transportation	2.90 (0.48)
		Routine, Others	1.16 (0.32)
		Manual	1.23 (0.55)
		Abstract	0.64 (1.24)
β	0.83 (0.03)		0.73 (0.06)

Note: The estimates of the structural parameters based on the estimator in Proposition C.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). See the main text for other details.

routine transportation occupations is around 3, while those for other occupation groups (other occupations in routine group, service, and abstract occupations) are not significantly different from 1 and thus do not reject the Cobb-Douglas. Therefore, the estimates for routine production and transportation indicate the special susceptibility of workers in these occupations to robot capital. Note also that the estimate of the EoS between occupations β does not change qualitatively between Case 1 and Case 2.

As in the literature of 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 Japan robot shock 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. To examine this point, I run the main reduced-form regression (3) using partitioned samples by occupation groups. Table 3 shows the results. The negative correlation between occupational wage changes and the Japan robot shock $-\psi_o^J$ is seen only in the group of production occupations and transportation occupations,

Table 3: Correlation between Wage and Robot Prices by Occupation Groups

VARIABLES	(1) $\Delta \ln(w)$	(2) $\Delta \ln(w)$	(3) $\Delta \ln(w)$	(4) $\Delta \ln(w)$	(5) $\Delta \ln(w)$
$-\psi^J$	-0.607***	-0.625***	-0.00285	-0.0717	-0.00742
	(0.109)	(0.0850)	(0.0435)	(0.120)	(0.0581)
Observations	55	25	109	106	29
R-squared	0.474	0.595	0.000	0.025	0.001
Occupation Group	Routine-Prod.	Routine-Tran.	Routine-Others	Abstract	Service

Note: The author's calculation based on JARA, O*NET, and US Census/ACS. The table shows regression coefficients of the main reduced-form specification (3) with separated samples according to occupation groups. Occupation group "Routine-Prod." indicates the production occupation within routine occupation, "Routine-Tran." indicates the transportation occupation within routine occupation, and "Routine-Others" indicates the other occupations within routine occupation. Robust standard errors are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

which is consistent with the heterogeneous elasticity of substitution between robots and labor found in Table 2. Appendix H.5 also shows the robot price variation within each occupation group to check the source of variation in these partitioned regressions.

4.4 Measuring Shocks and Model Fit

I apply the observed and simulated data to the linear regression model (3) to examine the model fit and the role of the automation shock in estimating the robot-labor EoS.[21] Specifically, I consider the following two simulations. First, I hit the Japan robot shock and the implied automation shock, and I call this counterfactual wage change as "targeted." In this case, the prediction of wage changes is consistent with the moment condition (23), and thus the linear regression coefficient α_1 of equation (3) is expected to be close to the one in Table 1. Second, I hit only the Japan robot shock but not the automation shock, and I call this counterfactual wage change as "untargeted." In this case, the moment condition (23) 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 from the targeted wage change reveals the size of this bias. Therefore, this exercise reveals how important it is to take into account the automation shock in estimation. The exact method for simulating data is standard and explained in Appendix D.

Table 4 shows the result of these exercises. The first column shows the estimates in column (3) of Table 1 again, 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 column confirms that the targeted moments match well 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 Japan robot shock. This is due to the positive correlation between the Japan robot shock $-\psi_o^J$

[21] As another model validation exercise, I predict the stock of robots by occupation and find that the model predicts the actual robot accumulation dynamics well, described in detail in Appendix J.1. Furthermore, Appendix J.2 gives a detailed discussion on the Japan robot shock and the backed-out implied automation shocks.

Table 4: Model Fit: Linear Regression with Observed and Simulated Data

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

Note: The author's calculation based on the dataset generated by JARA, O*NET, and the US Census. Column (1) is the coefficient of the Japan robot shock ψ^J in the reduced-form regression with IPW. Column (2) takes the US wage change predicted by GE with ψ^J as well as other shocks such as the implied automation shock $\widehat{a^{\text{imp}}}$. Column (3) takes the US wage change predicted by GE with shocks including the Japan robot shock, but counterfactually fixing the implied automation shock to be zero. Robust standard errors in parentheses.

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 (3) contains the positive bias due to this positive correlation. By contrast, the untargeted wage is free from this bias since its data-generating process does not contain the automation shock but only the Japan robot shock. Thus, the linear regression coefficient α_1 is higher than the one obtained from the real data. In other words, if I had wrongfully assumed that the economy did not experience the automation shock and believed the regression coefficient in Table 1 is bias-free, I would have estimated higher EoS by ignoring the actual positive correlation between $-\psi_o^J$ and $\widehat{a_o^{\text{imp}}}$. This thought experiment reveals that it is critical to take into account the automation shock in estimating the EoS between robots and labor using the Japan robot shock, and that the large EoS in my structural estimates are robust even after taking this point into account.

5 Counterfactual Exercises

Using the estimated model and shocks in the previous section, I examine the following two questions. The first question is about the distributional effects of robotization. For example, Autor, Katz, and Kearney (2008) argue that the wage inequality measured by the ratio of the wages between the 90th percentile and the 50th percentile (90-50 ratio) steadily increased since 1980.[22] Can the increased use of industrial robots explain the increase in the 90-50 ratio, at least from 1990, the baseline year of this study? If so, to which degree? The second question concerns the policy implication of regulating robot adoption. Due to the fear of automation, policymakers have proposed regulating industrial robots using robot taxes. What would be the short-run and long-run effects of taxing on robot purchases?[23]

5.1 The Distributional Effects of Robot Adoption

To study the contribution of robots to wage polarization, I begin by showing the pattern of robot accumulations over the occupational wage distribution revealed by my data. Figure 2a shows the average annual growth rates of observed robot stock between 1992 and 2007 for each decile of the occupational wage distribution in 1990. The figure clarifies that the relatively many robots were adopted in occupations in the middle deciles of the distribution.

By contrast, Panel 2b shows the steady-state predicted wage growths per annum due to the robotization shocks and the estimated model with the first-order solution given in equation (16). 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 (16) is 1.594. These numbers imply that a 6.4% increase in the 90-50 ratio can be explained by

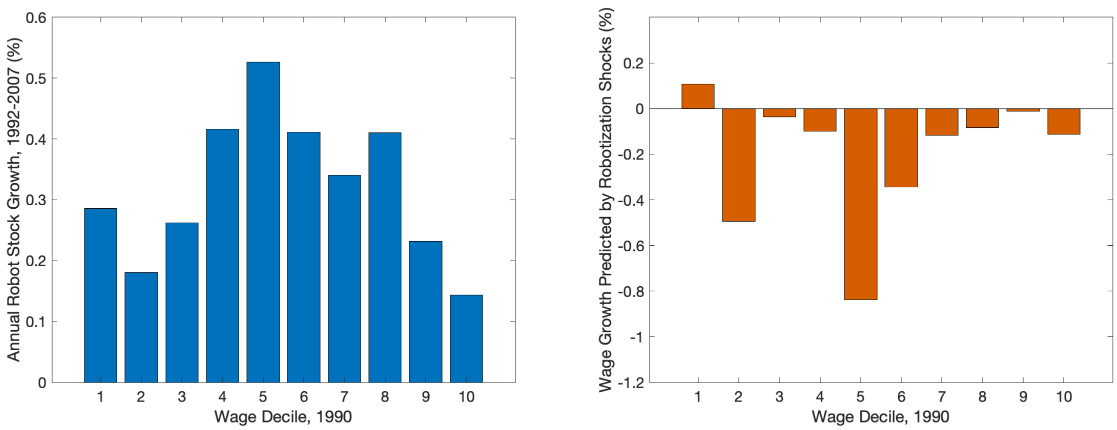
[22]Furthermore, as Heathcote, Perri, and Violante (2010) argue, the wage inequality comprises a sizable part of the overall economic inequality in the US.

[23]In Appendix J.5 and J.6, I also examine the effect of robot tax on occupational wages and workers' welfare and the role of trade liberalization of robots.

Figure 2: Robots, Wage Inequality, and Polarization

(a) Robot growths by Wage Decile

(b) The Effect of Robots on Wages



Note: The left panel shows the average annual growth rates of the observed robot stock between 1992 and 2007 for each of the ten deciles of the occupational wage distribution in 1990. The right panel shows the annualized occupational wage growth rates for each wage decile, predicted by the first-order steady-state solution of the estimated model given in equation (14).

the robotization shock captured in this paper. Appendix J.3 describes the counterfactual wage changes for each of the five occupation groups.

5.2 Robot Tax and Aggregate Income

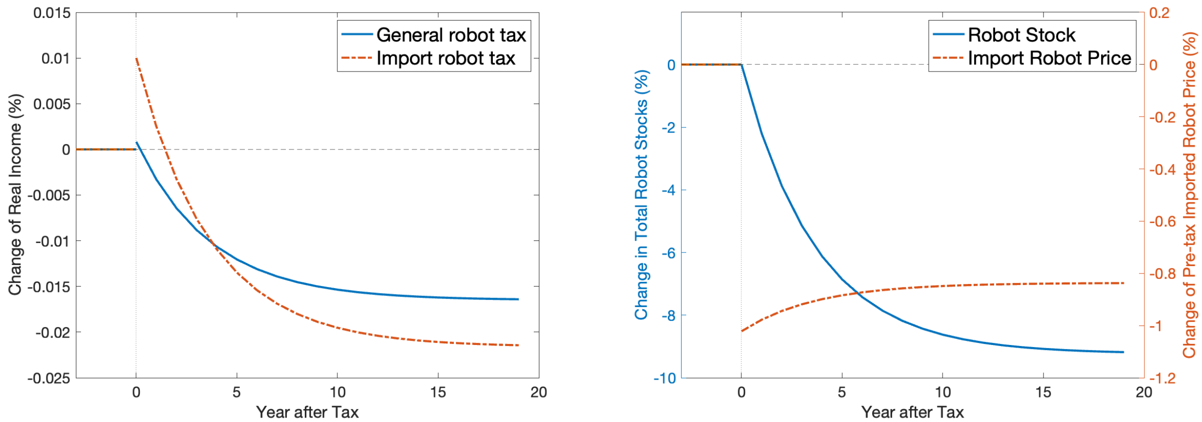
To study the effect of counterfactually introducing robot tax, consider an unexpected, unilateral, and permanent increase in the robot tax by 6% in the US, which I call the general tax scenario. I also consider the tax on only imported robots by 33.6%, and call it the import tax scenario, which implies the same amount of tax revenue as in the general tax scenario and makes the comparison straightforward between the two scenarios.[24] How do these robot tax schemes affect the US real income? Figure 3 provides an answer. In Figure 3a, 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. Second, in the short run, there is a positive effect but this effect turns negative quickly and continues

[24]The 6% rate of the general tax is more modest than the 30% rate considered in Humlum (2019) for the Danish case.

Figure 3: Effects of the Robot Tax

(a) US Real Income

(b) US Robot Stock and Import Robot Price



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

to be negative in the long run.

Why is there a short-run positive effect on real income? 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 let the equilibrium robot price go down along the supply curve. This reduction in the robot price contributes to compressing the cost of robot investment, and 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. This terms-of-trade manipulation is well-studied in the trade policy literature, but my setting is novel since it implies the upward sloping export supply curve from the GE. This point is discussed in detail in Appendix F.3.

The reason for the different effects on real income in the long run is as follows. The solid line in Figure 3b 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.[25] These results highlight the role costly robot capital (de-)accumulation plays in the effect of the robot tax on aggregate income.

Figure 3b 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. To further demonstrate the role of robot trade, I also consider an alternative model with no trade of robots due to prohibitively high robot costs and give the robot tax counterfactual exercise in Appendix J.4.

6 Conclusion

In this paper, I study the distributional and aggregate 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 the number of robots and the cost shock of buying robots from Japan (the Japan robot shock) across occupations in which robots are adopted. Second, I develop a general equilibrium model that features the trade of robots in a large open economy and endogenous robot accumulation with an adjustment cost. When estimating the model, I construct a model-implied optimal instrumental variable from the Japan robot shock in my dataset and the approximated solution of the model to identify the occupation-specific EoS between robots and labor.

The estimates of within-occupation EoS between robots and labor is heterogeneous

[25] 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.

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 to robot adaptation of workers in these occupations. The estimated model also implies that robots contributed to the wage polarization across occupations in the US from 1990-2007. A commonly advertised robot tax could increase the US real income in the short run but leads to a decline in the income in the long run due to the decreased steady-state robot stock. These exercises provide quantitative evidence of the distributional effects of robots and the impact of regulating robots in the short and long run.

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Appendix

A Discussion on the Cost of Using Robots

Before discussing the measurement of the robot cost, it is worthwhile to clarify how industrial robots work. A modern industrial robot is typically not 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). Furthermore, due to its complexity, installing robots in the production environment often requires hiring costly system integrators that offer engineering knowledge for the integration purpose. Therefore, the relevant cost of robots for adopters includes hardware, software, and integration costs.[26]

In this paper, I measure the price of robots by average price, or the total sales divided by the quantity of hardware. Thus, my measure of robot price should be interpreted as reflecting part of overall robot costs. Note that this follows the literature's convention due to the data limitation about the robot software and integration. Nevertheless, I will address this point in the model section by separately defining the observable hardware cost using my data and the unobserved components of the cost, and placing assumptions on the latter.

B The Full Model

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

[26] As Leigh and Kraft (2018) pointed out, the current industry and occupation classifications do not allow separating system integrators, making it hard to estimate the cost from these classifications. In addition, relevant costs associated with the robot still remain, e.g., maintenance fees, of which we also lack quantitative evidence. Although understanding these components of the costs is of first-order importance, this paper follows the literature convention and measure robots from market transaction of hardware.

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

$$Y_{i,t}^{G} = A_{i,t}^{G} \left\{ \alpha_{i,L} \left(T_{i,t}^{O} \right)^{\frac{\vartheta-1}{\vartheta}} + \alpha_{i,M} \left(M_{i,t} \right)^{\frac{\vartheta-1}{\vartheta}} + \alpha_{i,K} \left(K_{i,t} \right)^{\frac{\vartheta-1}{\vartheta}} \right\}^{\frac{\vartheta}{\vartheta-1}},$$

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

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

where $\varepsilon > 0$ is the elasticity of substitution. Since intermediate goods are traded across countries and aggregated by equation (B.1), 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.

Workers solve a dynamic discrete choice problem to select an occupation (Traiberman 2019; Humlum 2019). 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, Dvorkin, and Parro 2019). Since I follow a similar strategy, I relegate the formal problem statement and derivation to Appendix I.2. The worker's problem 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

$$\mu_{i,oo',t} = \frac{\left(\left(1-\chi_{i,oo',t}\right)\left(V_{i,o',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}}{\sum_{o''}\left(\left(1-\chi_{i,oo'',t}\right)\left(V_{i,o'',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}}, \tag{B.2}$$

$$V_{i,o,t} = \widetilde{\Gamma} C_{i,o,t}\left[\sum_{o'}\left(\left(1-\chi_{i,oo',t}\right)\left(V_{i,o',t+1}\right)^{\frac{1}{1+\iota}}\right)^{\phi}\right]^{\frac{1}{\phi}}, \tag{B.3}$$

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 $\Gamma\left(\cdot\right)$. For each i and t, employment level satisfies the law of motion

$$L_{i,o,t+1} = \sum_{o'} \mu_{i,o'o,t} L_{i,o',t}. \tag{B.4}$$

C Construction of the Instrumental Variable

Using Assumption 1, I develop a consistent and asymptotically efficient two-step estimator. Specifically, I follow the method developed by Adao, Arkolakis, and Esposito (2019), who extend the estimator of Newey and McFadden (1994) 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:

$$Z_{o,n} \equiv H_{o,n}\left(\boldsymbol{\psi}^{J}\right) = \mathbb{E}\left[\nabla_{\boldsymbol{\Theta}} \nu_{o}\left(\boldsymbol{\Theta}_{n}\right)|\boldsymbol{\psi}^{J}\right]\mathbb{E}\left[\nu_{o}\left(\boldsymbol{\Theta}_{n}\right)\left(\nu_{o}\left(\boldsymbol{\Theta}_{n}\right)\right)^{\top}|\boldsymbol{\psi}^{J}\right]^{-1}. \tag{C.5}$$

Then, I achieve the following result.

Proposition C.1. *Under Assumptions 1 and I.1, 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 (C.5).

Step 2: With $\mathbf{\Theta}_1$, estimate $\mathbf{\Theta}_2$ by $\mathbf{\Theta}_2 = \mathbf{\Theta}_{\boldsymbol{H}_1}$ using $Z_{o,1}$ defined in equation (C.5).

See Propositions F.1 in Appendix F.5 for discussion in further detail.

D 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 (20). With the point estimates in Table 2, the implied automation shock $\widehat{a_{o,t}^{\text{imp}}}$ using (21). 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 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 $\widehat{a_{o,t}^{\text{obs}}}$ to the first-order solution of the GE in equation (16), I obtain the prediction of changes in endogenous variables to these shocks to the first-order. Finally, applying the predicted changes to the initial data in $t_0 = 1992$, I obtain the predicted level of endogenous variables.