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

Daisuke Adachi†

February 4, 2022

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Abstract

I study the distributional effects of the rising imports of industrial robots across occupations. To answer this question, it is critical to know the substitutability of robots for workers, which requires data on robot prices. I match unique data on imported robot prices with the occupational task information to obtain the cost of using robots by occupation. The data reveal that the cost reduction by one-standard deviation induces a 0.2-0.3% drop in the US occupational wages, suggesting strong substitutability. This finding motivates me to develop a model where robots are traded and can substitute for labor with different elasticities of substitution (EoS) across occupations. Using a model-implied optimal instrumental variable, I estimate heterogeneous EoS between robots and workers. The values are higher than those of general capital goods in some routine occupations. The estimated model implies that the adoption of industrial robots explains a 6.4 percent of the observed increase in the 90-50th percentile ratio of US occupational wages.

*I thank Costas Arkolakis, Lorenzo Caliendo, Ana Cecilia Fieler, Elisa Giannone, Federico Huneeus, Shoya Ishimaru, Robert Johnson, Sam Kortum, Lei Li, Giovanni Maggi, Andreas Moxnes, Nitya Pandalai-Nayar, Shunya Noda, Yoko Okuyama, Justin Pierce, Peter Schott, Yuta Takahashi, Kosuke Uetake, Frederic Warzynski, Ray Zhang, and seminar participants at Aarhus, Kobe, National University of Singapore, North American Summer Meeting of the Econometric Society, Nottingham, Peking, and Yale for valuable comments. I acknowledge data provision from Daiji Kawaguchi and Yukiko U. Saito. All errors are my own.

†Department of Economics and Business Economics, Aarhus University. E-mail: daisuke.adachi@econ.au.dk.

1 Introduction

Among the recent technological change, the rising use of industrial robots shows unique trends.[1] In the last three decades, the market size of industrial robots has grown globally by 12% per annum. In these robot transactions, 41% are imported from other countries, revealing the sizable role of international trade. In addition, robots have heterogeneous effects on workers across occupations, raising a concern about the distributional effects of the rapid robot adoption. Pushed by this concern, policymakers have proposed various restriction measures on automation, 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 such taxes (e.g., Acemoglu and Restrepo 2020; Humlum 2019).

However, the distributional effects of the rising use of robots on the wage distribution depend on the substitutability of robots for workers. In fact, many robots are designed as capital goods that can directly replace workers' tasks instead of helping workers perform tasks. If robots and workers are strongly substitutable in a certain occupation, the relative demand for those workers drops, which affects that part of the occupational wage distribution significantly. Furthermore, regulation policies to control such a distributional effect would need to consider the trade and accumulation dynamics of robots since they affect the traded robot prices and the speed of the robot adoption, which matter for the country's aggregate welfare. Unfortunately, due to limited data to measure the cost of robots across occupations and the lack of a model capturing the robot trade and the dynamic accumulation of robots, our understanding of the distributional and aggregate im-

[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, a standard in the literature. A more formal definition given by ISO and example images of robots in such a definition are provided in Appendix D.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).

pacts of industrial robots is still limited.

In this paper, I study how introducing industrial robots affects the wage inequality between occupations and the aggregate welfare. First, I assemble a new dataset of the cost of robot adoption in each 4-digit occupation. Using this dataset, I find stylized facts about the robot cost reduction and its impact on the US occupational labor market. Second, to interpret these empirical facts, I develop a model where robots are internationally traded durable goods, are endogenously accumulated, and substitutes for labor within occupations. Third, using these data and model, I construct a model-implied optimal instrumental variable and provide the estimate of the elasticity of substitution (EoS) between robots and workers that can be heterogeneous across occupation. Finally, based on this estimated model, I perform counterfactual exercises to study the distributional and aggregate implication of robotization in the US since 1990.

My dataset is unique in the following two ways. First, it tracks not only the number of robots but also their monetary values. Second, the observation is disaggregated by the adopting country and the 4-digit occupation in which robots replace labor. To obtain such a dataset, I first use the information from the Japan Robot Association (JARA) about the shipment of Japanese robots to each country and by task, which comprises one-third of the world robot supply. I then combine the JARA data with the O*NET Code Connector's match score and the US Census/ACS data. Finally, I derive the robot cost shock by occupations from the average price after controlling for destination-country fixed effects. As a result, I obtain the dataset that links the US occupational labor market outcomes to the cost shock of robots imported from Japan, which I call the Japan robot shock throughout the paper.

The dataset reveals the following stylized facts. First, from 1990-2007, there is a sizable reduction in the average cost of a Japanese robot by more than 50%. Notably, this cost reduction is heterogeneous by occupations, as the cost growth rate ranges from -150% to 0% across occupations. Second, in the occupation that faces Japan robot shock, the growth rate of wage and employment decreased in the US. Specifically, a relative decrease of the cost of Japanese robots by one standard deviation drives an 0.2-0.3 percent decline in occupational wages per annum. This finding is robust to controlling for other occupational demand shocks, such as the China trade shock, and thus suggests responsiveness of relative demand for robot to labor to the robot cost reduction due to the strong substitutability of robots for labor.

However, the Japan robot shock measure is subject to a concern that it may reflect robot quality upgrading during the sample period. Furthermore, the above reduced-form empirical finding reveals the relative effects of the Japan robot shock on occupational wages, but not the absolute effects of robotization. To overcome these issues, I employ a dynamic open-economy general equilibrium equilibrium model of automation 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. In the model, trade of robots in a large-open economy setting implies that a robot tax affects the price of robots traded in the global market. Hence, a country may improve the aggregate welfare if it can reduce the cost of adopting robots by the tax. Second, the model describes the endogenous investment in robots with a convex adjustment cost, which implies sluggish accumulation of robot capital observed in the data. Therefore, compared to static models, the aggregate income implication of the robot tax is nuanced and different over the time horizon. Finally, a production function is characterized by occupation-specific EoS between robots and labor that varies across occupations as well as EoS between occupations. This production function yields rich predictions regarding the real-wage effect of robot capital accumulation because the stock of robots is different across occupations and because the unit of robots can substitute for workers differentially in each occupation.

To better understand the role of the occupation-specific EoS between robots and workers, I consider an automation shock à la Acemoglu and Restrepo (2020) in which robots can perform a larger share of tasks compared to labor. I analytically show that, in the equilibrium, the effect of the automation shock on occupational real wages is negatively associated with the robot-labor EoS, conditional on the changes in the cost share of robots among robots and labor. Intuitively, this result means that the higher the EoS, the larger the drop of labor demand given the automation shock because of the stronger substitution of labor with robots. Hence, it reveals the importance of identifying and estimating the EoS in my context.

To identify these robot-labor EoS, however, I confront an identification challenge that the Japan robot shock in my data can be correlated with the automation shock, and the automation shock affects the labor market outcomes simultaneously. To overcome this challenge, I use the GE structure and obtain the structural residual of labor market outcomes, which controls 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 provides me with the consistent estimates for the model parameters, but an optimal instrumental variable that increases the estimation precision.

I apply this estimation method and find that the EoS between robots and workers is around 2 when restricted constant across occupation. This estimate is significantly higher than the typical values of the EoS between labor and general capital like structure and equipment reported in the literature, 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. In contrast, the estimates in the other occupations are close to 1, so 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 high 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 compressed the wage growth of occupations in the middle deciles since these occupations tend to be in the middle of the occupational wage distribution in the baseline year. Quantitatively, it explains a 6.4 percent increase of the 90th-50th percentile wage ratio, a measure of wage inequality popularized by Goos and Manning (2007) and D. H. 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. Specifically, since countries trade robots, a government can exert monopsony power in the global robot market by taxing robot purchases, leading to a decrease in the before-tax price of imported robots in each period. In 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 manipulation 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. This finding provides a caution to policy measures proposed to slow down the adoption of industrial robots even when the country has the opportunity to levy the tax strategically.

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) establishes that the US commuting zones experiencing penetration of robots over 1992-2007 also saw decreased wages and total employment.[3] Humlum (2019) uses firm-level data on robot adoption and firm-worker-level panel data and estimates a model that incorporates a small-open economy of robot importers, a binary decision of robot adoption, and an EoS between occupations. Using these data and model, he studies the distributional effect of robots and a counter-

[3] Dauth et al. (2017) and Graetz and Michaels (2018) also use the industry-level aggregate data of robot adoption and its impact on labor markets.

factual robot tax.[4]

In contrast to these papers, my study features the following three elements. First, I use the data about the robot cost by occupation, which empirically reveal the impacts of the availability of robots on US occupations.[5] Second, I consider the trade of robots in a large-open economy setting, which implies that the effect of robots on the US real income is positive in the short-run as I show in the counterfactual exercise. Finally, these data and model allow estimating occupation-specific EoS between robots and labor. The estimated model implies that the wage-polarizing effect of the increase in robot use is larger than the prediction of the model with a conventional assumption on the robot-labor EoS, such as perfect substitutes.

Researchers pay attention to occupations in the automation literature as occupations matter when considering the distributional effects. While Jäger, Moll, and Lerch (2016) finds 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 on 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. The current paper adds to the understanding brought by these studies by providing 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.

Following the seminal work by D. H. Autor, Levy, and Murnane (2003), there is a

[4] 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), Netherlands (Bessen et al. 2019), Spain (Koch, Manuylov, and Smolka 2019), and the US (Dinlersoz, Wolf, et al. 2018).

[5] In a recent study, Caselli et al. (2021) also manually matches the robot activity from the International Federation of Robotics and labor occupations. Compared to their method, I use O*NET Code Connector's match score, which is a more comprehensive and objective measure of relevance for each robot application and labor occupation.

growing 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. Montobbio et al. (2020) extends 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. Specifically, my methodology gives a list of the pair of occupation and application associated with their relevance scores, measuring how close the pair is. Combined with the robot data by application, my dataset yields the value and the number of robots for all 4-digit occupations. Furthermore, the relevance scores are taken from a well-established occupation survey in the literature of occupation study.

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: these occupational workers' vulnerability to robots.

The rest of the paper is organized as follows. Section 2 describes my dataset of robots by occupations. I develop the general equilibrium model in 3, and estimate it using the model-implied instrumental variable in model 4. Using the estimated model, I study the effect of robotization and counterfactual robot taxes in Section 5. Section 6 concludes. Proofs for all theoretical derivations are in Appendix E.

2 Data and Stylized Facts

To approach the substitutability of robots for workers, I need the measures for the cost of using robots. In this section, I provide key data sources for this purpose: the Japan Robot

Association survey and O*NET 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 to obtain robot measures at the occupation level, and measuring the cost of using robots which I call the Japan robot shock. I then show stylized facts about robots and workers at the occupation level that suggest a large substitutability between robots and labor to motivate the model and estimation in later sections. Throughout the paper, the robot cost measurement is limited to the robot hardware, but not software or integration. Detailed discussion about this point is relegated to Appendix A.

2.1 Data Sources

The robot measures of my dataset is sourced from the Japan Robot Association (JARA), a general incorporated association composed of Japanese robot-producing companies. The number of member companies is 381 as of August 2020. JARA annually surveys all these member and some non-member companies producing robots 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, and is discussed in detail in Section 2.2 and in Appendix D.2 with examples. I digitize JARA's annual publication of the summary cross-tables starting from 1978.

Japan has been a major robot innovator, producer, and exporter. For example, the US imports 5 billion-dollar worth of Japanese robots as of 2017, 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 drop of Japanese robots' cost 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 evolution of Japanese robot cost. I will clarify the source of the shocks in detail in Section 3 and discuss the plausibility of this assumption in Appendix D.10 by comparing the JARA data and the data from International Federation of Robotics (IFR), a widely-used data source of

[6]Appendix D.5 shows the international robot flows, including Japan, the US, and the rest of the world.

robots in the world.

I also use Occupational Information Network OnLine (O*NET) Code Connector to convert robot applications to labor occupations. 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 for job orders. Using this service, one can provide any terms in search query and get occupations that are close to the search term. Furthermore, the search algorithm provides a match score that shows the relevance of each occupation to the search term. I use this match score to match robot applications and labor occupations. I use 324 of 4-digit-level occupations that exist throughout my sample period, which is discussed in detail in Appendix D.1.

2.2 Constructing the Dataset

With these data, I construct the cost of using Japanese robots and match it to the US labor market outcomes at the occupation level. I first describe the matching process between robot applications and labor occupations. Second, note that the past literature mainly focuses on the quantity of robots, but abstract away from the price or cost of robots (e.g., Acemoglu and Restrepo 2020; Humlum 2019).[7] Therefore, I describe the measurement method of robot costs.

2.2.1 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

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

requires multiple types of tasks to the worker. 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 D.2.

Specifically, let a denote robot application and o 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 O*NET-SOC occupation-level one X_o^R. First, I search occupations in 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 measures the occupation-level robot measures such as quantity and monetary values. Note that $\sum_o \omega_{oa} X_a^R = X_a^R$ since $\sum_o \omega_{oa} = 1$, which is a desired property that occupation-level robot measures sum back to the application level when summed across occupations. Further details of matching are described using examples in Appendix D.3.

Finally, I convert the O*NET-SOC-level occupation codes to OCC2010 occupation codes 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 D.1.

2.2.2 Japan Robot Shock

The above matching method provides the robot quantity $q_{i,o,t}^R$ and sales $(pq)_{i,o,t}^R$ in destination country i, occupation o, and year t. Using them, I construct the shocks to the users of robots in each occupation. Specifically, I start with the average price $p_{i,o,t}^R \equiv$

$(pq)^R_{i,o,t} / q^R_{i,o,t}$.[8] 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 and 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 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 independent of occupations. I use the remaining variation across occupations $\psi^J_{o,t}$ as a cost shock of robots by occupations, and specifically define $\psi^J_o \equiv \psi^J_{o,t_1}$ as a "Japan robot shock." Note that this methodology is in line with the past literature of automation that deals with the demand shock (Acemoglu and Restrepo 2020).

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 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 poses an identification threat, which I will describe in Section 4.2. 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 D.4.

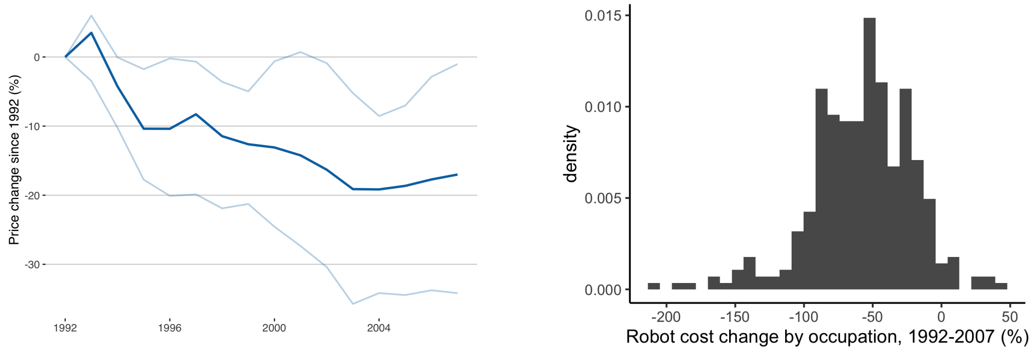
2.3 Stylized Facts

I show some facts about the Japan robot shock and its relation with the labor market outcome in the US. I define the initial year $t_0 = 1992$ (or for Census data $t_0 = 1990$), in which the JARA data starts tracking the destination-country level variable, and 1992-2007

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

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).

as the sample period, with notation $t_1 = 2007$.

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 decreasing trend of prices of general investment goods since 1980, as 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 $\psi^D_{i,t}$, as 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).

There are several interpretations of these price trends, such as the reduction in the cost to produce robots and quality changes. First, if the cost of producing robots decreases, the measured prices naturally drop. In the model, I will capture this pattern by positive Hicks-neutral productivity shock to robot producers. Second, if the quality of the robots increased over the period, the quality-adjusted prices may experience a larger decrease than what is observed in the average price measure. They are hard to separate in my data, and thus will be interpreted through the lens of the general equilibrium model by incorporating the robot producers' productivity and the robot quality separately, and examining the effects of each on the robot price, robot quantity, and labor market outcome.

Fact 2: Effects of the Japan robot shock on US occupations Using the variation of 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.[9] 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

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

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 are the female share,

[9]Specifically, following Autor, Dorn, and Hanson (2013), I take eight countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. Appendix D.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) $\Delta \ln(w)$	(4) $\Delta \ln(L)$	(5) $\Delta \ln(L)$	(6) $\Delta \ln(L)$
$\Delta \ln(c^R)$	0.116**		0.118**	0.358**		0.371***
	(0.0570)		(0.0569)	(0.148)		(0.142)
Exposure to China Trade		-0.477	-0.582		-3.537**	-3.868**
		(0.811)	(0.763)		(1.513)	(1.495)
Observations	324	324	324	324	324	324
R-squared	0.275	0.241	0.279	0.074	0.044	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 is 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.

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). Columns 1-3 take hourly wages as the outcome, while columns 4-6 take employment. Columns 3 and 6 are the main specifications that includes 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, one standard-deviation decrease of the robot cost (annually, 2.8%) implies the fall of occupational wage by 0.2-0.3% in 95% confidence interval. This finding suggests the substitutability between robots and workers because 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. In contrast, in Appendix D.8, I complement the findings in Table 1 by taking the similar approaches in the past literature such as Acemoglu and Restrepo (2020). 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 A. K. Khandelwal, Schott, and Wei (2013), and the regression without initial employment weights.

Although these regressions are informative about the drivers of robot adoption, they do not give an answer to the distributional and aggregate effect of the Japan robot shock. To derive these conclusive statements, I develop and estimate a general equilibrium model in the following sections.

3 Model

The basis of the model is a standard 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 the standard points are relegated to the Appendix. Section 3.1 states the assumptions, agents' optimization problems, and the equilibrium definition. After showing the solution method in Section 3.2, I discuss a 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 i, j, and l, where i means a non-robot good-exporting and robot-importing country, and j indicates a non-robot good-importing country, and l is a robot-exporting country, whenever I can. 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, which is discussed in detail later. Robots are differentiated by origin countries and occupations. 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 that $\tau^{g}_{ii,t} = 1$ 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 good (resp. robots) demand elasticity is ε (resp. ε^R), so that the price index in country j is $P^G_{j,t} = \left[\sum_i \left(p^G_{ij,t}\right)^{1-\varepsilon}\right]^{1/(1-\varepsilon)}$ (resp. $P^R_{j,o,t} = \left[\sum_i \left(p^R_{ij,o,t}\right)^{1-\varepsilon^R}\right]^{1/\left(1-\varepsilon^R\right)}$).

There are two factors for production of goods G: labor by occupation $L_{i,o,t}$ and robot capital by occupation $K^R_{i,o,t}$.[10] 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 robot 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 For each country i, good g, and period t, there is a given mass of producers. The producers of non-robot good-G input the occupation-o input $T^O_{i,o,t}$ and produce

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

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

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

by labor $L_{i,o,t}$ and robot capital $K^R_{i,o,t}$

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

where $\theta_o > 0$ is the elasticity of substitution between robots and labor within occupation o, and $a_{o,t}$ is the cost share of robot capital in tasks performed by occupation o.

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" (A. 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 E.4, 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.

For simplicity, robots R for occupation o are produced by investing non-robot goods $I^R_{i,o,t}$ with productivity $A^R_{i,o,t}$:[11]

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

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 term in the competitive market.

[11]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.

Discussion–The Production Function and Automation It is worth mentioning the relationship between production functions (4) and (5) and the way automation is treated in the literature. A standard approach to modeling the robot adoption in the literature, called the task-based approach, sets up the producers' allocation problem of factors (e.g., robots, labor) to a set of tasks. It then solves the allocation problem using some assumptions on the efficiency structure of performing tasks for each factor. In Appendix E, I show that this task-based approach implies occupation production function (5) with a GEV distribution on the task-efficiency structure. Intuitively, one can regard the occupation service as simply the aggregate of robot capital and labor inputs, after optimally allocating robots and workers to each task.

Given this result, the cost-share parameter $a_{o,t}$ of equation (5) has an additional interpretation. Namely, since the task-based approach consists of the allocation of factors to tasks, $a_{o,t}$ represents 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 $a_{o,t}$ as the *automation shock*. Recall that $a_{o,t}$ also represents the quality-upgrading, so the positive automation shock is the same exogenous change as robot quality upgrading in this paper. I discuss some real-world examples of the automation shock and its relationship to the models in the literature in Appendix E.1.

In this paper, I consider not only the automation shock, but also the Japanese robot shock. I call these two shocks "robotization shocks" collectively. The robotization shocks are likely to be correlated at the occupation level since 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 shown in Appendix D.2.

Finally, the robot-labor substitution parameter θ_o is a key elasticity that affects the changes in real wages when the robotization shocks hit. Specifically, I will show that θ_o is negatively related to the real wage changes conditional on the initial cost shares in Section 3.3. Hence, it is critical to get the value of the parameter to answer the welfare and policy questions of the paper. To the best of my knowledge, equation (5) is the most flexible formulation of substitution between robots and labor in the literature. For instance, 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 E.1 in Appendix E.3. I also show that my model can imply the production structure of Humlum (2019) in Lemma E.2 in the same Appendix.

Producers' Problem The producers' 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 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 to choose the quantity of new robots to purchase, or 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 investment and δ is the depreciation rate of robots. Second, I assume that the new investment is given by 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. [12] 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 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 E.1.

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

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

subject to accumulation equation (8) and (9), and given $\left\{K^R_{i,o,0}\right\}_o$. Note that the producer uses the household discount rate ι because they are owned by households. The standard Lagrangian multiplier method yields the Euler equations for investment, which I derive in Appendix E.4. 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 good markets clear as described in Appendix E.4. 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 derived in Appendix E.4.

[12]Equation (8) follows the formulation of the trade of capital goods in Anderson, Larch, and Yotov (2019) in the sense that 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).

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

Definition 1. In each period t, given state variables $\boldsymbol{S}_t$, a *temporary equilibrium* (TE) $\boldsymbol{x}_t$ is the set of prices $\boldsymbol{p}_t \equiv \{\boldsymbol{p}_t^G, \boldsymbol{p}_t^R, \boldsymbol{w}_t\}$ and flow quantities $\boldsymbol{Q}_t \equiv \left\{\boldsymbol{Q}_t^G, \boldsymbol{Q}_t^R, \boldsymbol{\mu}_t\right\}$ that satisfy: (i) given $\boldsymbol{p}_t$, workers choose occupation optimally by equation (B.2), (ii) given $\boldsymbol{p}_t$, producers maximize flow profit by equation (7) and demand robots by equation (E.15), and (iii) markets clear: Labor adds up as in equation (11), and goods market clear with trade balances as in equations (E.23) and (E.25).

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 transition conditions, sequential equilibrium determines all state variables given initial conditions as follows.

Definition 2. Given initial robot capital stocks and employment $\{\boldsymbol{K}_0^R, \boldsymbol{L}_0\}$, a *sequential equilibrium* (SE) is a sequence of vectors $\boldsymbol{y}_t \equiv \{\boldsymbol{x}_t, \boldsymbol{S}_t\}_t$ that satisfies the TE conditions and employment law of motion (B.4), value function condition (B.3), capital accumulation equation (8), producer's dynamic optimization (E.19) and (E.18).

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 $A^R_{i,o,t}$ in baseline period t_0, and combine all these changes into a column vector $\boldsymbol{\Delta}$. Write state variables $\boldsymbol{S}_t = \left[\boldsymbol{K}_t^{R\prime}, \boldsymbol{\lambda}_t^{R\prime}, \boldsymbol{L}_t^{\prime}, \boldsymbol{V}_t^{\prime}\right]^{\prime}$, and use "hat" notation to denote changes from t_0, or $\widehat{z}_t \equiv \ln(z_t) - \ln(z_{t_0})$ 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 $\widehat{\boldsymbol{A}_t} = \left[\boldsymbol{\Delta}^{\prime}, \widehat{\boldsymbol{S}}_t^{\prime}\right]^{\prime}$. 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.[13]

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

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

[13] 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 $\widehat{\boldsymbol{x}}_t = \widehat{\boldsymbol{w}}_t$.

where

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

which implies $\widehat{\boldsymbol{y}} = \overline{\boldsymbol{E}}\boldsymbol{\Delta}$, where matrix $\overline{\boldsymbol{E}} = \left(\overline{\boldsymbol{E}^{y}}\right)^{-1}\overline{\boldsymbol{E}^{\Delta}}$ represents the first-order 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 $\overline{\boldsymbol{D}_{t+1}^{y,TD}}$ and $\overline{\boldsymbol{D}_{t}^{y,TD}}$ such that $\overline{\boldsymbol{D}_{t+1}^{y,TD}}\check{\boldsymbol{y}}_{t+1} = \overline{\boldsymbol{D}_{t}^{y,TD}}\check{\boldsymbol{y}}_{t}$, where the superscript TD stands for transition dynamics, and $\check{z}_{t+1} \equiv \ln z_{t+1} - \ln z'$ and z' is the new steady state value for any variable z. Log-linearized sequential equilibrium satisfies the following first-order difference equation

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

Using conditions 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 G gives the details of the derivation of these matrices.

3.3 The Real-Wage Effect of Automation

Before moving on the estimation, I show an 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 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

$$A^K_{i,o,t} \equiv \left(A^G_{i,t}\right)^{\theta-1} a_{o,t},\ A^L_{i,o,t} \equiv \left(A^G_{i,t}\right)^{\theta-1} \left(1 - a_{o,t}\right). \tag{17}$$

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

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

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.[14] 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 $\widetilde{x}^G_{ij,t}$ 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.

[14] 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 I discussed in Section 3.1.

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

$$\widehat{\left(\frac{w_{i,o}}{P^G_i}\right)} = \frac{\widehat{\tilde{x}^L_{i,o}}}{1-\theta_o} + \frac{\widehat{\tilde{x}^O_{i,o}}}{1-\beta} + \frac{\widehat{\tilde{x}^G_{ii}}}{1-\varepsilon}. \tag{19}$$

Proposition 1 clarifies how the elasticity parameters and change of shares of input and trade affect real wages at the occupation level. Among the elasticity parameters, one can observe that if $\theta_o > 1$, then (i) the larger the fall of the labor share within occupation $\widehat{\tilde{x}^L_{i,o}}$, 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, $\widehat{\tilde{x}^L_{i,o}}$, $\widehat{\tilde{x}^O_{i,o}}$, and $\widehat{\tilde{x}^G_{ii}}$. The first term reveals the robot cost reduction relative to the labor cost. If $\theta_o > 1$, then the reduction in the price index or cost savings induced by robotization shocks dominates 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 $\left\{A^G_{i,t}\right\}$ implies

$$\widehat{\left(\frac{w_i}{P^G_i}\right)} = \frac{1}{1-\varepsilon}\widehat{\tilde{x}^G_{ii}},$$

which is the ACR formula. In the next section, motivated by the important role of the EoS parameters suggested 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

To study the effect of the adoption of Japanese robots on the US labor market, I aggregate the number of the sets of countries to be $N = 3$. Specifically, I define country index as follows: $i = 1$ as the US (USA), $i = 2$ as Japan (JPN), $i = 3$ as the Rest of the World (ROW). Therefore, I interpret country 1 as the country whose labor market outcome is of my interest, country 2 as the source country of the robot shocks. In addition, the set of other countries $i = 3$ creates the third-country effects of the robotization shock.

To allow the heterogeneity of the EoS between robots and labor across occupations while maintaining the estimation power, I define the occupation groups as follows. I first separate occupations into three broad occupation groups, Abstract, Service (Manual), and Routine following Acemoglu and David Autor (2011).[15] 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.,

[15] 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.

hand laborer), and Others (e.g., repairer). As a result, I obtain five occupation groups.[16] Within each group, I assume a constant EoS between robots and labor. Each occupation group is denoted by subscript g, so the robot-labor EoS for group g is θ_g.

I fix some parameters of the model at conventional values and define the target parameters of estimation. Specifically, the annual discount rate is $\iota = 0.05$ and the robot depreciation rate is 10 percent following Graetz and Michaels (2018).[17] 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 F.1. Following Leigh and Kraft (2018), I assume $\alpha^R = 2/3$. By Cooper and Haltiwanger (2006), I set $\gamma = 0.295$. I use the estimates from Traiberman (2019) and set $\phi = 0.8$. With these parametrization, structural parameters to be estimated are $\mathbf{\Theta} \equiv \left\{\theta_g, \beta\right\}$. I will use notation $d \equiv \dim\left(\mathbf{\Theta}\right)$ for the dimension of parameters.

Finally, to apply the two-step estimator defined below, 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 D.11. 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 negative of the cost shock to produce robots in Japan, I measure the robot efficiency gain by

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

[16] 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 $[10, 3540]$.

[17] 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. For ε, see Simonovska and Waugh (2014) or Caliendo and Parro (2015).

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

4.2 Estimation Method

Next, I discuss the identification challenge and how to work it around. I decompose the automation shock $\widehat{a_o}$ into the component $\widehat{a_o^{\text{obs}}}$ observed conditional on parameter θ_o and unobserved error component $\widehat{a_o^{\text{err}}}$ such that $\widehat{a_o} = \widehat{a_o^{\text{obs}}} + \widehat{a_o^{\text{err}}}$ for all o. Component $\widehat{a_o^{\text{obs}}}$ satisfies the steady-state change of relative demand of robots and labor

$$\left(\frac{\widehat{c_{i,o}^R K_{i,o}^R}}{w_{i,o} L_{i,o}}\right) = \frac{\widehat{a_o^{\text{obs}}}}{1 - a_{o,t_0}} + \left(1 - \theta_g\right) x_{12}^R \psi_o^J + \epsilon_o, \tag{21}$$

where x_{12}^R 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_o^J does not work as an instrumental variable (IV) in equation (21) because of a potential correlation between ψ_o^J and observed task-space expansion shock $\widehat{a_o^{\text{obs}}}$ as mentioned in Section 3.1.

To overcome the identification issue, I employ a method based on the GE model as follows. A key observation is that conditional on $\widehat{a_o^{\text{obs}}}$, the error component $\widehat{a_o^{\text{err}}}$ can be inferred from the observed endogenous variables. The steady-state solution matrix $\overline{\boldsymbol{E}}$ implies that there is a $O \times O$ sub-matrices $\overline{\boldsymbol{E}}_{w_1,\boldsymbol{a}}$ and $\overline{\boldsymbol{E}}_{w_1,\boldsymbol{A}_2^R}$ such that[18]

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

[18] I use the steady-state matrix $\overline{\boldsymbol{E}}$ instead of the transitional dynamics matrix $\overline{\boldsymbol{F}_t}$ for a computational reason. Since I have annual observation for occupational robot costs, it is potentially possible to leverage this rich variation for the structural estimation, which may permit me to estimate the EoS θ_o at a narrower occupation group level. However, the bottleneck of this approach is the computational burden to compute the dynamic solution matrix $\overline{\boldsymbol{F}_t}$. Specifically, dynamic substitution matrix $\overline{\boldsymbol{F}_{t+1}^y}$ in equation (15) is based on the conditions of Blanchard and Kahn (1980). This requires computing the eigenspace, as described in detail in Section G. This is computationally hard since we cannot rely on the sparse structure of the matrix $\overline{\boldsymbol{F}_{t+1}^y}$. In contrast, the estimation method in Proposition 2 does not involve such computation, but only requires computing the steady-state solution matrix $\overline{\boldsymbol{E}}$. Then I only need to invert steady-state substitution matrix $\overline{\boldsymbol{E}^y}$, which is feasible given the sparse structure of $\overline{\boldsymbol{E}^y}$.

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 and is generated from the linear combination of the unobserved component of the automation shocks:

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

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

Assumption 1. *(Moment Condition)*

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

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 robot efficiency change $\widehat{A_{2,o}^R}$. Instead, 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 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 since 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 of such threats 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 cost 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. Note that, if these are the case, the positive impact of Japan robot costs found in Section 2.3 shows the lower limit, and thus our qualitative results about strong substitutability are maintained.

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:

$$Z_{o,n} \equiv H_{o,n}\left(\boldsymbol{\psi}^J\right) = \mathbb{E}\left[\nabla_{\boldsymbol{\Theta}} \nu_o\left(\boldsymbol{\Theta}_n\right)|\boldsymbol{\psi}^J\right] \mathbb{E}\left[\nu_o\left(\boldsymbol{\Theta}_n\right)\left(\nu_o\left(\boldsymbol{\Theta}_n\right)\right)^\top |\boldsymbol{\psi}^J\right]^{-1}. \tag{24}$$

Then I have the following result.

Proposition 2. *Under Assumptions 1 and E.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 (24).

Step 2: With $\boldsymbol{\Theta}_1$, estimate $\boldsymbol{\Theta}_2$ by $\boldsymbol{\Theta}_2 = \boldsymbol{\Theta}_{\boldsymbol{H}_1}$ using $Z_{o,1}$ defined in equation (24).

See Propositions E.1 in Appendix E.6 for detailed discussion.

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. 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

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 2. 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.

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, or 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. I find that the EoS for routine production occupations and 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 susceptibility of workers in these occupations to accumulated robot capital. Finally, the estimate of the EoS between occupations β does not change qualitatively.

What is the source of identification of these large and heterogeneous EoS between robots and labor identified? As in the literature of estimating the capital-labor substitution elasticity, the positive correlation between the robot price and the wage (labor market outcome) suggests robots and labor are substitutes, or large θ_g. Intuitively, if θ_g is large, then given a percentage decrease in the cost of robots, the steady-state relative robot (resp. labor) demand responds strongly in the positive (resp. negative) direction. Reducing the occupation wage through the labor demand equation, the large robot-labor EoS yields a positive correlation between the robot price trend and the wage trend, as found in Figure D.8. Appendix D.9 further discusses this source of identification by studying the correlation between the Japan robot shock and the US wage change within each occupation group.

4.4 Measuring Shocks and Model Fit

I estimate the linear regression model (3) to examine the model fit and the role of the automation shock in estimating the robot-labor EoS.[19] The method for simulating the data is standard and explained in Appendix C. First, I hit all the shocks generated in the above paragraph, and I call this counterfactual wage change as the "targeted wage." 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 wage." In this case, the same moment condition is violated since the structural residual does not incorporate the automation shock. Therefore, this exercise reveals how important it is to take into account the automation shock in estimation. If the discrepancy of the regression coefficient of equation (3) between the data and the untargeted wage, the bias caused by not taking into account the automation shock is severe.

Table 3 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, and the third column is the estimate based on the untargeted wage. By comparing the first

[19] As another model validation exercise, I predict the stock of robots by occupation and find that the model predict the actual robot accumulation dynamics well, described in detail in Appendix F.2. Furthermore, Appendix F.3 gives detailed discussion about the Japan robot shock and the backed-out observed automation shocks.

Table 3: Model Fit: Linear Regression with Observed and Simulated Data

VARIABLES	(1) $\widehat{w}_{data}$	(2) $\widehat{w}_{\psi^J \widehat{a^{obs}}}$	(3) $\widehat{w}_{\psi^J}$
ψ^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 observed automation shock $\widehat{a^{obs}}$. Column (3) takes the US wage change predicted by GE with shocks including the Japan robot shock, but counterfactually fixing the observed automation shock to be zero. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

and second column, I confirm that the targeted moments match well as expected. Furthermore, examining the third column compared to the first column, one can see a stronger positive correlation between the simulated wage and the Japan robot shock. This is due to negative correlation between the Japan robot shock ψ_o^J and the observed automation shock $\widehat{a_o^{\text{obs}}}$, which is consistent with that robotic innovations that save cost (thus decreases ψ_o^J) and that upgrade quality (thus increases $\widehat{a_o^{\text{obs}}}$) are likely to happen at the same time.

More specifically, with the real and simulated data with the targeted wage, the regression specification (3) contains the negative bias due to this negative correlation. In contrast, the untargeted wage is free from this bias since its data generating process does not contain the automation 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 negative correlation between ψ_o^J and $\widehat{a_o^{\text{obs}}}$. 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.

5 Counterfactual Exercises

Using the estimated model and shocks in the previous section, I provide answers to the following questions. The first question is the distributional effects of robots. For example, D. H. 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.[20] Can the increased use of industrial robots explain the 90-50 ratio, at least from 1990, the baseline year of this study? If so, how much? 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?[21]

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. 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. Conditional on robot price changes, this pattern implies there are relatively large automation shocks on these occupations.

In contrast, the right panel shows the steady-state predicted wage growths per annum due to the shocks derived in Section 4.4 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 substitutability between robots and labor, I find that the counterfactual wage growth rate in the middle deciles of the initial wage distribution is relatively small. Quantitatively, the 90-50 ratio observed in 1990 and 2007

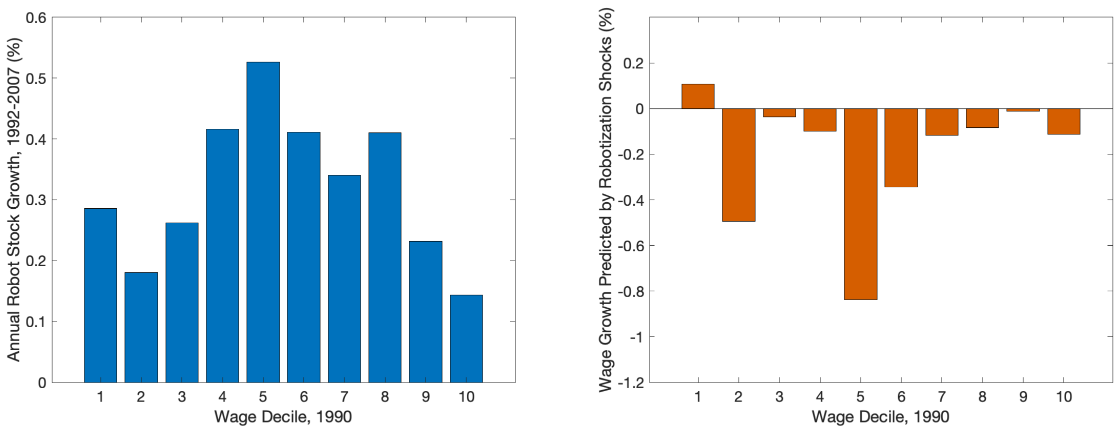
[20] Furthermore, as Heathcote, Perri, and Violante (2010) argue, the wage inequality comprises a sizable part of the overall economic inequality in the US.

[21] In Online Appendix, I 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 every ten deciles of the occupational wage distribution in 1990. The right panel shows the annualized wage growth rates predicted by the backed-out shocks and the estimated model's first-order steady-state solution given in equation (14).

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 percent increase in the 90-50 ratio can be explained by the robotization shock captured in this paper.

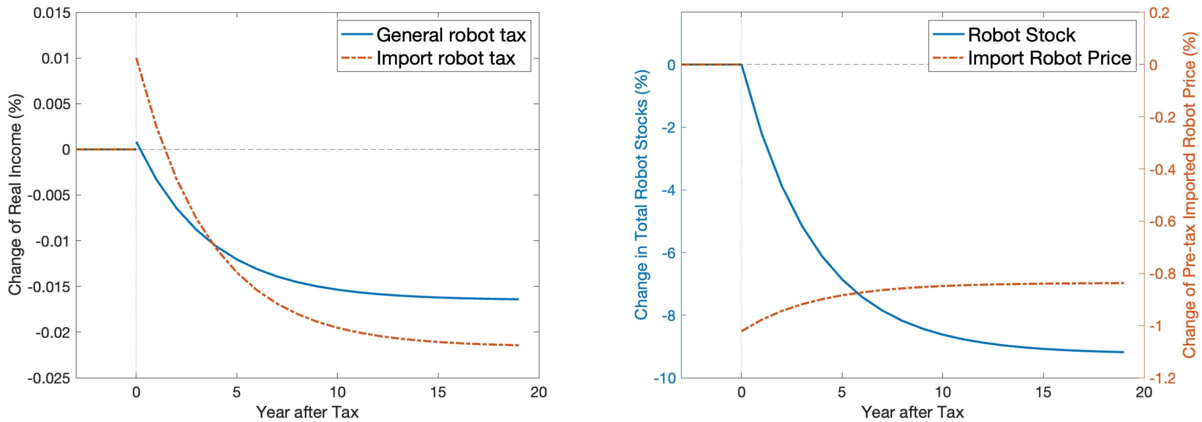
Note that these results are obtained given aggregating the effects on 4-digit occupational wages and the estimates of the robot-labor EoS. In other words, relative wages drastically drop in production and transportation (material-moving) occupations in the sample period. This is because of (i) the many robots were adopted in these occupations (Figure F.1) and (ii) the high estimates of EoS between robots and labor for these occupations (Table 2). To confirm these observations, Appendix F.4 describes the counterfactual wage changes for each of five occupation groups, and Appendix **??** performs the robotization exercise in case of lower EoS.

5.2 Robot Tax and Aggregate Income

I move on to the effect of counterfactually introducing robot tax. In the baseline economy, all countries levy zero robot tax. Consider an unexpected, unilateral, and permanent

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.

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 two scenarios.[22] How do these robot tax schemes affect the US real income? 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 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 good producer's 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 produced in the other country and let the equilibrium robot price go down along the supply curve. This reduction in the

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

robot price contributes to the increase in the firm's profit, raising the real income in the short-run. The short-run 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. Compared to this literature, this paper provides the upward sloping export supply curve from the general equilibrium, as opposed to the supply curve that is assumed to be upward sloping (e.g., Broda, Limao, and Weinstein 2008). Namely, when the demand for robots in a robot exporter country decreases, the resource to produce robots in the exporter country is freed and reallocated to produce the non-robot goods. In my case, the resource is the non-robot goods which are the input to robot production in equation (6). This increases the supply of non-robot goods in the robot-exporting country, depressing the price of non-robot goods. In turn, due to robot production function (6) again, this decrease in the non-robot goods price means the decrease of the cost of producing robots. Therefore, it reduces the price of robots produced in the exporter country.

Why do I have the different effect on real income in the long-run? 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 percent compared to the no-tax case. The small quantity of robot stocks reduces the firm profit, which contributes to low real income.[23] These results highlight the role of costly robot capital (de-)accumulation 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 is decreased, 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 show the

[23]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.

role of trade of robots, I also consider an alternative model with no trade of robots due to prohibitively high robot cost and give the robot tax counterfactual exercise in Appendix F.6.

6 Conclusion

In this paper, I study the distributional and aggregate effects of the increased use of industrial robots, with an emphasis that robots perform specified tasks and are internationally traded. I make three contributions. First, I construct a dataset that tracks the number of robot hardware and the cost shock of buying robots from Japan (the Japan robot shock), disaggregated by 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 that depends on the Japan robot shock in my dataset to identify the occupation-specific EoS between robots and labor.

The estimates of within-occupation EoS between robots and labor is heterogeneous and as high as 3 in production and material moving occupations. These estimates are significantly larger than estimates of the EoS of capital goods and workers, with a maximum of about 1.5, revealing the susceptibility to robot adaptation of workers in these occupations. The estimates also imply 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 about the distributional effects of robots and the impact of regulating robots in the short-run and the long-run.

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Appendix

A Discussion on the Robot Cost

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, therefore relevant cost of robots for adopters includes hardware, software, and integration costs.[24]

In this paper, I measure the price of robots by average price, or the total sales divided by the quantity of hardware. Thus, one should interpret that my measure of robot price reflects a 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 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

[24] 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. Plus, there still remains apparently relevant costs of robot use, like maintenance fee, about 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 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 include the 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 the previous literature utilized (e.g., Caliendo, Dvorkin, and Parro 2019). Since I follow the similar strategy, I relegate the formal problem statement and derivation to Appendix E.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 Simulation Method

The simulation process 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 $\widehat{A^R_{2,o,t}}$ using equation (20). With the point estimates in Table 2, the observed automation shock $\widehat{a^{\text{obs}}_{o,t}}$ using (21). To back out the efficiency shock of robots in the other countries, I assume that $\widehat{A^R_{i,o,t}} = \widehat{A^R_{i,t}}$ for $i = 1, 3$. Then by the robot trade prices $p^R_{ij,t}$ from BACI, I fit fixed effect regression $\Delta \ln\left(p^R_{ij,t}\right) = \widetilde{\psi}^D_{j,t} + \widetilde{\psi}^C_{i,t} + \widetilde{e}_{ij,t}$, and use $\widehat{A^R_{i,t}} = -\widetilde{\psi}^C_{i,t_1}$. The idea to back out the negative efficiency shock $\widetilde{\psi}^C_{i,t_1}$ 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 $\widehat{A^R_{i,o,t}}$ and $\widehat{a^{\text{obs}}_{o,t}}$ 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.