Robotization, Multinational Production, and Country Welfare *

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Abstract

This paper provides a comprehensive analysis of the impact of robot adoption on multinational production (MP) and country welfare. We develop a multi-country, multi-sector general equilibrium model incorporating labor-robot substitution to quantify the effects of robotization. Through counterfactual analyses, we examine global robotization, asymmetric robotization, and the role of MP in amplifying welfare effects. Our results indicate that global robotization enhances country welfare, especially in Asia and developing countries, yet contributes to polarized development, with highly robotized countries realizing substantial welfare gains while less robotized European countries face welfare declines. Additionally, asymmetric robotization benefits developed countries but imposes costs on others through intensified MP competition and reshoring. Lastly, we demonstrate that MP plays a critical role in amplifying the welfare benefits of robotization, highlighting that robotization alone is insufficient for sustained and equitable welfare growth.

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1 Introduction

In the context of the rising trend of de-globalization, multinational production (MP) remains crucial for countries to engage directly and deeply in global value chains. MP is significantly influenced by emerging technologies, as well as production and investment costs in both host and parent countries. Simultaneously, the global economy is experiencing a digital transformation, driven primarily by the adoption of industrial robots. These modern robots, capable of replacing or collaborating with human labor, boost productivity and lower production costs–a process known as robotization. Such technological advancements can further reinforce countries' comparative advantages within global trade and production networks.

Recent research (Artuc, Bastos and Rijkers, 2023; Koch, Manuylov and Smolka, 2021) has begun to integrate robotization into studies of economic openness by combining quantitative trade models (Grossman and Rossi-Hansberg, 2008; Eaton and Kortum, 2002; Caliendo and Parro, 2015) with task-based frameworks commonly used in the literature on robotics and labor market outcomes (Acemoglu and Restrepo, 2019; McAfee and Brynjolfsson, 2016). However, the literature has paid limited attention to the potential role of robotization in shaping comparative advantage within multinational production (MP) and its broader welfare effects. In Section 2, We utilize robot data from the International Federation of Robotics (IFR) and MP data from the OECD Analytical AMNE database to document some key stylized facts. Our findings show that robotization, which confers countries with a comparative productivity advantage, is positively correlated with both inward and outward MP. Additionally, we explore the phenomenon of reshoring, which in this study is defined as the scenario where the growth rate of domestic production surpasses that of outward MP. The data indicates that countries with higher levels of robotization, predominantly European and other developed countries, tend to exhibit more pronounced reshoring activities. Will robotization lead to a more open and deeply integrated global production system? Will it prompt production reshoring in certain countries? How might these changes in MP and trade networks affect country welfare moving forward?

To address these questions, we employ a quantitative general-equilibrium trade and MP model developed by Arkolakis et al. (2018) to assess the impact of robotization on globalization and welfare in the world economy. In our model, robots perform a subset of tasks, following the task-based framework introduced by Acemoglu and Autor (2011), and further developed by Acemoglu and Restrepo (2018). Additionally, in line with Caliendo and Parro (2015) and Du and Wang (2022), we incorporate the key feature of sectoral linkages, allowing us to analyze welfare effects in a more comprehensive manner. The core logic of this paper is that domestic robotization, by reducing production costs through labor displacement, influences firms' multinational production location choices, thus reshaping the global division of labor and ultimately impacting country welfare. Specifically, a reduction in domestic robot prices decreases domestic production costs and directly improves welfare. Lower production costs confer a comparative advantage in production, simultaneously affecting both inward and outward MP flows. On one hand, this productivity advantage attracts foreign firms to produce domestically, resulting in welfare gains from foreign technology. As domestic production expands, market size increases, further enhancing welfare through the market size effect. On the other hand, the productivity and scale advantages enable domestic firms to invest in foreign production sites, i.e., outward MP, allowing them to profit from offshoring and innovation, as outlined by Melitz (2003).

Our analysis focuses on 22 aggregate industries of 40 economies and a rest of the world (ROW). After calibration, we conduct three counterfactual analysis. In Scenario I, we assume a uniform 10% decrease in robot prices across all countries, representing an increase in global robotization. We find that: first, global robotization enhances global welfare and promotes greater openness by expanding trade but not MP due to competition and reshoring activities. The welfare effects are particularly pronounced in Asia and developing countries. The simulation results also highlight a polarized development pattern due to robotization, where highly robotized countries (with higher initial level of robotization) experience substantial welfare gains, while smaller, less robotized European countries face welfare declines. Through a decomposition of welfare effects, we observe that robotization affects welfare not only through direct cost-saving measures but also by influencing multinational production patterns. While most countries gain from inward MP, only highly robotized countries benefit primarily from outward MP. Second, global robotization creates a more balanced MP network, leading to more integrated regional production and trade networks. We also observe reshoring activities in both developing and developed countries, although they are more prominent in the latter.

In Scenario II, termed asymmetric robotization, we simulate a scenario where only a specific group of developed countries with higher initial levels of robotization benefit from robot price reductions. We find that the asymmetric robotization in selected developed countries improves global welfare but at the expense of other countries due to intense competition and increased production reshoring back to developed countries. Finally, in Scenario III, we assess the critical role of MP in amplifying the welfare effects of robotization by simulating a scenario in which the world faces higher MP and lower MP costs. We find that higher MP costs can diminish or even reverse the benefits of robotization while lower MP costs allow countries to achieve greater welfare gains, potentially reducing inequalities between economies. This highlights the importance of the MP channel to amplify the welfare effects of robotization and robotization alone is insufficient to sustain equitable welfare growth without MP channel.

Our study is related to and contributes to two strands of literature. The first strand related literature focuses on multinational production and its welfare effects. The welfare effects of MP encompass the direct effect, i.e., the entry of multinationals directly increases the host country's value added, employment, etc., and indirect effects through upstream and downstream input-output relationships (Cadestin et al., 2018). General equilibrium models are gradually applied to MP behavior research. Recent literature (Ramondo and Rodríguez-Clare, 2013; Shikher, 2014; Arkolakis et al., 2018; Tintelnot, 2017; Wang, 2021) has discussed the interaction between MP and trade flows. These papers all build a probabilistic representation of multi-country productivity and characterize multinationals choice of production sites. Our model is closely related to Arkolakis et al. (2018) but additionally incorporates the industry-level heterogeneity. Similar to Alviarez (2019) and Du and Wang (2022), this paper takes into account the multi-country, multi-industry heterogeneity, and adds the inter-industry input-output relationship on the basis of the existing model to measure the indirect effect of MP, i.e., the welfare changes brought about by the upstream and downstream input-output relationship.

Second, our paper belongs to the growing branch of literature that incorporates new technology like AI and industrial robots into openness studies. In terms of the model, our approach closely aligns with Artuc, Bastos and Rijkers (2023), who analyze the effects of robotization in the Global North on trade patterns, wages, and global welfare. They developed a quantitative Ricardian trade model incorporating the substitution of robots and labor by utilizing the task model commonly employed in robotics research (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018). Regarding the research focus, our paper contributes to the literature studying the effects of robotization on production reshoring. Using data from 1990 to 2015, Faber (2020) demonstrates that U.S. robotization has a significant negative impact on Mexican employment, with the decline in Mexican exports supporting the case for reshoring. Similarly, Krenz, Prettner and Strulik (2021) present a theoretical framework to examine firms' offshoring and reshoring decisions in the context of automation. They argue that while automation can drive previously offshored production back to domestic economies, it does not necessarily lead to wage improvements or job creation for low-skilled workers. Our study combines a new multinational production general equilibrium model with a robot and labor task framework to examine the effects of robotization on changes in multinational production patterns and the resulting welfare implications for countries.

The rest of the paper is structured as follows. In Section 2, we use IFR robots data and OECD Analytical AMNE data to show two main stylized facts of the relationship between robotization and MP flows. Section 3 introduces our model. In Section 4, we introduce our calibration procedure for three sets of parameters. Section 5 contains our main counterfactual simulations. In Section 6, we conclude our main findings.

2 Stylized Facts

In this section, we present several stylized facts regarding the relationship between robotization and multinational production across 22 aggregated industries in 40 economies, including the rest of the world (ROW). Table A.2 reports the country list. To quantify robotization, we utilize the metric of industrial robot usage per hour worked. The well-constructed dataset on the stock of robots is sourced from the International Federation of Robotics (IFR), which provides data on the stock of industrial robots by industry, country, and year. Following the approach of Acemoglu and Restrepo (2020), we address the approximately 30% of robots that remain unclassified by allocating them proportionally across industries based on the distribution of classified robots. Additionally, data on robots used in Canada and Mexico were inaccurately reported as being utilized in the United States until 2010. To correct for this, following the methodology of Artuc, Bastos and Rijkers (2023), we first calculated the share of robots in the NAFTA region that were operational in the U.S. in 2011. Subsequently, we adjusted the data for Canada and Mexico, assuming that robot usage in these countries, as well as in the U.S., grew at a consistent rate prior to 2011. This assumption maintains that the relative shares of robot usage across the three countries remained constant over this period. The data on annual hours worked were obtained from the World Input-Output Table (WIOT) Socio-Economic Accounts, which provide detailed documentation of the annual number of employees and total hours worked by employees across various industries[1].

We merge the robotization data with multinational production (MP) flows obtained from the 2024 version of the OECD Analytical AMNE database. This dataset provides a detailed breakdown of the bilateral output matrix by country, industry, and the country where the controlling entity is based. The AMNE database categorizes firms into three distinct groups: foreign affiliates (firms with at least 50% foreign ownership), domestic multinational enterprises (domestic firms with foreign affiliates), and domestic firms with no international investment activity. The AMNE database covers 41 industries across 76 countries, plus ROW, spanning the period from 2000 to 2019. For our analysis, we aggregated the 41 industries into 22 broader industry categories using the correspondence table provided in the Appendix Table A.1. The dataset distinguishes between domestic production flows and foreign production flows for each host country, splitting the total output of industries accordingly. In

[1] China's data is unavailable. We use the average data of Japan and South Korea to complement.

our analysis, inward MP flows are computed by summing the foreign production from all source countries for each destination country-sector pair. Similarly, outward MP flows are derived by summing the foreign production across all destination-sector pairs for each source country. As depicted in Figure 1, there is a positive correlation between countries' levels of robotization and their MP flows, both inward and outward. This suggests that countries with higher levels of robot usage tend to have a comparative advantage in the global production chain.

Next, we utilize data to explore the trending topic of reshoring. In this study, reshoring is defined and measured by comparing the growth rate of domestic production to the growth rate of outward MP. Specifically, reshoring is indicated when the growth rate of domestic production exceeds the growth rate of investments in offshore production activities. This metric captures the relative shift in production focus from international to domestic settings, signaling the reallocation of resources and production capacities back to the home country. The OECD Analytical AMNE database also reports activities such as output and trade value of domestic MNEs with foreign affiliates, which are the primary entities involved in both offshoring and reshoring. This allows us to better identify potential reshoring activities. If domestic MNEs production increases while a country's outward MP flows decrease, we classify this as evidence of reshoring. Following Krenz, Prettner and Strulik (2021), for a given industry, let $prod^d_{it}$ and $prod^o_{it}$ represent the domestic production and outward MP, respectively, for country i at time t. We define the reshoring intensity as: $RS_t = \frac{prod^d_{it}}{prod^d_{is}} - \frac{prod^o_{it}}{prod^o_{it}}$ with restriction that $RS_t > 0$.[2] The rationale for this measure is grounded in the core concept of reshoring, which represents a reversal of previous offshoring decisions. If domestic MNEs production grows faster than outward MP, it implies that firms are increasingly prioritizing home-country production over international expansion, which signals reshoring.

However, the domestic production value in the AMNE bilateral MP flows dataset is the aggregate production of both domestically-owned firms and domestic MNEs. Since our model does not separately identify domestic production from domestic MNEs, we assume that domestic production and the production of domestic MNEs move in the same direction. Figure A-1 illustrates the strong positive correlation between these two variables, indicating that increases in domestic production generally coincide with increases in the production of domestic MNEs. As a result, we also treat an increase in aggregate domestic production combined with a decrease in outward MP as an indicator of reshoring. We then compute the reshoring intensity RS_t, as defined above, using both the production of domestic MNEs and aggregate domestic production. After identifying countries that experienced reshoring

[2] We exclude samples where both domestic production and outward MP decline, as monotonic decreases would falsely indicate reshoring according to Krenz, Prettner and Strulik (2021).

($RS_t > 0$), we plot the relationship between changes in domestic production and robotization in 2014, as shown in Figure 2. We find that 10 countries experienced reshoring when using domestic MNE production changes in the measure of reshoring, compared to only 6 countries when using aggregate domestic production. This suggests that using aggregate production data in our model may underestimate the extent of reshoring activities. Overall, the figure indicates that countries with higher levels of robotization, most of which are European or developed countries, tend to exhibit greater reshoring activities. This trend can be attributed to domestic robotization reducing the incentive to invest abroad in search of lower labor costs for production.

3 Theoretical Model

We develop a general equilibrium model with trade in intermediate goods, I-O linkages, firms MP choice and composite tasks input which is produced by labor and robots. There are N countries and J sectors. The environment is monopolistic competition with free entry condition. Firms can produce anywhere in the world with varying productivity levels after paying entry cost. To the extent possible, we use index i to denote the firms country of origin (the source of MP flows), index ℓ to denote the location of production (the destination of MP flows), and index n to denote the country where the firm sells its product which can be parent countries i. Products include intermediate goods, which are tradeable, and composite goods, which are consumed in local markets as final goods. Moreover, these two types of goods can be used as inputs to each other, thus reflecting the I-O linkage.

3.1 Consumption

The representative consumer in each country n derives utility from consuming the final goods of each industry $j = 1, 2, \dots, J$. Consumer preferences are a two-tier structure: The upper tier is Cobb-Douglas form:

$$u(C_n) = \prod_{j=1}^{J} (C_n^j)^{\alpha_n^j}, \qquad \sum_{j}^{J} \alpha_n^j = 1 \tag{1}$$

where α_n^j is the expenditure share on sector j's goods. The lower tier, for each sector j, is a CES aggregation over varieties with elasticity of substitution σ^j (will be discussed later). Labor is mobile across sectors but immobile across countries. We denote w_n^L the labor wage.

3.2 Production

Each continuous intermediate good $\omega^j \in [0,1]$ in each sector j is potentially produced by a single firm in monopolistic competition. The inputs include composite goods from each sector and composite tasks. Firms ω^j from the country i can choose their production site ℓ associated with industry j around the world. A firm is characterized by a vector of productivity $z = (z^j_{i1}(\omega^j), z^j_{i2}(\omega^j), ..., z^j_{i\ell}(\omega^j))$, where $z^j_{i\ell}$ is the productivity of a firm ω^j originating in the country i producing in the country ℓ.

Before drawing productivities, a firm has to pay a fixed cost f^e in units of local labor. We treat the creation of firms as innovation following Melitz (2003) and Arkolakis et al. (2018). In the presence of multinational production (MP), a country is more likely to specialize in innovation if its multinationals offshore large outward MP. Conversely, a country tends to specialize in production if it attracts a high volume of inward MP. After drawing productivities, a firm finds the cheapest location from where to serve each market n. Hence the production function of intermediate goods is:

$$q^j_{i\ell}\left(\omega^j\right) = z^j_{i\ell}\left(\omega^j\right)\left[T^j_\ell\left(\omega^j\right)\right]^{\beta^j_\ell}\prod_{k}^{J}\left[m^{k,j}_\ell\left(\omega^j\right)\right]^{\beta^{k,j}_\ell} \tag{2}$$

where T^j_ℓ is the amount of composite tasks and $m^{k,j}_\ell$ is the composite goods from each industry. Composite goods are produced by aggregating intermediate goods using CES function which will be discussed later. $\beta^j_\ell, \beta^{k,j}_\ell$ denotes input share of composite tasks and composite goods which satisfy $\beta^j_\ell + \sum_k \beta^{k,j}_\ell = 1$.

Next, firms decide what price to charge. Firms incur three types of costs when operating outside their original countries and exporting goods across countries. First, there is an iceberg cost $\gamma^j_{i\ell}$ associated with using home technology from i to produce in ℓ, where $\gamma^j_{i\ell} \geq 1(\gamma^j_{\ell\ell} = 1)$ denotes the production or investment costs that multinationals face when operating in a different country. Second, trade from country ℓ to country n incurs a traditional iceberg cost $\tau^j_{\ell n} \geq 1(\tau^j_{nn} = 1)$. Third, there is also a fixed marketing cost F^j_n of entering the final market country n, valued in terms of labor in the destination country. This kind of marketing cost arising from hiring local labor to overcome the investment or sales barrier in destination countries. In addition, due to the CES preferences and monopolistically competitive markets, a firm originating in the country i would like to serve the market n by its affiliate in the country ℓ will charge a mark-up $\tilde{\sigma}^j = \frac{\sigma^j}{\sigma^j - 1}$ over its marginal costs:

$$c^j_{i\ell n} = B^j_\ell \frac{\xi^j_{i\ell n}}{z^j_{i\ell}} \tag{3}$$

with $\xi^j_{i\ell n} = \gamma^j_{i\ell}\tau^j_{\ell n}(w^{T,j}_\ell)^{\beta^j_\ell}\prod_{k=1}^J(P^k_\ell)^{\beta^{k,j}_\ell}$. $w^{T,j}_\ell$ is the (average) cost of unit composite task and P^k_ℓ is the price index of composite goods in sector k. $B^j_\ell = \prod_{k=1}^J(\beta^{k,j}_\ell)^{-\beta^{k,j}_\ell}(\beta^j_\ell)^{-\beta^j_\ell}$ is a constant.

Producers of composite goods in sector j of country n, supply Q^j_n at minimum cost by purchasing intermediate goods ω from the lowest cost suppliers across countries.

$$Q^j_n = \left(\int r^j_n(\omega^j)^{\frac{\sigma^j-1}{\sigma^j}}d\omega^j\right)^{\frac{\sigma^j}{\sigma^j-1}} \tag{4}$$

where $\sigma^j > 1$ is the elasticity of substitution between intermediate goods ω^j, $r^j_n(\omega^j)$ is the demand for the intermediate good, and $p^j_n(\omega^j)$ is the minimum price of the intermediate good from around the world. First order conditions give the demand for intermediate goods:

$$r^j_n(\omega^j) = \left(\frac{p^j_n(\omega^j)}{P^j_n}\right)^{-\sigma^j} Q^j_n \tag{5}$$

where P^j_n is the price index of composite goods:

$$P^j_n = \left(\int p^j_n(\omega^j)^{1-\sigma^j}d\omega^j\right)^{\frac{1}{1-\sigma^j}} \tag{6}$$

Note that composite goods are used as inputs in intermediates production and final consumption as well. Hence, the market clearing condition for composite goods is $Q^j_n = C^j_n + \sum_{k=1}^J\int m^{k,j}_n(\omega^j)d\omega^j$.

Finally, firms calculate the associate profits from MP and trade sales. The total expenditure on sector j goods in country n is given by $X^j_n = P^j_nQ^j_n$. The firm chooses to serve the market n only if its associated variable profits $\frac{p^j_nr^j_n}{\sigma^j}$ are enough to cover the fixed marketing cost $w^L_nF^j_n$ into the final market n. Then we can derive the maximum unit cost, i.e., the market entry cutoff $c^{j\,*}_n$ under which the firm will enter the market n is:

$$c^{j\,*}_n = \left(\frac{\sigma^j w^L_n F^j_n}{X^j_n}\right)^{\frac{1}{1-\sigma^j}} \frac{P^j_n}{\tilde{\sigma}^j} \tag{7}$$

3.3 Aggregation

Following Arkolakis et al. (2018) and Du and Wang (2022), we assume that the productivity vector of firms is randomly drawn from a multivariate Pareto distribution:

$$\begin{aligned}\text{Prob}\left[z_{i1}^j(\omega^j) \leq z_1, \ldots, z_{iN}^j(\omega^j) \leq z_N\right] = 1 - D_i^j \left[\sum_{\ell=1}^{N} A_\ell^j {z_\ell^j}^{-\frac{\theta^j}{1-\rho}}\right]^{1-\rho} \\ \textit{support} \quad z_\ell^j \geq \tilde{D}_i^j := {D_i^j}^{\frac{1}{\theta^j}} \left[\sum_{\ell=1}^{N} {A_\ell^j}^{\frac{1}{1-\rho}}\right]^{\frac{1-\rho}{\theta^j}}\end{aligned} \tag{8}$$

where $\rho \in [0,1)$ and $\theta^j > \max(1, \sigma^j - 1)$. The parameter θ^j determines the heterogeneity of productivity in j industries across countries, while ρ determines the heterogeneity of individual productivity vectors. We can think of D_i^j as a measure of the quality of ideas in country i, or productivity in innovation. In turn, A_ℓ^j determines country ℓ's productivity in production. $\tilde{D}_i^j$ is a weighting of the productivity of individual country pairs consisting of country i and producer ℓ.

Under the assumption that $\xi_{i\ell n}^j > \tilde{D}_i^j {c_n^j}^*$ which assures there exists firms from i will not choose to serve market n, the share of expenditure by country n on (intermediate) goods produced in country ℓ by firms from country i is:

$$\pi_{i\ell n}^j = \frac{X_{i\ell n}^j}{X_n^j} = \psi_{i\ell n}^j \lambda_{in}^j \tag{9}$$

where $\psi_{i\ell n}^j = \frac{A_\ell^j (\xi_{i\ell n}^j)^{-\frac{\theta^j}{1-\rho}}}{(\Psi_{in}^j)^{\frac{1}{1-\rho}}}$ denotes the probability that the country ℓ is the production site provided that country i is the origin of imports of sector j in country n and $\Psi_{in}^j = \left[\sum_{\ell=1}^N A_\ell^j {\xi_{i\ell n}}^{-\frac{\theta^j}{1-\rho}}\right]^{1-\rho}$. $\lambda_{in}^j = \frac{M_i^j D_i^j \Psi_{in}^j}{\sum_h M_h^j D_h^j \Psi_{hn}^j}$ represents the probability that the origin of goods imported by n is country i, and M_i^j is the mass of firms in the sector j of the country i. This equation shows that the multinationals export-platform networks or trilateral trade flows $\{X_{i\ell n}^j\}$ depend on technologies, factor prices, final market size, MP costs, and trade frictions. To link this structural equation with the actual bilateral MP data, we denote model-driven bilateral MP by $X_{i\ell}^{j,MP} = \sum_{n=1}^N X_{i\ell n}^j$.

The price index of the composite good of sector j can be expressed as:

$$P_n^{j^{-\theta^j}} = (\zeta^j)^{\theta^j} \left(\frac{w_n^L F_n^j}{X_n^j}\right)^{1-\frac{\theta^j}{\sigma^j-1}} \left[\sum_h M_h^j D_h^j \Psi_{hn}^j\right]$$
$$= (\zeta^j)^{\theta^j} \left(\frac{w_n^L F_n^j}{X_n^j}\right)^{1-\frac{\theta^j}{\sigma^j-1}} \left[\sum_h M_h^j D_h^j \left[\sum_{\ell=1}^{N} A_\ell^j \left(\gamma_{h\ell}^j \tau_{\ell n}^j (w_\ell^{T,j})^{\beta_\ell^j} \prod_{k=1}^{J} (P_\ell^k)^{\beta_\ell^{k,j}}\right)^{-\frac{\theta^j}{1-\rho}}\right]^{1-\rho}\right] \tag{10}$$

where $\zeta^j \equiv \left(\frac{(\tilde{\sigma}^j)^{1-\sigma^j}\theta^j}{\theta^j-\sigma^j+1}\right)^{1/\theta^j} \left(\frac{\sigma^j}{(\tilde{\sigma}^j)^{1-\sigma^j}}\right)^{\frac{\sigma^j-1-\theta^j}{\theta^j(\sigma^j-1)}}$.

3.4 Composite Tasks and Robots

Now we turn to figure out how the robots and tasks affect the model by re-shaping production function and price index. Composite tasks input T_ℓ^j need performing (sub) tasks $k \in [0,1]$ with equal intensity. All tasks k can be performed by labor L and a fraction of those can be also performed by robots R. We assume that tasks from 0 to K^j can be performed by robots or humans with CES form, while tasks between K^j and 1 can only be performed by workers. The subset of tasks that can be robotized is thus given by K^j, while the subset of tasks that cannot be robotized is given by $1-K^j$. K^j is the maximum number of tasks that industrial robots can perform, called the automation technology frontier and it is industry specific (Artuc, Bastos and Rijkers, 2023). We denote the automatable tasks with $T^{A,j}$ and non-automatable tasks with $T^{N,j}$. Hence the production of composite tasks is:

$$T_\ell^j = \min\{\frac{T_\ell^{A,j}}{K^j}, \frac{T_\ell^{N,j}}{1-K^j}\}$$

In order to perform one unit task k of variety ω, firm needs input $\phi^L\varepsilon^L(k)$ labor. If $k < K^j$, then alternatively $\phi^R\varepsilon^R(k)$ units of robots can also perform the same task. ϕ^L, ϕ^R are fixed cost shifter that applies to all tasks equally and $\varepsilon^L(k), \varepsilon^R(k)$ are random input components. Labor and robots both have their advantages in some tasks. To characterize these advantages, we assume $\varepsilon^L(k), \varepsilon^R(k)$ following Weibull $(v,1)$ distribution[3]. Denote the wage rate of labor w_ℓ^L and rental rate of robots w_ℓ^R. With this tractable distribution, we can solve for the optimal allocations of labor $K_\ell^{A,L,j}$ and robots $K_\ell^{R,j}$ in the subset of automatable

[3]The cumulative distribution function of Weibull $(v,1)$ distribution is $F(x;\beta,\alpha) = 1 - e^{-(\frac{x}{\alpha})^\beta}$ where the shape parameter $\beta = v$ and the scale parameter $\alpha = 1$.

tasks $T_\ell^{A,j}$ are[4]:

$$K_\ell^{A,L,j} = \frac{(w_\ell^L \phi^L)^{-v}}{(w_\ell^L \phi^L)^{-v} + (w_\ell^R \phi^R)^{-v}} K^j \tag{11}$$

and

$$K_\ell^{R,j} = \frac{(w^R \phi^R)^{-v}}{(w_\ell^L \phi^L)^{-v} + (w_\ell^R \phi^R)^{-v}} K^j \tag{12}$$

The ratio of tasks performed by workers between K^j and 1 is simply

$$K_\ell^{N,L,j} = 1 - K^j \tag{13}$$

We define the productivity-adjusted relative cost of robots to workers as

$$\varphi_\ell = \frac{\phi^R w_\ell^R}{\phi^L w_\ell^L} \tag{14}$$

which will play a key role in the model. Then equation (12) can be rewritten as

$$K_\ell^{R,j} = [1 + (\varphi_\ell)^v]^{-1} K^j \tag{15}$$

where $K_\ell^{R,j}$ depends only on: (i) the automation frontier, K^j, (ii) the elasticity of substitution between robots and workers, $1+v$; and (iii) the productivity-adjusted relative price of robots and workers, φ_ℓ. A decline in the price of robots, w_ℓ^R, or an increase in wages, w_ℓ^L, lead to an increase in the number of robotized tasks.

The average unit cost of tasks from 0 to K^j is given by the following standard CES function[5]:

$$w_\ell^{T_A,j} = \eta \left(\left(\phi^R w_\ell^R\right)^{-v} + \left(\phi^L w_\ell^L\right)^{-v} \right)^{-\frac{1}{v}} \tag{16}$$

and depends on wages, the unit cost of robots, and the elasticity of substitution between robots and workers. Where $\eta = \Gamma(1 + \frac{1}{v})$. Since tasks between K^j and 1 can only be performed by workers, their average cost is given by

$$w_\ell^{T_N,j} = \eta \phi^L w_\ell^L \tag{17}$$

where $w_\ell^{T_A,j} < w_\ell^{T_N,j}$ because $\frac{w_\ell^{T_A,j}}{w_\ell^{T_N,j}} = (1 + (\varphi_\ell)^{-v})^{-\frac{1}{v}} = \left(1 - \frac{K_\ell^{R,j}}{K^j}\right)^{\frac{1}{v}} < 1$. Thus, the average cost of tasks that can be robotized is always smaller than the average cost of tasks that cannot be robotized.

[4]Producers use robots if $\phi^L \varepsilon^L(k) w_\ell^L / \phi^R \varepsilon^R(k) w_\ell^R > 1$ for a given task k, and employ workers otherwise.

[5]By the Weibull distribution assumption, we can prove that the elasticity between labor and robots using in the task below K^j is constant $= 1 + v$. Hence we can use a CES aggregator to calculate the automation tasks produced with the optimal composition of factors

Thus the cost of composite tasks is:

$$w_\ell^{T,j} = K^j w_\ell^{T_A,j} + (1-K^j) w_\ell^{T_N,j} \tag{18}$$

Define the cost deflator Ω_ℓ^j as the relative cost of producing one unit of composite task with and without robots. Using (15)-(18), we can express it as:

$$\Omega_\ell^j = \frac{K^j w_\ell^{T_A,j} + (1-K^j)\, w_\ell^{T_N,j}}{w_\ell^{T_N,j}} = 1 - K^j + K^j \left(1 - \left[1 + (\varphi_\ell)^v\right]^{-1}\right)^{\frac{1}{v}} \tag{19}$$

When domestic robotization increases, cost deflator Ω_ℓ^j decreases which means the price of a composite task is lower than wage.

With (11)-(13), we can derive out the number of workers performing subtasks below and above K^j to produce T_ℓ^j units of tasks respectively,

$$L_\ell^{A,j} = T_\ell^j K_\ell^{A,L,j} \frac{w_\ell^{T_A,j}}{w_\ell^L}$$
$$L_\ell^{N,j} = T_\ell^j K_\ell^{N,L,j} \frac{w_\ell^{T_N,j}}{w_\ell^L}$$

with the total labor demand $L_\ell^j = L_\ell^{A,j} + L_\ell^{N,j}$.

Hence, by combining above equations, the production function of T_ℓ^j with $\frac{w_\ell^{T_A,j}}{w_\ell^{T_N,j}} = \left(1 - \frac{K_\ell^{R,j}}{K^j}\right)^{\frac{1}{v}}$, we can express the equilibrium labor demand per unit of task as

$$\Xi_\ell^j \equiv (\eta\phi^L)^{-1} \frac{L_\ell^j}{T_\ell^j} = \left(1 - K^j\right) + K^j \left(1 - \left[1 + (\varphi_\ell)^v\right]^{-1}\right)^{1+\frac{1}{v}} \tag{20}$$

Note that the cost share of labor and robots in the total cost of tasks are respectively equal to

$$\frac{w_\ell^L L_\ell^j}{w_\ell^T T_\ell^j} = \frac{\Xi_\ell^j}{\Omega_\ell^j} \tag{21}$$

$$\frac{w_\ell^R R_\ell^j}{w_\ell^T T_\ell^j} = 1 - \frac{\Xi_\ell^j}{\Omega_\ell^j} \tag{22}$$

which are important for calibration and simulation sections.

As illustrated in Artuc, Bastos and Rijkers (2023), the reduction in w_ℓ^R leads to a decrease in the average cost of performing tasks, reflected in the fall of Ω_ℓ^j. Simultaneously, the demand for labor for a given number of tasks also declines, as indicated by the reduction in

Ξ_ℓ^j. Notably, as shown by the Figure 6 in their paper, the decline in labor demand occurs at a faster rate than the decline in task costs, which may exert downward pressure on wages and reduce employment in the robotized sector. However, the lower production costs also lead to an expansion in output within the robotized industry, which could increase labor demand and potentially raise wages. Thus, the overall effect of robotization on sectoral employment and wages remains theoretically ambiguous, depending on the balance between these opposing forces.

3.5 Multinational Production and Prices

Using (2) and Ξ_ℓ^j we can rewrite the production function as:

$$q_{i\ell}^j\left(\omega^j\right) = z_{i\ell}^j\left(\omega^j\right)(\eta\phi^L)^{-\beta_\ell^j}\left[\frac{L_\ell^j\left(\omega^j\right)}{\Xi_\ell^j}\right]^{\beta_\ell^j}\prod_k^J\left[m_\ell^{k,j}\left(\omega^j\right)\right]^{\beta_\ell^{k,j}} \tag{23}$$

Using (3) and Ω_ℓ^j we can rewrite the cost function as:

$$c_{i\ell n}^j(\omega^j) = B_\ell^j\frac{\xi_{i\ell n}^j}{z_{i\ell}^j(\omega^j)} = \frac{B_\ell^j(\eta\phi^L)^{\beta_\ell^j}}{z_{i\ell}^j(\omega^j)}\gamma_{i\ell}^j\tau_{\ell n}^j(\Omega_\ell^j w_\ell^L)^{\beta_\ell^j}\prod_{k=1}^J(P_\ell^k)^{\beta_\ell^{k,j}}$$

where the smaller the cost deflator Ω_ℓ^j indicates the lower the cross-country production cost after using industrial robots.

And the price index for composite goods (10) is now:

$$P_n^{j^{-\theta^j}} = (\zeta^j)^{\theta^j}\left(\frac{\sigma w_n F_n^j}{X_n^j}\right)^{1-\frac{\theta^j}{\sigma^j-1}}\left[\sum_h M_h^j D_h^j\left[\sum_{\ell=1}^N\kappa_\ell^j A_\ell^j\left(\gamma_{h\ell}^j\tau_{\ell n}^j(\Omega_\ell^j w_\ell^L)^{\beta_\ell^j}\prod_{k=1}^J(P_\ell^k)^{\beta_\ell^{k,j}}\right)^{-\frac{\theta^j}{1-\rho}}\right]^{1-\rho}\right] \tag{24}$$

where $\kappa_\ell^j = (\eta\phi^L)^{-\frac{\beta_\ell^j\theta^j}{1-\rho}}$. Hence, the price index of intermediate goods is related to robotization and can impact other sectors by input-output linkages.

3.6 Equilibrium

We can express the equilibrium using a vector $\left\{w_i^L, M_i^j, P_i^j, X_i^j\right\}$ based on the convenient property of multivariate Pareto distribution, because the total fixed marketing cost and total net profit of multinationals are fixed proportions of trilateral trade flows $\left\{X_{i\ell n}^j\right\}$. The fixed marketing cost has a share of $s_j^m = \frac{\theta^j-(\sigma^j-1)}{\theta^j\sigma^j}$ and the total net profits of firms have a share $s_j^f = \frac{1}{\sigma^j} - s_j^m = \frac{\sigma^j-1}{\theta^j\sigma^j}$ in the $\left\{X_{i\ell n}^j\right\}$, respectively.

Thus, We consider three market clearing conditions and the free entry condition. First, the market clearing condition for goods requires that total expenditure on goods j is the sum of the expenditure on composite goods by firms and the expenditure by households. Using the value of production $Y_\ell^j = \sum_{i,n} X_{i\ell n}^j$

$$X_\ell^j = \alpha_\ell^j Y_\ell + \sum_{k=1}^{J} \beta_\ell^{j,k} (1 - \frac{1}{\sigma^k}) \sum_{i,n} X_{i\ell n}^k \tag{25}$$

with

$$Y_\ell = w_\ell^L L_\ell + \underbrace{\sum_j \sum_{k,n} s_j^f X_{\ell kn}^j}_{\text{Net profits:}\Pi_\ell} + \sum_j w_\ell^R R_\ell^j + \Delta_\ell \tag{26}$$

where Δ_ℓ is the aggregate trade and MP imbalances (Arkolakis et al., 2018). In practice, we allocate the world total imbalances to each country using their production share as weights and then solve an initial equilibrium.

Second, the factor market clearing condition for a country ℓ requires the total labor income is equal to the sum of two parts: the production wage when ℓ is the production site, the marketing wage when ℓ is the final market. Marketing wage is the entry cost paid by foreign firms which can be considered as they hiring local workers to do advertisement in order to enter the market ℓ. Hence, robotization can affect the wages directly by production site and also indirectly by multinational production channels. The equilibrium wage is determined by the labor market clearing condition.

$$\underbrace{w_\ell^L L_\ell}_{\text{Laobr income}} = \sum_j \left[\underbrace{\left(1 - \frac{1}{\sigma^j}\right) \beta_\ell^j \sum_{i,n} X_{i\ell n}^j \frac{\Xi_\ell^j}{\Omega_\ell^j}}_{\text{Production Wage}} + \underbrace{s_j^m \sum_{i,k} X_{ik\ell}^j}_{\text{Marketing Wage}} \right] \tag{27}$$

and because $\frac{w_\ell^R R_\ell^j}{w_\ell^L L_\ell^j} = \frac{\Omega_\ell^j - \Xi_\ell^j}{\Xi_\ell^j}$, the robots market clearing condition for a country ℓ which determines the amount of robots is:

$$w_\ell^R R_\ell^j = (1 - \frac{1}{\sigma^j}) \beta_\ell^j \sum_{i,n} X_{i\ell n}^j \frac{\Omega_\ell^j - \Xi_\ell^j}{\Omega_\ell^j} \tag{28}$$

Finally, the free entry condition determines the mass of firms:

$$M_i^j w_i^L f^e = s_j^f \sum_{\ell,n} X_{i\ell n}^j \tag{29}$$

Definition 3.1. *Given parameters with initial values of* $\{X^j_{i\ell n}, w^R_\ell, \varphi_\ell, \Xi^j_\ell, \Omega^j_\ell\}$*, the equilibrium is a vector* $\{\boldsymbol{w}^L, \boldsymbol{M}, \boldsymbol{P}, \boldsymbol{X}\}$ *satisfies conditions (3), (9), (24)-(29).*

3.7 Equilibrium of Relative Changes

In order to investigate counterfactual effects of robots' price on multinational production, trade and welfare around the world, We use the exact hat algebra popularized by Dekle, Eaton and Kortum (2008) to solve for the counterfactual state of the global economy in response to any change in model fundamentals.

Definition 3.2. *Let* x' *denote the counterfactual value of a variable* x *and* $\hat{x} \equiv x'/x$ *the change ratio. Given exogenous shocks* $\hat{\gamma}^j_{i\ell}, \hat{\tau}^j_{\ell n}, \hat{w}^R_\ell$ *and initial robot-related parameters* $\{\Omega^j_\ell, \Xi^j_\ell, \varphi_\ell\}$ *and trilateral flows* $X^j_{i\ell n}$*. Then the equilibrium vector* $\left\{\hat{w}^L_i, \hat{M}^j_i, \hat{P}^j_i, \hat{X}^j_i\right\}$ *can be solved by the system of equations:*

1. Goods market clearing:

$$X^j_\ell \hat{X}^j_\ell = \alpha^j_\ell Y_\ell \hat{Y}_\ell + \sum_{k=1}^{J} \beta^{j,k}_\ell (1 - \frac{1}{\sigma^k}) \sum_{i,n} X^k_{i\ell n} \hat{\pi}_{i\ell n} \hat{X}^k_n \tag{30}$$

   with

$$Y_\ell \hat{Y}_\ell = w^L_\ell \hat{w}^L_\ell L_\ell + \sum_j s^f_j \sum_{k,n} X^j_{\ell kn} \hat{\pi}^j_{\ell kn} \hat{X}^j_n + \sum_j w^R_\ell \hat{w}^R_\ell R^j_\ell \hat{R}^j_\ell + \Delta_\ell \tag{31}$$

2. Factors market clearing:

$$w^L_\ell \hat{w}^L_\ell L_\ell = \sum_j \left[(1 - \frac{1}{\sigma^j}) \beta^j_\ell \sum_{i,n} X^j_{i\ell n} \hat{\pi}^j_{i\ell n} \hat{X}^j_n \frac{\Xi^j_\ell \hat{\Xi}^j_\ell}{\Omega^j_\ell \hat{\Omega}^j_\ell} + s^m_j \sum_{i,k} X^j_{ik\ell} \hat{\pi}^j_{ik\ell} \hat{X}^j_\ell \right] \tag{32}$$

$$w^R_\ell \hat{w}^R_\ell R^j_\ell \hat{R}^j_\ell = (1 - \frac{1}{\sigma^j}) \beta^j_\ell \sum_{i,n} X^j_{i\ell n} \hat{\pi}^j_{i\ell n} \hat{X}^j_n \frac{\Omega^j_\ell \hat{\Omega}^j_\ell - \Xi^j_\ell \hat{\Xi}^j_\ell}{\Omega^j_\ell \hat{\Omega}^j_\ell} \tag{33}$$

3. Expenditure shares:

$$\hat{\pi}^j_{i\ell n} = \hat{\psi}^j_{i\ell n} \hat{\lambda}^j_{in} \tag{34}$$

   where $\hat{\psi}^j_{i\ell n} = \frac{(\hat{\xi}^j_{i\ell n})^{-\frac{\theta^j}{1-\rho}}}{(\hat{\Psi}^j_{in})^{\frac{1}{1-\rho}}}$, $\hat{\Psi}^j_{in} = \left[\sum_\ell^N \psi^j_{i\ell n} (\hat{\xi}^j_{i\ell n})^{\frac{-\theta^j}{1-\rho}}\right]^{1-\rho}$, $\hat{\lambda}^j_{in} = \frac{\hat{M}^j_i \hat{\Psi}^j_{in}}{\sum_k \lambda^j_{kn} \hat{M}^j_k \hat{\Psi}^j_{kn}}$ and

$$\hat{\xi}^j_{i\ell n} = \hat{\gamma}^j_{i\ell} \hat{\tau}^j_{\ell n} (\hat{\Omega}^j_\ell \hat{w}^L_\ell)^{\beta^j_\ell} \prod_{k=1}^{J} (\hat{P}^k_\ell)^{\beta^{k,j}_\ell} \tag{35}$$

4. Price index

$$\hat{P}_n^j = \left[\left(\frac{\hat{w}_n^L}{\hat{X}_n^j} \right)^{-\frac{\theta^j-(\sigma^j-1)}{\sigma^j-1}} \sum_k \lambda_{kn}^j \hat{M}_k^j \hat{\Psi}_{kn}^j \right]^{-\frac{1}{\theta^j}}, \tag{36}$$

5. Free entry

$$\hat{M}_i^j \hat{w}_i M_i^j w_i f^e = s_j^f \sum_{\ell,n} X_{i\ell n}^j \hat{\pi}_{i\ell n}^j \hat{X}_n^j. \tag{37}$$

3.8 Welfare change

Because of the robots revenue $w_\ell^R R_\ell^j$ and net profits from multinationals, change in real income or country welfare,is not equal to real wage. Using the change of real income equation (31) we can decompose the country welfare as:

$$\ln \hat{W}_n = \ln \frac{\hat{Y}_n}{\hat{P}_n} = \ln \frac{\hat{w}_n^L}{\hat{P}_n} + \ln \left[\frac{w_n^L L_n}{Y_n} + \frac{\Pi_n}{Y_n} \frac{\hat{\Pi}_n}{\hat{w}_n^L} + \frac{w_n^R R_n}{Y_n} \frac{\hat{w}_n^R \hat{R}_n}{\hat{w}_n^L} \right] \tag{38}$$

where $P_n = \prod_j \left(\frac{P_n^j}{\alpha_n^j} \right)^{\alpha_n^j}$ is the aggregate consumption price index and $\Pi_n = \sum_j \sum_{\ell,k} s_j^f X_{n\ell k}^j$ is the net overseas profits earn by firms from country n. The equation here tells that, given the improvement of robotization, countries can be affected not only from changes in real wages but also from increased profits due to expanded global sales activities and additional rental income generated from robot usage.

Next, following Caliendo and Parro (2015) and Du and Wang (2022) we can decompose the real wage change into seven items and finally we get the decomposition of country welfare as

$$\ln \hat{W}_i = \underbrace{\sum_{j=1}^{J}\left[-\frac{\alpha_i^j}{\theta^j}\ln\hat{\lambda}_{ii}^j\right]}_{\text{Gains from foreign finals (GFF)}} + \underbrace{\sum_{j=1}^{J}\left[-\frac{\alpha_i^j(1-\beta_i^j)}{\theta^j\beta_i^j}\ln\hat{\lambda}_{ii}^j\right]}_{\text{Gains from foreign intermediates (GFI)}} + \underbrace{\sum_{j=1}^{J}\left[-\alpha_i^j\ln\hat{\Omega}_i^j\right]}_{\text{Gains from robots (GR)}}$$
$$+\underbrace{\sum_{j=1}^{J}\sum_{k=1}^{J}\left[-\alpha_i^j\frac{\beta_i^{k,j}}{\beta_i^j}\ln(\frac{\hat{P}_i^k}{\hat{P}_i^j})\right]}_{\text{Sectoral IO linkages (SEC)}} + \underbrace{\sum_{j=1}^{J}\left[-\frac{\alpha_i^j(1-\rho)}{\theta^j\beta_i^j}\ln\hat{\psi}_{iii}^j\right]}_{\text{Gains from offshoring (GOF)}} \tag{39}$$
$$+\underbrace{\sum_{j=1}^{J}\left[\frac{\alpha_i^j}{\theta^j\beta_i^j}\left(\frac{\theta^j}{\sigma^j-1}-1\right)\ln(\frac{\hat{X}_i^j}{\hat{w}_i^L})\right]}_{\text{Market size effects (MS)}} + \underbrace{\sum_{j=1}^{J}\left[\frac{\alpha_i^j}{\theta^j\beta_i^j}\ln\hat{M}_i^j\right]}_{\text{Gains from innovation (INV)}}$$
$$+\underbrace{\ln\left[\frac{w_i^L L_i}{Y_i}+\frac{\Pi_i}{Y_i}\frac{\hat{\Pi}_i}{\hat{w}_i^L}+\frac{w_i^R R_i}{Y_i}\frac{\hat{w}_i^R\hat{R}_i}{\hat{w}_i^L}\right]}_{\text{Profits and Robots Revenue (PTR)}}$$

The first and second terms (GFF and GFI) are combined to represent the foreign technology effect which is the impact derived from the consumption of imported final goods and intermediate goods produced by foreign firms, irrespective of where they are produced. Unlike Caliendo and Parro (2015), where imports are the sole focus, inward MP also exposes a country to foreign products. If foreign multinationals enter a country in large quantities, they bring in new final and intermediate goods, further enhancing welfare.

The third term (GR) reflects the direct gains from robots, which are negatively correlated with the cost deflator, Ω_ℓ^j. The fourth term (SEC) represents the I-O linkage effect, capturing the welfare impact arising from industry j's use of industry k's composite goods, specifically the welfare improvement due to a reduction in the price index (or cost) of these composite goods. The fifth term (GOF) is the firm outsourcing effect, capturing the benefits that country i derives from MP using its own technology and importing the resulting products back for domestic consumption.

The sixth term (MS) represents the local market size effect, which primarily reflects the welfare change due to an expansion in the home market size and the associated increase in consumption potential. The seventh term (INV) is the innovation effect, capturing welfare gains from a country's focus on innovation, particularly as more multinational firms expand their outward MP. Lastly, the final term (PR) is the gains from overseas profits and robots revenue which is a mixed part. Country benefits if they have larger overseas sales across countries and use more robots.

Intuitively, a reduction in domestic robot prices would decrease domestic production costs and directly improve welfare through gains from robots (GR) and robots revenue (PTR). Lower production costs confer a comparative advantage in production, which can simultaneously affect both inward and outward MP flows. On one hand, this productivity advantage attracts more foreign firms to produce domestically, leading to welfare gains from foreign technology effects (GFF and GFI). Additionally, as domestic production expands, market size increases, further enhancing welfare through the market size effect. On the other hand, the productivity and scale advantages enable domestic firms to invest in foreign production sites, i.e., outward MP, allowing them to profit from offshoring through the gains from offshoring (GOF), larger profits (PTR) and innovation effects (INV), as defined by (Arkolakis et al., 2018; Melitz, 2003).

4 Data and Calibration

This section introduces our calibration procedure. For the counterfactual analysis, we follow the approach of Artuc, Bastos and Rijkers (2023) by setting the change in robot prices, w_ℓ^R, as the exogenous shock. It is important to note that a change in robot rental rates, w_ℓ^R, has the same effect on the relative cost of robots to workers, φ_ℓ, as a change in the productivity parameter, ϕ^R. To solve the counterfactual resulting from the change in robot prices, three sets of variables need to be calibrated. First, we calibrate robot-related parameters: the automation frontier K^j, the robot-labor elasticity $1 + v$, the initial relative price of robots φ_ℓ, the initial cost deflator Ω_ℓ^j and the initial labor demanded for unit task Ξ_ℓ^j. Second, we calibrate the trilateral trade flows, $X_{i\ell n}^j$. Third, we set a group of exogenous basic parameters $\{\sigma^j, \theta^j, \rho, \alpha_\ell^j, \beta_\ell^j, \beta_\ell^{k,j}\}$.

4.1 Data

The bilateral industry level multinational production data come from OECD Analytical AMNE database, which breaks down bilateral output matrix by country, industry and country where the controlling entity is based.[6] We use this data to distinguish the industry-level output by country of origin. The bilateral industry level trade data come from OECD Inter-Country Input-Output tables (ICIO). Industrial Robots data come from International Federation of Robotics (IFR), which documents the stock of industrial robots by industry, country and year. The World Input Output Database (WIOD) is used to calibrate some key parameters of the model. Based on the availability of data, we focus on adjusted 22 industries of 40 economies and rest of the world (ROW).

[6] https://www.oecd.org/en/data/datasets/multinational-enterprises-and-global-value-chains.html

4.2 Calibration

Robot-related parameters: The model characterizes how robotization can reduce production costs when producers shift from labor to robots as the effective relative price of robots declines. The automation frontier K^j limits the feasibility of this shift, and the elasticity of substitution $1+v$ between robots and workers disciplines its pace. We borrow the calibration result of automation frontier K^j from Artuc, Bastos and Rijkers (2023). Based on the text matching algorithm, they constructed an occupation level measure of replaceability using data from IFR on robot applications and the US census of occupational classifications by comparing IFR application categories with the description of occupations. Then they merged the replaceability to 1980 IPUMS data using 1990 occupation classification and constructed the industry level job replaceability through dividing the sum product of replaceability and annual hours worked by total hours worked.

Furusawa, Kusaka and Sugita (2022) estimate the average elasticity of substitution between robots and low-skilled (high-skilled) workers is 1.9227 (1.0386). Artuc, Bastos and Rijkers (2023) set the elasticity as 10 in practice and they point out elasticity which is greater than 5 is preferred. We assume $v = 3$ which means the elasticity of substitution between labor and robots is $1 + v = 4$, which is close to the average of their results.

To calibrate the initial (productivity adjusted) relative price of robots φ_ℓ, we need first calibrate the share of the labor cost in the total cost of tasks $\frac{w_\ell^L L_\ell^j}{w_\ell^T T_\ell^j}$. We use GDP per capita from Penn World Table and worked hours from WIOD Socio-Economic Accounts to calibrate the annual labor wage and annual worked hours, respectively. We get each country's unit price of robots using their export and import data. From 2022, UN Comtrade documents the import (export) quantity and value of industrial robots (HS6 code 842870). Using each country's trade data of the industrial robots to the world in 2022, we calculate w_ℓ^R by weighted averaging export and import unit price[7]. We assume that robots can be rented for 5% of their price annually. Taking these numbers, from the cost share of labor shown by equation (21), we can calculate $\frac{\Xi_\ell^j}{\Omega_\ell^j} = \frac{w_\ell^L L_\ell^j}{w_\ell^T T_\ell^j} = \frac{\text{GDP per capita}}{\frac{\text{Robots}}{\text{Working hours}} \times w_\ell^R \times 0.05 + \text{GDP per capita}}$. And it is also a function of φ_ℓ and K^j:

$$\frac{\Xi_\ell^j}{\Omega_\ell^j} = \frac{1 - K^j + K^j \left(1 - \left[1 + (\varphi_\ell)^v\right]^{-1}\right)^{1+\frac{1}{v}}}{1 - K^j + K^j \left(1 - \left[1 + (\varphi_\ell)^v\right]^{-1}\right)^{\frac{1}{v}}} \tag{40}$$

Given K^j, we can solve for the initial relative price of robots φ_ℓ. Using the equation (19) and (20), we can compute the initial cost deflator Ω_ℓ^j and initial labor demanded in unit task

[7]The import and export quantities of robots in some countries are estimated by UN Comtrade, so there are non integers present.

Ξ_ℓ^j. Table 1 reports calibration results of robots related parameters. We can find that larger developed countries and most developing countries have higher initial level of robotization.

Trilateral Trade Flows: Trilateral trade flow plays a key role in our analysis and there are no macro level data. Following Wang (2021), we use the moment method to calibrate these flows. Recall the trade share equation:

$$X_{i\ell n}^j = \pi_{i\ell n}^j X_n = \frac{A_\ell^j (\xi_{i\ell n}^j)^{-\frac{\theta^j}{1-\rho}}}{(\Psi_{in}^j)^{\frac{1}{1-\rho}}} \frac{M_i^j D_i^j \Psi_{in}^j}{\sum_k M_k^j D_k^j \Psi_{kn}^j} X_n \tag{41}$$

where $\xi_{i\ell n}^j = \gamma_{i\ell}^j \tau_{\ell n}^j (w_\ell^{T,j})^{\beta_\ell^j} \prod_{k=1}^J (P_\ell^k)^{\beta_\ell^{k,j}}$. Define two moments estimating parameters for moment methods:

$$\begin{aligned} \tilde{D}_{i\ell}^j &= (M_i^j D_i^j)^{-\frac{1}{\theta^j}} \gamma_{i\ell}^j, \\ \tilde{\tau}_{\ell n}^j &= (A_\ell^j)^{-\frac{1-\rho}{\theta^j}} \tau_{\ell n}^j (w_\ell^{T,j})^{\beta_\ell^j} \prod_{k=1}^J (P_\ell^k)^{\beta_\ell^{k,j}} \end{aligned} \tag{42}$$

Hence given the exogenous parameters $\{\rho, \theta^j\}$, the model predicted trilateral trade flows can be expressed in terms of two moments estimating parameters $\tilde{\mathbf{D}} \equiv \{\tilde{D}_{i\ell}^j\}$ and $\tilde{\boldsymbol{\tau}} \equiv \{\tilde{\tau}_{\ell n}^j\}$:

$$X_{i\ell n}^j(\tilde{\mathbf{D}}, \tilde{\boldsymbol{\tau}}) = \frac{(\tilde{D}_{i\ell}^j)^{-\frac{\theta^j}{1-\rho}} (\tilde{\tau}_{\ell n}^j)^{-\frac{\theta^j}{1-\rho}} \left[\sum_{\ell=1}^N (\tilde{D}_{i\ell}^j)^{-\frac{\theta^j}{1-\rho}} (\tilde{\tau}_{\ell n}^j)^{-\frac{\theta^j}{1-\rho}}\right]^{-\rho}}{\sum_k \left[\sum_h (\tilde{D}_{kh}^j)^{-\frac{\theta^j}{1-\rho}} (\tilde{\tau}_{hn}^j)^{-\frac{\theta^j}{1-\rho}}\right]^{1-\rho}} \tag{43}$$

Using the real bilateral trade data $\tilde{X}_{\ell n}^{j,trade}$ and real bilateral MP data $\tilde{X}_{i\ell}^{j,mp}$ to solve for $\tilde{\mathbf{D}} \equiv \{\tilde{D}_{i\ell}^j\}$ and $\tilde{\boldsymbol{\tau}} \equiv \{\tilde{\tau}_{\ell n}^j\}$ by two sets of moments $(2 \times N^2 \times J)$:

$$\frac{\sum_i X_{i\ell n}^j(\tilde{\mathbf{T}}, \tilde{\boldsymbol{\tau}})}{X_n^j} = \frac{\tilde{X}_{\ell n}^{j,trade}}{X_n^j}, \quad \frac{\sum_n X_{i\ell n}^j(\tilde{\mathbf{T}}, \tilde{\boldsymbol{\tau}})}{\sum_{k,n} X_{k\ell n}^j(\tilde{\mathbf{T}}, \tilde{\boldsymbol{\tau}})} = \frac{\tilde{X}_{i\ell}^{j,mp}}{\sum_k \tilde{X}_{k\ell}^{j,mp}} \tag{44}$$

Finally, the trilateral trade flows can be recovered from equation (43). Figure 3 and 4 demonstrate the accuracy of the model calibrated trade and MP shares and value. The results show that the calibrated shares and log values of these variables align closely with the real data, exhibiting a strong positive correlation. This consistency confirms the feasibility of the MP and trade flow calibrations used in this study.

Exogenous basic parameters: The elasticity of substitution among goods σ^j come from Broda and Weinstein (2006). We set the MP productivity vector distribution parameter $\rho = 0.1$ from Wang (2021) and borrow the trade elasticity θ^j from Du and Wang (2022). From WIOD 2016 table, we directly calibrate the input-output relationship across sectors $\beta_\ell^{k,j}$ which is the input share of composite goods and the share of final consumption goods

α_ℓ^j. We also get the input share of composite tasks $\beta_\ell^j = 1 - \sum_{k=1}^J \beta_\ell^{k,j}$ which is set as the value-added share in WIOD table. Table 2 reports selected exogenous industry level parameters and the automation frontier K^j.

5 Counterfactual Analysis

We begin by simulating Scenario I, in which the robot price in each country decreases by 10%, representing an increase in robotization. This scenario is used to illuminate the effects of global robotization on countries' welfare, openness, and multinational production (MP) networks. Next, we simulate Scenario II, where only a specific group of developed countries with higher initial levels of robotization benefit from robotization. We define this scenario as asymmetric robotization to reflect the real-world context, where there is an asymmetric development in the usage and technology of robots between Northern and Southern countries. Finally, we examine the critical role of MP in amplifying the welfare effects of robotization by simulating Scenario III, in which the world also experiences higher and lower MP costs.

5.1 Scenario I: Global Robotization

In this subsection, we simulate a scenario where each countries' robot unit price w_ℓ^R decreased by 10% with other exogenous shocks unchanged. During all counterfactuals we set 18 tradable sectors with the utility, construction, education and service sectors non-tradable. After simulation, we discuss the change of welfare, openness and MP network.

5.1.1 Welfare and Openness

Table 3 presents the changes in welfare (real income), real wage and employment following a 10% global reduction in robot prices. First, the increased intensity of robot use, driven by falling prices, has led to a decline in labor employment across all countries, with an average drop of 0.846%. This displacement effect makes most countries suffer in real wages decreasing. Countries with initially high levels of robotization, such as Germany, Japan, and the United States, experience employment reductions of 2.761-3.892%, with employment proxied by the number of workers required per unit of task. Despite this, we observe that real wages in those countries continue to rise. By incorporating the multinational production part, our model decomposes wages into production wages and marketing wages (see equation (27)). Production wages, derived from goods production, are directly suppressed by robotization due to labor substitution. However, robotization also boosts productivity and output, potentially increasing the demand for labor and raising returns to workers. As a result, the net effect on production wages remains theoretically ambiguous. In contrast, marketing wages are generated by the entry of multinational firms, which necessitates the hiring of workers for marketing activities (an expression of entry costs). Higher levels of robotization enhance a country's competitiveness in attracting inward MP, thereby indirectly boosting marketing wages. The net effect of these two components determines the change in real wages. Figure 5 illustrates the changes in these two types of wages globally. Our findings indicate that all countries experience an increase in output, leading to an increase in production wages in some countries, particularly those with higher initial levels of robotization. Additionally, marketing wages show a more substantial increase. Thus, our model captures an additional mechanism (inward MP) through which robotization can increase labor wages, even as robots displace workers in production.

Second, global robotization has heterogeneous welfare effects across countries and even makes world develop unequally. The world average increase in welfare and real wage are 0.543% and 0.305%, respectively. We find developing countries are much better off. The average increase in welfare and real wage of developing countries are 1.738% and 1.001% which are 7 times those of developed countries, 0.254% and 0.136%. Difference in welfare also exists across regions (see Table 5). Asia experiences the greatest welfare gains from global robotization, with an increase of 2.360%, approximately 1.5 times the gains observed in the Americas (1.569%), while Europe (-0.001%) and the rest of the world (-0.513%) even suffer negative welfare effects. These results suggest that global robotization has promoted growth in Asia and other developing countries, but has had slightly adverse effects on European countries.

Third, a closer examination reveals a clear polarization in welfare outcomes: countries with higher initial level of robotization experience substantial welfare gains, while smaller, less automated European countries face welfare declines. Japan (5.188%), Italy (4.307%), and the United States (3.861%) are the top beneficiaries of a 10% reduction in global robot prices. These large economies, equipped with advanced manufacturing capabilities and robust automation infrastructure, are well positioned to leverage robot cost reductions to deepen engagement in global production chains, resulting in significant welfare improvements.Emerging economies with a solid robotization foundation also capture benefit, as evidenced by the welfare gains in Indonesia (3.066%), China (2.914%), and India (2.610%). In contrast, several small European countries experience welfare declines, including Ireland (1.480%), Malta (1.013%), and Estonia (0.510%). This wide range of welfare outcomes among advanced economies suggests that highly robotized countries, such as Japan, Italy, and the United States, stand to benefit the most, while others may face challenges. This divergence could increase inequality within the developed world.

Next, from equation (39), we can decompose the welfare changes for selected countries (most are highly robotized countries), as shown in Table 4, with the full results for all countries presented in Table A.3. Notably, we do not report GOF (gains from offshoring), as this value is zero for all countries, indicating that domestic robotization does not impact imports from affiliates of domestic MNEs. For these selected countries, robotization reduces the cost deflator, Ω_ℓ^j, which represents the relative cost of performing a unit task with and without robots, thereby directly increasing welfare for each country through GR (gains from robots) effects. Furthermore, robotization endows countries with comparative productivity advantages, which attract inward MP. This impact is captured by GFF (gains from foreign finals) and GFI (gains from foreign intermediates) and also contributes to the expansion of domestic production, reflected in MS (gains from market size). We observe that countries, particularly developed countries such as Japan, Italy, and the United States, benefit significantly from the expansion of domestic production, possibly due to reshoring. However, the effects of inward MP are negative for these highly robotized countries, as they tend to rely more on domestic production and less on foreign firms and offshoring. Instead, most developing countries gains from GFF and GFI because of more inward MP. Finally, INV (gains from innovation) and PTR (gains from overseas profits), which primarily captures welfare effects from outward MP, is positive for highly robotized countries but negative for others. This suggests that robotization strengthens the ability of MNEs in more robotized countries to invest abroad by leveraging productivity and scale advantages. However, this shift allows these countries to quickly dominate MP flows, thereby crowding out the outward MP of other countries and diminishing their potential for innovation and overseas profit gains and thus total welfare. In summary, robotization influences welfare not only through direct domestic cost-saving effects but also indirectly by reshaping multinational production patterns.

To more intuitively examine the sources of welfare changes, we now turn to the effects of robotization on openness. As shown in Table 5, robotization increases global exports by 0.223% but decreases outward MP by 0.236%. Additionally, domestic production rises even further, suggesting the presence of reshoring activities. Figure 6 illustrates the changes in trade and MP values for each country. Robotization enhances the openness of countries with a comparative advantage in its use. Japan exhibits the largest change in trade, primarily due to its high initial level of robotization and significant role in the global division of labor. We find that developing countries, such as India, Indonesia, China, and Mexico, become more open as they experience larger changes in both trade and MP. This aligns with the welfare effects, where developing countries realize greater gains. In contrast, only developed countries with high initial robotization levels such as Japan, Korea, the United States, and Germany become more open. Other developed countries tend to reduce their outward MP and exports, leading to increased reshoring. These findings suggest that robotization has shifted global production power toward a select group of developed countries with advanced technology, enabling them to realize greater outward MP. However, this does not imply that developing countries are disadvantaged. On the contrary, robotization provides them with a cost advantage in production, resulting in larger inflows of foreign multinationals and further economic benefits.

5.1.2 Multinational Production Network

In this part, we discuss the changes in the global MP and trade network under Scenario I. Figures 7 and 8 illustrate the baseline and counterfactual MP and trade networks, respectively. The arrows represent MP (or trade) outflows, with darker colors indicating larger flow volumes. Each node represents a country, and the size of the node reflects the magnitude of MP (or trade) in which the country is engaged. First, the United States remains central, maintaining strong ties with major economies such as China, the United Kingdom, Japan, and France. In the counterfactual scenario, the connections between key economic players (e.g., USA-CHN, USA-DEU) become more pronounced, suggesting that robotization strengthens existing trade and production relationships among core economies. Second, following a 10% reduction in robot prices, the global MP network becomes more balanced. China and Germany take on more prominent roles within their respective regions. Specifically, China's outward MP into other Asian countries increases by 3.91%, closely aligning with the 3.5% increase in domestic production. A similar pattern is observed in Germany, leading to a more integrated European production network. Third, we observe both increased centrality and stronger connections among developed countries. The United States, Germany, and other developed Europe economies become even more central and tightly interconnected in the counterfactual scenario. This implies that as robot prices decline, these countries may internalize more production within their own networks, potentially reducing their reliance on global outsourcing and reshoring more production activities.

To examine the reshoring trend, we analyze the regional bilateral MP and trade changes reported in Table 5. First, panel (a) reveals strong reshoring activities in Europe and other developed countries, as evidenced by a decrease in outward MP alongside an increase in domestic production. Similarly, the Americas exhibit a reshoring trend, with the growth rate of domestic production outpacing that of outward MP. Next, panel (b) indicates that intraregional trade connections are strengthening overall. While ROW experiences a slight decline in intraregional trade, other regions show growth, signaling a shift toward a regional trade focus. Additionally, although Europes trade links with the Americas and within Europe have strengthened, its weakening trade connection with Asia is evident in a 2.608% decline in European exports to Asia. As a result, the world's trade networks have not become more compact. Finally, bilateral MP flows reveal a more pronounced pattern of reshoring. As shown in Panel (c), the growth rate of intraregional MP in the Americas closely matches the growth rate of outward MP to other regions, whereas Europe shows an increase in intraregional MP alongside a decrease in outward MP to other regions. Thus, we conclude that robotization leads to significant reshoring and the expansion of domestic markets for European and developed countries.

Next, Figure 9 visualizes the impact of robotization on reshoring at the country level. Panel (a) highlights the relationship between domestic production and outward MP, which aligns with the reshoring intensity measure discussed in Section 2. According to our definition of reshoring, a country experiences reshoring activities if the change in domestic production exceeds the change in outward MP. Note that as discussed in Section 2, our measure here even underestimates the number of reshoring activities. We observe that 20 countries experience reshoring, driven by reduced domestic production costs resulting from robotization. Most developed countries, like Italy, France, and South Korea, have rehsoring activities. Contrary to common perceptions, developing countries are also reshoring production due to technological advancements, increasingly leveraging local production capabilities. Among these, India and Indonesia exhibit the highest and second highest reshoring intensity, respectively, indicating the largest disparity between domestic production growth and outward MP growth. However, in these countries, both domestic and outward production are increasing, albeit at different rates. In contrast, some countries show a notable decline in outward production alongside an increase in domestic production. This pattern is particularly evident in European countries such as the UK, Sweden, Portugal, and Denmark. This finding is consistent with the findings in Panel (c) of Table 5. Hence, reshoring resulting from robotization can happen in both developed and developing countries but is more evident in European and developed countries.

5.2 Scenario II: Asymmetric Robotization

From Section 2 and results above, we find that robotization in European and other developed countries may increase their reshoring activities, potentially exerting negative effects on other countries. To explore this further, we simulate an asymmetric robotization scenario in which only selected developed countries experience a reduction in robot unit prices, ranging from 10% to 50%. These selected countries include Germany, Japan, the United States, Italy, South Korea, Spain, France, and the UK, all of which possess both higher levels of development and initial robotization. We expect that these countries would experience significant welfare gains from asymmetric robotization, albeit at the expense of welfare losses in other countries, potentially leading to a more polarized global development. This may occur for two reasons: (i) the selected countries could export and invest more of their expanded output internationally, crowding out the openness of other economies; and (ii) they could also engage in reshoring, which would reduce the demand for foreign goods and production, negatively affecting other countries' welfare.

Figure 10 illustrates the trends in welfare changes across different countries under various scenarios of robot price reductions (10% to 50%) in the selected developed countries. First, we observe sharp welfare declines, particularly in developed economies like Australia, Finland, and Switzerland, which experience significant welfare losses. These countries may be adversely impacted by increased global competition, as the selected group of developed countries with cheaper labor begin to automate at lower costs and thus dominate world production. Figure 11 and 12 confirms that the welfare losses for these countries, as well as for most others, are primarily driven by sharp declines in export and outward MP.

In conclusion, asymmetric robotization in the selected developed countries benefits these countries while harming others, as they reap the rewards of robotization at the expense of reduced welfare in less developed economies.

5.3 Scenario III: The role of MP

Multinational production (MP) is a crucial channel through which robotization impacts wages, real GDP, and welfare. Countries can leverage outward MP to export their productivity advantages, while inward MP can help mitigate the negative effects of labor substitution on wages. To explore how MP moderates the impact of robot price reductions on both individual and country welfare, we conduct counterfactual simulations under two scenarios. In the first scenario, we assess the effects of a 10% global reduction in robot prices combined with a 10% increase in MP costs (robotization with high MP costs) to determine whether higher MP costs suppress the welfare gains from robotization. In the second scenario, we consider a 10% global reduction in robot prices combined with a 10% decrease in MP costs (robotization with low MP costs) to determine whether lower MP costs improve the welfare gains from robotization. By comparing the original simulation with these two scenarios, we gain deeper insight into the critical role of MP in shaping the welfare effects of robotization.

Figure 13 reports our simulation results. The Robotization scenario (black line) consistently leads to positive welfare and real wage changes for most countries. However, in the robotization with high MP cost scenario, we observe sharp declines in welfare and real wages across many countries. Higher MP costs limit countries' participation in global production chains, preventing them from fully leveraging their comparative advantages. Developing countries like China, India, and Brazil experience relatively small declines in the high MP cost scenario and even see improvements under the robotization with high MP Cost scenario. These economies may be better positioned to take advantage of robotization due to their stable position in multinational production networks. In some developed economies, such as Germany, Switzerland, and the UK, the welfare change of robotization are even reversed. This underscores that rising MP costs can diminish the gains from robotization, highlighting the importance of MP networks in realizing robotizations full potential.

Conversely, we observe greater welfare gains when MP costs are low. Countries with lower MP costs can better capture the benefits of robotization, as they can more easily attract inward MP and invest in outward MP. This effect is particularly evident in smaller or less robotized countries, such as Malta, Norway, and Ireland, where welfare and wage outcomes improve significantly. These findings suggest that economies integrated into MP networks benefit more from robotization when MP costs remain low. Moreover, lower MP costs enable all countries to gain from robotization, potentially reducing the polarized development seen with sole robotization. Thus, maintaining low MP costs is essential for maximizing the comparative advantages of robotization. Without this support, the benefits of automation may be unevenly distributed, potentially worsening inequalities between economies that can effectively engage in MP and those that cannot.

These findings underline the significance of the MP channel in determining how robotization affects global welfare and wage levels. The MP channel amplifies the positive effects of robotization, especially when MP costs are low. This suggests that robotization alone is insufficient to drive sustained and equitable growth in welfare and wages if MP costs rise. The MP channel, which involves cross-border production, is a crucial determinant of how well economies can leverage robotization for growth.

6 Conclusion

This paper demonstrates that global robotization has heterogeneous country welfare and reshapes trade and multinational production (MP) patterns, while asymmetric robotization can negatively affect some countries due to increased competition in MP and reshoring activities. We utilize robot data from the International Federation of Robotics (IFR) and MP data from the OECD Analytical AMNE database to construct the key variables used in our analysis of stylized facts. Our findings show that robotization, which confers countries with a comparative productivity advantage, is positively correlated with both inward and outward MP. Additionally, we explore the phenomenon of reshoring, which in this study is defined as the scenario where the growth rate of domestic production surpasses that of outward MP. The data indicates that countries with higher levels of robotization, predominantly European and other developed countries, tend to exhibit more pronounced reshoring activities.

Building on these facts, we develop a multi-country, multi-sector general equilibrium model that incorporates both trade and multinational production (MP). By integrating a task-based model that depicts labor and robot substitution, we quantify the effects of robotization, defined as the reduction in production costs when increased robot usage is driven by declining robot prices. We then conduct three counterfactual analysis. In Scenario I, we assume a uniform 10% decrease in robot prices across all countries, representing an increase in global robotization. In Scenario II, termed asymmetric robotization, we simulate a scenario where only a specific group of developed countries with higher initial levels of robotization benefit from robot price reductions. Finally, in Scenario III, we assess the critical role of MP in amplifying the welfare effects of robotization by simulating a scenario in which the world faces higher and lower MP costs.

Our findings reveal several key insights. First, global robotization enhances global welfare and promotes greater openness by expanding trade but not MP due to competition and reshoring activities. The welfare effects are particularly pronounced in Asia and developing countries. However, the simulation results highlight a polarized development pattern due to robotization, where highly robotized countries (with higher initial level of robotization) experience substantial welfare gains, while smaller, less robotized European countries face welfare declines. Through a decomposition of welfare effects, we observe that robotization affects welfare not only through direct cost-saving measures but also by influencing multinational production patterns. While most countries gain from inward MP, only highly robotized countries benefit primarily from outward MP. Second, global robotization creates a more balanced MP network, leading to more integrated regional production and trade networks. We also observe reshoring activities in both developing and developed countries, although they are more prominent in the latter. Third, asymmetric robotization in selected developed countries improves global welfare but at the expense of other countries due to intense competition and increased production reshoring back to developed countries. Finally, we show that with lower MP cost, the benefits of robotization can be evenly distributed, potentially improving inequalities between economies. This highlights the importance of the MP channel to amplify the welfare effects of robotization and robotization alone is insufficient to sustain equitable welfare growth without MP channel.

7 Tables and Figures

Table 1: Robots Related Parameters (Selected)

Country	w_ℓ^R	φ_ℓ	Ω_ℓ^j	Ξ_ℓ^j	Country	w_ℓ^R	φ_ℓ	Ω_ℓ^j	Ξ_ℓ^j
Germany	23134	1.594	0.969	0.889	Austria	24681	4.315	0.998	0.993
South Korea	24127	1.657	0.972	0.898	Netherlands	22448	4.319	0.998	0.993
Japan	25605	1.732	0.975	0.909	Portugal	29468	4.360	0.998	0.993
US	15957	1.902	0.981	0.928	Romania	28774	4.403	0.998	0.993
Italy	24194	1.934	0.982	0.931	Australia	25505	4.667	0.999	0.994
Spain	28802	2.315	0.989	0.957	Canada	17652	4.947	0.999	0.995
India	13921	2.321	0.989	0.957	Denmark	26041	5.076	0.999	0.996
Brazil	46437	2.333	0.989	0.958	Finland	22079	5.330	0.999	0.996
China	5754	2.345	0.989	0.959	Slovenia	24803	5.391	0.999	0.996
France	27574	2.383	0.990	0.960	ROW	24732	5.637	0.999	0.997
Indonesia	26924	2.469	0.991	0.964	Bulgaria	29148	7.192	1.000	0.998
Mexico	24732	2.702	0.993	0.972	Switzerland	10145	7.632	1.000	0.999
Czechia	26853	2.894	0.994	0.977	Greece	24732	9.421	1.000	0.999
Turkey	25207	2.944	0.994	0.978	Norway	28554	9.742	1.000	0.999
Poland	24732	3.205	0.996	0.983	Ireland	25463	10.333	1.000	0.999
Hungary	26442	3.387	0.996	0.985	Croatia	29761	10.713	1.000	1.000
UK	25450	3.388	0.996	0.985	Estonia	23680	13.982	1.000	1.000
Slovakia	25573	3.910	0.998	0.990	Lithuania	29913	14.032	1.000	1.000
Belgium	26178	3.957	0.998	0.991	Latvia	24732	17.597	1.000	1.000
Sweden	24646	4.069	0.998	0.992	Malta	24732	18.356	1.000	1.000
Russia	24732	4.178	0.998	0.992					

Note: w_ℓ^R is unit price of robots which is calculated in 2022 trade data from UN Comtrade. φ_ℓ is the productivity adjusted relative cost of robots to workers. Ω_ℓ^j is the initial cost deflator which is defined as the relative cost of producing one unit of task with and without robots. Ξ_ℓ^j is the number of workers demanded to produce a unit of task. All industry level variables here are averaged across industries.

Table 2: Industry Level Parameters

Industry	Name	K^j	σ^j	θ^j
1	Agriculture	0.288	3.7	4.5
2	Mining	0.338	3.91	6.03
3	Food Product	0.495	3.32	2.52
4	Textiles	0.659	3.8	2.95
5	Wood	0.509	4.1	4.78
6	Paper	0.327	2.8	4.5
7	Petroleum	0.324	7	7.3
8	Chemical	0.429	2.5	7.9
9	Rubber	0.605	3.2	4.54
10	Mineral Products	0.522	2.6	2.76
11	Basic Metal	0.557	4.2	6.5
12	Metal Product	0.587	2.6	5.49
13	Electronics	0.404	2.7	2.97
14	Electrical	0.438	2.9	4.74
15	Machinery	0.403	3.1	3.01
16	Motor vehicles	0.507	3.23	4.5
17	Other vehicles	0.381	4.45	4.1
18	Other Manufacturing	0.438	2.32	1.42
19	Utility	0.363	4	7.21
20	Construction	0.308	4	4.5
21	Education	0.475	4	4.5
22	Service	0.241	4	4.5

Table 3: Welfare, Wages and Employment Changes % : Scenario I

Country	Welfare	Wage	Employment	Country	Welfare	Wage	Employment
AUS	-0.292	-0.238	-0.219	IRL	-1.480	-0.507	-0.025
AUT	-0.226	-0.145	-0.287	ITA	4.307	2.653	-2.798
BEL	-0.418	-0.192	-0.386	JPN	5.188	3.213	-3.340
BGR	-0.483	-0.443	-0.061	KOR	1.802	0.837	-3.323
BRA	2.191	1.262	-1.673	LTU	-0.513	-0.415	-0.008
CAN	-0.371	-0.177	-0.194	LVA	-0.652	-0.474	-0.004
CHE	-0.004	0.050	-0.049	MEX	0.597	0.228	-1.056
CHN	2.914	1.865	-1.654	MLT	-1.013	-0.457	-0.004
CZE	-0.649	-0.576	-0.900	NLD	-0.762	-0.272	-0.305
DEU	3.315	1.824	-3.892	NOR	-0.762	-0.457	-0.026
DNK	-0.397	-0.235	-0.184	POL	0.536	0.292	-0.695
ESP	1.936	1.107	-1.735	PRT	-0.112	-0.109	-0.282
EST	-0.510	-0.385	-0.009	ROU	-0.189	-0.152	-0.280
FIN	-0.610	-0.432	-0.150	ROW	-0.513	-0.448	-0.119
FRA	2.016	1.180	-1.603	RUS	-0.187	-0.208	-0.310
GBR	-0.015	0.039	-0.611	SVK	-1.129	-0.812	-0.392
GRC	-0.507	-0.380	-0.028	SVN	-0.330	-0.279	-0.142
HRV	-0.286	-0.223	-0.018	SWE	-0.151	-0.143	-0.340
HUN	-0.740	-0.453	-0.605	TUR	1.234	0.691	-0.884
IDN	3.066	2.001	-1.623	USA	3.861	2.287	-2.761
IND	2.610	1.572	-1.729				
World	0.543	0.305	-0.846				
Developing	1.738	1.001	-1.508				
Developed	0.254	0.136	-0.686				

Note: Scenario I simulates a 10% of robots price globally. Welfare refers to real income change $\hat{W}_n = \prod_j \left(\frac{\hat{Y}_n}{\hat{P}_n^j}\right)^{\alpha_n^j}$. Wage change refers to real wage change $\prod_j \left(\frac{\hat{w}_n^L}{\hat{P}_n^j}\right)^{\alpha_n^j}$. Employment change is average changed number of workers demanded for a unit of task $\hat{\Xi}_\ell^j$.

Table 4: Welfare and Decomposition % of Selected Countries: Scenario I

Country	Welfare	GFF	GFI	GR	SEC	MS	INV	PTR
Japan	5.188	-0.124	-0.305	0.639	0.457	0.879	1.667	1.975
Italy	4.307	-0.067	-0.165	0.540	0.023	0.982	1.340	1.654
USA	3.861	-0.063	-0.136	0.483	0.039	0.794	1.170	1.574
Germany	3.315	-0.149	-0.254	0.843	-0.029	0.563	0.849	1.492
Indonesia	3.066	0.080	-0.028	0.327	0.519	0.561	0.542	1.065
China	2.914	-0.028	-0.150	0.348	0.457	0.533	0.705	1.049
India	2.610	0.015	-0.018	0.355	0.064	0.573	0.582	1.038
Brazil	2.191	0.040	0.015	0.325	0.038	0.462	0.381	0.929
France	2.016	0.041	0.033	0.284	0.028	0.457	0.336	0.837
Spain	1.936	0.041	0.031	0.321	0.054	0.422	0.238	0.830
South Korea	1.802	-0.056	-0.105	0.714	0.144	0.041	0.099	0.965
Mexico	0.597	0.075	0.097	0.206	-0.006	0.085	-0.229	0.369
UK	-0.015	0.238	0.271	0.102	0.002	0.124	-0.698	-0.054
Russia	-0.187	0.086	0.123	0.055	-0.125	0.063	-0.410	0.021
Australia	-0.292	0.078	0.134	0.037	0.000	-0.051	-0.437	-0.054
Canada	-0.371	0.238	0.503	0.033	0.015	-0.037	-0.929	-0.194

Note: Scenario I simulates a 10% of robots price globally. Welfare refers to real wage change $\hat{W}_n = \prod_j \left(\frac{\hat{Y}_n}{\hat{P}_n^j}\right)^{\alpha_n^j}$. GFF is gains from foreign finals. GFI is gains from foreign intermediates. GR is gains from robots. SEC is sectoral IO linkages. MS is market size effects. INV is gains from innovation. PTR is gains from overseas profit and robots revenue.

Table 5: Overall and Regional Openness Change %: Scenario I

Panel (a): Overall openness change				
	Export	Outward MP	Domestic	Welfare
World	0.223	-0.236	0.992	0.543
Developing	2.075	1.505	2.322	1.738
Developed	-0.226	-0.658	0.670	0.254
Americas	2.013	1.766	2.141	1.569
Asia	2.545	3.070	2.909	2.360
Europe	-0.453	-1.222	0.427	-0.001
ROW	-3.613	-2.776	-0.635	-0.513
Panel(b): Regional bilateral trade change (from rows to columns)				
	Americas	Asia	Europe	ROW
Americas	4.126	1.108	4.662	3.741
Asia	5.356	3.304	4.563	3.027
Europe	1.146	-2.608	2.409	0.570
ROW	-5.001	-4.849	-0.642	-0.210
Panel (c): Regional bilateral MP change (from rows to columns)				
	Americas	Asia	Europe	ROW
Americas	4.286	2.750	5.615	2.399
Asia	7.578	3.498	6.322	3.561
Europe	-0.432	-1.725	1.994	-1.735
ROW	0.721	-7.903	0.041	-0.635

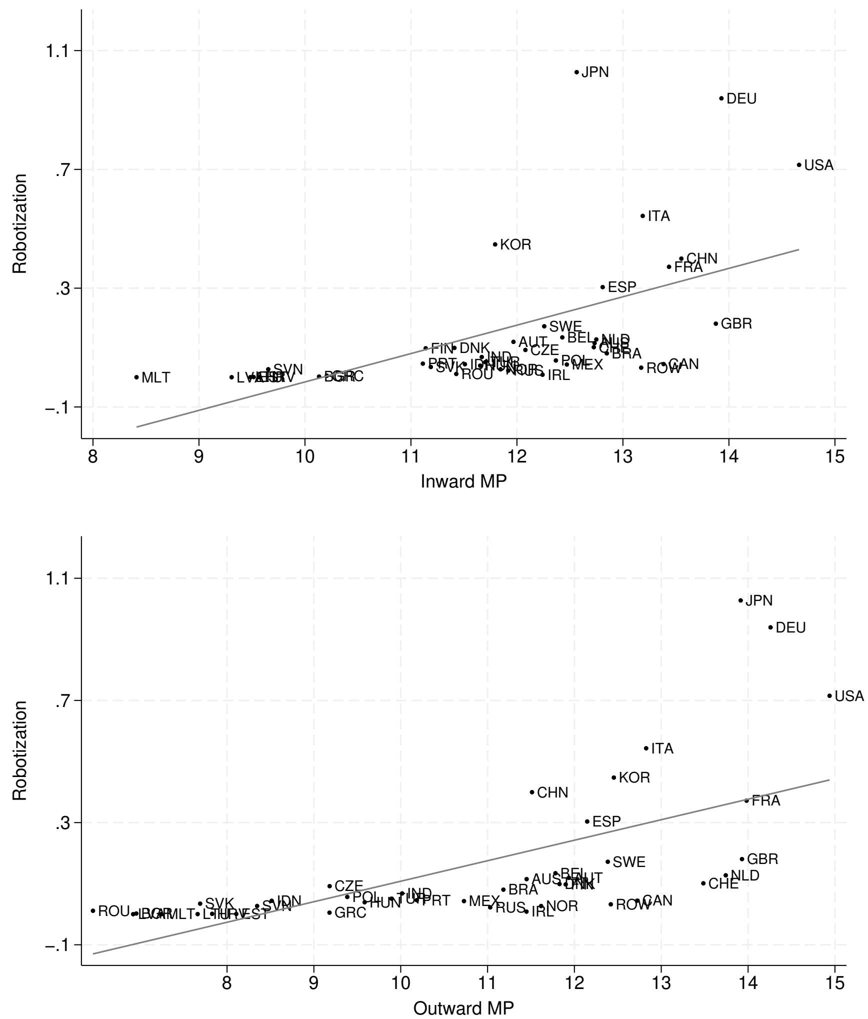
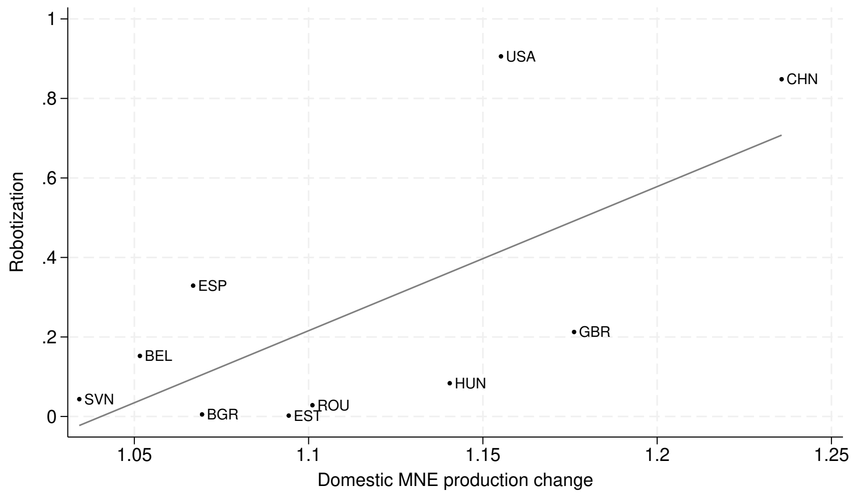
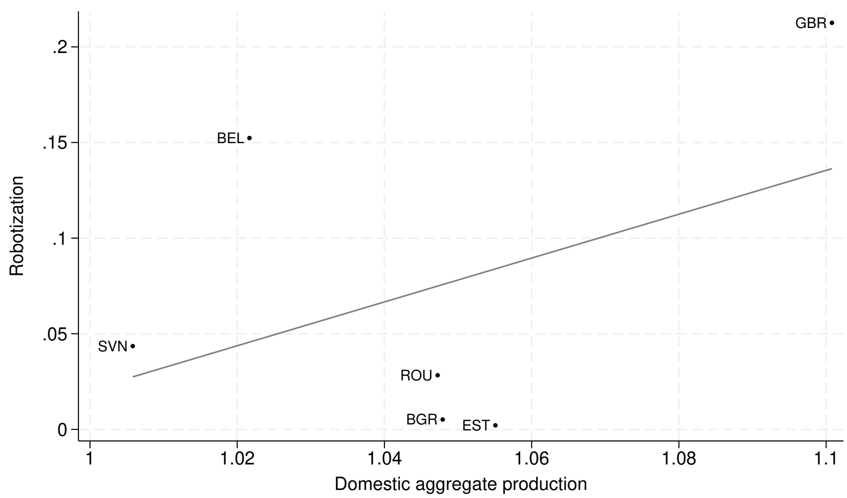


Figure 1: Robotization and Country Level MP flows

Note: Country data are averaged across year and industry. The y axis is the $log(1 + robots/hours)$. The x axis of the above subfigure is log of inward MP flow (million dollar). The x axis of the below subfigure is log of outward MP flow (million dollar).



(a) Reshoring identified using domestic MNEs production



(b) Reshoring identified using domestic aggregate production

Figure 2: Robotization and Reshoring in 2014

Note: Domestic aggregate production is the sum of production of domestically-owned firms and domestic MNEs (who have affiliates outside the country). Changes are computed as the ratio of production value in current year to previous year. Countries in the figure are those with $RS_t > 0$. The y axis is the $log(1 + robots/hours)$.

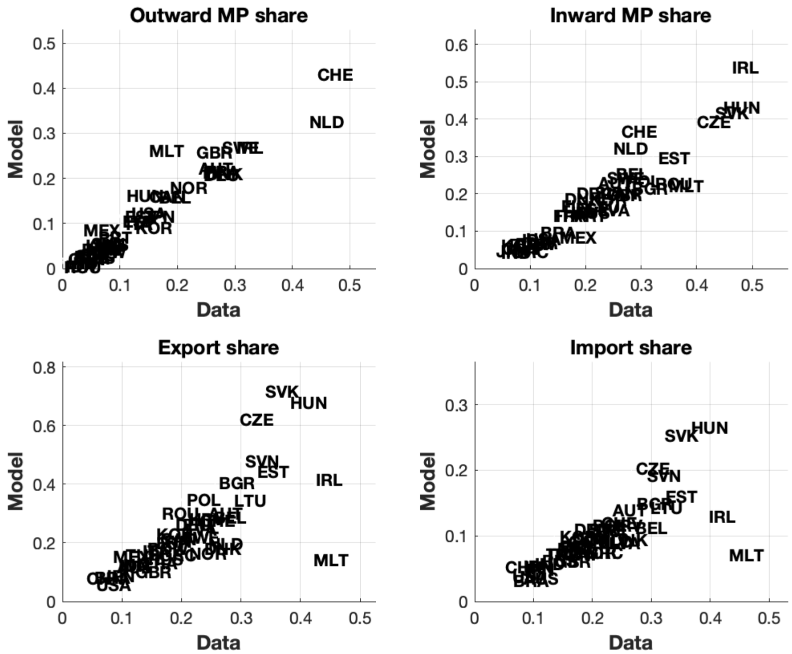


Figure 3: Moments Result (Shares)

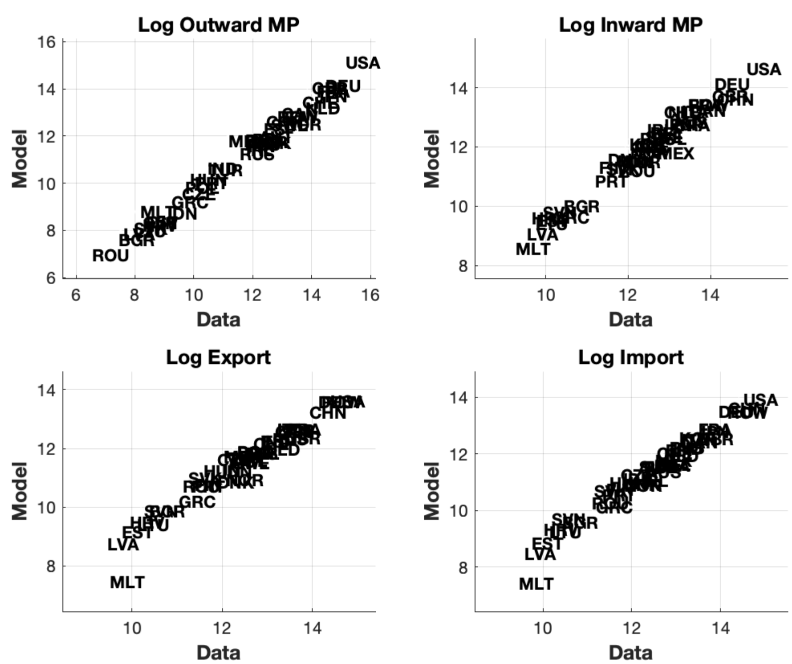


Figure 4: Moments Result (Values)

Note: Figures report model predicted MP and trade compared with data.

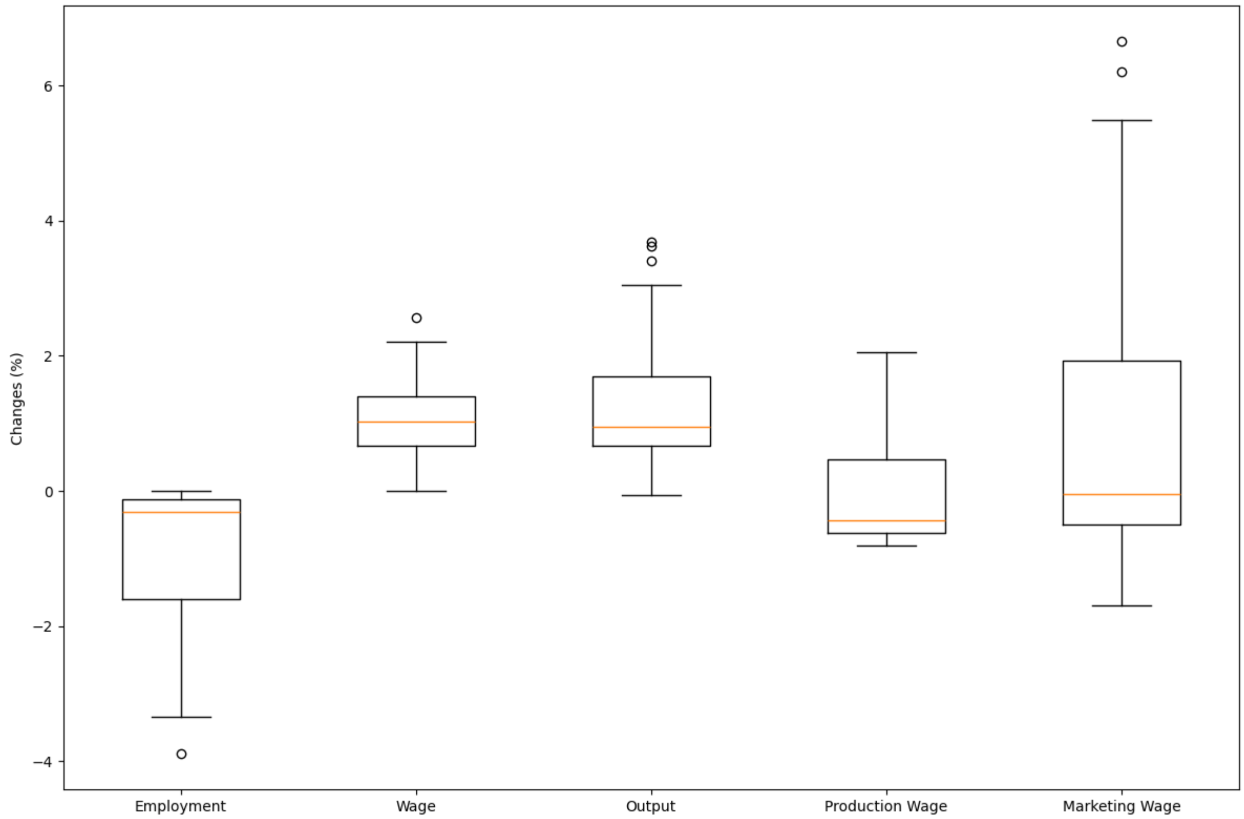
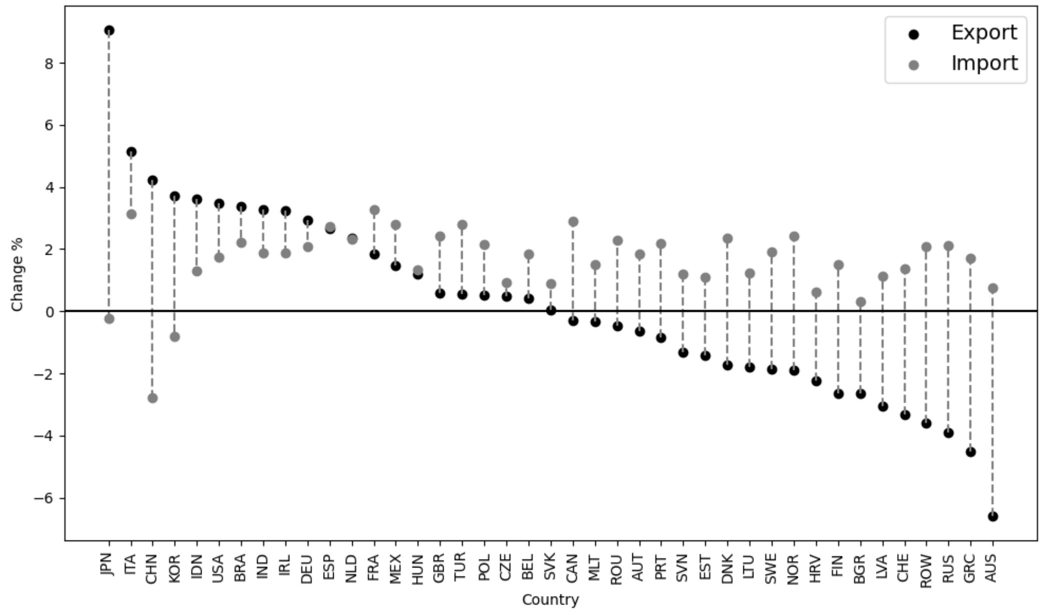
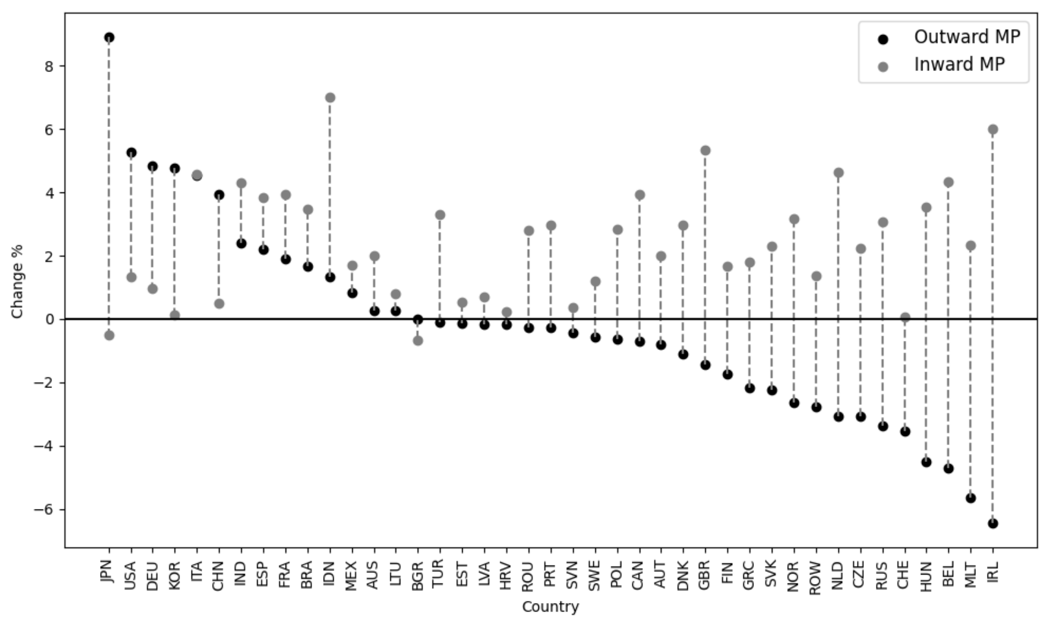


Figure 5: Decomposition of Nominal Wages

Note: The figure presents changes in employment, nominal output, and real wages, along with a decomposition of real wage changes for all countries. It is important to note that the real wage change does not equal the sum of production and marketing wage changes; rather, it reflects a weighted average of these two components.

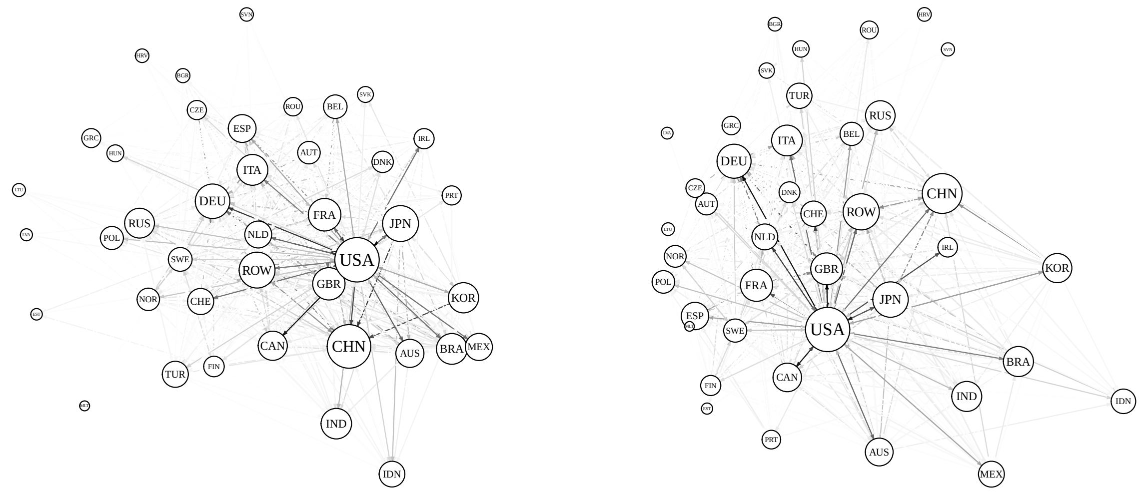


(a) Trade



(b) MP

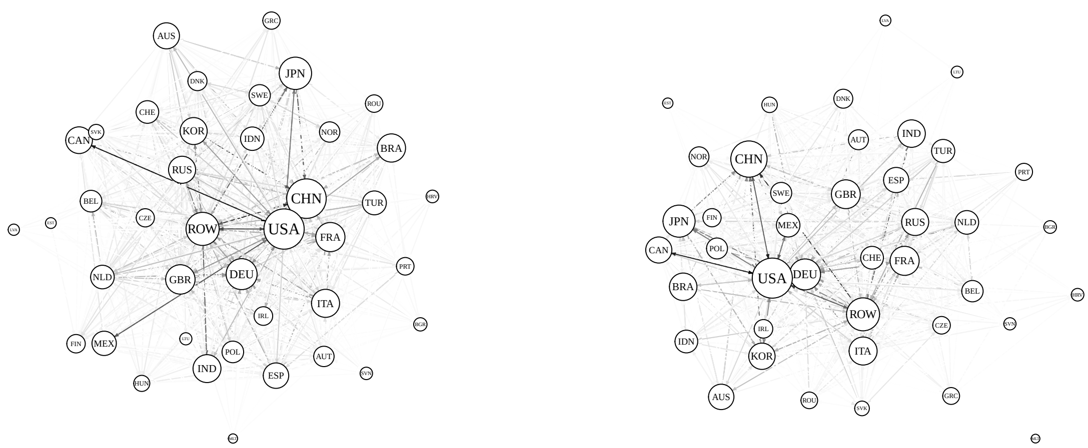
Figure 6: Trade and MP Changes % : Scenario I



(a) Baseline

(b) Counterfactual

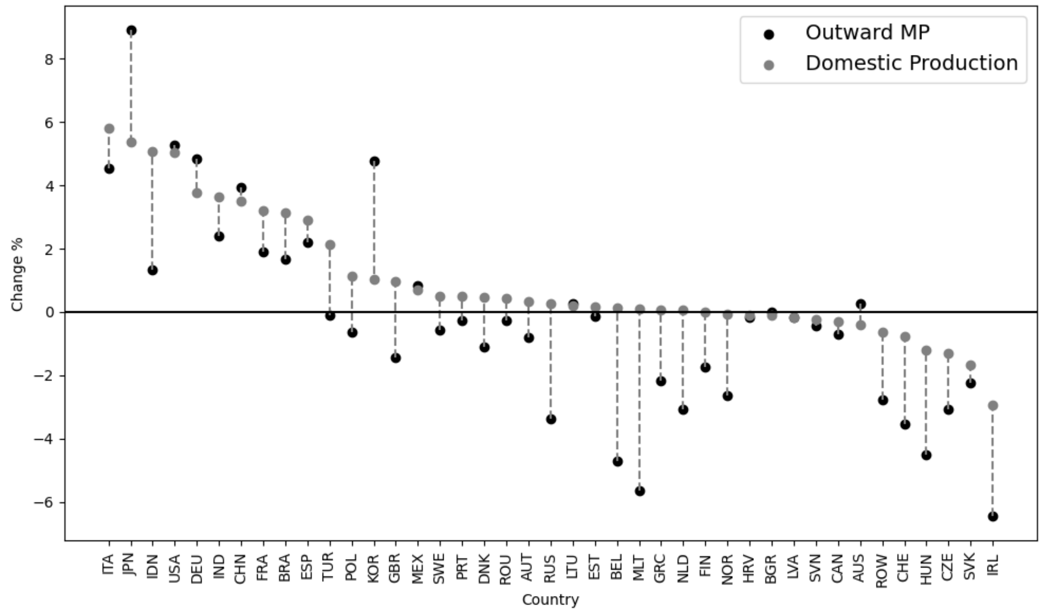
Figure 7: Multinational Production Network Changes % : Scenario I



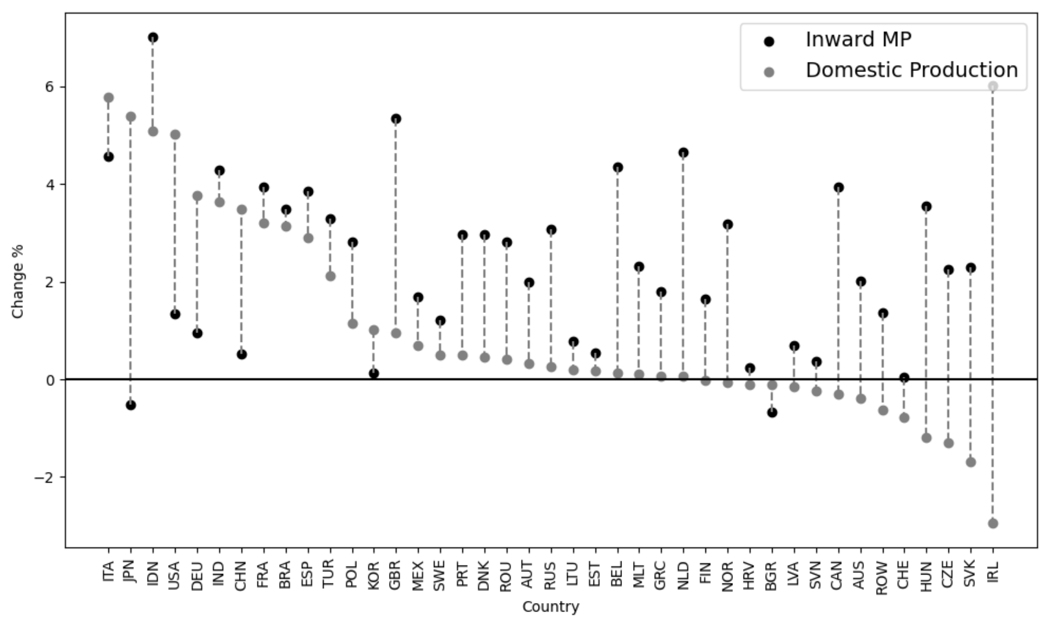
(a) Baseline

(b) Counterfactual

Figure 8: Trade Network Changes % : Scenario I



(a) Domestic VS Outward



(b) Domestic VS Inward

Figure 9: Domestic Production and MP Changes % : Scenario I

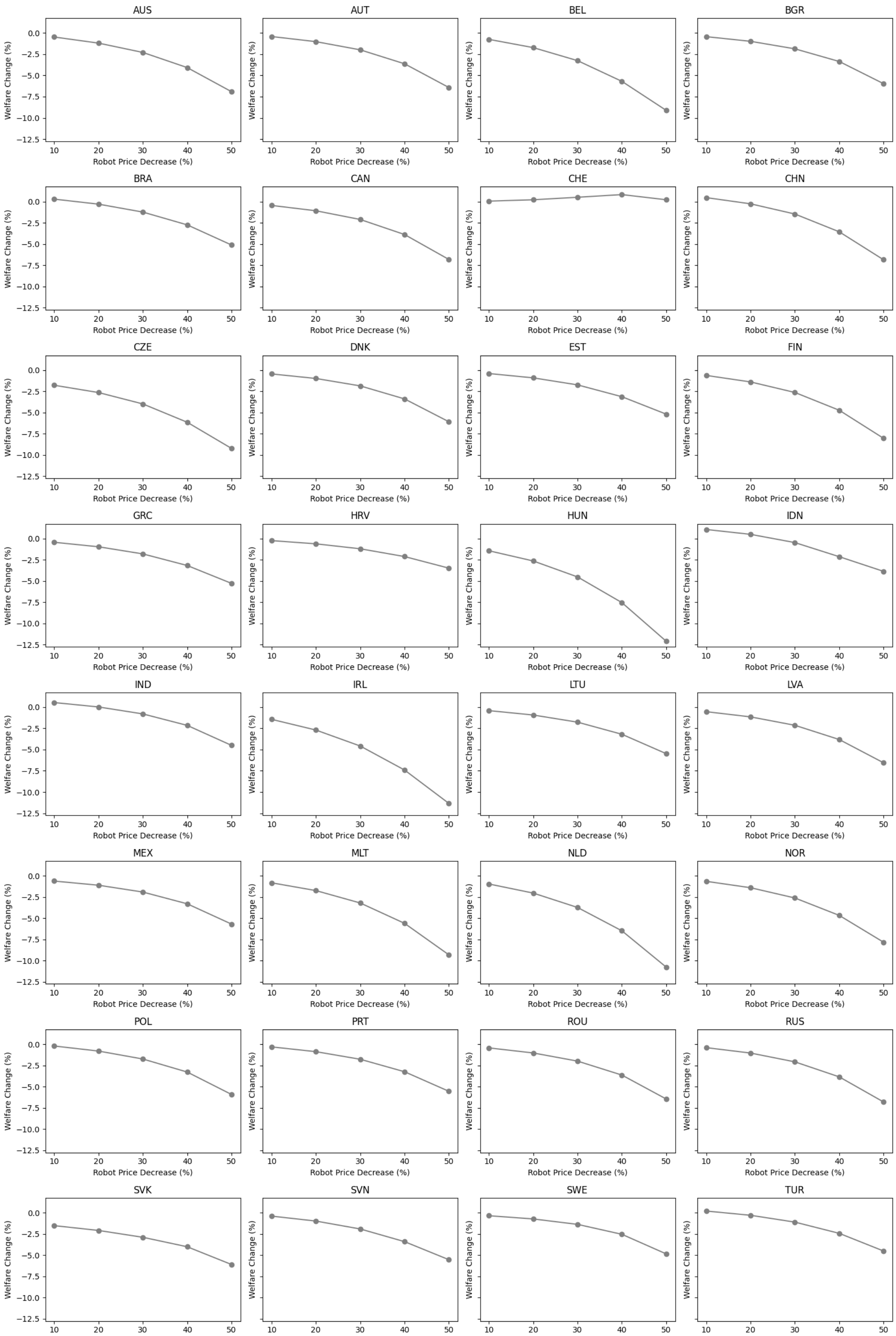


Figure 10: Non-selected Countries' Welfare Change %: Scenario II

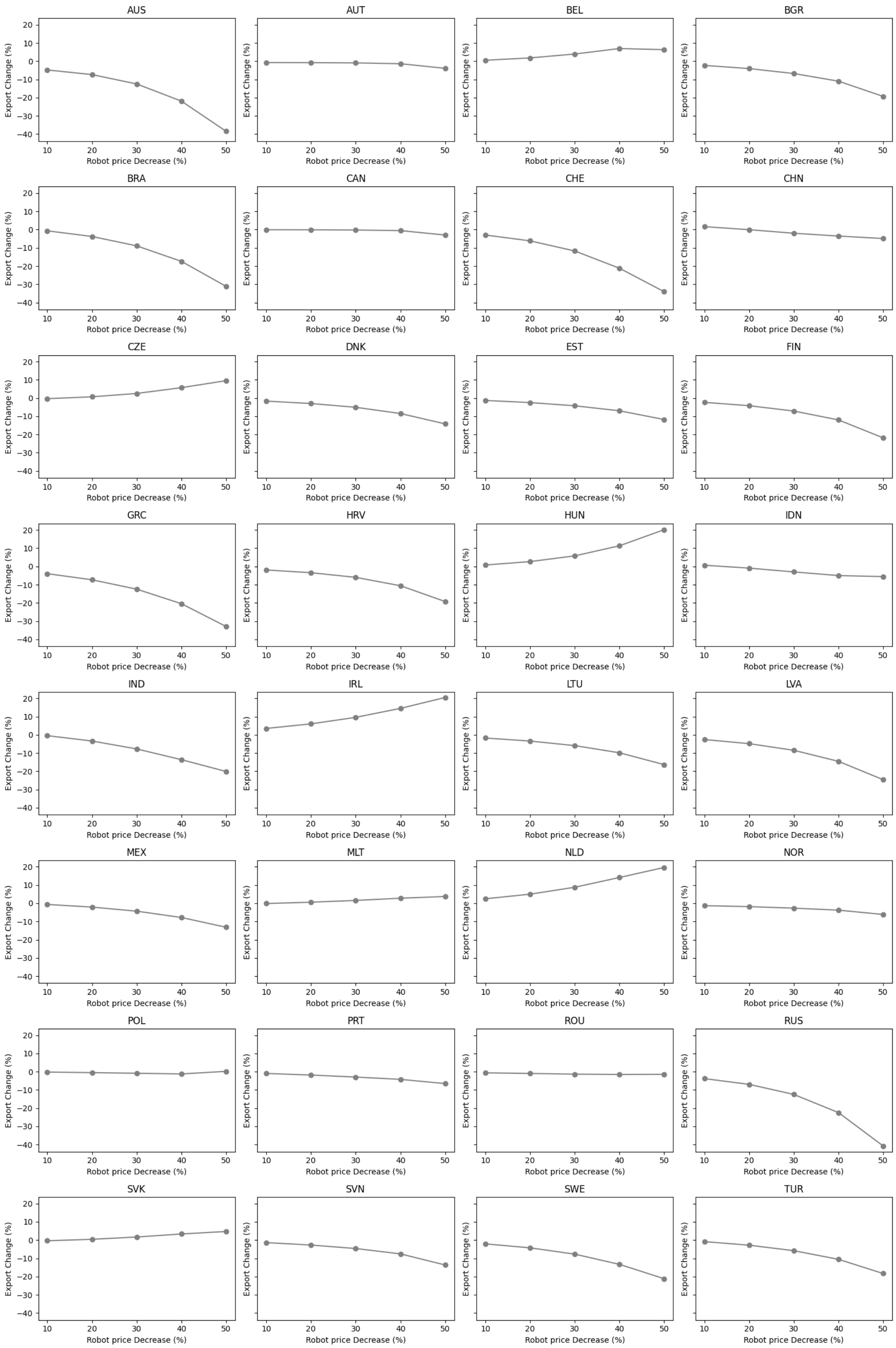


Figure 11: Non-selected Countries' Export Change %: Scenario II

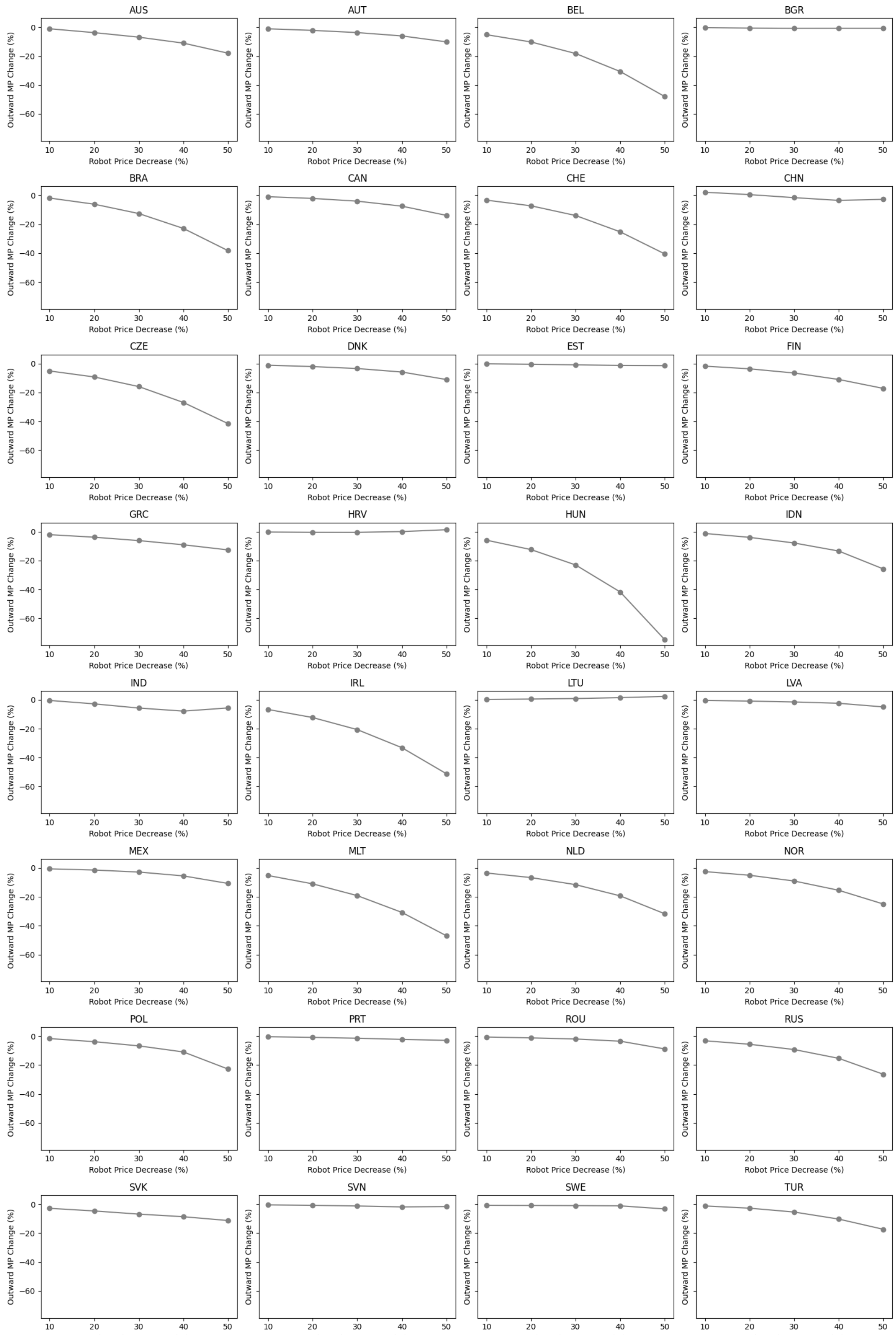
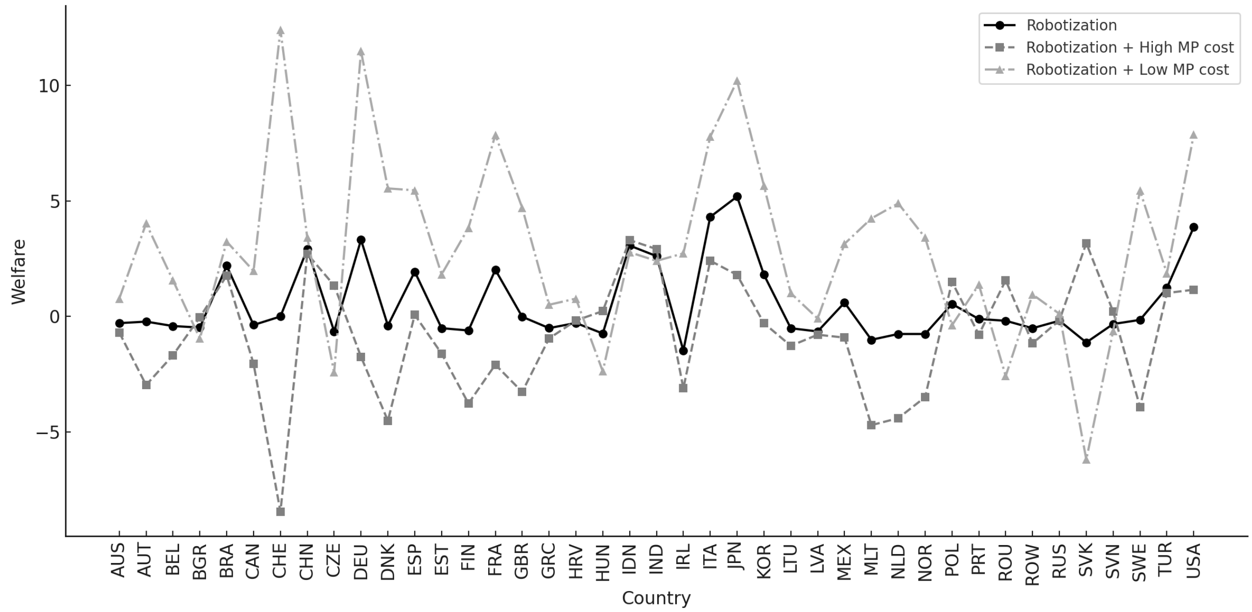
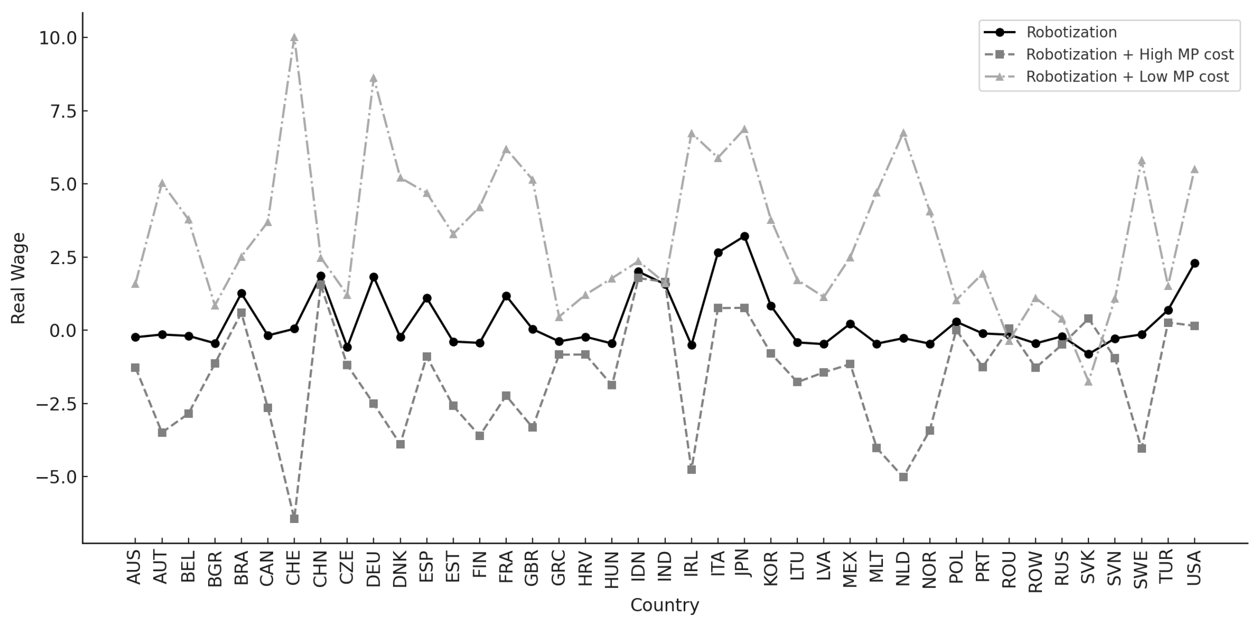


Figure 12: Non-selected Countries' Outward MP Change %: Scenario II



(a) Welfare Change %



(b) Real wage Change %

Figure 13: Effects of Robotization (Different MP cost) : Scenario III

Note: This figure reports results of scenario III with scenario I. Scenario I simulates a 10% global reduction of robots price (solid lines). Scenario III simulates a 10% global reduction of robots price with a 10% higher MP cost (gray dashed line with square markers) and a 10% global reduction of robots price with a 10% lower MP cost (gray dashed line with triangular markers) .

A Results Appendix

Table A.1: Industry Classification Correspondence

Code	Name	IFR	AMNE	WIOD	ICIO
1	Agriculture	A-B	A01T03	A01, A02, A03	01T02, 03
2	Mining	C	B05T09	B	05T06, 07T08, 09
3	Food Product	10-12	C10T12	C10-12	10T12
4	Textiles	13-15	C13T15	C13-15	13T15
5	Wood	16	C16	C16	16
6	Paper	17-18	C17T18	C17, C18	17T18
7	Petroleum	20-21	C19	C19	19
8	Chemical	19-21, 229	C20, C21	C20, C21	20, 21
9	Rubber	22	C22	C22	22
10	Mineral Products	23	C23	C23	23
11	Basic Metal	24, 289	C24	C24	24
12	Metal Product	25	C25	C25	25
13	Electronics	260-263, 265, 275, 279	C26	C26	26
14	Electrical	271	C27	C27	27
15	Machinery	28	C28	C28	28
16	Motor vehicles	29, 291, 299, 2931-2934, 2939, 2999	C29	C29	29
17	Other vehicles	30	C30	C30	30
18	Other Manufacturing	91	C31T33	C31-C32, C33	31T33
19	Utility	E	D35_E36T39	D35, E36, E37-E39	35, 36T39
20	Construction	F	F41T43	F	41T43
21	Education	P	P85	P85	85
22	Service	90	G-O, Q-T	G-O, Q-U	Others

Note: Table reports the industry classification we used, as well as the corresponding codes in the IFR, OECD AMNE, WIOD and OECD ICIO data sets.

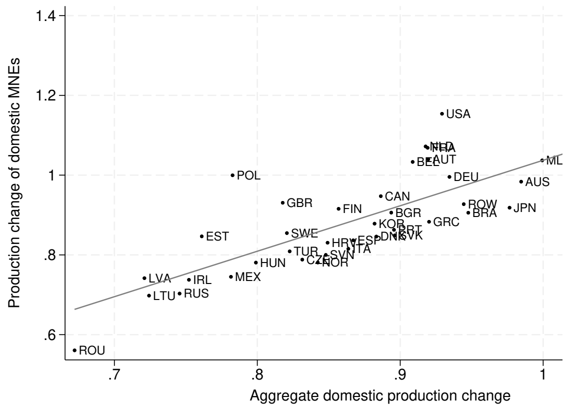
Table A.2: Country List and Robotization

iso3code	Name	Robotization	Ind	iso3code	Name	Robotization	Ind
AUS	Australia	0.710	3	IRL	Ireland	0.053	9
AUT	Austria	0.736	16	ITA	Italy	3.354	16
BEL	Belgium	0.829	16	JPN	Japan	6.342	16
BGR	Bulgaria	0.014	12	KOR	South Korea	2.762	13
BRA	Brazil	0.497	16	LTU	Lithuania	0.003	9
CAN	Canada	0.274	16	LVA	Latvia	0.001	16
CHE	Switzerland	0.625	9	MEX	Mexico	0.265	16
CHN	China	2.466	16	MLT	Malta	0.001	9
CZE	Czechia	0.568	16	NLD	Netherlands	0.786	9
DEU	Germany	5.798	16	NOR	Norway	0.165	12
DNK	Denmark	0.610	12	POL	Poland	0.349	16
ESP	Spain	1.874	16	PRT	Portugal	0.283	16
EST	Estonia	0.005	9	ROU	Romania	0.069	16
FIN	Finland	0.602	12	ROW	Rest of World	0.200	13
FRA	France	2.295	16	RUS	Russia	0.138	16
GBR	UK	1.114	16	SVK	Slovakia	0.214	16
GRC	Greece	0.032	20	SVN	Slovenia	0.166	16
HRV	Croatia	0.008	9	SWE	Sweden	1.060	16
HUN	Hungary	0.242	9	TUR	Turkey	0.314	16
IDN	Indonesia	0.271	9	USA	US	4.415	16
IND	India	0.421	16				

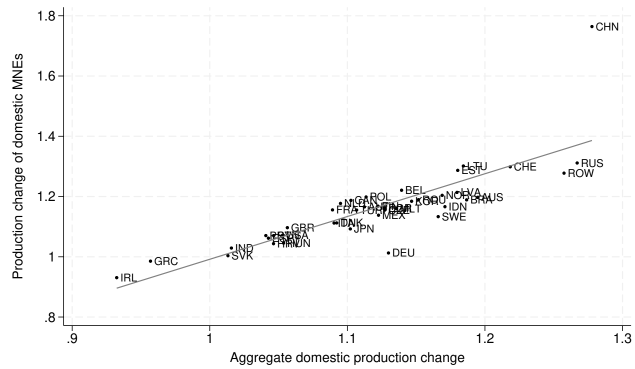
Note: Table reports country list we used. Robotization is computed as robots used per hour worked, $log(1 + robots/hours)$. In this table countries' robotization is averaged across time and normalized by the world average value. Robots and hours worked data come from IFR and WIOD respectively. Ind refers to the industry with highest robotization level in each country.

Table A.3: Welfare and Decomposition % of All Countries: Scenario I

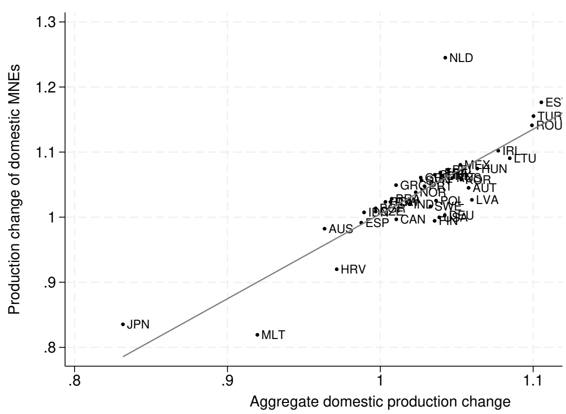
Country	Welfare	GFF	GFI	GR	SEC	GOF	MS	INV	PTR
AUS	-0.292	0.078	0.134	0.037	0.000	0.000	-0.051	-0.437	-0.054
AUT	-0.226	0.203	0.324	0.051	-0.033	0.000	0.022	-0.713	-0.081
BEL	-0.418	0.306	0.471	0.070	-0.020	0.000	0.049	-1.067	-0.226
BGR	-0.483	0.096	0.229	0.011	-0.130	0.000	-0.057	-0.592	-0.040
BRA	2.191	0.040	0.015	0.325	0.038	0.000	0.462	0.381	0.929
CAN	-0.371	0.238	0.503	0.033	0.015	0.000	-0.037	-0.929	-0.194
CHE	-0.004	-0.150	-0.069	0.008	0.001	0.000	-0.133	0.393	-0.054
CHN	2.914	-0.028	-0.150	0.348	0.457	0.000	0.533	0.705	1.049
CZE	-0.649	0.422	0.725	0.180	-0.027	0.000	-0.248	-1.629	-0.074
DEU	3.315	-0.149	-0.254	0.843	-0.029	0.000	0.563	0.849	1.492
DNK	-0.397	0.187	0.231	0.032	0.015	0.000	0.030	-0.730	-0.162
ESP	1.936	0.041	0.031	0.321	0.054	0.000	0.422	0.238	0.830
EST	-0.510	0.154	0.240	0.002	-0.025	0.000	-0.048	-0.707	-0.125
FIN	-0.610	0.122	0.210	0.026	-0.165	0.000	-0.003	-0.622	-0.178
FRA	2.016	0.041	0.033	0.284	0.028	0.000	0.457	0.336	0.837
GBR	-0.015	0.238	0.271	0.102	0.002	0.000	0.124	-0.698	-0.054
GRC	-0.507	0.059	0.079	0.005	-0.024	0.000	-0.029	-0.469	-0.128
HRV	-0.286	0.005	0.045	0.003	0.010	0.000	-0.013	-0.274	-0.063
HUN	-0.740	0.597	0.805	0.119	0.002	0.000	-0.117	-1.859	-0.287
IDN	3.066	0.080	-0.028	0.327	0.519	0.000	0.561	0.542	1.065
IND	2.610	0.015	-0.018	0.355	0.064	0.000	0.573	0.582	1.038
IRL	-1.480	1.188	1.147	0.005	0.001	0.000	0.053	-2.901	-0.973
ITA	4.307	-0.067	-0.165	0.540	0.023	0.000	0.982	1.340	1.654
JPN	5.188	-0.124	-0.305	0.639	0.457	0.000	0.879	1.667	1.975
KOR	1.802	-0.056	-0.105	0.714	0.144	0.000	0.041	0.099	0.965
LTU	-0.513	0.111	0.239	0.002	-0.006	0.000	-0.039	-0.722	-0.098
LVA	-0.652	0.059	0.128	0.001	-0.024	0.000	-0.054	-0.584	-0.178
MEX	0.597	0.075	0.097	0.206	-0.006	0.000	0.085	-0.229	0.369
MLT	-1.013	0.215	0.247	0.001	0.001	0.000	-0.036	-0.884	-0.556
NLD	-0.762	0.417	0.548	0.052	0.022	0.000	0.064	-1.375	-0.489
NOR	-0.762	0.172	0.383	0.004	0.069	0.000	-0.081	-1.004	-0.305
POL	0.536	0.164	0.245	0.133	-0.011	0.000	0.182	-0.422	0.244
PRT	-0.112	0.134	0.204	0.052	-0.031	0.000	0.039	-0.506	-0.003
ROU	-0.189	0.230	0.295	0.055	-0.004	0.000	0.035	-0.762	-0.038
ROW	-0.513	0.054	0.169	0.022	-0.153	0.000	-0.028	-0.512	-0.064
RUS	-0.187	0.086	0.123	0.055	-0.125	0.000	0.063	-0.410	0.021
SVK	-1.129	0.592	0.799	0.078	-0.003	0.000	-0.316	-1.962	-0.317
SVN	-0.330	0.116	0.238	0.028	0.003	0.000	-0.080	-0.584	-0.051
SWE	-0.151	0.125	0.186	0.060	-0.039	0.000	0.046	-0.521	-0.008
TUR	1.234	0.048	0.032	0.177	0.008	0.000	0.300	0.126	0.543
USA	3.861	-0.063	-0.136	0.483	0.039	0.000	0.794	1.170	1.574



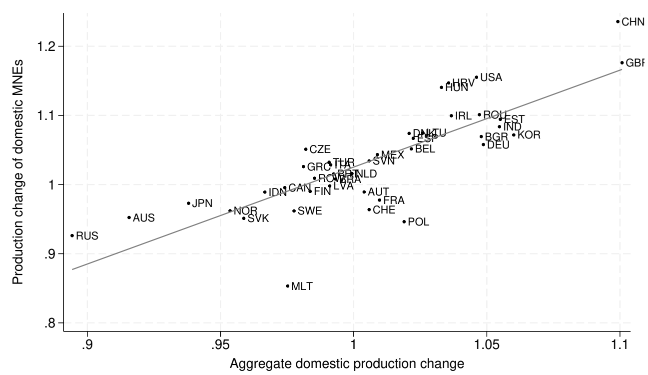
(a) 2009



(b) 2011



(c) 2013



(d) 2014

Figure A-1: Aggregate domestic production change and domestic MNEs production change

Note: This figure reports the relationship between domestic aggregate production change and domestic MNEs production change. Domestic aggregate production is the sum of production of domestically-owned firms and domestic MNEs (who have affiliates outside the country). Changes are computed as the ratio of production value in current year to previous year.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, tasks and technologies: Implications for employment and earnings." In *Handbook of labor economics*. Vol. 4, 1043–1171. Elsevier.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The race between man and machine: Implications of technology for growth, factor shares, and employment." *American economic review*, 108(6): 1488–1542. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and new tasks: How technology displaces and reinstates labor." *Journal of economic perspectives*, 33(2): 3–30. Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2418.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*, 128(6): 2188–2244.

Alviarez, Vanessa. 2019. "Multinational Production and Comparative Advantage." *Journal of International Economics*, 119: 1–54.

Arkolakis, Costas, Natalia Ramondo, Andrés Rodríguez-Clare, and Stephen Yeaple. 2018. "Innovation and production in the global economy." *American Economic Review*, 108(8): 2128–2173. ISBN: 0002-8282 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Artuc, Erhan, Paulo Bastos, and Bob Rijkers. 2023. "Robots, tasks, and trade." *Journal of International Economics*, 145: 103828. Publisher: Elsevier.

Broda, Christian, and David E. Weinstein. 2006. "Globalization and the Gains from Variety." *The Quarterly Journal of Economics*, 121(2): 541–585.

Cadestin, Charles, Koen De Backer, Isabelle Desnoyers-James, Sébastien Miroudot, Davide Rigo, and Ming Ye. 2018. "Multinational Enterprises and Global Value Chains: The OECD Analytical AMNE Database."

Caliendo, Lorenzo, and Fernando Parro. 2015. "Estimates of the Trade and Welfare Effects of NAFTA." *The Review of Economic Studies*, 82(1): 1–44. ISBN: 0034-6527 Publisher: Oxford University Press.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum. 2008. "Global Rebalancing with Gravity: Measuring the Burden of Adjustment." *IMF Staff Papers*, 55(3): 511–540.

Du, Xiayi, and Zi Wang. 2022. "Multinationals, Global Value Chains, and the Welfare Impacts of Economic Sanctions." *Economics Letters*, 220: 110870.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, geography, and trade." *Econometrica*, 70(5): 1741–1779. ISBN: 0012-9682 Publisher: Wiley Online Library.

Faber, Marius. 2020. "Robots and reshoring: Evidence from Mexican labor markets." *Journal of International Economics*, 127: 103384.

Furusawa, Taiji, Shoki Kusaka, and Yoichi Sugita. 2022. "The Impacts of AI, Robots, and Globalization on Labor Markets: Analysis of a Quantitative General Equilibrium Trade Model." In *Robots and AI.* 123–149. Routledge.

Graetz, Georg, and Guy Michaels. 2018. "Robots at work." *Review of Economics and Statistics*, 100(5): 753–768. Publisher: MIT Press One Rogers Street, Cambridge, MA 02142-1209, USA journals-info .

Grossman, Gene M., and Esteban Rossi-Hansberg. 2008. "Trading tasks: A simple theory of offshoring." *American Economic Review*, 98(5): 1978–1997. Publisher: American Economic Association.

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2021. "Robots and Firms." *The Economic Journal*, 131(638): 2553–2584.

Krenz, Astrid, Klaus Prettner, and Holger Strulik. 2021. "Robots, reshoring, and the lot of low-skilled workers." *European Economic Review*, 136: 103744. Publisher: Elsevier.

McAfee, Andrew, and Erik Brynjolfsson. 2016. "Human work in the robotic future: Policy for the age of automation." *Foreign Affairs*, 95(4): 139–150. Publisher: JSTOR.

Melitz, Marc J. 2003. "The impact of trade on intraindustry reallocations and aggregate industry productivity." *econometrica*, 71(6): 1695–1725. ISBN: 0012-9682 Publisher: Wiley Online Library.

Ramondo, Natalia, and Andrés Rodríguez-Clare. 2013. "Trade, Multinational Production, and the Gains from Openness." *Journal of Political Economy*, 121(2): 273–322.

Shikher, Serge. 2014. "International Production, Technology Diffusion, and Trade." *The Journal of International Trade & Economic Development*, 23(1): 111–154.

Tintelnot, Felix. 2017. "Global Production with Export Platforms." *The Quarterly Journal of Economics*, 132(1): 157–209.

Wang, Zi. 2021. "Headquarters gravity: How multinationals shape international trade." *Journal of International Economics*, 131: 103477. ISBN: 0022-1996 Publisher: Elsevier.