Global Robots

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Abstract

The diffusion of automation technology generates debates about the future of work, leading to calls for policy interventions. The ongoing discussions center on the production and employment decisions of technology adopters. In this paper, I show that supply-side adjustments are sizable and amplify the effects of policy interventions. I study the global market of industrial robots, a leading type of automation technology, where 10 multinational enterprises (MNEs) account for 90% of sales. To evaluate how these MNEs react to policy changes, I collect new data on their characteristics and global sales networks. I then develop and estimate a multi-country general equilibrium model featuring oligopolistic multinational robot sellers. Using this model, I find that MNEs' market entry and pricing responses amplify by about 40% the aggregate and distributional effects of policies targeting robot adoption. I also show that local policies can produce global effects through MNEs' sales networks.

Keywords: Multinational Enterprises, Market Power, Automation

JEL Classification: F1, F16, F23, L13, O33

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1 Introduction

Automation technologies, including robotics and artificial intelligence, are crucial production inputs in the global economy. These technologies autonomously perform several complex tasks, fostering productivity growth. However, their diffusion also generates displacement and inequality concerns. For these reasons, academics and policymakers discuss about policies to support or restrict automation (Brynjolfsson and McAfee, 2014; Acemoglu and Johnson, 2023).

The ongoing debate centers on the choices made by technology adopters and their labor market implications. However, policy changes are also likely to prompt adjustments on the supply side. In the automation industry, where production is often dominated by a few large multinational enterprises (MNEs), supply-side responses may be sizable and represent a determining factor for the ultimate effects of any policy.

In this paper, I offer two contributions. First, I shed new light on how MNEs supplying automation technology respond to policy interventions. Second, I show that their market power can substantially amplify policy outcomes. I focus on the global robot industry. This is an ideal setting because robots are a leading type of automation technology.[1] Their global stock has increased fivefold over the past 20 years, sparking research on their diffusion (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Moreover, the industry is highly concentrated, with 10 MNEs accounting for 90% of global sales and having automation provision as their primary activity.

I consider supply-side adjustments in market entry and pricing choices. Both margins are key. Robots are sophisticated machines, and sellers offer various "integration services" to users (e.g., customization and maintenance), which require proximity to final demand. Therefore, local competition among global sellers is a crucial determinant of the price of robots and, consequently, their adoption.

I collect new data on the leading multinational robot sellers in the world, which I use to document novel facts about the global robot industry. I then develop and estimate a quantitative multi-country general equilibrium model featuring oligopolistic multinational robot sellers. Using the model, I find that supply-side responses to policies targeting robot adoption amplify the aggregate and distributional outcomes of these policies by about 40%. I also show that multinational robot sellers' responses transmit internationally the effects of local policy changes.

[1] I study industrial robots, defined by the International Organization for Standardization as "automatically controlled, reprogrammable multipurpose manipulators". See Section 2 for more details.

The data come from various sources. From the list of members of the International Federation of Robotics (IFR), I identify the MNEs that produce and sell industrial robots. Information about the location of their headquarters (HQ), financial accounts, and ownership structure comes from the Bureau van Dijk's Orbis dataset. I also scrape the website of each MNE to geolocate their sales branches that offer robots and integration services. I retrieve over 600 sales branches worldwide. About 90% of them are in Orbis. Countries' characteristics, such as the number of robots adopted, market size, and trade flows, come from commonly-used data sources.

The final dataset is a cross-section of 10 multinational robot sellers and 45 countries, pooling information between 2019 and 2021. Multinational robot sellers have HQ mainly in Japan and central Europe. The 45 countries I consider account for 90% of global GDP. I use the data to document three new facts. First, robot sales decrease as the distance between destination countries and the sellers' HQ increases, which is consistent with gravity. Second, robot sales in the average country are highly concentrated. The Herfindahl-Hirschman Index (HHI) in the average country equals 34%, consistent with robot sellers having market power (Shapiro, 2010). Third, countries in which more robots are adopted also exhibit higher GDP and greater wage dispersion.

Informed by these facts, I develop a multi-country general equilibrium model featuring oligopolistic multinational robot sellers. Each market consists of households and perfectly competitive final goods producers. Households buy final goods and supply either routine or non-routine labor inelastically. Firms use robots and both types of labor to produce final goods. As in Acemoglu and Restrepo (2018), robots are substitutes to routine workers and complements to non-routine ones. Final goods are traded internationally subject to iceberg trade costs, creating linkages across markets.

Robot supply is modeled following the literature on oligopolistic competition in international trade (Atkeson and Burstein, 2008). It has two key features. First, upon paying an entry cost, robot sellers can serve multiple markets. Second, within each market, they compete to sell an indivisible bundle of generic robots and integration services to users. This bundle, which I refer to as a "product", is considered non-tradable and produced where it is sold.[2] Robot sellers are heterogeneous in terms of appeal to final goods producers. More appealing robot sellers enter more markets, have higher market shares, and charge higher markups.

[2] I impose this assumption to abstract from the proximity-concentration trade-off in the production of generic robots and analyze competition in destination markets. According to Leigh and Kraft (2018), two-thirds of the total cost paid by robot users comes from integration services.

The model generates two predictions about the effects of robot sellers' market entry and pricing choices in the global economy. First, the entry of new sellers in a market increases competition, leading to a reduction in the local price of robots. In turn, the cost of producing final goods decreases and output increases. Given the non-neutrality of robots, wage inequality increases. Second, as goods in one market become more affordable, their demand rises relative to goods produced in other locations. Consequently, output expansion in a market comes at the expense of production elsewhere.

Bringing the model to the data requires taking a stand on the geographical boundaries of the markets in which robot sellers compete. In practice, I use a K-means algorithm to group 45 countries into 12 larger markets based on geographical proximity. The structural parameters of the model must also be determined. The households' and final goods producers' parameters are standard and can be directly calibrated from the data or existing literature. The robot sellers' parameters are new, and I develop a simulated method of moments (SMM) procedure to estimate them.

The SMM estimator targets moments that are informative of robot sellers' entry choices and sales, market competition, and market size. It recovers the mean and standard deviation of the appeal distribution across robot sellers, the cost of entering markets, and the elasticity of substitution between the different products offered by robot sellers. While jointly estimated, each parameter is intuitively informed by specific targeted moments, which are accurately replicated. I validate the model by showing that it matches untargeted seller and market-level moments.

I use the model to assess how robot sellers respond to policies targeting robot adoption and quantify the impact of their responses on various outcomes. I examine the implementation of an EU-wide value-added robot tax paid by robot adopters. This policy was discussed by the European Parliament in 2017 as part of a law to protect workers exposed to automation, and it has prompted extensive research on the taxation of automation technology (Thuemmel, 2022; Guerreiro, Rebelo and Teles, 2022; Costinot and Werning, 2023). I consider a 5% tax, in line with the short-run optimal robot tax rate estimated for the US by Guerreiro et al. (2022).

I explore two scenarios. In the first, in line with the existing literature, robot sellers cannot adjust market entry choices and markups after the tax is introduced. In the second, they can adjust along both margins. It is ex-ante ambiguous how supply-side adjustments affect policy outcomes. If robot prices strongly respond to local competition, sellers' market entry and exit choices may amplify them. Conversely, the ability to adjust markups, implying imperfect pass-through, may generate attenuation.

In the first scenario, a tax reduces robot demand and increases the production price of final goods, generating a 2.4% output loss in the EU. However, losses are not evenly borne. Routine households experience an increase in real wages because of their substitutability with robots, while non-routine ones face a loss due to their complementarity. Overall, wage inequality decreases by 4.7%.

In the second scenario, since a tax shrinks the total size of the market, some robot sellers exit the EU, leading incumbents to increase their markups. In turn, robot prices increase more than in the first scenario, amplifying all outcome changes relative to the first case. Comparing changes across outcomes and between scenarios indicates that supply-side adjustments reinforce the aggregate and distributional effects of a tax by about 40%. Because foreign robot sellers tend to be less appealing, an EU-wide tax disproportionally affects sellers headquartered outside the EU. They experience higher exit and lose market shares in favor of European robot sellers.

Since markets are linked via international trade, a tax also produces ripple effects that extend beyond the EU. By increasing robot demand in non-EU markets relative to EU ones, a tax triggers robot sellers' entry beyond the EU. Therefore, these markets experience opposite outcomes than EU ones. Also in this case, supply-side adjustments amplify aggregate and distributional outcomes by about 40%.

The model can be also used to evaluate a rich set of additional policies. For example, I show how supply-side adjustments shape optimal robot taxation, compare unilateral and multilateral robot taxes, and discuss the effects of robot adoption subsidies. I also show that policies aimed at curbing the market power of robot sellers are subject to a trade-off between efficiency and equity given the non-neutrality of robots.

Overall, this paper delivers two takeaways. First, the responses of multinational robot sellers to policies targeting the adoption of robots amplify the ultimate impact of these policies. Second, local policies can have global effects if markets are interconnected via trade and multinational robot sellers' activities.

Related Literature. This paper contributes to several strands of the literature. At its core, it contributes to the literature on quantitative models of MNEs' activities (e.g., Irarrazabal, Moxnes and Opromolla, 2013; Ramondo and Rodríguez-Clare, 2013; Ramondo, 2014; Tintelnot, 2017; Antràs, Fort and Tintelnot, 2017; Arkolakis, Ramondo, Rodríguez-Clare and Yeaple, 2018; Alviarez, 2019; Head and Mayer, 2019). From a theoretical perspective, this paper offers two contributions. First, instead of focusing on horizontal, vertical, or export-platform foreign direct investment (FDI), it introduces a novel model of distribution FDI tailored to the robot industry. Second, the paper relaxes the conventional assumption of monopolistic competition among MNEs, allowing for oligopolistic competition. From an empirical point of view, this work introduces new data about MNEs in the robot industry. Reassuringly, the fact that multinational activity follows gravity continues to hold in this new sector.

This paper also contributes to the literature on oligopoly in international trade (e.g., Markusen, 1981; Brander and Krugman, 1983; Brander and Spencer, 1985; Atkeson and Burstein, 2008; Edmond, Midrigan and Xu, 2015; Neary, 2016; Parenti, 2018; Gaubert and Itskhoki, 2021; Impullitti, Licandro and Rendahl, 2022). While the existing literature focuses on how imperfect competition between firms shapes international trade patterns and trade policy, this paper presents evidence of how firms' strategic behaviors interact with and influence the outcomes of regulations beyond trade policy.

By documenting how a few firms dominate the global robot industry, this paper also connects with the literature on global market power (e.g., De Loecker and Eeckhout, 2018; De Loecker, Eeckhout and Unger, 2020; Alviarez, Head and Mayer, 2020; Autor, Dorn, Katz, Patterson and Van Reenen, 2020; Leone, Macchiavello and Reed, 2023). Properly adapted, the model developed in this paper can be used to assess the role of market power in transmitting shocks in other globally concentrated input markets.

Finally, this paper contributes to the literature on the labor market effects of automation technology (e.g., Acemoglu and Restrepo, 2018; Graetz and Michaels, 2018; Bessen, Goos, Salomons and Van den Berge, 2019; Acemoglu and Restrepo, 2020; Acemoglu, Lelarge and Restrepo, 2020; Koch, Manuylov and Smolka, 2021; Aghion, Antonin, Bunel and Jaravel, 2020; Dauth, Findeisen, Suedekum and Woessner, 2021; Hubmer and Restrepo, 2021; Hémous and Olsen, 2022; Acemoglu, Koster and Ozgen, 2023) and the implications of policies targeting automation (e.g., Humlum, 2021; Beraja and Zorzi, 2022; Thuemmel, 2022; Guerreiro et al., 2022; Costinot and Werning, 2023). The main contribution is highlighting the role of market structure on the supply side in shaping the outcomes of policies favoring or constraining automation technology.

The paper unfolds as follows. Section 2 provides information about the industry. Section 3 introduces the data. Section 4 describes the empirical facts. Section 5 contains the model. Section 6 discusses model estimation. Section 7 shows the effects of a robot tax. Section 8 presents additional counterfactuals. Section 9 concludes.

2 Industry Background

This section provides background information about robots and the robot industry.

2.1 Industrial Robots

Industrial robots (henceforth robots) are defined by the International Organization for Standardization (ISO) as "automatically controlled, reprogrammable multipurpose manipulators, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (ISO 8372:2012). The International Federation of Robotics (IFR), a non-profit organization that represents robot sellers, national producers' associations, and research institutes around the world, remarks that the ability to perform different tasks without any human supervision is the main feature of these machines (International Federation of Robotics, 2020). Using data between 1990 and 2007 on US labor markets, Acemoglu and Restrepo (2020) document that autonomy makes robots more substitutable for workers in routine occupations compared to computers and other automation technology.

Robots belong to six different types (articulated, cartesian, cylindrical, spherical, parallel, and SCARA—Selective Compliance Assembly Robot Arm) mainly differing in terms of number of arms and payload. Notwithstanding, they are classified as relatively homogenous goods. There is a single six-digit HS code associated with industrial robots (847950), and the same holds true in the US ten-digit HTS product classification, the most disaggregated one in international trade data. For comparison, another product for which the six-digit and ten-digit product classifications coincide is white portland cement. By contrast, within the six-digit code associated with "durum wheat (excluding seed for sowing)" (100119) there are four 10-digit HTS varieties.

2.2 The Global Robot Industry

The global robot industry is organized along three main stages: production, integration, and adoption (see Figure A.1). Japan assembles nearly half of the world's new robots each year. Other major production centers are China, Germany, Italy, South Korea, and the US (International Federation of Robotics, 2020). More details regarding the locations where robots are produced and the technological requirements of the production process are in Appendices C.1 and C.2, respectively.

In the early 1990s, industrial robots were mostly employed in the automotive industry. However, over the last 20 years, their adoption has grown across diverse manufacturing sectors, such as chemicals, electronics, pharmaceuticals, and even agriculture. Overall, their global stock has increased fivefold. China, Germany, Japan, South Korea, and the US are the major destination markets for robots (International Federation of Robotics, 2020). Robot adopters tend to be large manufacturing companies (Acemoglu et al., 2020; Koch et al., 2021), often active in multiple countries (Leone, 2023).

The integration stage is a key feature of the industry. Robots are sophisticated machines, and their adoption is often associated with a broader restructuring of production. As a result, users acquire both the generic robot and "integration services" from sellers. These services involve providing guidance to users in selecting the appropriate automation solution, product customization to adapt a generic robot to a specific production task, and post-sale support like installation, replacement, and ongoing maintenance. Appendix C.3 provides examples based on case studies available from the robot sellers' websites. Leigh and Kraft (2018) estimate that integration services account for about two-thirds of the final price paid by users.

The bundling of robots and integration services is crucial. While robots are tradable, integration services require proximity to final demand. Therefore, sellers must establish a retail network of branches in each market they serve, regardless of where production facilities are located.

3 Data

This section presents new data about robot sales and the additional data sources.

3.1 Multinational Robot Sellers

Identity. I obtain a list of robot sellers using the directory of members of the IFR. The original directory contains 85 members. Among them, there are 26 firms that produce and sell robots. The remaining members are either national associations or research institutes. To identify industry leaders, I resort to business-related sources and the Bureau van Dijk's Orbis dataset, proceeding in two steps. First, I search for these 26 firms in magazines discussing trends in the industrial robot sector. Second, I select the companies that consistently emerge as industry leaders across searches. The final list includes ABB, Comau, Epson, Fanuc, Kawasaki, Kuka, Nachi-Fujikoshi, Omron, Staubli, and Yaskawa. Using Orbis, I verify that these 10 sellers account for approximately 90% of the global market share.[3] Among them, ABB, Fanuc, Kuka, and Yaskawa alone hold approximately 54% of the global market share, as shown in Figure A.2. These concentration patterns align with existing industry reports (UBS, 2020).[4]

Characteristics. I gather several characteristics of robot sellers from Orbis, encompassing information about financial accounts (e.g., sales, employment, total fixed assets, and R&D expenses), sectors of activity, ownership structure, and innovation. Ownership information includes details about sellers' shareholders and the location of sellers' headquarters (HQ). Additionally, it includes the location, sectors of activity, and financial accounts of all sellers' subsidiaries, even those unrelated to robots. All firms are MNEs with subsidiaries in multiple countries. Using Orbis Intellectual Property, I also collect information about robot-related patents. Among the 26 sellers registered with the IFR, the top 10 accounting for 90% of global sales also hold 81% of the global stock of robot-related patents. See Appendix C.2 for more details.

Global Sales Network. Section 2 emphasizes the importance for robot sellers of establishing a retail network in each market they serve. Unfortunately, this information cannot always be obtained from Orbis for two reasons. First, Orbis only links branches to sellers if they share a common owner (usually the multinational seller itself). However, business-related case studies available on the robot sellers' websites suggest that some branches may also function as franchises. Second, even among affiliates, branches that supply robots and integration services cannot be unambiguously identified when information about their sector of activity is missing from Orbis.

To address this limitation, I create a web scraping algorithm to retrieve information about branches supplying robots and integration services directly from the websites of the top 10 robot sellers. The algorithm works in two steps. First, it navigates to the "Where to find us" section of each seller's website, where a list of retail branches across the world is provided. Second, it extracts and stores the name and geographical

[3]This share refers to 2021 but it is stable over time. Because Orbis does not report turnover by sector, I compute global market shares using sellers' total turnover. Since automation provision is the primary activity of these firms, their total sales are an accurate proxy for their size in the industry. This is not the case for other automation sectors. For example, Amazon and Microsoft dominate cloud computing services, but their total sales in Orbis likely reflect income from their other main activities. This makes the robot industry appealing to study market structure in the automation sector.

[4]For reference, Figure A.3 shows that firms in the robot industry are relatively small compared to leading companies in other sectors, such as cars, smartphones, semiconductors, and computers.

location of each branch. Figure A.4 illustrates two examples of the online information retrieved. The first branch is a subsidiary of Kuka, while the second is a franchise selling ABB robots. Appendix D.1 provides additional information about the algorithm.

The algorithm identifies 603 sales branches located in multiple countries, which are shown in Figure A.5. Among all branches, 538 (89%) can be found in Orbis, and information about their financial accounts and corporate structure is collected. Ownership details are available for 409 (75%) branches. Approximately 65% of them are subsidiaries. The remaining 35% are franchises. However, since each franchise is only listed on a single seller's website, I do not distinguish between branches owned by sellers and those operating at arm's length.

Market Shares. I measure the market share of a seller in each market using its share of branches in that market. This choice is motivated by the importance of physical proximity to end-users for sales, and rests on the assumption that robot sellers with more local branches have higher sales. In Appendix D.2, I provide evidence in support of this assumption using Orbis information about branch-level sales data. I also provide additional comparisons between market shares based on branches and sales.[5] I prefer the definition of market shares based on branches over the one based on sales because the latter cannot always be defined due to missing information in Orbis. I defer a formal treatment of the relevant markets in which sellers compete until Section 6.

3.2 Additional Data Sources

Robot Adoption. Data about robot adoption come from the IFR, which aggregates cross-country firm-level information and computes the number of robots used in every country by industry (roughly matching the NACE4 classification) and year. These data are considered as very reliable and have been extensively used in previous research (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021).

International Trade. Information about bilateral trade flows between countries by industry (ISIC Review 4) is obtained from the World Input-Output Tables (WIOT). Bilateral trade flows by specific goods (HS6 classification) come from the CEPII BACI dataset. These data also report the value and quantity of trade in robots.

[5] In Appendix E.1, I extend the model in Section 5 to provide a micro-foundation for the positive correlation between the number of branches and robot sellers' sales in a market.

To complement the trade data, I collect bilateral information about physical and cultural distance between countries. Physical distance, measured as the distance between the two most populated cities of a country pair in kilometers, comes from the CEPII gravity database. Cultural distance, measured as the probability that two random individuals in two countries speak the same language, comes from Gurevich, Herman, Toubal and Yotov (2021). Finally, I obtain information on bilateral trade costs, computed using the method developed by Novy (2013), from the ESCAP-World Bank Trade Cost Database.

Country Characteristics. I gather information about the characteristics of countries where robot sellers have branches from various data sources. Information about GDP (in PPP), total population, employment, and value added by industry comes from the World Development Indicators (WDI) database of the World Bank. Information on the share of income accruing to labor in each country is provided by the Sustainable Development Goals database of the United Nations (SDG UN).

3.3 Final Sample

Sample Description and Summary Statistics. The matched dataset is a cross-section of 10 multinational robot sellers and 45 countries, accounting for 90% of total robot sales and global GDP. Information about sellers and their branches is relative to 2021. Information from other data sources refers to 2019. The only exception is WIOT, whose latest available year is 2014.

Table 1 shows that there is substantial variation in multinational robot sellers' market entry choices and sales. For instance, Kuka and Yaskawa have sales branches in 41 and 27 countries, with an average of 2.80 and 1.44 branches per country, respectively. On the other hand, ABB and Fanuc serve fewer countries, 17 and 16 respectively, but have a higher average number of branches, 7.59 and 4.38 respectively. In general, the top 4 multinational robot sellers serve more countries and have higher market shares than the others, as shown in Figure A.6. Their sustained superior performance is widely recognized within the industry (Leigh and Kraft, 2018).

Sellers also serve different countries in terms of market size, measured as the number of robots adopted, and distance from their HQ. There is also substantial dispersion in their total sales. This heterogeneity will ultimately inform the structural parameters of the model governing the robot sellers' decisions.

Table 1. Summary Statistics

Name	HQ	No. Countries	No. Branches	Log Robot Stock	Log Dist. from HQ	Log Sales
ABB	CH	17	7.59	12.03	8.39	10.36
Fanuc	JP	16	4.38	13.15	8.98	8.70
Yaskawa	JP	27	1.44	12.58	9.04	8.33
Kuka	DE	41	2.80	12.36	8.48	8.23
Kawasaki	JP	12	2.33	13.41	8.84	9.41
Epson	JP	8	4.00	12.14	9.59	9.13
Omron	JP	23	2.30	12.87	8.97	8.74
Nachi-Fujikoshi	JP	16	3.69	13.18	8.91	7.61
Staubli	CH	31	1.23	12.60	8.45	5.70
Comau	IT	23	1.74	12.71	8.35	5.54

Note: The table shows summary statistics for each of the top 10 multinational robot sellers. *HQ* is the robot sellers' HQ country. *No. Countries* is the number of countries that robot sellers serve. *No. Branches* is the average number of branches that robot sellers operate in the countries they serve. *Log Robot Stock* is the log of the average number of robots used in the countries served by sellers. *Log Dist. from HQ* is the log of the average distance between the two most populated cities of the robot sellers' HQ and served destination countries in kilometers. *Log Sales* is the log of robot sellers' total revenues in million USD.

Data Validation. While the 10 robot sellers I focus on dominate the industry, there may be concerns regarding the accuracy of the procedure used to construct their sales network. For instance, omissions in online listings or misclassification of sales branches could introduce measurement error in the sample. To address this concern, I show that the self-collected information about global sales networks is consistent with robot adoption patterns and the sellers' global presence from other established sources.

First, there is a significant 75% correlation between the number of sales branches and the number of robots used, as reported by the IFR, at the country level. The correlation stays unchanged even after controlling for market size. Second, there is a significant 77% correlation between the number of branches that sellers headquartered in country o open in country d and the export value of robots from o to d, as reported in the BACI dataset. The correlation is robust to controlling for origin and destination fixed effects, as well as the distance between country pairs. This result corroborates the argument made in Section 2 that robot sales are mediated by local branches.

Last, there is a significant 48% correlation between whether sellers have a sales branch in a country and whether they have other subsidiaries in that country (including those unrelated to robots), as reported in Orbis. The correlation is robust to controlling for seller and country fixed effects, suggesting that robot sales positively correlate with other the activities carried out by multinational sellers. Additional details can be found in Appendix D.3.

4 Empirical Facts

This section introduces three novel facts about the global robot industry.

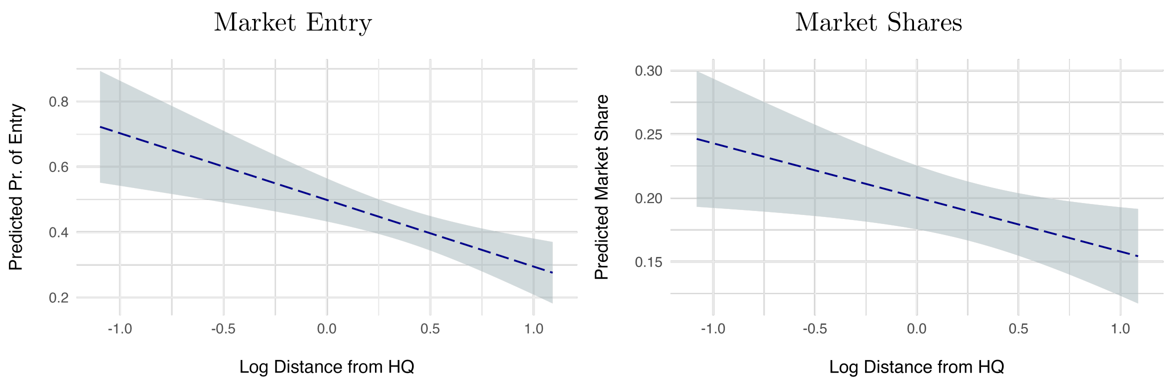
Fact 1. *Robot sellers' entry choices and sales follow gravity.*

I estimate the following equation:

$$y_{s(o)d} = \alpha + \beta \textit{Log Distance from HQ}_{s(o)d} + \varepsilon_{s(o)d}. \tag{1}$$

$y_{s(o)d}$ is either a binary variable equal to 1 if seller s headquartered in country o has at least one branch in country d or the market share of seller s in country d. *Log Distance from HQ*$_{s(o)d}$ is the log distance between the two most populated cities of the sellers' HQ and destination country in kilometers, while $\varepsilon_{s(o)d}$ is the error term. The parameter of interest is β, which captures the marginal change in $y_{s(o)d}$ as sellers move away from their HQ. I standardize log distance to have zero mean and unit variance in the sample. Therefore, α measures the outcome variable in the average country in terms of log distance from the HQ. Figure 1 shows the predicted values of equation (1) and the corresponding 95% confidence interval.

Figure 1. The Gravity of Market Entry and Market Shares



Note: The left panel of the figure plots the predicted entry probability of robot seller s in country d as a function of the log distance between the two most populated cities of the seller's HQ and destination country in kilometers. The right panel of the figure plots the predicted market share of seller s in country d as a function of the same log distance. I standardize log distance to have zero mean and unit variance in the sample, and I plot the predicted values over its $[-1, 1]$ interval. Equation (1) is estimated via OLS.

The first column of Table B.1 indicates that a one-unit standard deviation increase in the log distance from HQ correlates with a reduction in the entry probability of about

13 percentage points, corresponding to a 28% reduction relative to the unconditional probability of entry in the sample. This correlation is robust to controlling for destination country and seller-level fixed effects, as shown in the second and third columns of Table B.1. A similar pattern arises when measuring distance between countries using the bilateral measure of cultural proximity developed by Gurevich et al. (2021), as shown in the first three columns of Table B.2.

The fourth column of Table B.1 shows that a one-unit standard deviation increase in log distance correlates with a significant reduction in market shares of about 4 percentage points, corresponding to a 18% reduction relative to the average market share in the sample. The results are robust to including destination country and seller-level fixed effects, as shown in the fifth and sixth columns of Table B.1, and using a cultural measure of bilateral distance, as shown in the last three columns of Table B.2.

Overall, there is evidence that sellers' market entry choices and market shares decrease as bilateral frictions between the HQ and destination countries increase. This finding is consistent with the gravity model of international trade (Tinbergen, 1962; Head and Mayer, 2014), which has been also documented to hold for the production activity of MNEs (Keller and Yeaple, 2013; Antràs and Yeaple, 2014). Therefore, this section suggests that well-known facts about multinational activity continue to hold in a previously unexplored sector. Consistent with this fact, the model allows for heterogenous robot sellers and gravity in their entry choices and sales.

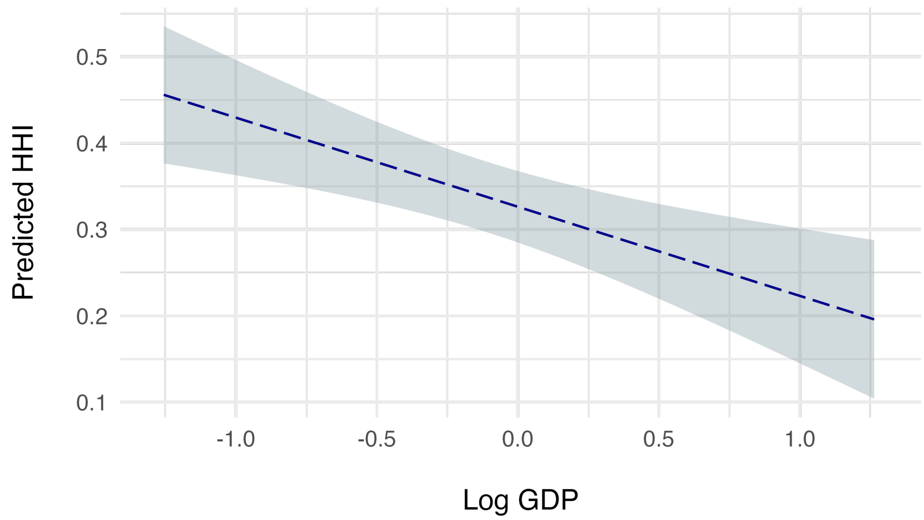
Fact 2. *Robot sales in the average country are concentrated.*

I estimate the following equation:

$$HHI_d = \alpha + \beta Log\ GDP_d + \varepsilon_d. \tag{2}$$

I compute the Herfindahl–Hirschman Index (HHI) at the country level as $HHI_d = \sum_s s_{sd}^2$, being s_{sd} the market share of seller s in market d. I proxy the size of country d from its log GDP (in PPP to ensure comparability). ε_d is the error term. The parameter of interest is β, which captures the marginal change in HHI_d as countries become larger. I standardize log GDP to have zero mean and unit variance in the sample. Therefore, α is the HHI in the average country in terms of size. Figure 2 shows the predicted values of equation (2) and the corresponding 95% confidence interval.

Figure 2. Market Concentration and Country Size



Note: The figure plots the predicted Herfindahl–Hirschman Index (HHI) in country d as a function of its log GDP. I standardize log GDP to have zero mean and unit variance in the sample, and I plot the predicted values over its $[-1, 1]$ interval. Equation (2) is estimated via OLS.

The HHI equals 34% in the average country, as indicated in the first column of Table B.3. As shown in the second column of Table B.3, a one-unit standard deviation increase in GDP correlates with a significant reduction in the HHI of about 7 percentage points, or 20% compared to the HHI in the average country. It is useful to resort to the Horizontal Merger Guidelines of the Federal Trade Commission (FTC) to interpret these numbers.[6] The FTC classifies markets into "unconcentrated" (HHI $<$ 15%), "moderately concentrated" (15% $\leq$ HHI $\leq$ 25%), and "highly concentrated" (HHI $>$ 25%). The fact that the HHI in the average sample country falls in the third category supports the hypothesis that robot sellers have market power. Accordingly, the model features oligpolistic competition between multinational robot sellers.

Fact 3. *Countries with more robots have higher output and greater wage dispersion.*

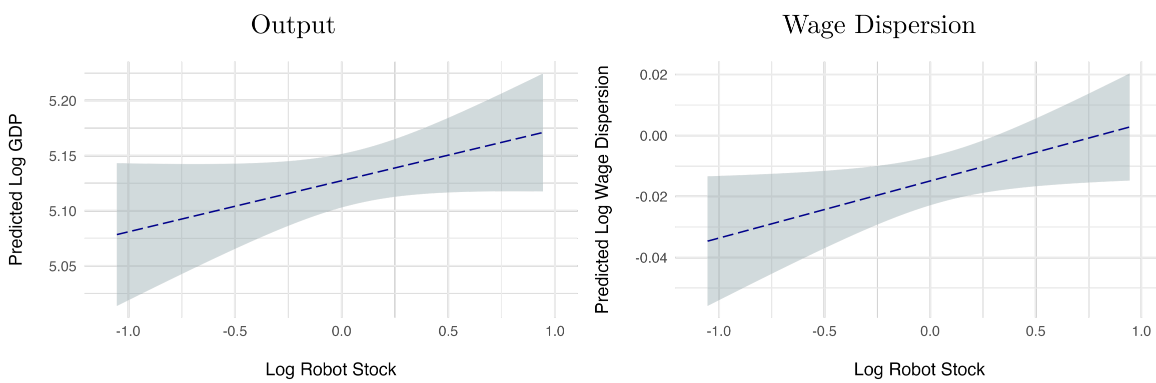
I estimate the following equation:

$$y_d = \alpha + \beta Log\ Robots_d + \varepsilon_d. \tag{3}$$

[6]This HHI definition used here implies that each country is a market in which sellers compete. Although this is reasonable for some countries, it may be inadequate for small ones belonging to the same economic or geographical areas. The estimates of equation (2) must be interpreted bearing in mind this caveat. In Section 6, I propose a definition of markets that addresses this issue.

y_d is either the log GDP of country d or the log ratio of labor value added in services to manufacturing in that country. I use labor value added as a proxy for average wages, and interpret a higher ratio as greater wage dispersion between sectors. *Log Robots*$_d$ is the log stock of robots in country d, while ε_d denotes the error term. The parameter of interest is β, which captures the marginal change in y_d as more robots are adopted in country d. I standardize the log stock of robots to have zero mean and unit variance in the sample. Therefore, α measures the outcome variable in the average country in terms of log stock of robots. Figure 3 shows the predicted values of equation (3) and the corresponding 95% confidence interval.

Figure 3. Robots, Output and Wage Dispersion



Note: The left panel of the figure plots the predicted log GDP of country d as a function of the log stock of robots in that country. The right panel of the figure plots the predicted log ratio of labor value added in services to manufacturing in country d as a function of the same log stock of robots. I use labor value added as a proxy for average wages, and interpret a higher ratio as greater wage dispersion between sectors. I standardize the log stock of robots to have zero mean and unit variance in the sample, and I plot the predicted values over its $[-1, 1]$ interval. Equation (3) is estimated via OLS.

The first column of Table B.4 indicates that a one-unit standard deviation increase in the log stock of robots correlates with a 2% higher GDP. This correlation is robust to controlling for log population, a shown in the second column. The third column of Table B.4 shows that a one-unit standard deviation increase in the log stock of robots correlates with a 0.5% wage dispersion increase. Also in this case, the correlation is robust to controlling for log population, as shown in the last column. Altogether, Figure 3 suggests that countries using more robots are characterized by higher total output and greater wage dispersion. The model replicates this fact and generates the correlations in Figure 3 as an equilibrium outcome.

5 Theoretical Framework

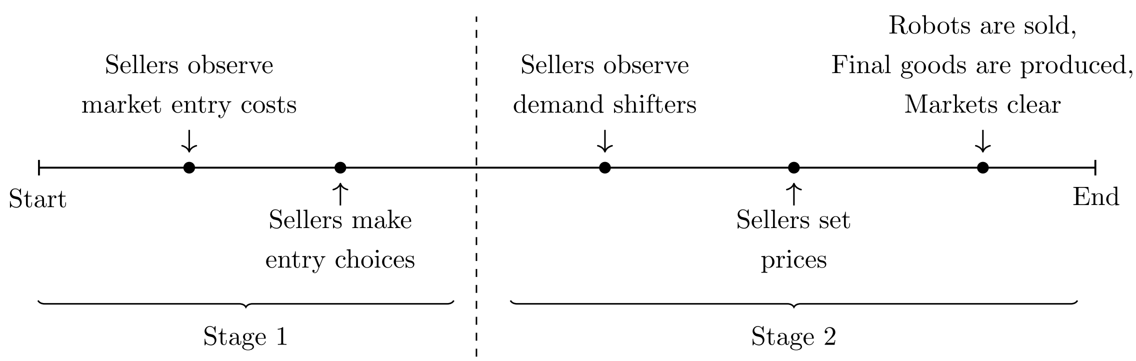
This section contains a general equilibrium multi-country model accounting for the features of the robot industry.

5.1 Economic Environment

Set Up. The economy consists of $\mathcal{M}$ markets, denoted by o (origin) or d (destination). Each market consists of households and final goods producers. Households buy final goods and supply either routine (r) or non-routine (n) labor inelastically. Final goods, produced by perfectly competitive firms using robots and both types of labor, are sold domestically or abroad. A set of $\mathcal{S}$ oligopolistic multinational sellers, each denoted by s, is active in robot industry. Robot sellers differ in terms of their appeal to final goods producers.

There are two stages. In the first, after observing market entry costs, robot sellers decide which markets to serve. In the second, conditional on entry, sellers compete to sell robots to local final goods producers. I denote $M_s \subseteq \mathcal{M}$ the set of markets that s enters and $S_d \subseteq \mathcal{S}$ the set of active sellers in a market. The sets S_d and M_s are determined in equilibrium, whereas $\mathcal{S}$ and $\mathcal{M}$ are exogenous and held constant throughout. Figure 4 shows the timeline of the events.

Figure 4. Timeline of the Events



Note: The figure shows the timeline of the events in the model.

Robot sellers make profits in equilibrium. Following Chaney (2008), I assume that profits are redistributed to households in destination markets proportionally to their labor income.

Households' Preferences. The utility of households of type $i \in \{r, n\}$ living in market d is:

$$C_d(i) = \left(\sum_{o \in \mathcal{M}} C_{od}(i)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \qquad \theta > 1. \tag{4}$$

$C_{od}(i)$ denotes the consumption level of final goods originating from o that households of type i consume in d. The parameter θ is the elasticity of substitution across goods. The disposable income of households of type i is:

$$E_d(i) = w_d(i)\bar{L}_d(i) + s_d(i)\Pi. \tag{5}$$

$w_d(i)$ denotes the market wage of households of type i and $\bar{L}_d(i)$ is their exogenous labor supply. Households also receive a share $s_d(i)$ of robot sellers' profits, denoted by Π, proportionally to their labor income:

$$s_d(i) = \frac{w_d(i)\bar{L}_d(i)}{\sum_{d \in \mathcal{M}} \sum_{i \in \{n,r\}} w_d(i)\bar{L}_d(i)}. \tag{6}$$

Final Goods Production. To produce final goods, perfectly competitive firms combine robots R_d, routine workers $L_d(r)$, and non-routine workers $L_d(n)$. R_d is a substitute of $L_d(r)$ and a complement to $L_d(n)$. Final goods are produced using technology:

$$Y_d = A_d X_d^{\beta} L_d(n)^{1-\beta}, \quad X_d = \left(R_d^{\eta} + L_d(r)^{\eta}\right)^{\frac{1}{\eta}}, \qquad \beta \in (0,1), \quad \eta \in (0,1]. \tag{7}$$

A_d denotes total factor productivity. The elasticity of substitution between R_d and $L_d(r)$ is $1/(1-\eta)$. Following Guerreiro et al. (2022), Appendix E.2 shows that equation (7) can be derived from a task-based model as in Acemoglu and Restrepo (2018). The income share accruing to non-routine labor is $1 - \beta$.

The Robot Industry. Multinational robot sellers make two decisions. First, upon paying an entry cost, they choose which markets to serve. Second, conditional on entry, sellers compete to sell an indivisible bundle of generic robots and integration services to final goods producers. The bundle offered by seller s in market d is called a "product" and denoted by R_{sd}. Due to the crucial role played by integration services, products are considered non-tradable and created in the same market where they are sold.[7] Final goods producers in each market combine robot sellers' products as:

$$R_d = \left(\sum_{s \in S_d} \phi_{sd}^{\frac{1}{\sigma}} R_{sd}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1. \tag{8}$$

Robot sellers are horizontally and vertically differentiated. Horizontal differentiation stems, among others, from the fact that sellers have their brands and may occupy different locations within a market. The elasticity of substitution between their products is σ. The source of vertical differentiation is ϕ_{sd}, a demand shifter capturing sellers' appeal to final goods producers in a market. For instance, sellers that provide more integration services may have a higher ϕ_{sd}. Robot sellers compete à la Bertrand in each market. As is standard in the literature of oligopolistic competition in general equilibrium (e.g., Atkeson and Burstein, 2008; Gaubert and Itskhoki, 2021), sellers take into account the effects of their choices on their market shares and those of their competitors, but not on economy-wide variables. Robot sellers hire local non-routine labor to pay entry costs f and sell products. Their gross and net profits are, respectively:

$$\bar{\pi}_{sd} = (r_{sd} - w_d(n))R_{sd} \qquad \text{and} \qquad \pi_{sd} = \bar{\pi}_{sd} - w_d(n)f. \tag{9}$$

r_{sd} is the price set by seller s in market d. Aggregate profits are $\Pi = \sum_{d \in \mathcal{M}} \sum_{s \in S_d} \pi_{sd}$.

International Trade. International trade in final goods is subject to iceberg trade costs. The cost of delivering one unit of good from origin o to destination d is $P_{od} = \tau_{od} p_o$, where $\tau_{od} \geq 1$ and the triangle inequality holds. I denote by p_o the producer price index associated with equation (7).

5.2 Equilibrium

Households. Households choose $C_{od}(i)$ to maximize equation (4) subject to equations (5) and (6). Solving their problem delivers the following expenditure function, which governs bilateral trade flows in final goods between markets:

$$P_{od} C_{od}(i) = \left(\frac{P_{od}^{1-\theta}}{\sum_{o \in \mathcal{M}} P_{od}^{1-\theta}} \right) (w_d(i) \bar{L}_d(i) + s_d(i) \Pi). \tag{10}$$

[7] In Appendix E.3, I extend the model and allow generic robots to be produced in one market and exported to another, where they are sold bundled with integration services.

Final Goods Producers. Final goods producers choose R_d, $L_d(r)$, and $L_d(n)$ to maximize profits. Solving their problem yields the following input demand functions:

$$R_d = \frac{\beta \bar{\iota}_d p_d Y_d}{r_d}, \qquad L_d(r) = \frac{\beta(1-\bar{\iota}_d) p_d Y_d}{w_d(r)}, \qquad L_d(n) = \frac{(1-\beta) p_d Y_d}{w_d(n)}. \tag{11}$$

The variable $\bar{\iota}_d$ denotes the share of X_d^η produced by robots:

$$\bar{\iota}_d = \frac{R_d^\eta}{R_d^\eta + L_d(r)^\eta}. \tag{12}$$

The producer price index associated with equation (7) is:

$$p_d = \frac{\bar{\beta}}{A_d} \left[\bar{\iota}_d^\eta r_d^{-\eta} + (1-\bar{\iota}_d)^\eta w_d(r)^{-\eta} \right]^{-\frac{\beta}{\eta}} w_d(n)^{1-\beta}. \tag{13}$$

Where $\bar{\beta} = \beta^{-\beta}(1-\beta)^{\beta-1}$.

Robot Sellers: Pricing. Equations (8) and (11) imply the following robot demand:

$$R_{sd} = \phi_{sd} r_{sd}^{-\sigma} r_d^{\sigma-1} \beta \bar{\iota}_d p_d Y_d. \tag{14}$$

Sellers set r_{sd} to maximize equation (9) given equation (14). Equilibrium prices are:

$$r_{sd} = \frac{\varepsilon_{sd}}{\varepsilon_{sd}-1} w_d(n). \tag{15}$$

Markups are defined as $\mu_{sd} = \varepsilon_{sd}/(\varepsilon_{sd}-1)$, where ε_{sd} is the own-price demand elasticity. Under Bertrand competition the demand elasticity reads:[8]

$$\varepsilon_{sd} = \sigma - (\sigma-1) s_{sd}. \tag{16}$$

The market share of seller s in market d, denoted by s_{sd}, is given by:

$$s_{sd} = \frac{\phi_{sd} r_{sd}^{1-\sigma}}{\sum_{s \in S_d} \phi_{sd} r_{sd}^{1-\sigma}}. \tag{17}$$

Equations (15), (16), and (17) describe robot sellers' pricing strategies. Although this system does not have a closed-form solution, it implies that sellers with higher ϕ_{sd} have

[8]Under Cournot competition, the elasticity is $\varepsilon_{sd} = \left[\frac{1}{\sigma}(1-s_{sd}) + s_{sd}\right]^{-1}$.

higher market shares, face less elastic demand, and charge higher markups at a given equilibrium. The price index associated with equation (8) is:

$$r_d = \left(\sum_{s \in S_d} \phi_{sd} r_{sd}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{18}$$

Robot Sellers: Entry. To ensure the uniqueness of the equilibrium of the entry game, I let robot sellers make entry choices in decreasing order of ϕ_{sd}. Equation (9) implies that the profits of each seller are decreasing in the number its competitors. Let j be the last seller who finds it profitable to enter market d, and let j' be the next potential entrant. The following break-even condition must hold in each market:

$$\bar{\pi}_{jd} \geq w_d(n) f_d > \bar{\pi}_{j'd}. \tag{19}$$

Equation (19) pins down the equilibrium number of robot sellers. In Section (6), I will assume that ϕ_{sd} is a draw from a distribution with seller-specific mean. Since the realized demand shifters have a market-specific component, the order in which sellers enter is allowed to differ by market. Still, sellers with higher average appeal enter more markets. In the model, a multinational is a seller present in least two markets.

Market Clearing Conditions. A market equilibrium consists of a vector of prices $\{r_d, w_d(n), w_d(r)\}$ such that households maximize utility, final goods producers and robot sellers maximize profits, and markets clear. The market clearing conditions to be fulfilled in each market are:

$$p_o Y_o = \sum_{d \in \mathcal{M}} \sum_{i \in \{n,r\}} \left(\frac{P_{od}^{1-\theta}}{\sum_{o \in \mathcal{M}} P_{od}^{1-\theta}} \right) (w_d(i) \bar{L}_d(i) + s_d(i)\Pi), \tag{20}$$

$$\bar{L}_d(r) = \frac{\beta(1 - \bar{\iota}_d) p_d Y_d}{w_d(r)}, \tag{21}$$

$$\bar{L}_d(n) = \frac{(1-\beta) p_d Y_d}{w_d(n)} + R_d + |S_d| f. \tag{22}$$

Equation (20) is the final goods market clearing condition. As standard in trade models, the nominal output of market o is pinned down by the international demand for its goods. Equations (21) and (22) govern the equilibrium of the markets for routine and non-routine labor, respectively. $|S_d|$ is the number of active sellers in market d. By

Walras' law, one of the market clearing conditions is redundant. In practice, I choose $w_d(n)$ in one market as the numéraire and discard the corresponding non-routine labor market clearing condition.

5.3 The Role of Market Structure in the Robot Industry

This section provides insights into how robot sellers' market entry and pricing choices affect equilibrium outcomes. I proceed in three steps. First, I consider a closed economy with symmetric sellers, for which an analytical solution can be derived. Then, I extend the example to a two-market economy with international trade in final goods. Finally, I argue that the insights of these restricted models continue to hold in the general case with heterogeneous sellers and multiple markets. Derivations are in Appendix E.4.

Symmetric Sellers and Closed Economy. Let $|\mathcal{M}| = 1$ and $\phi_{sd} = \phi$. Variables' subscripts can be omitted. Sellers' prices admit the following closed-form solution:

$$r = \frac{\varepsilon}{\varepsilon - 1} w(n), \qquad \varepsilon = \sigma - (\sigma - 1)s, \qquad s = \frac{1}{|S|}. \tag{23}$$

Let $\eta = 1$ for simplicity but without loss of generality. Let $w(n)$ be the numéraire. The industry-level robot price and price index functions become:

$$\check{r} = |S|^{\frac{1}{1-\sigma}} \phi^{\frac{1}{1-\sigma}} r, \qquad p = \frac{\bar{\beta}}{A} \check{r}^{\beta}. \tag{24}$$

Notice that $\eta = 1$ implies $\check{r} = w(r)$. Suppose that a new robot seller enters this economy. Treating the number of sellers as a continuous variable for simplicity, equation (23) implies that entry reduces incumbents' prices:

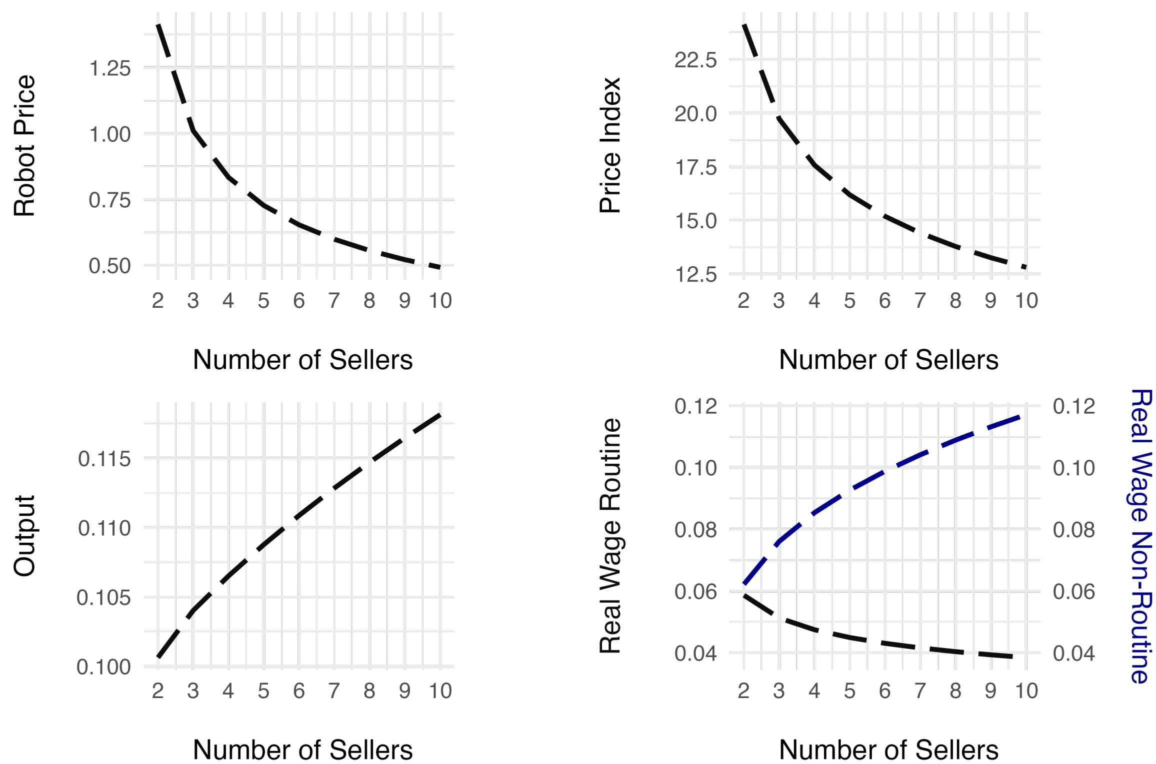
$$\frac{\partial r}{\partial |S|} \frac{|S|}{r} = \frac{1 - \sigma}{\varepsilon(\varepsilon - 1)|S|} < 0. \tag{25}$$

Equation (24) implies that entry also reduces the aggregate robot price and price index:

$$\frac{\partial \check{r}}{\partial |S|} \frac{|S|}{\check{r}} = \frac{1}{1 - \sigma} + \frac{1 - \sigma}{\varepsilon(\varepsilon - 1)|S|} < 0, \qquad \frac{\partial p}{\partial |S|} \frac{|S|}{p} = \frac{\beta}{1 - \sigma} + \frac{\beta(1 - \sigma)}{\varepsilon(\varepsilon - 1)|S|} < 0. \tag{26}$$

As a result, robot demand and total production Y increase, and so does wage inequality, defined as $w(n)/w(r)$, because $w(r)$ decreases at the same rate of $\check{r}$. Therefore, more competition in the robot industry generates an efficiency-versus-equity trade-off. Figure 5 provides a numerical example, treating $|S|$ as an integer.

Figure 5. Entry in the Robot Industry - Closed Economy

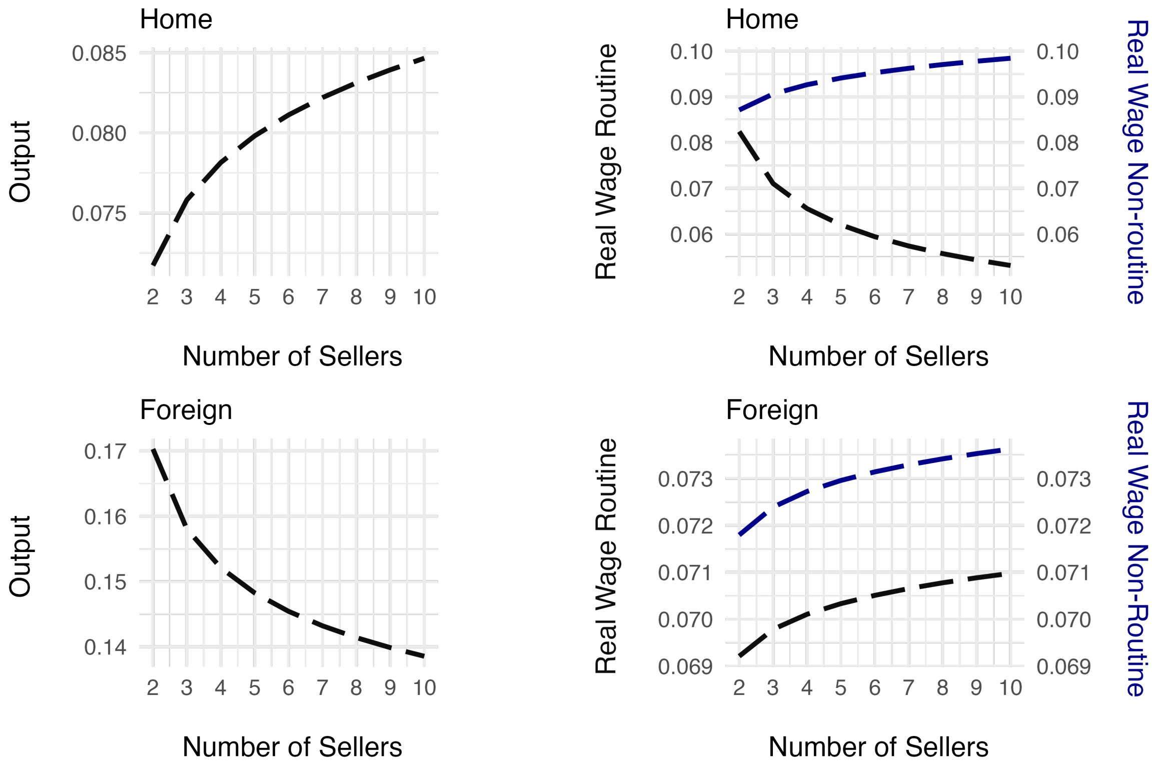


Note: I simulate an economy consisting of one market initially hosting two symmetric robot sellers. I set $\bar{L}(n) = \bar{L}(r) = 1$, $A = 0.1$, and choose model parameters to match those in Section 6. For the numéraire, I use $w(n) = 1$. Then, I progressively increase the number of robot sellers, recompute the equilibrium allocation each time, and show the effects of entry on different outcomes.

Symmetric Sellers and Two-Market Economy. While keeping $\phi_{sd} = \phi$ and $\eta = 1$, I now let $|\mathcal{M}| = 2$ and denote markets by Home (H) and Foreign (F), respectively. Let $w_H(n)$ be the numéraire. Suppose that new sellers enter Home. Since equations (23) and (24) continue to hold in Home, entry delivers similar effects to those described in the closed-economy case in that market.

What happens in Foreign? Because markets are connected via international trade in final goods, a reduction in p_H makes all households increase imports from Home as per equation (10), reducing the total output of Foreign. However, by reducing the cost of imported goods, entry in Home increases the real wage of all households in Foreign. Figure 6 provides a numerical example, treating again $|S|$ as an integer. The top panels show the effects in Home, while the bottom ones the effects in Foreign.

Figure 6. Entry in the Robot Industry - Open Economy



Note: I simulate an economy consisting of two markets initially hosting two symmetric robot sellers each. I set $\bar{L}_d(i) = 1$ for all (i, d), $A_d = 0.1$ for all d, and $\tau_{od} = 1$ if $o = d$ and $\tau_{od} = 1.05$ if $o \neq d$. I choose model parameters to match those in Section 6. For the numéraire, I use $w_H(n) = 1$. Then, I progressively increase the number of robot sellers in Home, recompute the equilibrium allocation each time, and show the effects of entry in Home on different outcomes in Home and Foreign.

The General Case. The outcomes shown in Figure 6 also apply to the case of multiple countries. While it provides analytical tractability, sellers' symmetry is not necessary to generate the predictions in Figures 5 and 6. As long as sellers enter in decreasing order of ϕ_{sd}, the same patterns persist. However, the impact of entry in a single market on the rest of the world is more diluted.

Taking stocks, the model predicts that the entry of new sellers in a market boosts competition, leading to an increase in robot adoption and output in that market. To the extent that markets are linked via international trade, such expansion comes at the expense of production in other markets. Given the non-neutrality of robots, these gains and losses are not evenly distributed across workers.

6 Quantification

This section discusses estimation, identification, and model fit.

6.1 Empirical Implementation

Market Definition. I use a K-means algorithm to aggregate the original 45 countries into larger sub-entities corresponding to markets in the model. The purpose of the aggregation is twofold. First, it accounts for the fact that robot sellers may use branches in one country to serve adopters in adjacent ones, which may happen especially in small countries within the same geographical and economic areas (e.g., Belgium and The Netherlands). Second, it reduces the dimensionality of the robot sellers' entry problem while preserving size differences across markets.

The algorithm merges countries with similar latitude and longitude and belonging to the same continent and creates 12 markets. I choose this number to balance between interpretable clusters and dimensionality reduction. The merged markets inherit the average characteristics of the countries belonging to them, and I sum the number of branches across countries by seller before computing market shares.

Figure A.7 shows the result of the clustering procedure. The European continent is divided into three markets approximately corresponding to eastern countries (e.g. Austria and Hungary), western-northern countries (e.g., Germany and Sweden), and central-southern countries (e.g., Italy and France).[9] Asia is divided into two markets. The first includes China and India, and the second Japan and South Korea. South America is also divided into two markets, one including central countries (e.g., Mexico and Colombia) and one made of central-southern ones (e.g., Brazil and Argentina). Australia and New Zealand belong to the same market, whereas the US, Canada and South Africa constitute separate ones.

Exogenous Variables. The model features the following exogenous variables: the number of routine workers, $\bar{L}_d(r)$, the number of non-routine workers, $\bar{L}_d(n)$, the productivity of the final goods producers, A_d, and bilateral trade costs, τ_{od}. The first three variables come from the WDI database of the World Bank. I approximate $\bar{L}_d(r)$ using total employment in manufacturing and $\bar{L}_d(n)$ using total employment in the services

[9] I define Europe according to the geographical definition provided by the United Nations, rather than the political definition based on EU member states. This approach simplifies the classification of countries such as Switzerland and Norway during the clustering process.

sector. This approximation is justified by the fact that 99% of the stock of robots in the IFR data was employed in manufacturing in 2019. Moreover, the IFR does not report any adoption of robots in services, implying that workers in that sector cannot be replaced by robots. I compute A_d using the weighted average of labor productivity in manufacturing and services, where the weights are given by the employment share of each sector. Trade costs τ_{od} come from the ESCAP World Bank database.

6.2 Estimation Procedure and Identification

Each block of the model (households, final goods producers, and robot sellers) is governed by the respective set of parameters. Households' choices depend on the trade elasticity, $1-\theta$. The choices of final goods producers depend on the elasticity of substitution between robots and routine workers, $1/(1-\eta)$, and the production share of non-routine workers, $1-\beta$. Robot sellers' choices are governed by the demand shifters, ϕ_{sd}, the elasticity of substitution between products, σ, and market-level entry costs, f. The parameters of the first two blocks are standard and can be calibrated from previous literature and the data. The parameters of the last block are new, and I use a simulated method of moments (SMM) algorithm to estimate them.

Calibration. As standard in the international trade literature, I set $\theta = 5$ to obtain a trade elasticity of -4 (Simonovska and Waugh, 2014; Head and Mayer, 2014). Following Guerreiro et al. (2022), I let $\eta = 1$. I calibrate β to match the average labor share in the data. In the model, the (manufacturing) labor share in market d is given by $ls_d = 1 - \beta\bar{\iota}_d$. I measure ls_d using SDG UN. I compute $\bar{\iota}_d$ using equation (12) and data from the IFR and WDI, expressing the number of routine workers in hundred units. The value of β that satisfies the definition is 0.6. This value is slightly larger than the 0.52 value estimated by Guerreiro et al. (2022) for the US. This difference can be explained by the fact that most countries in my sample are less services-intensive than the US.

Simulated Method of Moments. Sellers draw ϕ_{sd} from the following log-normal distribution, with mean and variance to be estimated:

$$\log \phi_{sd} = \phi_i + \kappa \log \text{Distance from HQ}_{sd} + \zeta u_{sd}, \quad i \in \{\text{Top 4}, \text{Rest}\}. \tag{27}$$

The demand shifter of seller s in market d is a function of its average appeal, the physical distance of market d from its HQ, and an i.i.d. normally distributed random shock with zero mean and unit variance. To minimize the computational burden of the SMM procedure, instead of estimating the average appeal of each seller, I let the top 4 sellers in the data (ABB, Kuka, Fanuc, and Yaskawa) draw demand shifters from a distribution with a potentially higher mean than the others, i.e., I expect $\widehat{\phi}_{\text{Top 4}} \geq \widehat{\phi}_{\text{Rest}}$. Moreover, I expect $\widehat{\kappa} < 0$ based on the first fact in Section 4. The vector of parameters to be estimated is $\Theta = \{\phi_{\text{Top 4}}, \phi_{\text{Rest}}, \kappa, \zeta, \sigma, f\}$.

The SMM procedure consists of a loop with three nests: an outer loop searching over the vector of parameters Θ, a middle loop solving the model general equilibrium allocation, and an inner loop finding the solution to the robot sellers' problem. For each candidate vector Θ, I draw B matrices of ϕ_{sd} from equation (27),[10] solve the model at each draw, and compute the model-implied moments $m(\Theta)$ as an average across draws. Then, I match simulated moments to the data ones $\bar{m}$ to minimize the SMM objective function $\mathcal{L}(\Theta) = (m(\Theta) - \bar{m})' W (m(\Theta) - \bar{m})$, being W a weighting matrix.

Solving the model is challenging due to the interdependence of the inner and middle loops. This feedback is disciplined by guessing a vector of wages for each market, solving the robot sellers' problem in each of them, and iterating until a fixed point is reached. Convergence of inner loop entails a discrete search over the number of incumbent sellers, as per equation (19), and a non-linear search over their prices in equation (15). Convergence of the middle loop is achieved by a linear inversion of equations (20), (21), and (22), which reduces the computational burden of the search. See Appendix F for more details about the model solution and the SMM procedure.

Identification. I target eight data moments to estimate six parameters. The selected moments are informative about robot sellers' entry choices (i.e., number of served markets and their distance from the HQ), their sales (i.e., market shares), competition (i.e., number of sellers by market), and market size (i.e., number of robots adopted). I assign equal weight to each moment by choosing W to be the identity matrix.

Although the structural parameters are jointly estimated, each of them is informed in an intuitive way by distinct targeted moments. The parameter $\phi_{\text{Top 4}}$ serves to match the average log number of markets entered by the top 4 robot sellers and their average market shares, whereas ϕ_{Rest} helps matching those of the other sellers. All else

[10] I use $B = 50$. I draw normally distributed i.i.d. shocks u_{sd} using Sobol sequences to cover the support of the normal distribution more efficiently than if points were randomly drawn (Train, 2009).

equal, higher values of both parameters translate into more entered markets and higher market shares. The parameter κ is chosen to replicate the average log distance between the robot sellers' HQ and the markets they enter, while ζ aids matching the standard deviation of the distribution of market shares across sellers. A higher κ reduces robot sellers' appeal in more distant markets, whereas a higher ζ makes the realized demand shifters more sensitive to i.i.d. shocks and less to fundamentals.

I choose σ to match the average log stock of robots in the data. Identification rests on the fact that all else equal, higher σ translates into lower markups, lower prices, and a higher number of robots adopted. Finally, f serves to match the average log number of robot sellers per market. A higher f reduces the number of entrants.

6.3 Estimation Results

Model Parameters. Table 2 reports the calibrated and estimated parameter values.

Table 2. Summary of the Model Parameters

Parameter	Description	Value	95% CI	Source/Target
Calibrated				
θ	Trade Elasticity	5.00		Head and Mayer (2014)
β	Income Share of $L_d(r)$ and R_d	0.60		WDI and SDG UN
η	$L_d(r)$ vs R_d Elasticity	1.00		Guerreiro et al. (2022)
Estimated				
ϕ_H	Average Demand Shifters (Top 4)	1.86	[1.74, 4.21]	Mean Log Markets and Mkt Shares (Top 4)
ϕ_L	Average Demand Shifters (Rest)	1.19	[0.85, 3.16]	Mean Log Markets and Mkt Shares (Rest)
κ	Elasticity to Dist. from HQ	-0.75	[-1.51, -0.69]	Mean Log Dist. from HQ
ζ	Demand Shifters St. Dev.	0.98	[0.42, 2.77]	St. Dev. Market Shares
f	Market-Level Entry Costs	0.69	[0.26, 2.42]	Mean Log No. of Sellers by Market
σ	Elasticity of Substitution b/ween R_{sd}	2.50	[2.31, 5.59]	Mean Log Stock of Robots

Note: The table contains the values of the parameters of the model. The top panel reports the value of the parameters calibrated without solving the model. The bottom panel contains those estimated by the SMM procedure. Bootstrap standard errors in parenthesis are computed using the method of Bernard et al. (2022), which I describe in Appendix F.2.

As expected, the top 4 robot sellers have higher average appeal than the others. Moreover, robot sellers' appeal to final goods producers decreases as they enter markets more distant from their HQ. On average, nominal entry costs amount to about 23% of robot sellers' revenues. The estimated value of σ implies a markup of approximately 70% at the average sample market shares, which falls at the higher end of the range provided by the literature in other industries (De Loecker et al., 2020).

Model Fit. Table 3 shows that the model accurately matches the targeted moments. Table 4 demonstrates that the model also replicates moments not targeted during the

Table 3. Simulated vs Data Moments

Description	**Simulated Moments**	**Data Moments**
Mean Log No. of Markets (Top 4)	2.32	2.29
Mean Log No. of Markets (Rest)	2.12	2.07
Mean Market Share (Top 4)	0.17	0.17
Mean Market Share (Rest)	0.10	0.12
Mean Log Dist. from HQ	9.05	9.01
St. Dev. Market Shares	0.05	0.07
Mean Log No. of Sellers by Market	1.91	1.99
Mean Log Stock of Robots	4.71	4.71

Note: The table reports the data moments targeted by the SMM procedure and the simulated ones implied by the estimated model. The stock of robots is expressed in thousand units in the data. The value of the SMM objective function at the solution is 0.01.

SMM procedure. The first column shows the log of robot sellers' total sales, while columns 2, 3, and 4 contain the average HHI, the average log of GDP per capita, and the average log of export values across markets, respectively. The null hypothesis of equal means cannot be rejected for any outcome.

Table 4. Model Fit on Non-Targeted Moments

	Log Sales$_s$	HHI$_d$	GDP per capita$_d$	Export Values$_d$
Data	8.17	0.27	10.0	10.6
Model	7.79	0.21	11.6	11.3
P-value	0.51	0.41	0.56	0.79

Note: The table shows the model fit non non-targeted moments. Columns contain moments. The first row contains their average data value, while the second row shows their model-implied average value. The last row is the p-value associated with the null hypothesis that these two values are equal.

Finally, the model replicates the dispersion in robot prices across markets observed in the data. The correlation between the model-implied robot prices calculated using equation (18) and the import prices (unit values) obtained from the BACII dataset equals 84%. Overall, these results support the model's reliability in capturing salient features of the robot industry and the global economy.

7 A Tax on Robot Adoption

This section discusses the effects of policies targeting the adoption of robots.

7.1 Design and Implementation

The Debate in the European Union. In 2017, the EU Parliament debated the introduction of a tax on automation technology, including robots, to mitigate its potential adverse effects on employment and wages of directly exposed workers. In particular, the Committee on Legal Affairs of the European Parliament was concerned that "*[...] the development of robotics and AI may result in a large part of the work now done by humans being taken over by robots, so raising concerns about the future of employment*".[11] Although the proposal was ultimately voted down, discussions about policies regulating (or encouraging) the adoption of automation technology continue to pervade the academic and policy debates (Brynjolfsson and McAfee, 2014; Shiller, 2017; Acemoglu and Johnson, 2023). Inspired by them, I use the model to evaluate how multinational robot sellers react to policies constraining robot adoption and how their responses shape the outcomes of these policies.

Introducing a Tax in the Model. In line with previous literature (Thuemmel, 2022; Guerreiro et al., 2022), I consider the introduction a value-added robot tax paid by robot adopters. Let $t_d \in (0, 1)$ if $d \in$ EU and 0 otherwise. The new price of robots can be expressed as:

$$r_d = \frac{\beta \bar{\iota}_d p_d Y_d}{(1 + t_d) R_d}. \tag{28}$$

Wage equalization between robots and routine workers requires $w_d(r) = (1 + t_d) r_d$. Equation (14) can be modified as:

$$R_{sd} = \phi_{sd} r_{sd}^{-\sigma} r_d^{\sigma-1} \frac{\beta \bar{\iota}_d p_d Y_d}{1 + t_d}. \tag{29}$$

A tax reduces the quantity of robots that final users demand, shrinking the effective size of local robot markets. A tax generates revenues $T_{EU} = \sum_{d \in \mathcal{M}} \mathbb{1}\{d \in EU\} t_d r_d R_d$, which are distributed as a lump-sum payment to EU households.

[11] See https://www.europarl.europa.eu/doceo/document/JURI-PR-582443_EN.pdf?redirect for the full proposal of the Committee on Legal Affairs of the European Parliament.

Counterfactual Scenarios. I consider two counterfactual scenarios. In the first, I assume that robot sellers are unable to adjust their entry choices and markups once the tax is implemented. Therefore, a tax leads to a reduction in the quantity of robots adopted without altering their pre-tax market-level price. This scenario mimics the standard approach in the literature (Humlum, 2021; Beraja and Zorzi, 2022; Thuemmel, 2022; Guerreiro et al., 2022; Costinot and Werning, 2023).

In the second scenario, I allow robot sellers to change the set of markets they serve and the markups they charge in each market. Responses along these margins may amplify or attenuate the effects of a tax. On the one hand, if robot prices strongly respond to local competition, robot sellers' market entry and exit choices may magnify the effects of taxing robot adopters. On the other, robot sellers' ability to change markups, implying imperfect pass-through, may generate attenuation.

For all scenarios, I simulate the introduction of a 5% robot tax, which aligns with the short-run optimal tax rate estimated for the US by Guerreiro et al. (2022). Appendix F.3 describes the algorithm used to perform the counterfactuals.

7.2 Results

The Effects in the EU. Table 5 shows the effects of a 5% EU-wide value-added tax on robot adoption in the average EU market. The table is organized into three panels. Panel A shows how a tax changes the number of robot sellers and the average markup charged by incumbent sellers. Panel B shows the effects on final goods producers. It provides information on the changes in the robot price they pay, the number of robots they use, their production prices, and total output. Panel C focuses on household-level outcomes. It includes changes in wage inequality between non-routine and routine households, as well as their respective real wage. All outcomes are presented as percentage changes relative to the baseline scenario without the tax.

In the first scenario, the number of robot sellers and their markups remain unchanged by design. Final goods producers experience a 4.99% increase in robot prices, leading to a 6.78% reduction in robot demand. Accordingly, unit production costs rise by 2.97% and output decreases by 2.40%. Due to their different substitution patterns with robots, routine households gain 0.21% in real wages, while non-routine households experience a 4.61% real wage loss. Overall, wage inequality is reduced by 4.75%.

In the second scenario, the tax leads to a 4.54% reduction in the number of robot sellers, generating an 0.82% increase in the average markup of the incumbents, denoted

Table 5. The Effects of an EU-wide Robot Tax in the EU

Outcome	Variable	First Scenario	Second Scenario	% Change
Panel A: Robot Sellers				
Number of Sellers	S_d	0.00%	-4.54%	
Markups	$\bar{\mu}_d$	0.00%	0.82%	
Panel B: Final Goods Producers				
Robot Price	r_d	4.99%	5.74%	15.03%
Robot Stock	R_d	-6.78%	-9.80%	44.54%
Producer Price Index	p_d	2.97%	3.19%	7.41%
Output	Y_d	-2.40%	-2.83%	17.92%
Panel C: Households				
Real Wage Routine	$w_d(r)/P_d$	0.21%	0.50%	138.10%
Real Wage Non-Routine	$w_d(n)/P_d$	-4.61%	-5.51%	19.52%
Wage Inequality	$w_d(n)/w_d(r)$	-4.75%	-5.87%	23.58%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average EU market. Panel A shows the effects on robot sellers. Panel B shows the effects on final goods producers. Panel C shows the effects on households. In the first scenario, robot sellers are unable to adjust their entry choices and markups once the tax is implemented. In the second, they can change the set of markets served and the markups charged in each market. In the first two columns, outcomes changes are relative to the initial equilibrium without tax. The last column displays the percentage change in each outcome between the second and first scenario.

as $\bar{\mu} = \frac{1}{|S_d|}\sum_{s\in S_d}\mu_{sd}$. As a result, final goods producers and households experience larger outcome changes compared to the first scenario. Final goods producers face a 5.74% increase in robot prices, 15.03% more than in the first scenario. They also reduce the number of robots used by 9.80%, 44.54% more than in the first case. Production prices rise by 3.19%, and output decreases by 2.83%. These changes are 7.41% and 17.92% larger than those observed in the first scenario, respectively. Wage inequality decreases by 5.87%, representing a 23.58% larger reduction compared to the first scenario. Routine households experience 1.38 times larger gains in real wages, while non-routine ones incur 19.52% greater losses compared to the first scenario.

Overall, a robot tax creates an efficiency-versus-equity trade-off in the EU. Comparing changes across outcomes and between scenarios, allowing sellers to endogenously respond reinforces the effects of a tax by approximately 40% in the average EU market.

The Effects Beyond the EU. Since markets are linked via international trade, a tax also produces effects beyond the EU. Table 6 shows the effects of a 5% EU-wide value-added tax on robot adoption in the average non-EU market.

Table 6. The Effects of an EU-wide Robot Tax Beyond the EU

Outcome	**Variable**	**First Scenario**	**Second Scenario**	**% Change**
Panel A: Robot Sellers				
Number of Sellers	S_d	0.00%	0.24%	
Markups	$\bar{\mu}_d$	0.00%	-0.01%	
Panel B: Final Goods Producers				
Robot Stock	R_d	0.21%	0.23%	9.52%
Output	Y_d	0.21%	0.22%	4.76%
Panel C: Households				
Consumer Price Index	P_d	2.04%	2.22%	8.82%
Real Wage Routine	$w_d(r)/P_d$	-2.34%	-2.70%	15.38%
Real Wage Non-Routine	$w_d(n)/P_d$	-2.36%	-2.69%	13.98%
Wage Inequality	$w_d(n)/w_d(r)$	0.01%	0.03%	200.00%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average non-EU market. Panel A shows the effects on robot sellers. Panel B shows the effects on final goods producers. Panel C shows the effects on households. In the first scenario, robot sellers are unable to adjust their entry choices and markups once the tax is implemented. In the second, they can change the set of markets served and the markups charged in each market. In the first two columns, outcomes changes are relative to the initial equilibrium without tax. The last column displays the percentage change in each outcome between the second and first scenario.

Since an EU-wide robot tax makes EU final goods more expensive, both EU and non-EU households reallocate their expenditures towards non-EU markets, inducing non-EU final goods producers to demand more robots to scale up output. In the first scenario, the average non-EU market experiences a 0.21% increase in total output and in the number of employed robots. Given the non-neutrality of robots, these gains are not evenly distributed, and wage inequality slightly increases. Because the tax makes goods imported from the EU more expensive, the consumer price index rises by 2.04%, and all households experience a real wage loss of about 2.35%.

In the second scenario, the increased demand for robots leads to sellers entering non-EU markets, increasing their number by 0.24% and reducing average incumbents' markups. Consequently, the average non-EU market experiences a 9.52% higher increase in robot adoption and a 4.76% higher increase in output compared to the first scenario. In turn, the increase in wage inequality is twice as large as in the first case. However, as sellers leave EU markets, non-EU households face an 8.82% higher increase in consumer prices compared to the first case, amplifying the loss in real wages of routine and non-routine households by 15.38% and 13.98%, respectively.

Overall, an EU-wide robot tax reallocates the demand for robots from EU to non-

EU markets, boosting production and wage inequality beyond the EU. Similar to Table 6, allowing sellers to endogenously adjust their entry choices and markups reinforces the effects of the tax by approximately 40% across outcomes and between scenarios.

7.3 Further Discussion

The Role of Gravity. The estimated $\widehat{\kappa} < 0$ in Table 2 implies that robot sellers become less attractive to final users as they move away from their HQ. Consequently, one would anticipate that domestic sellers enter their HQ market before foreign sellers, as per equation (19). In this context, an EU-wide robot tax has a disproportionate impact on sellers headquartered outside the EU. Table B.5 provides evidence for this asymmetric effects. In the equilibrium with a tax, the average Asian seller serves 3.88% fewer EU markets than in an equilibrium without. By contrast, the average EU seller experiences a smaller reduction in the number of EU markets served, equal to 0.81%. Exit rates among Asian sellers translate into an average 2.44% reduction in market shares within the EU. In contrast, since exit is less frequent among EU sellers, the average incumbent belonging to this group experiences a 0.50% market share increase.

The Role of International Trade in Final Goods. Table 6 highlights how a local tax can have global effects when markets are linked via international trade and sellers' entry choices. Tables B.6 and B.7 offer additional evidence on the relationship between international trade in final goods and market structure in the global robot industry in transmitting the effects of a local robot tax across the world. Specifically, I compare the second-scenario outcomes in Tables 5 and 6 with those obtained in a counterfactual economy where bilateral trade costs on final goods are 20% higher. Both tables reveal a complementarity between trade costs and market structure: the same robot adoption tax produces smaller effects both in the EU and beyond when trade costs are higher. This happens because higher trade costs lead to lower sensitivity of households' import shares in equation (10) to changes in prices. Consequently, the reallocation of demand for final goods across markets is muted, and so is the reallocation of robot supply.

Optimal Robot Tax. The model can be also used to study optimal taxation on robot adoption, and how it differs depending on the responses of multinational robot sellers. To do so, I assume that an EU social planner chooses τ_{EU} to maximize total households' welfare in EU markets. I define welfare in each market as a Cobb-Douglas of the utility levels of local routine and non-routine households. Formally, the planner has preferences $\sum_{d \in \mathcal{M}} \mathbb{1}\{d \in EU\} C_d(r)^{\alpha} C_d(n)^{1-\alpha}$, $\alpha \in (0,1)$. I solve her problem for a grid of values of α under the two scenarios I consider in Tables 5. Since ignoring the responses of robot sellers underestimates the gains of routine households and losses of non-routine ones, it is ex-ante unclear if the optimal robot tax should be higher or lower in the second scenario at any given α. Table B.8 shows the results. There are two takeaways. First, as expected, the optimal robot tax increases with the weight assigned by the planner to routine workers (α). Second, allowing sellers to adjust their entry choices and markups yields a higher optimal tax for any α. On average, the optimal tax is 13% higher in the second scenario. Interestingly, the optimal tax rates in Table B.8 are consistent with those found by Guerreiro et al. (2022) for the US.

Unilateral Versus Multilateral Taxation. Table B.9 compares the second-scenario outcomes in Tables 5 and 6 with those resulting from a worldwide 5% value-added tax on robot adoption. The table shows that a multilateral robot tax shuts down the asymmetric effects produced by a unilateral one. A worldwide tax indeed reduces the number of active robot sellers (increasing incumbents' markups), output, and wage inequality everywhere. In this sense, a multilateral tax may eliminate the incentives for governments to retaliate against or take advantage of unilateral taxes introduced in foreign jurisdictions.

The Distribution of Outcomes Changes within the EU and non-EU Areas. Tables 5 and 6 show the effects of an EU-wide robot tax in the average EU and non-EU markets. I inspect the distribution of the outcome changes between markets within the EU and non-EU areas in Table B.10. Although there is variation in the magnitude of the changes, their sign is consistent across the different moments of the distribution within each area.

A Subsidy on Robot Adoption. The model can also be easily employed to simulate the effects of subsidizing robots. Following a similar reasoning as for the tax, I examine the implementation of an EU-wide 5% discount on the price of robots paid by final producers funded by taxing EU households. Table B.11 shows the effects in the average EU and non-EU markets, allowing robot sellers to endogenously adjust entry choices and markups once the tax is introduced. As one may expect, all outcomes exhibit the opposite direction compared to Tables 5 and 6.

8 Additional Counterfactuals

This section discusses the effects of policies aimed at boosting competition in the robot industry. It is worth noticing that the model can also be used to study a range of additional policy interventions, such as the implementation of minimum wages, place-based interventions, as well as trade policies.

8.1 Promoting Competition in Robot Sales

The Debate. A tax introduces an (exogenous) wedge between the price charged by robot sellers and the one paid by robot adopters. Given the imperfectly competitive market structure of the robot industry, the model also accounts for another (endogenous) wedge between robot sellers' marginal retail costs and the price they charge to users, i.e., markups.

Recent literature has highlighted that firms' market power, even if confined to specific sectors, can have substantial detrimental effects for the economy as a whole (Edmond et al., 2015; De Loecker et al., 2020; Autor et al., 2020; Edmond, Midrigan and Xu, 2023). In light of this debate, I investigate what are the effects of promoting competition in the robot industry.

Counterfactuals Design and Results. I evaluate the effects of policies aimed at reducing markups in the global robot industry by fostering competition among multinational robot sellers. In particular, I simulate the effects of a 25% reduction in the entry costs that robot sellers must pay to serve each market. I study how this reduction changes competition among robot sellers, output, and wage inequality worldwide. Table B.12 shows the results, again distinguishing between EU and non-EU markets. I present all outcomes as percentage changes relative to the baseline scenario with the initially estimated level of entry costs.

Lowering costs encourages entry in all markets. Increased competition reduces robot sellers' markups and, therefore, robot prices everywhere. Given the non-neutrality of robots, global output gains are paralleled by a worldwide increase in wage inequality. These findings suggest that distortions in the robot sector are potentially large, and their costs are not evenly distributed. Similar to a tax or subsidy on robot adoption, policies aimed at increasing competition in the robot industry are therefore subject to a trade-off between efficiency and equity.

9 Conclusions

Automation technology enhances production but generates concerns about job displacement, leading to an academic and policy debate about the appropriate policies to favor or discourage its adoption. The current debate focuses on how policy interventions impact technology adopters. In this paper, I show that supply-side adjustments to policy changes are sizable and amplify the effects of these policies. I study the global robot industry. This is an ideal setting for two reasons. First, because robots are a leading automation technology. Second, because the industry is highly concentrated, with 10 multinational enterprises accounting for 90% of global sales.

I collect new data about the characteristics and global sales of the leading multinational robot sellers worldwide. Next, I develop and estimate a quantitative multi-country general equilibrium model accounting for the role of multinational robot seller in the robot industry. Using the model, I show that multinational sellers' market entry and pricing responses to policies targeting robot adoption substantially amplify the aggregate and distributional effects of these interventions. Since robot sellers' choices are linked across markets, their responses also transmit the effects of a local policies beyond local borders.

Overall, this paper conveys two messages. First, any policy proposal regarding robot adoption should encompass not just the responses of robot adopters but also consider those of robot sellers. Second, policymakers of different countries may need to coordinate their efforts to avoid unintended ripple effects.

Properly adapted, the theoretical frameworks developed in this paper can be used to investigate the role of market power in other segments of the automation industry and other global input markets.

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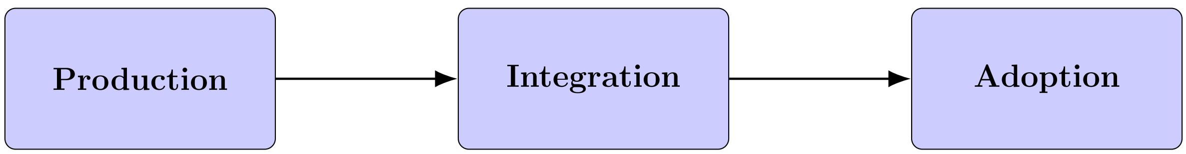
Appendices

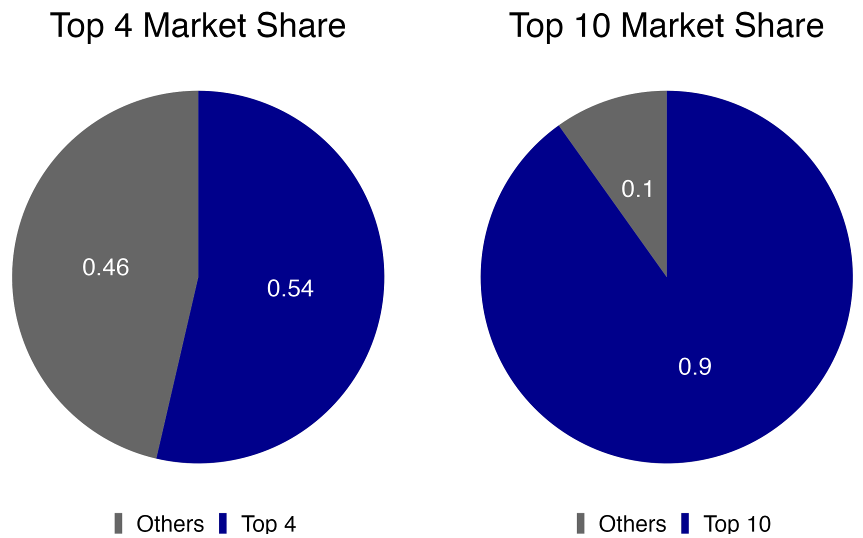
A Figures

Figure A.1. The Supply Chain of Industrial Robots



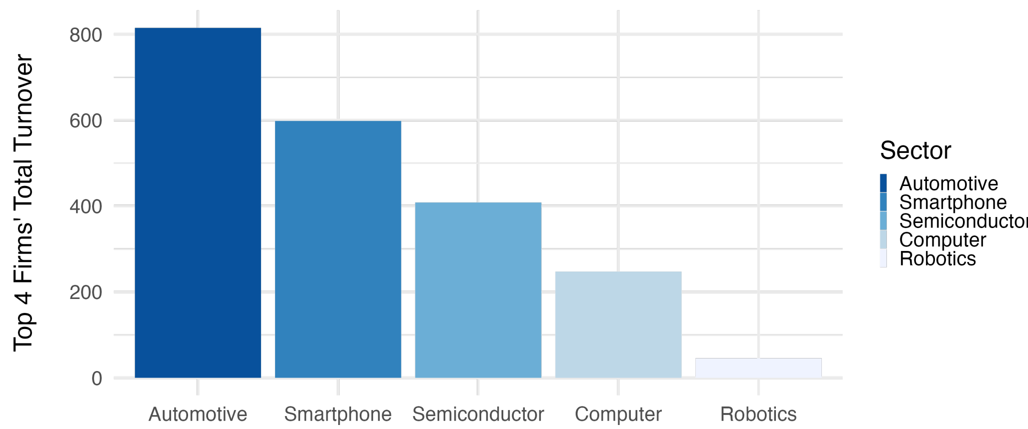
Note: The figure shows the typical supply chain of industrial robots. Nearly half of the world's production of robots takes place in Japan. During the integration stage, final users purchase robots and "integration services" such as customization, installation, and ongoing maintenance from sellers. Robots are typically used by large manufacturing firms.

Figure A.2. Market Shares in the Global Robot Industry



Note: The figure shows market shares in 2021. Robot sellers are also active in other capital-intensive production activities, including the manufacturing of semiconductors, collision sensors, and service and collaborative robots. Since Orbis does not consistently provide a breakdown of sales by sector of activity, I calculated the market shares using the total turnover of the 26 robot sellers registered with the IFR across all their sectors of activity. However, since automation provision is the primary activity of these firms, their total sales are an accurate proxy for their size in the industry.

Figure A.3. Total Turnover of Top 4 Producers by Sector



Note: The figure compares the total revenues (in billion USD in 2021) of the top 4 robot sellers with the total revenues of the top 4 sellers in the automotive, smartphone, semiconductor, and computer industries in terms of revenues in Orbis. The top 4 sellers in the automotive industry are Volkswagen, Toyota, Ford, and General Motors. In the smartphone industry, the top 4 sellers are Apple, Huawei, Xiaomi, and Oppo. The semiconductor industry's top 4 sellers include Samsung, Intel, TSMC, and SK HYNIX. The computer industry's top 4 sellers are Dell, Lenovo, HP, and Acer. It's worth noting that Samsung is also a top smartphone seller. However, the ranking in the figure remains unchanged whether I include Samsung in the smartphone industry or exclude it from the sample. To compile these lists, I used Orbis Bureau van Dijk in the following manner: First, I identified the industry code associated with each of the four industries under consideration. Second, I retrieved all firms that reported one of these four codes as their main sector of activity. Third, within each sector, I ranked firms based on their total revenues and selected the top 4. It's important to mention that Orbis does not consistently report revenues by sector of activity. Therefore, I assigned firms to one sector only while creating the ranking based on the total revenues from all their activities.

Figure A.4. Examples of Websites with Information about Branches

Example 1: A Branch of Kuka

KUKA Systems North America LLC.

6600 Center Drive
Sterling Heights, MI 48312
USA

Google Maps

Example 2: A Branch of ABB

TSR Solutions LLC

Contact information

Address:
9490 ASPEN HILL CIR
80124 LONE TREE
United States

Address in Local language:
9490 ASPEN HILL CIR
80124 LONE TREE
United States

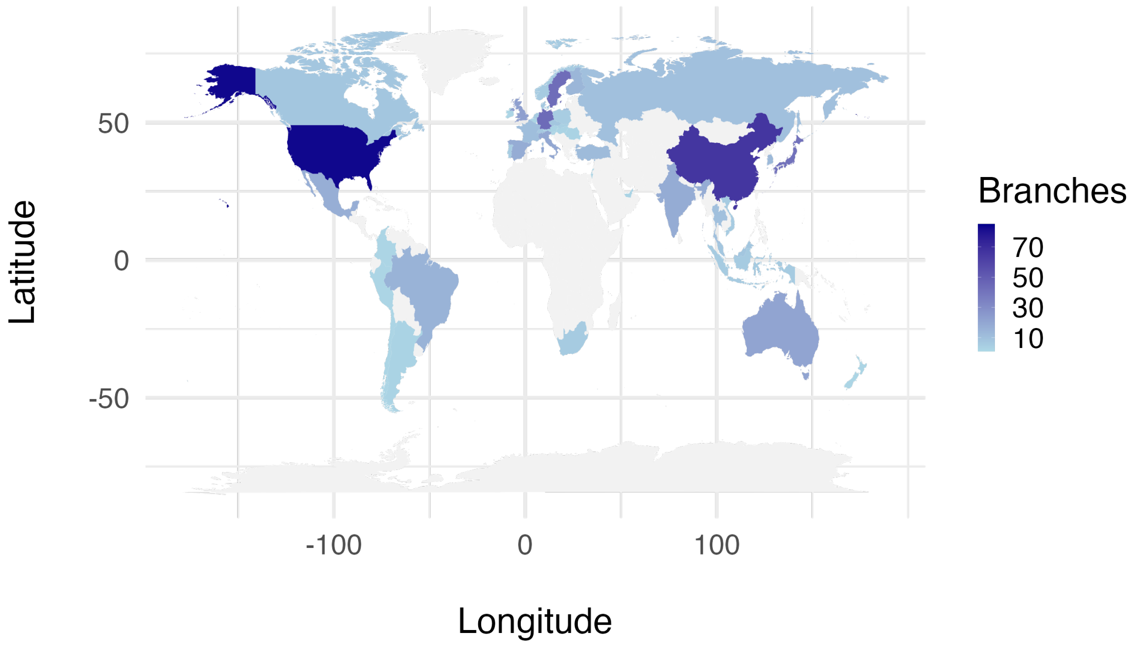
Website: http://tsrsolutions.co
Phone: +1 720 480-3484
Email: sales@tsrsolutions.co

List of authorized area

Product	Robotics
Partnership	ABB Value Provider
Channel type	System Integrator
Countries Served	United States
Product Line	Electrical & electronics (3C)
	Robotics

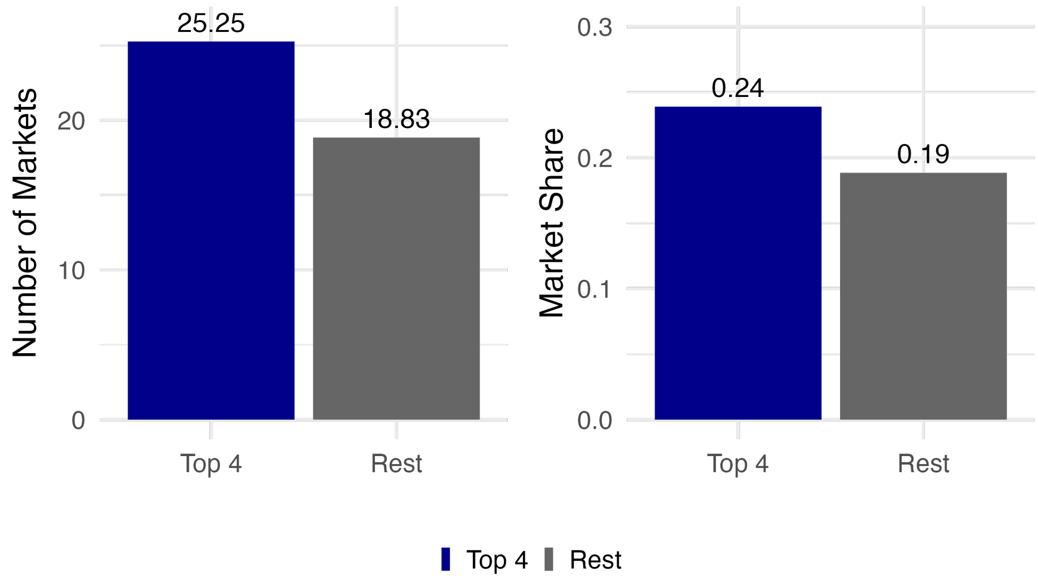
Note: The figure shows an example of a website containing information about robot sales branches. The typical information displayed is the branch name and address, as in Example 1. Sometimes, additional information like the telephone number, web address, list of countries served, and product lines are reported, as in Example 2.

Figure A.5. The Global Footprint of Robot Sellers



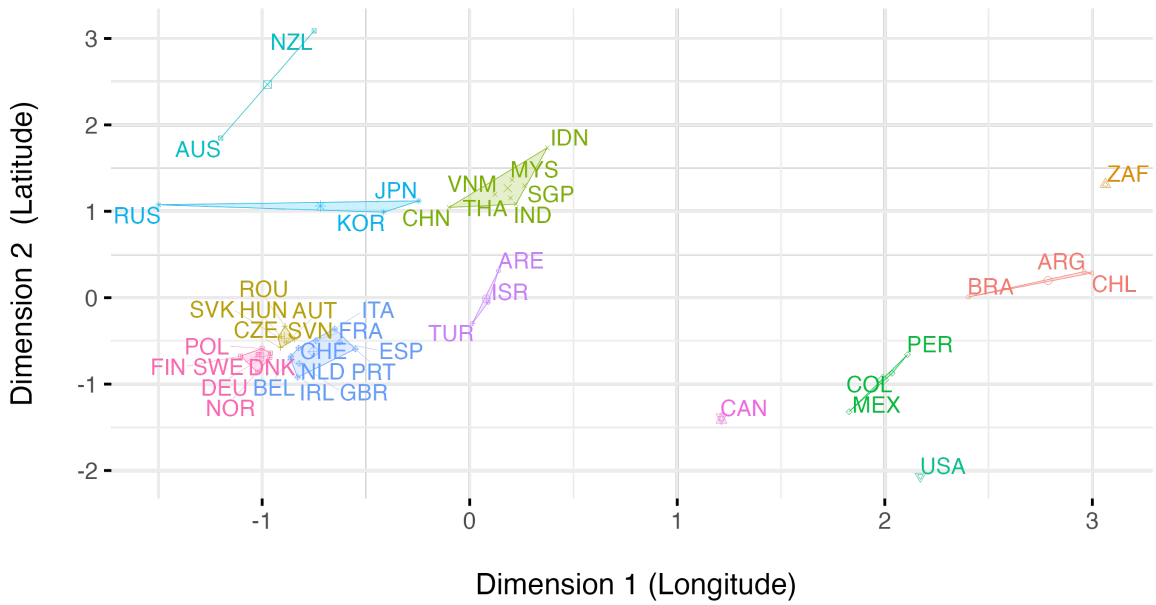
Note: The figure shots the number of branches per country. China, Germany, Japan, South Korea, and the US are the five largest destination countries.

Figure A.6. Differences between Robot Sellers



Note: The left panel of the figure shows the average number of markets served by the top 4 multinational robot sellers versus the other 6 sellers, labeled "Rest". The right panel of the figure shows the average market shares of the two groups.

Figure A.7. Market Definition



Note: The figure shows the definition of 12 markets used in the quantitative model. Markets are aggregated using a K-means algorithm that merges countries with similar latitude and longitude and belonging to the same continent. The resulting markets inherit the average of the characteristics of the countries belonging to them.

B Tables

Table B.1. The Gravity of Market Entry and Market Shares /1

Dependent Variables:	$Entry_{s(o)d}$			$Market\ Share_{s(o)d}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Physical Distance from $HQ_{s(o)d}$	-0.14***	-0.18***	-0.14***	-0.04***	-0.05***	-0.04***
	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.010)
Country FE	No	Yes	Yes	No	Yes	Yes
Seller FE	No	No	Yes	No	No	Yes
Observations	450	450	450	214	214	214
Estimator	OLS	OLS	OLS	OLS	OLS	OLS

Note: An observation is a robot seller-destination country pair. In the first three columns, the dependent variable is a binary variable equal to 1 if seller s from HQ o enters in market d and zero otherwise. In the last three, it is the market share of seller s from HQ o in market d. *Log Physical Distance from* $HQ_{s(o)d}$ is the log of the distance between the two most populated cities of the seller HQ and destination market in kilometers. I standardize this variable to have zero mean and unit variance in the sample. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.2. The Gravity of Market Entry and Market Shares /2

Dependent Variables:	*Entry*$_{s(o)d}$			*Market Share*$_{s(o)d}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Cultural Distance from HQ$_{s(o)d}$	0.04*	0.05	0.05*	0.006	0.03***	0.03***
	(0.02)	(0.03)	(0.03)	(0.006)	(0.01)	(0.010)
Country FE	No	Yes	Yes	No	Yes	Yes
Seller FE	No	No	Yes	No	No	Yes
Observations	450	450	450	214	214	214
Estimator	OLS	OLS	OLS	OLS	OLS	OLS

Note: An observation is a robot seller-destination country pair. In the first three columns, the dependent variable is a binary variable equal to 1 if seller s from HQ o enters in market d and zero otherwise. In the last three, it is the market share of seller s from HQ o in market d. *Cultural Distance from HQ*$_{s(o)d}$ is the index of Gurevich et al. (2021) to measure the linguistic proximity of the seller HQ and the destination market. I standardize this variable to have zero mean and unit variance in the sample. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.3. MARKET CONCENTRATION

Dependent Variable:	HHI_d	
	(1)	(2)
Intercept	0.34***	0.34***
	(0.02)	(0.02)
Log GDP$_d$		-0.07***
		(0.01)
Observations	45	45
Estimator	OLS	OLS

Note: An observation is a destination country. The dependent variable is $\text{HHI}_d = \sum_s s_{sd}^2$, where s_{sd} is the market share of seller s in market d. *Log GDP* $_d$ is the log GDP in the destination country (in 2010 USD PPP). I standardize this variable to have zero mean and unit variance in the sample. Heteroscedasticity robust SE in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.4. Robots, Output and Wage Inequality

Dependent Variables:	*Log GDP*$_d$		*Log Wage Dispersion*$_d$	
	(1)	(2)	(3)	(4)
Log Robots$_d$	0.02***	0.02***	0.005***	0.005**
	(0.005)	(0.005)	(0.002)	(0.002)
Log Population$_d$		0.06		-0.01
		(0.15)		(0.07)
Observations	45	45	45	45
Estimator	OLS	OLS	OLS	OLS

Note: An observation is a destination country. In the first two columns, the dependent variable is the log GDP of country d. In the last two, it is the log ratio of value added in services to manufacturing in country d, which I use to proxy wage inequality between sectors. *Log Robots*$_d$ is the log stock of robots in country d. I standardize this variable to have zero mean and unit variance in the sample. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.5. THE EFFECTS OF AN EU-WIDE ROBOT TAX ON DIFFERENT SELLERS

HQ	**Δ Number of EU Markets**	**Δ Market Share in EU Markets**
Asia	-3.88%	-2.44%
Europe	-0.81%	0.50%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average non-EU market for sellers headquartered in different areas. All outcomes changes are relative to the initial equilibrium without tax.

Table B.6. The Complementarity Between Market Structure and Trade Costs - Average EU Market

Outcome	**Variable**	**Actual Trade Costs**	**High Trade Costs**	**% Change**
Panel A: Robot Sellers				
Number of Sellers	S_d	-4.54%	-1.81%	-60.13%
Markups	$\bar{\mu}_d$	0.82%	0.25%	-69.51%
Panel B: Final Goods Producers				
Robot Stock	R_d	-9.80%	-6.71%	-31.53%
Output	Y_d	-2.83%	-2.32%	-18.02%
Panel C: Households				
Wage Inequality	$w_d(n)/w_d(r)$	-5.87%	-5.05%	-13.97%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average EU market. Panel A shows the effects on robot sellers. Panel B shows the effects on final goods producers. Panel C shows the effects on households. I compare two scenarios. In the first, I leave trade costs at their level observed in the data. In the second, trade costs between all country pairs are increased by 20%. In the first two columns, outcomes changes are relative to the initial equilibrium with actual trade costs. The last column displays the percentage change in each outcome between the second and first scenario.

Table B.7. The Complementarity Between Market Structure and Trade Costs - Average non-EU Market

Outcome	Variable	Actual Trade Costs	High Trade Costs	% Change
Panel A: Robot Sellers				
Number of Sellers	S_d	0.24%	0.21%	-12.50%
Markups	$\bar{\mu}_d$	-0.01%	-0.01%	0.00%
Panel B: Final Goods Producers				
Robot Stock	R_d	0.23%	0.21%	-8.70%
Output	Y_d	0.22%	0.20%	-9.09%
Panel C: Households				
Wage Inequality	$w_d(n)/w_d(r)$	0.03%	0.02%	-33.33%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average non-EU market. Panel A shows the effects on robot sellers. Panel B shows the effects on final goods producers. Panel C shows the effects on households. I compare two scenarios. In the first, I leave trade costs at their level observed in the data. In the second, trade costs between all country pairs are increased by 20%. In the first two columns, outcomes changes are relative to the initial equilibrium with actual trade costs. The last column displays the percentage change in each outcome between the second and first scenario.

Table B.8. Optimal EU-wide Tax on Robot Adoption

α	**First Scenario**	**Second Scenario**	**% Change**
0.3	4.55%	5.16%	13.41%
0.4	4.78%	5.52%	15.48%
0.5	5.39%	6.38%	18.37%
0.6	5.87%	6.67%	13.63%
0.7	8.98%	9.34%	4.01%

Note: The table shows the optimal EU-wide tax on robot adoption. I assume that a European social planner chooses τ_{EU} to maximize total households' welfare in EU markets, defined as $\sum_{d \in \mathcal{M}} \mathbb{1}\{d \in EU\} C_d(r)^{\alpha} C_d(n)^{1-\alpha}$, $\alpha \in (0,1)$. I solve the planner's problem for a grid of values of α under two scenarios. In the first, robot sellers are unable to adjust their entry choices and markups once the tax is implemented. In the second, they can change the set of markets served and the markups charged in each market. The last column displays the percentage change in each outcome between the second and first scenario.

Table B.9. An EU-wide versus a Worldwide Robot Tax

Outcome	**Variable**	**EU-wide Tax**	**Worldwide Tax**
Panel A: EU			
Number of Sellers	S_d	-4.54%	-2.16%
Markups	$\bar{\mu}_d$	0.82%	0.27%
Output	Y_d	-2.83%	-0.66%
Wage Inequality	$w_d(n)/w_d(r)$	-5.87%	-5.22%
Panel B: Non-EU			
Number of Sellers	S_d	0.24%	-0.42%
Markups	$\bar{\mu}_d$	-0.01%	0.04%
Output	Y_d	0.22%	-2.87%
Wage Inequality	$w_d(n)/w_d(r)$	0.03%	-4.85%

Note: The table compares the effects of a 5% unilateral (EU-wide) and multilateral (worldwide) value-added tax on robot adoption. Panel A shows the effects in the average EU market. Panel B shows the effects in the average non-EU market. All outcomes changes are relative to the initial equilibrium without tax.

Table B.10. The Effects of an EU-wide Robot Tax Within EU and non-EU Markets

Counterfactual	EU	Mean	Q25	Median	Q75
Panel A: Robot Stock					
First Scenario	0	0.209%	-0.006%	-0.005%	0.032%
First Scenario	1	-6.781%	-7.093%	-4.164%	-3.958%
Second Scenario	0	0.228%	0.002%	0.021%	0.214%
Second Scenario	1	-9.798%	-10.430%	-3.819%	-3.672%
Panel B: Output					
First Scenario	0	0.212%	-0.005%	-0.004%	0.039%
First Scenario	1	-2.404%	-2.468%	-2.282%	-2.072%
Second Scenario	0	0.215%	0.023%	0.029%	0.119%
Second Scenario	1	-2.828%	-2.955%	-1.931%	-1.780%
Panel C: Wage Inequality					
First Scenario	0	-0.008%	-0.008%	-0.003%	-0.002%
First Scenario	1	-4.751%	-4.762%	-4.762%	-4.750%
Second Scenario	0	0.031%	-0.005%	0.004%	0.100%
Second Scenario	1	-5.867%	-5.977%	-4.762%	-4.762%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption the across EU and non-EU markets. Each panel refers to a different outcome, and I compare two scenarios. In the first scenario, robot sellers are unable to adjust their entry choices and markups once the tax is implemented. In the second, they can change the set of markets served and the markups charged in each market. All outcomes changes are relative to the initial equilibrium without tax.

Table B.11. The Effects of an EU-wide Robot Subsidy

Outcome	**Variable**	**Value**
Panel A: EU		
Number of Sellers	S_d	3.33%
Markups	$\bar{\mu}_d$	-0.12%
Output	Y_d	2.67%
Wage Inequality	$w_d(n)/w_d(r)$	5.63%
Panel B: Non-EU		
Number of Sellers	S_d	-0.22%
Markups	$\bar{\mu}_d$	0.03%
Output	Y_d	-0.22%
Wage Inequality	$w_d(n)/w_d(r)$	-0.05%

Note: The table summarizes the effects of a 5% EU-wide value-added subsidy on robot adoption in the EU and beyond. Panel A shows the effects in the average EU market. Panel B shows the effects in the average non-EU market. All outcomes changes are relative to the initial equilibrium without subsidy.

Table B.12. Boosting Competition in the Robot Industry

Outcome	**Variable**	**Value**
Panel A: EU		
Number of Sellers	S_d	5.96%
Markups	$\bar{\mu}_d$	-0.49%
Output	Y_d	0.70%
Wage Inequality	$w_d(n)/w_d(r)$	1.08%
Panel B: Non-EU		
Number of Sellers	S_d	4.43%
Markups	$\bar{\mu}_d$	-0.27%
Output	Y_d	0.39%
Wage Inequality	$w_d(n)/w_d(r)$	0.64%

Note: The table summarizes the effects of a 25% worldwide reduction in market-level entry costs. Panel A shows the effects in the average EU market. Panel B shows the effects in the average non-EU market. All outcomes changes are relative to the initial equilibrium with the estimated entry costs.

C Additional Background

This appendix contains additional background information about the robot industry.

C.1 The Location of Production Facilities

I employ the following procedure to identify countries in which the top 10 multinational robot manufacturers (see Section 3) have production facilities.

- Using the R package `concordance`,[12] I identify that robots (HS 847959) are produced by firms in the "Other General Purpose Machinery Manufacturing" industry (NAICS 3339).
- Using Orbis, I construct the global network of subsidiaries of the top 10 robot manufacturers. I identify 1032 subsidiaries in total. Next, I check the main sector of activity of each subsidiary, as indicated by their NAICS code. This information is non-missing for 819 (80%) subsidiaries.
- I select the subsidiaries reporting NAICS 3339 as their main industrial activity in 2021, and I consider them as the manufacturers' production facilities.
- I compute the number of production facilities per country.

The procedures identifies production facilities in the following countries: Belgium, Canada, China, Czech Republic, Germany, Great Britain, Italy, Japan, Norway, Slovakia, Slovenia, South Korea, Sweden, the Netherlands, and the US. I cross-check this list with information about the export of robots from the BACII dataset. Reassuringly, the correlation between the number of production facilities and the export value of robots at the country level is 55%. The correlation is significant at the 1% level.

C.2 Technological Requirements for Robot Production

Robot production involves three main stages: design, fabrication, and assembly. The design stage has high technological requirements. Fabrication and assembly are capital-intensive activities, and robots are usually assembled by other robots. Three elements suggest that high initial sunk and fixed production costs can help explain the concentration in robot sales documented in Section 3.

[12] Steven Liao, In Song Kim, Sayumi Miyano, Hao Zhang (2020). concordance: Product Concordance. R package version 2.0.0. https://CRAN.R-project.org/package=concordance

- The top 10 robot producers started developing robots around 50 years ago. For instance, ABB launched its first robot in 1978, Fanuc in 1974, Kuka in 1973, and Yaskawa in 1977. The other six firms in the top 10 started producing robots between the end of the 1970s and the beginning of the 1980s. These information comes from the sellers' websites.

- Using Orbis, I find that the average top 10 robot producer reports a share of R&D expenses over sales equal to 3.5%. For reference, the average non-top 10 producer registered with the IFR reports a share of 2.8%. It is also useful to benchmark this share against that reported by firms in other sectors. To do so, I compute the share of R&D expenses over sales for the top 500 firms in Orbis in terms of sales, employment, and fixed assets. This set includes Apple, Alphabet, Microsoft, among others. Notably, no top 10 robot producer belongs to this list. Although the average top 500 firm in Orbis reports 12 times higher sales than the average top 10 robot producer, its share of R&D expenses over sales is equal to 2.9%, which is 6 percentage points lower than that of the average top 10 robot producer.

- Using Orbis Intellectual Property (IP), a Bureau van Dijk's dataset containing information about patents and their ownership, I find that concentration in sales aligns with concentration in patents. I proceeded in three steps:
  - I download from Orbis IP all patents that contain the word "industrial robots" in the title, abstract, or description.
  - Whenever not reported in English, I translate the patent assignee name using the Google Translate R API.[13] Then, I match patents to their owners in Orbis.
  - Among the 26 firms registered with the IFR, the top 10 accounting for 90% of global sales also hold 81% of the stock of active patents in 2021. Their patents also receive more citations on average (4 for the top 10 sellers vs. 3.3 for the others) and have longer expiry dates (2032 for the top 10 sellers vs. 2026 for the others).

[13] See https://github.com/ropensci/googleLanguageR.

C.3 Case Studies about Integration Services

Case studies available on the sellers' websites illustrate the central role of integration services. The typical case study describes a firm seeking help to automate parts of its production (e.g., stacking crates, handling products, or lifting components), and how a local branch of a robot seller helped the firm by selecting a standardized robot and tailoring it to its needs. I provide three examples below:

- A Swiss firm producing turf wanted to automate the operation of palletizing is harvest. To do so, the company resorted to the help of a Swiss branch of Fanuc who adapted and mounted a robot to the rear of an harvester to facilitate the palletization of turf rolls. Additional details can be found here.

- A Brazilian meat producer wanted to develop an automated high-speed line for producing and handling simultaneously different types of meat. To achieve this goal, the company contacted a Brazilian branch of ABB, who installed different robots at the meat producer's plant to pick both light and heavy products and palletizing them. Additional details can be found here.

- A food company approached a US branch of KUKA to automate the process of stacking milk crates on pallets in the cold storage warehouse. The branch selected a suitable robot for the company and customized it to be able to work in a unusually cold environment. Additional details can be found here.

D Data Appendix

This appendix contains additional information about the data.

D.1 Web Scraping Algorithm

I construct the global sales network of the top 10 multinational robot sellers identified in Section 3 using the following procedure:

- I access the "Where to Find Us" section on the firms' websites, where they provide information about their global footprint. Typically, firms list the location of their HQ, sales branches of robots and other products, education and training centers.

- Using the Python library `Selenium`,[14] I web scrape the name and geographical address of each entity listed in that section. Whenever available, I also collect additional information (e.g., product sold and services offered).

Data cleaning involves two steps:

- I separate sales branches where costumers can purchase robots and integration services from entities performing other activities (e.g., training or production centers, consumers' help desks, and research laboratories). This step is uncontroversial since companies report this information on their website.

- I distinguish between branches selling robots and providing integration services and those commercializing other products (e.g., precision machinery, engines, generators, drives, and computer systems). This step is straightforward when companies directly report the information on their websites. However, in cases where the information is not explicitly stated, I apply the following conservative rules. First, if the branch name hints at non-robot sales (e.g., contains "electronic provider"), I exclude it from the sample. Second, I exclude branches located in countries where the IFR does not document any robot usage. I keep branches selling both robots and other products.

D.2 Measurement of Market Shares

Information about sales is available for 300 (55%) of the 538 branches that can be found in Orbis. Using this sub-sample, I can compare two measures of market share.

[14] See `https://github.com/seleniumbase/SeleniumBase`.

The first is based on the number of branches that a seller has in a country. Formally:

$$s_{sd}^{(1)} = \frac{b_{sd}}{\sum_{s \in S_d} b_{sd}}.$$

b_{sd} is the number of branches of seller s in country d, and S_d is the set of sellers selling in d. The second measure is based on the sales of the branches that a seller has in a country. Formally:

$$s_{sd}^{(2)} = \frac{\sum_{b \in B_{sd}} v_{b(s)d}}{\sum_{s \in S_d} \sum_{b \in B_{sd}} v_{b(s)d}}.$$

$v_{b(s)d}$ denotes sales of branch b belonging to seller s in country d in USD millions. B_{sd} is the set of branches that s has in d. The Pearson correlation between $s_{sd}^{(1)}$ and $s_{sd}^{(2)}$ is 67%***. The Spearman correlation is 53%.

The first two columns of Table D.1 show that the positive and significant correlation between the two measures is robust to controlling for seller and country fixed effects. Because country fixed effects absorb the denominators of $s_{sd}^{(1)}$ and $s_{sd}^{(2)}$, there is also a positive correlation between the number of branches and sales in (log) levels, as shown by the last two columns of the table.

Overall, sellers with more branches also appear to sell more. I prefer $s_{sd}^{(1)}$ over $s_{sd}^{(2)}$ because it can be constructed for more seller-market pairs.

Table D.1. Measuring Market Shares

Dependent Variables:	*Mkt Share (Sales)$_{sd}$*		*Log Sales$_{sd}$*	
	(1)	(2)	(3)	(4)
Mkt Share (Branches)$_{sd}$	0.83***	0.48**		
	(0.07)	(0.24)		
Log Branches$_{sd}$			1.1***	0.77***
			(0.19)	(0.25)
Country FE	No	Yes	No	Yes
Seller FE	No	Yes	No	Yes
Observations	133	133	133	133
R^2	0.45	0.55	0.22	0.64
Within R^2		0.06		0.10
Estimator	OLS	OLS	OLS	OLS

Note: An observation is a robot seller-destination country pair. *Mkt Share (Sales)$_{sd}$* is the market share of seller s in country d based on the sales of its branches. *Mkt Share (Branches)$_{sd}$* is the market share of seller s in country d based on its number of branches. *Log Sales$_{sd}$* are the total sales of the branches of seller s in market d. *Branches$_{sd}$* is the number of branches of seller s in country d. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

D.3 Data Validation

I validate the own-collected information about global sales networks against three established data sources (IFR, BACII, and Orbis).

- I estimate the following country-level equation:

$$Robots_d = \alpha + \beta \ Branches_d + \gamma \ Controls_d + \varepsilon_d.$$

  $Robots_d$ is the number of robots in country d reported by the IFR. $Branches_d$ is the self-collected number of multinational sellers' branches in country d. $Controls_d$ include Log GDP per capita. ε_d is the error term. Table D.2 shows the estimates. $Number\ of\ Branches_d$ explains 57%-58% of the variation in $Number\ of\ Robots_d$.

Table D.2. Robots vs Branches

Dependent Variable:	$Robots_d$	
	(1)	(2)
$Branches_d$	2.3***	2.4***
	(0.74)	(0.75)
Controls	No	Yes
Observations	45	45
R^2	0.57	0.58
Estimator	OLS	OLS

Note: An observation is a destination country. $Robots_d$ is the number of robots in country d. $Branches_d$ is the number of branches in country d. Controls include include Log GDP per capita. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

  Additionally, $Corr(Branches_d, Robot\ Stock_d) = 75\%^{***}$.

- I estimate the following equation bilateral equation:

$$Trade\ in\ Robots_{od} = \beta \ Branches_{od} + \gamma \ Controls_{od} + FE_o + FE_d + \varepsilon_{od}.$$

Trade in Robots$_{od}$ is the export value of robots (HS 847950) from o to d in million current USD reported in the BACI dataset. *Branches*$_{od}$ is the self-collected number of branches that multinational sellers headquartered in o open in d. *Controls*$_{od}$ include Log of bilateral distance in kilometers. FE_o are origin fixed effects, FE_d destination fixed effects, and ε_{od} the error term. Table D.3 shows the estimates. Even after controlling for origin and destination fixed effects, as well as bilateral distance, *Number of Branches*$_{od}$ explains 61% of the within R^2 of *Trade in Robots*$_{od}$.

Table D.3. Trade vs Branches

Dependent Variable:	*Trade in Robots*$_{od}$		
	(1)	(2)	(3)
Branches$_{od}$	10.5***	11.8***	11.3***
	(3.8)	(3.9)	(3.9)
Origin FE	No	Yes	Yes
Destination FE	No	Yes	Yes
Controls	No	No	Yes
Observations	133	133	133
R^2	0.60	0.75	0.75
Within R^2		0.61	0.61
Estimator	OLS	OLS	OLS

Note: An observation is an origin-destination country pair. *Trade in Robots*$_{od}$ is the export value of robots (HS 847950) from o to d in million current USD. *Branches*$_{od}$ is the self-collected number of branches that multinational sellers headquartered in o open in d. Controls include Log of bilateral distance in kilometers. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Additionally, $Corr(Branches_{od}, Trade\ in\ Robots_{od}) = 77\%^{***}$.

- I estimate the following seller-country level equation:

$$B_{s(o)d} = \beta\ S_{s(o)d} + FE_s + FE_d + \varepsilon_{s(o)d}.$$

$B_{s(o)d}$ is either an indicator equal to 1 if multinational seller s from HQ o has at least one branch in country d (extensive margin) or the number of branches that s has in country d (intensive margin). $S_{s(o)d}$ is either an indicator equal to 1 if seller s from HQ o has at least one subsidiary in country d (extensive margin) or the number of subsidiaries that s has in country d (intensive margin). Subsidiaries include those unrelated to robots, as reported in Orbis. FE_s and FE_d are seller and country fixed effects, and $\varepsilon_{s(o)d}$ the error term. Table D.4 shows the estimates. The presence of sales branches is positively correlated with the presence of subsidiaries, even after controlling for FE_s and FE_d.

Table D.4. Branches vs Subsidiaries

Dependent Variables:	*Branch Dummy*$_{sd}$		*Branches*$_{sd}$	
	(1)	(2)	(3)	(4)
Subsidiary Dummy$_{sd}$	0.44***	0.32***		
	(0.03)	(0.04)		
Subsidiaries$_{sd}$			0.16***	0.10**
			(0.06)	(0.05)
Country FE	No	Yes	No	Yes
Seller FE	No	Yes	No	Yes
Observations	920	920	155	155
R^2	0.24	0.57	0.14	0.52
Within R^2		0.11		0.05
Estimator	OLS	OLS	OLS	OLS

Note: An observation is a robot seller-destination country pair. *Branch Dummy*$_{s(o)d}$ is an indicator equal to 1 if seller s from HQ o has at least one branch in country d. *Subsidiary Dummy*$_{s(o)d}$ is an indicator equal to 1 if seller s from HQ o has at least one subsidiary in country d. *Branches*$_{s(o)d}$ is the number of branches that seller s from HQ o has at least one branch in country d. *Subsidiaries*$_{s(o)d}$ is the number of subsidiaries that seller s from HQ o has at least one branch in country d. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Additionally, $Corr(Subsidiaries_{s(o)d}, Branches_{s(o)d}) = 48\%^{***}$ at the extensive margin and $38\%^{***}$ at the intensive margin.

E Theoretical Appendix

E.1 Multi-Branch Multinational Robot Sellers

I extend the model presented in Section 5 to feature multi-branch multinational robot sellers. While this model delivers similar predictions as the baseline one, it provides a micro-foundation for the fact that sellers that open more branches in a market also sell more robots.

Nested Robot Demand. I assume that seller s in market d supplies an indivisible bundle of generic robots and integration services, which I refer to as a "product" and define by $\check{R}_{sd}$. In turn, this product is a bundle of the varieties offered by branches b of seller s in market d, which I denote $R_{b(s)d}$. Formally, R_d used by final goods producers defined as:

$$R_d = \left(\sum_{s \in S_d} \phi_{sd}^{\frac{1}{\sigma}} \check{R}_{sd}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad \check{R}_{sd} = \left(\sum_{b \in B_{sd}} R_{b(s)d}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \quad \rho \geq \sigma > 1. \tag{E.1}$$

Notation follows from equation (8). Combining the first-order conditions of equations (7) and (E.1), the demand faced by each branch can be expressed as:

$$R_{b(s)d} = \phi_{sd} r_{b(s)d}^{-\rho} \check{r}_{sd}^{\rho-\sigma} r_d^{\sigma-1} \beta \bar{\iota}_d p_d Y_d. \tag{E.2}$$

$r_{b(s)d}$ is the price charged by branch b of seller s in market b, r_{sd} is the price index of seller s in market d, and r_d is the market-level price of robots. Branches internalize the effect of their choices on the sector price index r_d but not on economy-wide variables.

Profit Maximization. Sellers choose the number of branches to open in each market and the prices charged by each of their branches. Let B_{sd} be the set of branches that s operates in d. I assume that seller s in market d solves the following problem:

$$\max_{\{r_{sd}, b_{sd}\} \geq 0} \sum_{b \in B_{sd}} (r_{b(s)d} - w_d(n)) R_{b(s)d} - w_d(n) \frac{b_{sd}^{1+\frac{1}{\lambda}}}{1+\frac{1}{\lambda}} - w_d(n) f, \quad \lambda > 0 \tag{E.3}$$

$$\text{s.t. equation (E.2)} \tag{E.4}$$

$b_{sd}^{1+\frac{1}{\lambda}} / \left(1 + \frac{1}{\lambda}\right)$ is a convex cost of opening branches.

Equilibrium Conditions. Since demand shifters ϕ_{sd} are seller-by-market specific and retail costs $w_d(n)$ market-specific, sellers equalize the markups charged by their branches, which gives rise to a symmetric pricing rule within sellers in equilibrium.[15] Hence, the demand function in equation (E.2) can be expressed as:

$$R_{sd} = \phi_{sd} r_{sd}^{-\sigma} b_{sd}^{\frac{\rho-\sigma}{1-\rho}} r_d^{\sigma-1} \beta \bar{\iota}_d p_d Y_d. \tag{E.5}$$

The sellers' maximization problem can be formulated as:

$$\max_{\{r_{sd}, b_{sd}\} \geq 0} (r_{sd} - w_d(n)) b_{sd} R_{sd} - w_d(n) \frac{b_{sd}^{1+\frac{1}{\lambda}}}{1+\frac{1}{\lambda}} - w_d(n) f, \quad \lambda > 0 \tag{E.6}$$

$$\text{s.t. equation (E.5).} \tag{E.7}$$

The first-order conditions associated with this problem deliver the following equilibrium expressions for the price of robots and number of branches:

$$r_{sd} = \frac{\varepsilon_{sd}}{\varepsilon_{sd} - 1} w_d(n), \quad b_{sd} = \left[\frac{(r_{sd} - w_d(n))(\sigma - 1)(1 - s_{sd}) \tilde{R}_{sd} \phi_{sd}}{(\rho - 1) w_d(n)} \right]^{\lambda}. \tag{E.8}$$

$\tilde{R}_{sd}$ is quality-adjusted robot demand. The market share of seller s in market d is:

$$s_{sd} = \frac{\phi_{sd} b_{sd}^{\frac{1-\rho}{1-\sigma}} r_{sd}^{1-\sigma}}{\sum_{s \in S_d} \phi_{sd} b_{sd}^{\frac{1-\rho}{1-\sigma}} r_{sd}^{1-\sigma}}. \tag{E.9}$$

All else equal, sellers with higher ϕ_{sd} open more branches, sell more robots, and charge higher markups.

Closing the Model. The other equilibrium conditions are unchanged, except for the non-routine labor market clearing condition which now reads:

$$\bar{L}_d(n) = \frac{(1-\beta) p_d Y_d}{w_d(n)} + R_d + \sum_{s \in S_d} \frac{b_{sd}^{1+\frac{1}{\lambda}}}{1+\frac{1}{\lambda}} + |S_d| f_d. \tag{E.10}$$

[15]This equilibrium condition parallels the one derived by Hottman, Redding and Weinstein (2016) for multi-product firms.

E.2 A Task-Based Approach to Final Good Production

In this section, I summarize the argument established by Guerreiro et al. (2022) to derive equation (7) from a task-based model as in Acemoglu and Restrepo (2018). Let the production function of final goods producers be, for $\rho > 1$ and $\beta \in (0,1)$:

$$Y_d = A_d \left(\int_0^1 y_d(\iota)^{\frac{\rho-1}{\rho}} \mathrm{d}\iota \right)^{\frac{\beta\rho}{\rho-1}} L_d(n)^{1-\beta}. \tag{E.11}$$

Each task can be performed by a robot bundle $R_d(\iota)$ and/or routine workers $L_d(r,\iota)$:

$$y_d(\iota) = \mathbf{1}\{\iota_d \leq \bar{\iota}_d\}\gamma_d(\iota)R_d(\iota) + \psi_d(\iota)L_d(r,\iota), \tag{E.12}$$

being $\gamma_d(\iota)$ and $\psi_d(\iota)$ the productivity or robots and routine workers, respectively. Equation (E.11) clarifies that tasks $\iota_d \leq \bar{\iota}_d$ can be performed by robots and routine workers. By contrast, tasks $\iota_d > \bar{\iota}_d$ can be only performed by routine workers. As Guerreiro et al. (2022), I introduce the following assumption:

Assumption 1. *$\gamma_d(\iota) = \zeta \iota_d^{\frac{\eta-1}{\eta}}$ and $\psi_d(\iota) = \zeta(1-\iota_d)^{\frac{\eta-1}{\eta}}$, with $\zeta = \left(1 + \frac{(\eta-1)(\rho-1)}{\eta}\right)^{\frac{1}{\rho-1}}$ and $(1-\eta)(\rho-1) < \eta$.*

Under this assumption, Guerreiro et al. (2022) show that there exists a unique pivotal task $\bar{\iota}_d$ such that robots are employed in tasks $\iota \leq \bar{\iota}_d$ and labor elsewhere. The pivotal task reads:

$$\bar{\iota}_d = \frac{R_d^\eta}{R_d^\eta + L_d(r)^\eta} \in (0,1). \tag{E.13}$$

Moreover, equation (E.11) boils down to equation (7). The producer price index in the final good sector is, for $\bar{\beta} = \beta^{-\beta}(1-\beta)^{\beta-1}$:

$$p_d = \frac{\bar{\beta}}{A_d} \left[\bar{\iota}_d^\eta r_d^{-\eta} + (1-\bar{\iota}_d)^\eta w_d(r)^{-\eta} \right]^{-\frac{\beta}{\eta}} w_d(n)^{1-\beta}. \tag{E.14}$$

r_d is the rental price of robots in market d.

E.3 Alternative Marginal Cost Specifications

The baseline model assumes that robot sellers only need local non-routine workers to sell products (i.e., indivisible bundles of generic robots and integration services). I impose this assumption to abstract from the production and exports of generic robots and focus on competition in sales in destination markets. In this section, I discuss how to allow for production and trade in generic robots.

Accounting for Production and Trade in Generic Robots. Generic robots are produced by MNEs in their HQ market o, exported to a destination market d, and sold there bundled with integration services. MNEs need non-routine labor to produce generic robots in o.[16] As in the baseline model, selling generic robots bundled with integration services in d requires local non-routine labor. In this case, the marginal cost of selling robots in market d is:

$$t_{od} w_o(n)^{\gamma} w_d(n)^{1-\gamma}, \quad \gamma \in (0,1). \tag{E.15}$$

Let $t_{od} = 1$ if $o = d$ and $t_{od} \geq 1$ if $o \neq d$. This term captures the trade cost that MNE s from market o faces when selling robots in a foreign market d. This specification implies that entry in the robot sector of market d is constrained both by the available amount of non-routine workers in d as well as in the HQ country, and equation (22) should be modified accordingly. If robot production requires paying a fixed cost in terms of non-routine labor in the HQ country, this cost must be subtracted from MNEs' profits in equation (9).

[16]This assumption can be relaxed to allow robot production require both routine and non-routine workers in the HQ.

E.4 Derivations

This section shows the derivations generating Figure 5.

Entry Reduces Incumbents' Prices. The price of any symmetric incumbent robot seller is, for $w(n) = 1$:

$$r = \mu = \frac{\sigma - (\sigma - 1)\frac{1}{|S|}}{\sigma - (\sigma - 1)\frac{1}{|S|} - 1}. \tag{E.16}$$

Therefore:

$$\frac{\partial r}{\partial |S|}\frac{|S|}{r} = \frac{\partial \log r}{\partial |S|}|S| = \left(\frac{(\sigma-1)(\varepsilon-1)\frac{1}{|S|^2} - (\sigma-1)\varepsilon\frac{1}{|S|^2}}{\mu(\varepsilon-1)^2}\right)|S| \tag{E.17}$$

$$= \frac{(1-\sigma)}{\varepsilon(\varepsilon-1)^2|S|} < 0. \tag{E.18}$$

Entry Reduces the Aggregate Robot Price. The log of the aggregate price of robots is:

$$\log \check{r} = \frac{1}{1-\sigma}\log|S| + \log r + \frac{1}{1-\sigma}\log\phi. \tag{E.19}$$

Therefore:

$$\frac{\partial \check{r}}{\partial |S|}\frac{|S|}{\check{r}} = \frac{\partial \log \check{r}}{\partial |S|}|S| = \left(\frac{1}{(1-\sigma)|S|} + \frac{1}{r}\frac{\partial r}{\partial |S|}\right)|S| \tag{E.20}$$

$$= \frac{1}{(1-\sigma)} + \frac{\partial r}{\partial |S|}\frac{|S|}{r} \tag{E.21}$$

$$= \frac{1}{(1-\sigma)} + \frac{(1-\sigma)}{\varepsilon(\varepsilon-1)^2|S|} < 0. \tag{E.22}$$

Entry Reduces the Price Index. The log of the aggregate price index is:

$$\log p = \log\left(\frac{\bar{\beta}}{A}\right) + \beta\log\check{r} \tag{E.23}$$

Therefore:

$$\frac{\partial p}{\partial |S|}\frac{|S|}{p} = \frac{\partial \log p}{\partial |S|}|S| = \beta\frac{\partial \check{r}}{\partial |S|}\frac{|S|}{\check{r}} = \frac{\beta}{(1-\sigma)} + \frac{\beta(1-\sigma)}{\varepsilon(\varepsilon-1)^2|S|} < 0. \tag{E.24}$$

F Quantitative Appendix

F.1 Algorithm to Solve the Model

Given the parameters in Table 2, the model can be solved using the following algorithm:

1. Guess a value of $w_d(n)$ and r_d for each market as well as aggregate profits Π;
2. Set $r_d = w_d(r)$ in each market;
3. Find $p_d = \bar{\beta} w_d(r)^{\beta} w_d(n)^{1-\beta}/A_d$, $\bar{\beta} = \beta^{-\beta}(1-\beta)^{\beta-1}$;
4. Find Y_d using equation (20);
5. Find $\bar{\iota}_d$ using equation (21);
6. Compute the expenditure on robots $\beta \bar{\iota}_d p_d Y_d$ in each market;
7. Solve the sellers' sequential entry game market-by-market:
   (a) Let $S = 1$. Use a fixed-point search to find r_{sd} from equation (15);
   (b) Compute profits π_{sd};
   (c) If $\pi_{sd} > w_d(n) f_d$, let $S = 2$ and repeat from (7.a);
   (d) Stop when last entrant would make negative profits.
8. Find a new vector of market-level robot prices r'_d and aggregate profits Π';
9. Find a new vector of market-level non-routine wages $w_d(n)'$ (up to a numéraire);
10. Iterate until $||r_d - r'_d|| < tol$, $||w_d(n) - w_d(n)'|| < tol$, and $|\Pi - \Pi'| < tol$.

When searching for the fixed point of the robot sellers' problem and the GE allocation, I follow Gaubert and Itskhoki (2021) and update prices taking a half step between the old guess and the new one at each iteration.

Notice that equation (15) is only defined for $S \geq 2$. When initializing the inner loop to solve the sellers' problem, I modify equation (15) assuming that the seller behaves as a local monopolist. In this case, the optimal pricing rule can be written as:

$$r_{sd} = \frac{\sigma}{\sigma - 1} w_d(n). \tag{F.25}$$

F.2 Simulated Method of Moments Algorithm

The SMM procedure to find the parameters to be estimated in Table 2 reads as follows:

1. Draw B matrices with dimension $|\mathcal{S}| \times |\mathcal{M}|$ of normally distributed i.i.d. shocks with mean zero and unit variance, being $|\mathcal{S}|$ the total number of sellers and $|\mathcal{M}|$ the total number of markets. I use Sobol sequences to cover the support of the normal distribution more efficiently than if numbers were drawn at random. In practice, I set $B = 50$;
2. Guess a vector of parameters Θ;
3. For each of the B matrices of random shocks:
   (a) Compute demand shifters using equation (27);
   (b) Solve the model using the algorithm described in Section F.1;
   (c) Compute the model-implied moments of interest and store them.
4. Compute the average model-implied moments of interest across the B samples. Denote $m(\Theta)$ the resulting vector;
5. Update the guess of Θ to minimize the SMM objective function $\mathcal{L}(\Theta) = (m(\Theta) - \bar{m})' W (m(\Theta) - \bar{m})$.

In operationalize this procedure in two steps. First, I adopt an adaptive radius limited differential evolution algorithm to find the starting values of the SMM routine.[17] Second, I run a local search using a standard quasi-Newton algorithm around these values. In practice, this second step stops after a few iterations and only marginally reduces the SMM objective function.

The standard errors in Table 2 are computed using the bootstrap procedure of Bernard et al. (2022). The procedure is performed as follows. First, for each bootstrap sample, I draw sellers and markets with replacement until I obtain the same sample size as in the data. Second, I compute the empirical moments used in the SMM procedure for each bootstrap sample. Third, I estimate the model parameters at each sample using the procedure described above. The standard errors in Table 2 are the standard deviation of the distribution of the estimates across samples. I employ 50 replications.

[17] This algorithm is available through the Julia package `BlackBoxOptim.jl`, and it is shown to perform well in finding the global minimum of non-linear problems.

F.3 Implementation of The Counterfactual Scenarios

In the first scenario, the counterfactual outcomes are computed as follows:

1. For each of the B matrices of ϕ_{sd} demand shifters used in the SMM procedure (see Section F.2):
    (a) Solve the model without tax using the algorithm described in Section F.1;
    (b) Store the number of sellers per market S_d and their demand shifters ϕ_{sd};
    (c) Find the equilibrium of the model without and with tax given S_d and ϕ_{sd}. This can be done by using the algorithm described in Section F.1 but skipping step 7;
    (d) Compute the percentage changes in the outcomes of interest between equilibria.
2. Compute the average change in the outcomes of interest across the B draws.

In the second scenario, the counterfactual outcomes are computed as follows:

1. For each of the B matrices of ϕ_{sd} demand shifters used in the SMM procedure (see Section F.2):
    (a) Solve the model without tax using the algorithm described in Section F.1;
    (b) Solve the model with tax using the algorithm described in Section F.1;
    (c) Compute the percentage changes in the outcomes of interest between equilibria.
2. Compute the average change in the outcomes of interest across the B draws.

I assume that a robot tax is implemented before robot sellers make entry choices. In the first scenario, this choice is inconsequential because entry choices and markups are held constant. In the second, it requires solving the problem of robot sellers in an economy without and with taxes (i.e., one in which $\tau_d = 0$ everywhere and one in which $\tau_{EU} = 5\%$).