

Global Robots

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Abstract

The diffusion of automation technology raises questions about the future of work, leading to calls for regulation. The ongoing discussions center on the decisions of technology adopters. In this paper, I study how supply-side adjustments shape the effects of policy interventions. I focus on the global market of industrial robots, a leading type of automation technology, where a few multinational enterprises (MNEs) dominate sales. To evaluate how these MNEs respond 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 transmit internationally and amplify the aggregate and distributional effects of policies targeting robots.

Keywords: Multinational Enterprises, Market Power, Automation

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

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1 Introduction

The diffusion of automation technologies, including robotics and artificial intelligence, raises questions about the future of work. On the one hand, these technologies autonomously perform several complex tasks, fostering productivity growth. On the other, their adoption also brings about job displacement and inequality concerns. For these reasons, academics and policymakers discuss about policies to regulate automation (Brynjolfsson and McAfee, 2014; Acemoglu and Johnson, 2023).

The current discussions center on the impact of policy interventions on the production and employment decisions of technology adopters. Responses from the supply side are overlooked. However, since the global supply of automation technologies is often dominated by a few large multinational enterprises (MNEs), these responses may be sizable and represent a determining factor for the ultimate effects of any policy.

Studying the supply of automation technologies is challenging, as there is no comprehensive dataset about automation suppliers and their global activities. Additionally, a theoretical framework that accounts for the features of the automation industry is necessary to disentangle adjustments in supply and demand after a policy change.

In this paper, I address these challenges in the context of the global market of industrial robots (henceforth “robots”),¹ an industry where four MNEs account for more than 50% of global sales (Leigh and Kraft, 2018). This is an ideal setting for two reasons. First, robots are a leading type of automation technology, contributing to about 10% of the total market value of the automation industry (UBS, 2020). Second, there is an extensive body of literature about the adoption of robots and their labor market effects. Therefore, I can introduce novel aspects of robot supply within established frameworks for the demand side (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2018, 2020; Hémous and Olsen, 2022).

I offer two contributions. First, I gather new data about MNEs supplying robots in the global economy. Second, I provide a quantitative general equilibrium model to evaluate how their responses shape the effects of policies targeting robot adoption, such as taxes. Using the model, I find that supply-side responses amplify the aggregate and distributional outcomes of these policies by about 20% and transmit their effects internationally. I also study interventions that aim at boosting competition among robot sellers, and show that they generate a trade-off between efficiency and equity.

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

A feature of the robot industry is that sales entail a bundle of generic robot arms and “integration services”. These services, including customization and setup, are meant to tailor pre-built robots to specific production tasks and account for two-thirds of the final price paid by users (Leigh and Kraft, 2018). While generic robots are tradable, integration services are not. Therefore, robot sellers must establish a retail network in each market they serve. This industry feature informs my data collection procedure and guides the assumptions of the model I provide.

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. By scraping the website of each MNE, I also geolocate their branches that sell generic robots and integration services to users worldwide. I retrieve over 600 sales branches in total. 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. These 10 multinational robot sellers have HQ mainly in Japan and central Europe and account for about 90% of global robot sales. The 45 countries I consider account for more than 90% of world GDP.

Using these data, I document two new facts about the global robot industry. First, robot sales decrease as the distance between destination countries and the robot sellers’ HQ increases. This fact suggests that multinational robot sellers face bilateral frictions that increase with distance from their HQ, which is consistent with gravity.² An implication of gravity is that local shocks disproportionately affect foreign robot sellers. Second, robot sales in destination countries are highly concentrated, with only half of all robot sellers serving the average country in the data. This granularity in sales means that marginal changes in the number of robot sellers active in a market deliver sizable changes in the number of robots adopted.

These facts inform, and are replicated by, 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

²Several factors may explain the existence of these frictions, including home bias in robot demand, robot sellers’ limited knowledge of foreign markets, or coordination costs increasing with distance.

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 oligopoly in international trade (Atkeson and Burstein, 2008; Gaubert and Itskhoki, 2021). 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 in destination markets using non-routine local labor.³ Robot sellers are heterogeneous in terms of appeal to final goods producers. More appealing robot sellers enter more markets and charge higher markups.

Bringing the model to the data requires defining the markets in which robot sellers compete. In practice, I group 45 countries into 12 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 calibrated from the data or existing literature. The robot sellers’ parameters are new, and I estimate them using a simulated method of moments (SMM) procedure.

The SMM estimator targets moments that are informative of robot sellers’ entry choices and sales, market competition, and robot adoption. 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 policy interventions targeting robot adoption and quantify the impact of their responses on aggregate 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 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).⁴

³This assumption allows me to abstract from the proximity-concentration trade-off in the production of generic robots and analyze competition in destination markets. It is supported by the fact that robot prices are determined by integration services supplied locally (Leigh and Kraft, 2018).

⁴Guerreiro et al. (2022) show that when the worker type is unobserved, it is optimal to tax robots

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. Without supply-side responses, a tax reduces robot demand and increases the price of final goods, generating an output loss in the EU. However, losses are not evenly borne. Income inequality decreases, with routine workers experiencing an increase in welfare because of their substitutability with robots, and non-routine workers facing a welfare loss due to their complementarity.

In the second scenario, a tax shrinks the total size of the market, and some robot sellers leave the EU. Exit induces a reallocation of market shares to incumbents, who raise their markups, leading to a stronger increase in the price of robots and a larger output loss than in the first case. Income inequality decreases by more than in the first scenario, with smaller welfare gains accruing to routine workers and stronger welfare losses for non-routine ones. Overall, supply-side responses reinforce the aggregate and distributional effects of a tax on robot adoption by about 20%. In terms of policy implications, the results suggest that a welfare-maximizing European Social Planner should set lower robot taxes when robot sellers adjust to it.

By increasing the price of EU goods, an EU-wide robot tax also increases consumer prices and reduces the welfare of all households beyond the EU. These results are robust to using different tax rates and alternative market structure assumptions.

The model can be also used to evaluate a rich set of additional policies, including those directly targeting supply. Recent literature has highlighted that firms' market power, even if confined to specific sectors, can have detrimental welfare effects (Edmond, Midrigan and Xu, 2023). In light of this debate, I investigate what are the effects of promoting competition among robot sellers. Counterfactual results show that increased competition reduces markups and prices, raising final goods production. If the pro-competitive effects of policy interventions are strong enough, all types of workers can be made better off. However, the non-neutrality of robots implies that non-routine workers experience disproportionately larger gains.

Related Literature. At its core, this paper 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

if the planner aims to redistribute income towards routine workers. Instead of providing a foundation for the tax, this paper explores how the responses of robot sellers interact with and influence the outcomes of a robot tax.

and Tintelnot, 2017; Arkolakis, Ramondo, Rodríguez-Clare and Yeaple, 2018; Alvarez, 2019; Head and Mayer, 2019). From a theoretical perspective, it offers two contributions. First, instead of focusing on horizontal, vertical, or export-platform foreign direct investment (FDI), this paper provides a model of distribution FDI tailored to the robot industry. Second, it relaxes the conventional assumption of monopolistic competition among MNEs, allowing for oligopolistic competition. From an empirical standpoint, this work introduces new data on MNEs in the robot industry.

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; Crowley, Han and Prayer, 2024). The existing literature focuses on how imperfect competition between firms shapes international trade and influences trade policy. This paper shows how firms' strategic behaviors 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; Alvarez, Head and Mayer, 2020; Autor, Dorn, Katz, Patterson and Van Reenen, 2020; Leone, Macchiavello and Reed, 2024). 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 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 robot industry. Section 3 introduces the data. Section 4 describes the empirical facts. Section 5 contains the model. Section 6 discusses 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 at the factory gate. There is a single six-digit HS code associated with 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 these 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 other 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](#)), 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 associated with a broader restructuring of production ([Koch et al., 2021](#)). Besides the factory-gate generic robot, users also purchase “integration services” from sellers. These services involve guidance 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 generic 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.⁵ 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).⁶

Characteristics. I gather several characteristics of robot sellers from Orbis, including information about financial accounts (e.g., sales, employment, total fixed assets, and R&D expenses), sectors of activity, ownership structure, and innovation. Ownership information encompasses 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 2.2 emphasizes that robot sellers need a retail network in each market to provide integration services to their customers. Unfortunately, information about retail networks 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

⁵This 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.

⁶For 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.

across the world is provided. Second, it extracts and stores the name and geographical 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.

Using this procedure, I identify 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 I collect information about their financial accounts and corporate structure. 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 robot 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.⁷ 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.

⁷In Appendix E.1, I extend the model in Section 5 to provide a micro-foundation for the positive correlation between robot sellers’ number of branches and 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 \(2021\)](#). 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. Information about the characteristics of the countries served by robot sellers come from various sources. From the World Development Indicators (WDI) database of the World Bank, I collect information about GDP (in 2010 USD PPP), total population, employment, value added by industry, and land area. The geographical coordinates of each country come from the CEPII gravity database. Information about market access, computed using the method developed by [Redding and Venables \(2004\)](#), is obtained from the CEPII Market Potentials Database.

3.3 Final Sample

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, except for the CEPII Market Potentials and WIOT databases, whose latest available years are 2004 and 2014, respectively.

Table 1 shows that there is substantial variation in multinational robot sellers' market entry choices and sales. For instance, Kuka and Yaskawa enter 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.

Sellers serve different countries in terms of 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 decisions of robot sellers.

Table 1. SUMMARY STATISTICS

Name	HQ	No. Countries	No. Branches	Log Dist. from HQ	Log Sales
ABB	CH	17	7.59	8.39	10.36
Fanuc	JP	16	4.38	8.98	8.70
Yaskawa	JP	27	1.44	9.04	8.33
Kuka	DE	41	2.80	8.48	8.23
Kawasaki	JP	12	2.33	8.84	9.41
Epson	JP	8	4.00	9.59	9.13
Omron	JP	23	2.30	8.97	8.74
Nachi-Fujikoshi	JP	16	3.69	8.91	7.61
Staubli	CH	31	1.23	8.45	5.70
Comau	IT	23	1.74	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 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 procedure used to construct their sales network. For instance, omissions in online listings or misclassification of sales branches could introduce measurement error. To mitigate these concerns, I show that the self-collected information about global sales networks is consistent with other established sources.

First, there is a 75% correlation between the number of sales branches and 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 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 2.2 that robot sales are mediated by local branches, with limited scope for direct imports from countries where production takes place.

Last, there is a 48% correlation between whether sellers have a 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 multinational sellers’ activities. See Appendix D.3 for more details about data validation.

4 Empirical Facts

This section documents novel facts about the robot industry and their implications.

4.1 Gravity

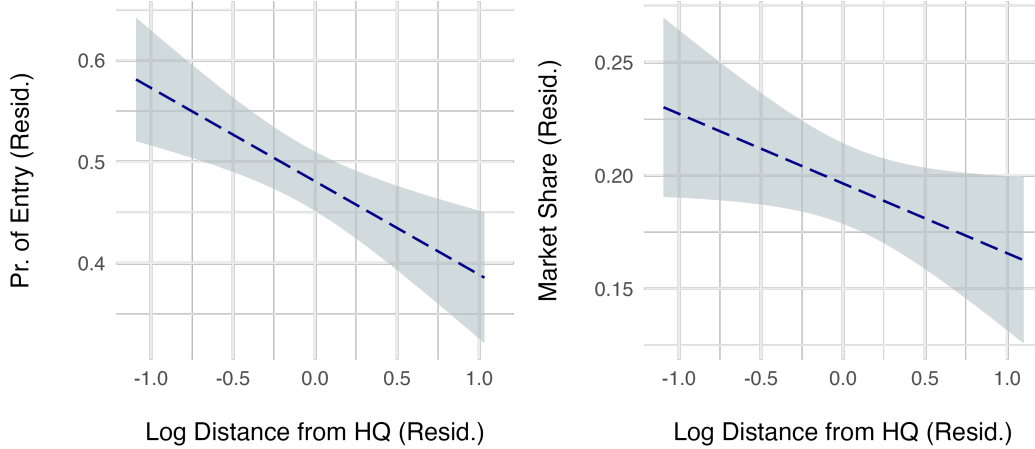
Fact 1. *Robot sellers' entry choices and sales follow gravity.*

I establish this fact by estimating the following equation:

$$y_{s(o)d} = \beta \text{Log Distance from HQ}_{s(o)d} + \delta \text{Controls}_{s,d} + \varepsilon_{s(o)d}. \quad (1)$$

$y_{s(o)d}$ 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 (conditional on entry). *Log Distance from HQ* $_{s(o)d}$ is the log distance between the sellers' HQ and destination countries in kilometers. *Controls* $_{s,d}$ includes seller and country fixed effects, while $\varepsilon_{s(o)d}$ is the error term. Identification comes from within-seller variation after controlling for any country-level characteristics. Figure 1 shows the predicted values of equation (1).

Figure 1. THE GRAVITY OF MARKET ENTRY AND MARKET SHARES



Note: The left panel 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 plots the predicted market share of seller s in country d as a function of the same log distance. All variables are shown after partialling out seller and country fixed effects. 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 the sellers' HQ reduces the probability of entry by about 13 percentage points (p.p.), corresponding to a 28% reduction relative to the unconditional entry probability in the sample. Such an increase in distance also reduces market shares by about 3.8 p.p., corresponding to an 18% reduction relative to the average market share in the sample, as shown in the third column. The results are robust to using a cultural measure of bilateral proximity, as shown in the second and fourth columns.

Overall, there is evidence that multinational robot sellers face bilateral frictions at the extensive and intensive margins that increase with distance from their HQ, which is consistent with gravity.⁸ Several factors may underlie these frictions, including home bias in robot demand, robot sellers' limited knowledge of the needs of adopters in distant countries, or coordination costs increasing with distance from the HQ.

Implication of Fact 1. *Local shocks disproportionately affect foreign robot sellers.*

An implication of gravity is that demand shocks in any given country disproportionately affect robot sellers coming from more distant origins. To document this heterogeneity, I estimate the following equation:

$$\begin{aligned} \mathbb{E}[\text{No. Sellers}_{od}] = \exp & [\alpha \text{Log Distance from HQ}_{od} + \beta \text{Remoteness}_d \\ & + \gamma (\text{Log Distance from HQ}_{od} \times \text{Remoteness}_d) \\ & + \delta \text{Controls}_{o,d}]. \end{aligned} \quad (2)$$

No. Sellers_{od} is the number of robot sellers headquartered in country *o* that have at least one branch in country *d*. *Log Distance from HQ_{od}* is the log distance between the sellers' HQ and destination countries in kilometers. *Remoteness_d* is the inverse of the market access measure developed by Redding and Venables (2004), and captures demand in each country divided by the cost of reaching that country. A higher value implies a smaller market access and, therefore, is expected to reduce the number of active robot sellers.⁹ *Controls_{o,d}* includes origin fixed effects, bilateral controls (i.e., same-continent indicator and cultural proximity), and, depending on the specification,

⁸Gravity is a strong empirical regularity for trade flows (Head and Mayer, 2014) and MNEs' activities (Keller and Yeaple, 2013; Antràs and Yeaple, 2014; Gumpert, 2018). It is reassuring that well-known facts about multinational activity continue to hold in a previously unexplored sector.

⁹This variable is measured by CEPII in 2004. Thus, it is not affected by entry patterns in the robot industry in my sample, which refer to 2021.

either destination country fixed effects or destination country-level controls (i.e., GDP per capita, population, and total land area).

I estimate equation (2) on a balanced sample at the bilateral level to account for the extensive and intensive margins of robot sellers' entry. Identification comes from bilateral variation after controlling for origin and destination-level characteristics.

Table B.2 reports the estimation results. Consistently with Table B.1, the number of robot sellers operating in a country diminishes as the distance from their HQ increases. As expected, reducing market access leads to a reduction in the number of active sellers. The negative and statistically significant coefficient associated with the interaction term highlights the main implication of gravity: negative shocks to market access disproportionately reduce the number of robot sellers coming from more distant origins.

4.2 Granularity

Fact 2. *Robot sales in destination countries are highly concentrated.*

I establish this fact by estimating the following equation:

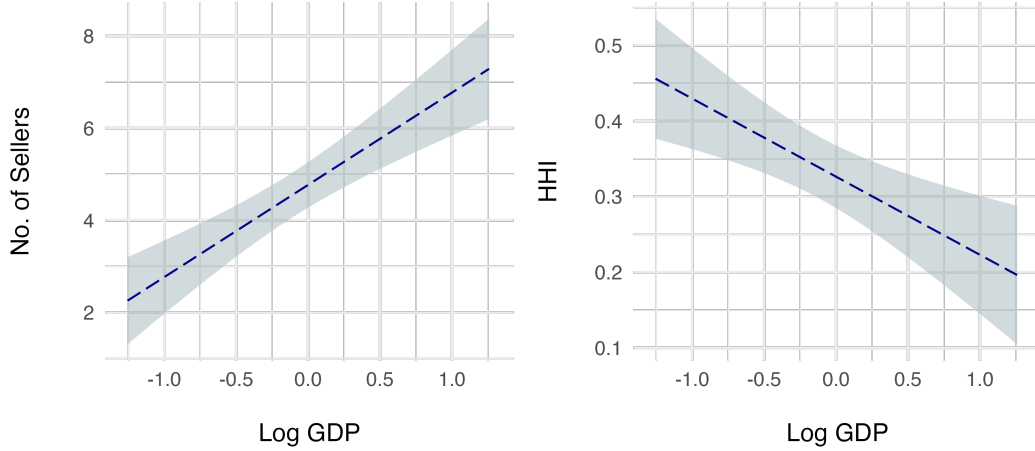
$$y_d = \alpha + \beta \text{Log Market Size}_d + \varepsilon_d. \quad (3)$$

y_d is either the total number of robot sellers active in country d or the Herfindahl–Hirschman Index (HHI) in that country.¹⁰ Market size of country d is approximated by its log GDP (in 2010 USD PPP). ε_d is the error term. The parameter β captures the marginal change in y_d as market size increases. I standardize log GDP to have zero mean and unit variance in the sample. Therefore, α indicates the number of robot sellers or HHI in the average country in terms of size. Figure 2 shows the predicted values of equation (3).

As shown by the first two columns of Table B.3, the average country in terms of market size hosts about 5 robot sellers, corresponding to an HHI of about 34%. It is useful to resort to the Horizontal Merger Guidelines of the Federal Trade Commission (FTC) to interpret these numbers. The FTC classifies markets into “unconcentrated”

¹⁰I define $HHI_d = \sum_{s \in S_d} s_{sd}^2$, being s_{sd} the market share of robot seller s in country d and S_d the set of robot sellers active in country d . This HHI definition 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. In Section 6, I propose a definition of markets that addresses this issue.

Figure 2. CONCENTRATION AND MARKET SIZE



Note: The left panel plots the predicted number of robot sellers in country d as a function of the log GDP of country d . The right panel plots the predicted HHI in country d as a function of the log GDP of country d . 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 (3) is estimated via OLS.

(HHI $< 15\%$), “moderately concentrated” ($15\% \leq \text{HHI} \leq 25\%$), 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. As expected, larger markets host more robot sellers and, therefore, are more competitive, as shown in the last two columns of Table B.3.

Implication of Fact 2. *Marginal changes in the number of robot sellers deliver sizable changes in robot adoption.*

Unlike under perfect competition, granularity suggests that marginal changes in the number of robot sellers active in a country have a non-negligible impact on the quantity of robots adopted. To test this hypothesis, I estimate the following equation:

$$\text{Log}(1 + \text{New Installments}_d) = \alpha + \beta \text{Log Number of Sellers}_d + \delta \text{Controls}_d + \varepsilon_d. \quad (4)$$

$\text{New Installments}_d$ is new robot installments in country d in 2019.¹¹ The variable $\text{Log Number of Sellers}_d$ is the log number of robot sellers active in country d . Controls_d

¹¹This variable is computed by the IFR as the difference between the stock of robots in 2019 and 2018 in each country. Since there are no new installments in 10 countries out of 45 in my sample in 2019, I use the log of one plus new installments to avoid losing observations. Table B.8 shows that the results are robust to using a PPML estimator with a control function approach to account for endogeneity.

includes market size (i.e., GDP per capita and population) and geographical location (i.e., latitude and longitude) controls. ε_d is the error term. The parameter β measures the elasticity of robot adoption to the number of robot sellers.

Estimating equation (4) via OLS is likely subject to bias, as robot sellers may locate in countries with higher investment in robots to begin with. To mitigate endogeneity concerns, I instrument the log number of robot sellers in country d with the total inverse distance (in logs) of country d from the robot sellers' HQ countries.

This instrumental variable aims to capture exogenous changes in the frictions that robot sellers from any origin face when entering country d . As shown by Table B.1, reducing these frictions encourages market entry. Conditional on the included controls, identification relies on the (exclusion restriction) assumption that reducing frictions between country d and the robot sellers' HQ countries solely influences robot adoption by increasing the number of robot sellers in country d . As explained in Section 2.2, robot sales require physical proximity between robot adopters to sellers. Therefore, alternative channels that might pose concerns in other industries (e.g., direct imports from HQ countries) are less relevant in the robot industry.¹²

A separate concern with distance-based instruments, like the one proposed here, is their correlation with a country's distance from the equator, which is associated with inferior institutions and lower investment levels in general (Rodriguez and Rodrik, 2000; Feyrer, 2019). Equation (4) includes controls for GDP per capita and geographical location to address these concerns.

The first column of Table B.4 presents the first-stage estimates. As expected, the instrument is positively and significantly correlated with the log number of robot sellers, confirming that reducing frictions between country d and the robot sellers' HQ countries increases the number of incumbents in country d . This result is robust to the inclusion of country-level controls, as shown in the second column. The second and third columns report the second-stage OLS estimates, which indicate a positive correlation between new robot installments and the number of active robot sellers in a country. The last two columns show the second-stage IV estimates, which are not statistically different from the OLS ones. The value of the first-stage Kleibergen-Paap statistics well above 10 confirms the relevance of the instrument.

According to the last column of Table B.4, a one percent rise in the number of

¹²To reinforce this argument, Table D.3 shows that bilateral variation in the number of sellers' branches explains two-thirds of the variation of trade in robots in the data even after controlling for bilateral distance and origin and destination-country fixed effects.

active robot sellers in a country corresponds to a 4.7% increase in robot installations. In absolute terms, the entry of one new robot seller in the average country results in approximately 77 new robot installations, corresponding to a 5% increase relative to the median number of robot installations in the data. Overall, Table B.4 provides evidence in support of the notion that robot adoption is sensitive to changes in the number of robot sellers.

This result is robust to using alternative instruments, estimation samples, outcome variables, and estimators. Table B.5 replaces the baseline IV with instruments derived from the fitted values of gravity regressions with different set of controls akin to Feyrer (2019). The interpretation of these alternative instruments aligns with that of the baseline one. Table B.6 reproduces Table B.4 while excluding the top five markets for robots (i.e., China, Germany, Japan, South Korea, and the US) from the estimation sample. Table B.7 measures robot adoption with the log of robot imports (HS 847950) rather than new installments. Table B.8 presents the results of the Pseudo-Poisson Maximum Likelihood (PPML) estimator combined with a control function (CF) approach.¹³ This final robustness test shows that the baseline results are not driven by the use of the “log of one plus” transformation of the outcome variable (Chen and Roth, 2024).

4.3 Taking Stock of the Empirical Facts

This section documents two novel facts about the global robot industry: (i) gravity in robot sellers’ entry choices and sales and (ii) granularity in robot sales in destination countries. An implication of gravity is that local shocks disproportionately affect foreign robot sellers. An implication of granularity is that marginal changes in the number of robot sellers active in a market deliver non-negligible changes in the number of robots adopted. These facts inspire, and are replicated by, the model introduced in Section 5.

5 Theoretical Framework

This section provides a general equilibrium multi-country model that incorporates the features of the robot industry described thus far.

¹³The first stage is the same as in Table B.4. However, while the IV estimator replaces the endogenous variable with its first-stage fitted values, the CF approach entails adding the first-stage residuals alongside the endogenous variable in the second stage. See Wooldridge (2015) for more details.

5.1 Economic Environment

Set Up. The global 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.

There exists a set of \mathcal{S} multinational robot sellers, each denoted by s . Robot sellers differ in terms of their appeal to final goods producers. This source of heterogeneity generates gravity in robot sales, as per Section 4.1. To account for granularity, as per Section 4.2, I let robot sellers compete oligopolistically within the robot industry.

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 exogenously given.

In equilibrium, robot sellers generate profits. Following the approach of Chaney (2008), I assume that these profits are distributed among households in proportion to their labor income.

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

$$C_d(i) = \left(\sum_{o \in \mathcal{M}} C_{od}(i)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \quad \theta > 1. \quad (5)$$

$C_{od}(i)$ 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:

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

$w_d(i)$ 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. The welfare level of households of type i can

be expressed as:

$$\mathcal{W}_d = \frac{E_d(i)}{P_d}. \quad (7)$$

P_d denotes the consumer price index in market d .

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:

$$Y_d = A_d X_d^\beta L_d(n)^{1-\beta}, \quad X_d = (R_d^\eta + L_d(r)^\eta)^{\frac{1}{\eta}}, \quad \beta \in (0, 1), \quad \eta \in (0, 1]. \quad (8)$$

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 (8) 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 in terms of local non-routine labor, they choose which markets to serve. These costs capture, among others, the cost of setting up branches. 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} . This bundle is considered non-tradable and produced in the destination market using local non-routine labor.¹⁴ Final goods producers in each market combine robot sellers’ products as:

$$R_d = \left(\sum_{s \in S_d} \phi_{sd}^{\frac{1}{\sigma}} R_{sd}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \quad \sigma > 1. \quad (9)$$

Robot sellers are horizontally and vertically differentiated. Horizontal differentiation stems, among others, from the fact that sellers have their own brand and may open branches in different locations within a market. The elasticity of substitution between the products that they sell is σ .

¹⁴In 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.

The source of vertical differentiation is ϕ_{sd} , a demand shifter reflecting the appeal of robot sellers to final goods producers. In Section 6, I will assume that demand shifters are drawn from a log-normal distribution. Since demand shifters are seller-by-market specific, robot sellers are allowed to be more attractive in some markets (e.g., the HQ market) compared to others (e.g., markets distant from the HQ). Thus, ϕ_{sd} flexibly captures several frictions that are consistent with gravity, such as home bias in robot demand, the limited knowledge of distant markets by robot sellers, or the presence of coordination costs that increase with distance from the HQ.¹⁵

Robot sellers compete oligopolistically à la Bertrand in each market.¹⁶ As is standard in the literature of oligopoly in general equilibrium (e.g., [Atkeson and Burstein, 2008](#); [Gaubert and Itskhoki, 2021](#)), robot 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' gross and net profits are, respectively:

$$\bar{\pi}_{sd} = (r_{sd} - w_d(n))R_{sd} \quad \text{and} \quad \pi_{sd} = \bar{\pi}_{sd} - w_d(n)f. \quad (10)$$

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 (8).

5.2 Equilibrium

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

$$P_{od}C_{od}(i) = \left(\frac{P_{od}^{1-\theta}}{\sum_{o \in \mathcal{M}} P_{od}^{1-\theta}} \right) E_d(i). \quad (11)$$

¹⁵In this model, demand shifters are isomorphic to productivity shocks.

¹⁶The results of the counterfactual exercises are robust to assuming Cournot or monopolistic competition, as discussed in Section 7.2.

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:

$$R_d = \frac{\beta \bar{\iota}_d p_d Y_d}{r_d}, \quad L_d(r) = \frac{\beta(1 - \bar{\iota}_d) p_d Y_d}{w_d(r)}, \quad L_d(n) = \frac{(1 - \beta) p_d Y_d}{w_d(n)}. \quad (12)$$

r_d is the price of robots in market d , while $\bar{\iota}_d$ is the share of X_d^η produced by robots:

$$\bar{\iota}_d = \frac{R_d^\eta}{R_d^\eta + L_d(r)^\eta}. \quad (13)$$

The producer price index associated with equation (8) is:

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

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

Robot Sellers: Pricing. Equations (9) and (12) imply the following robot demand:

$$R_{sd} = \phi_{sd} r_{sd}^{-\sigma} r_d^{\sigma-1} \beta \bar{\iota}_d p_d Y_d. \quad (15)$$

Sellers set r_{sd} to maximize equation (10) given equation (15). Equilibrium prices are:

$$r_{sd} = \frac{\varepsilon_{sd}}{\varepsilon_{sd} - 1} w_d(n). \quad (16)$$

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:

$$\varepsilon_{sd} = \sigma - (\sigma - 1)s_{sd}. \quad (17)$$

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

$$s_{sd} = \frac{\phi_{sd} r_{sd}^{1-\sigma}}{\sum_{s \in S_d} \phi_{sd} r_{sd}^{1-\sigma}}. \quad (18)$$

Equations (16), (17), and (18) describe robot sellers' pricing strategies. Although this system does not have a closed-form solution, it implies that robot sellers with higher ϕ_{sd} have higher market shares, face less elastic demand, and charge higher markups at

a given equilibrium. The robot price associated with equation (9) is:

$$r_d = \left(\sum_{s \in S_d} \phi_{sd} r_{sd}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \quad (19)$$

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 (10) 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:

$$\bar{\pi}_{jd} \geq w_d(n)f > \bar{\pi}_{j'd}. \quad (20)$$

Equation (20) pins down the equilibrium number of robot sellers. Since the realized demand shifters have a market-specific component, the order in which robot sellers enter is allowed to differ by market. Still, robot 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:

$$p_o Y_o = \sum_{d \in \mathcal{M}} \sum_{i \in \{n, r\}} \left(\frac{P_{od}^{1-\theta}}{\sum_{o \in \mathcal{M}} P_{od}^{1-\theta}} \right) E_d(i), \quad (21)$$

$$\bar{L}_d(r) = \frac{\beta(1 - \bar{\iota}_d) p_d Y_d}{w_d(r)}, \quad (22)$$

$$\bar{L}_d(n) = \frac{(1 - \beta) p_d Y_d}{w_d(n)} + R_d + |S_d|f. \quad (23)$$

Equation (21) is the final goods market clearing condition, determining output in each market. Equations (22) and (23) govern the equilibrium of routine and non-routine labor markets, respectively. $|S_d|$ is the number of active sellers in market d . Due to Walras' law, one market clearing condition is redundant. In practice, I select $w_d(n)$ in one market as the numéraire and discard the corresponding 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:

$$r = \frac{\varepsilon}{\varepsilon - 1} w(n), \quad \varepsilon = \sigma - (\sigma - 1)s, \quad s = \frac{1}{|S|}. \quad (24)$$

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

$$\tilde{r} = |S|^{\frac{1}{1-\sigma}} \phi^{\frac{1}{1-\sigma}} r, \quad p = \frac{\bar{\beta}}{A} \tilde{r}^\beta. \quad (25)$$

Notice that $\eta = 1$ implies $\tilde{r} = w(r)$. Suppose that a new robot seller enters this economy. Treating the number of sellers as a continuous variable for simplicity, equation (24) implies that entry reduces incumbents' prices:

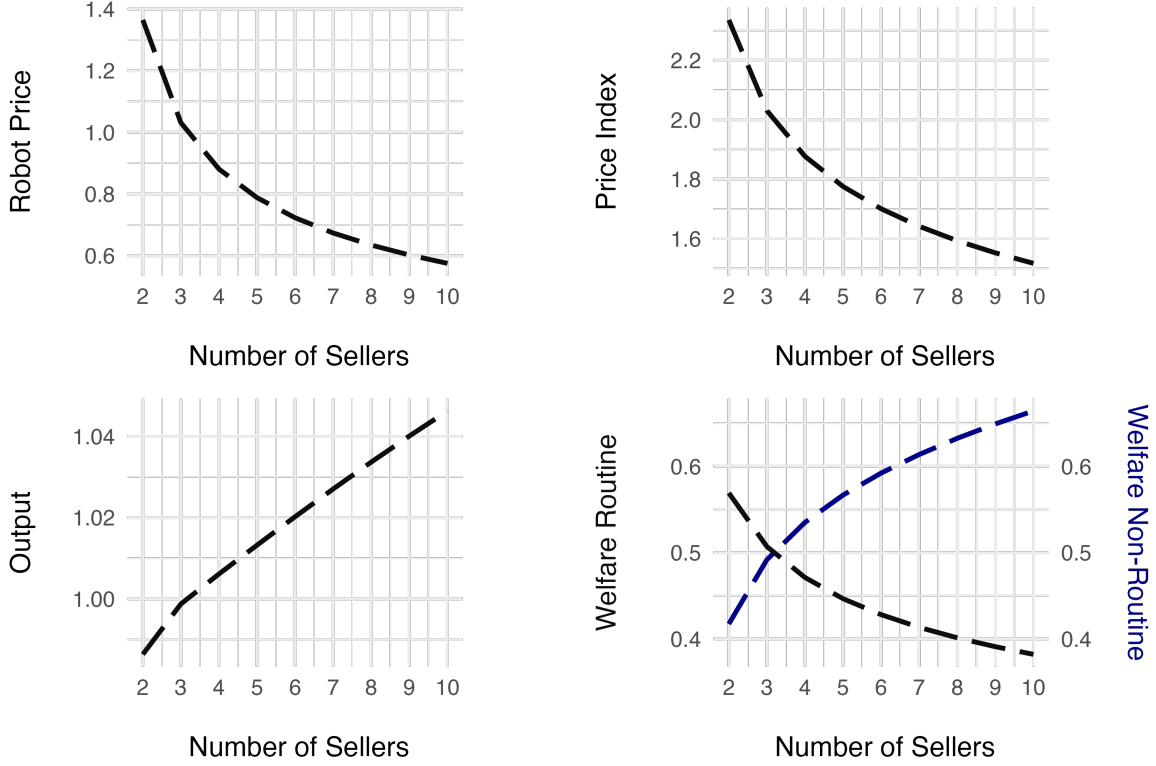
$$\frac{\partial r}{\partial |S|} \frac{|S|}{r} = \frac{1 - \sigma}{\varepsilon(\varepsilon - 1)|S|} < 0. \quad (26)$$

Equation (25) implies that entry also reduces the industry-level robot price and final goods price index:

$$\frac{\partial \tilde{r}}{\partial |S|} \frac{|S|}{\tilde{r}} = \frac{1}{1 - \sigma} + \frac{1 - \sigma}{\varepsilon(\varepsilon - 1)|S|} < 0, \quad \frac{\partial p}{\partial |S|} \frac{|S|}{p} = \frac{\beta}{1 - \sigma} + \frac{\beta(1 - \sigma)}{\varepsilon(\varepsilon - 1)|S|} < 0. \quad (27)$$

As a result, robot demand and total production Y increase, and so do wage and income inequality, defined as $w(n)/w(r)$ and $E(n)/E(r)$ respectively, because $w(r)$ decreases at the same rate of \tilde{r} . Therefore, more competition in the robot industry generates an efficiency-versus-equity trade-off. Figure 3 provides a numerical example, treating $|S|$ as an integer.

Figure 3. ENTRY IN THE ROBOT INDUSTRY - CLOSED ECONOMY

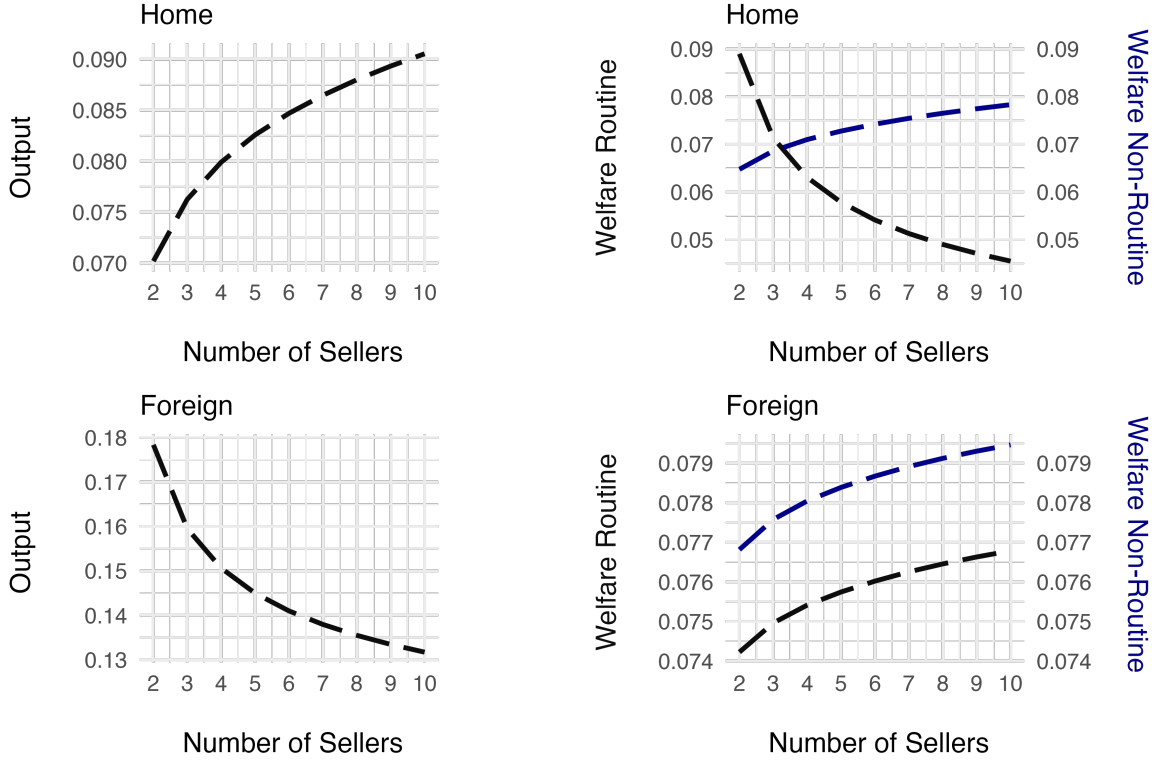


Note: I simulate an economy consisting of one market initially hosting two symmetric robot sellers. I set $\bar{L}(n) = \bar{L}(r) = 1$, $A = 0.1$, and choose model parameters to match those in Section 6. For the numéraire, I use $w(n) = 1$. Then, I progressively increase the number of robot sellers, 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 the Home market. Since equations (24) and (25) continue to hold in the Home market, entry delivers similar effects to those described in the closed-economy case in that market.

What happens in the Foreign market? 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 (11), reducing the total output of Foreign. However, by reducing the cost of imported goods, entry in the Home market increases the welfare of all households in the Foreign market. Figure 4 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 4. ENTRY IN THE ROBOT INDUSTRY - OPEN ECONOMY



Note: I simulate an economy consisting of two markets, Home and Foreign, 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 the Home and Foreign markets.

The General Case. While it provides analytical tractability, robot sellers' symmetry is not necessary to generate the predictions in Figures 3 and 4. As long as robot sellers enter in decreasing order of ϕ_{sd} , the same patterns persist. The outcomes shown in Figure 4 also apply to the case of multiple countries. However, the impact of entry in a single market on the rest of the world is more diluted in a multi-country economy.

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 different 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. Hungary and Romania), western-northern countries (e.g., Germany and Sweden), and central-southern countries (e.g., Italy and France).¹⁷ 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 agriculture and manufacturing and $\bar{L}_d(n)$

¹⁷I 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.

using total employment in the services sector. This approximation is justified by the fact that 99% of the stock of robots in the IFR data are employed in agriculture and manufacturing. No industrial robots are adopted 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 agriculture, manufacturing, and services, where the weights are given by the employment share of each sector. Trade costs between country pairs, τ_{od} , come from the ESCAP World Bank database.

6.2 Estimation Procedure and Identification

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 their products, σ , and market-level entry costs, f . I calibrate θ , η , and β from previous literature and the data. I use a simulated method of moments (SMM) algorithm to estimate ϕ_{sd} , σ , and f .

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 $\eta = 1$, which implies perfect substitution between robots and routine workers. Thus, routine workers' wages are equalized to robot prices and pinned down by competition among robot sellers in local markets. I calibrate β to match the average share of value added of the agricultural and manufacturing sectors in the sample. The implied value of β is 0.34.

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

$$\phi_{sd} = \exp\{\phi_i + \kappa \text{Log Distance from HQ}_{sd} + \zeta u_{sd}\}, \quad i \in \{\text{Top 4, Rest}\}. \quad (28)$$

The demand shifter of robot 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 robot 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 $\hat{\phi}_{\text{Top 4}} \geq \hat{\phi}_{\text{Rest}}$. Consistently with the frictions discussed in Section 4.1 and 5.1, I expect $\hat{\kappa} < 0$. 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 (28),¹⁸ 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.

To solve the model, I extend the solution algorithm developed by [Gaubert and Itskhoki \(2021\)](#) for a two-country economy to a multi-country one. This requires guessing wages for each market, solving the robot sellers' problem in each of them, and iterating until a fixed point is reached. Convergence of the inner loop entails a discrete search over the number of sellers, as per equation (20), and a non-linear search over their prices in equation (16). Convergence of the middle loop is achieved by a linear inversion of equations (21), (22), and (23), which helps to reduce the computational burden of the search. See Appendix F for more details.

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 robot adoption (i.e., number of robots used). 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 robot sellers. All else 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 robot sellers. A higher κ reduces

¹⁸I use $B = 200$. 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](#)).

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
<i>Calibrated</i>				
θ	Trade Elasticity	5.00		Head and Mayer (2014)
β	Income Share of X_d	0.34		WDI
η	$L_d(r)$ vs R_d Elasticity	1.00		Guerreiro et al. (2022)
<i>Estimated</i>				
ϕ_H	Average Demand Shifters (Top 4)	3.26	[2.43, 4.41]	Mean Log Markets and Mkt Shares (Top 4)
ϕ_L	Average Demand Shifters (Rest)	2.03	[1.40, 3.04]	Mean Log Markets and Mkt Shares (Rest)
κ	Elasticity to Dist. from HQ	-0.91	[-1.13, -0.86]	Mean Log Dist. from HQ
ζ	Demand Shifters St. Dev.	1.81	[1.21, 2.10]	St. Dev. Market Shares
f	Market-Level Entry Costs	1.75	[1.16, 2.49]	Mean Log No. of Sellers by Market
σ	Elasticity of Substitution b/w R_{sd}	3.84	[2.96, 6.52]	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 a higher average appeal than the others, though the 95% confidence intervals around the two parameters partially overlap. Moreover, robot sellers' appeal to final goods producers decreases as they enter markets more distant from their HQ, which is consistent with gravity in Section 4.1.

On average, entry costs amount to about 20% of robot sellers' revenues. Positive entry costs align with the fact described in Section 4.2 that only a subset of robot sellers are active in each market.

The estimated value of σ implies a markup of approximately 42% at the average sample market shares, with a standard deviation of 17%. This number falls within 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 3. MODEL FIT ON TARGETED MOMENTS

Description	Data Moments	Simulated Moments
Mean Log No. of Markets (Top 4)	2.29	2.32
Mean Log No. of Markets (Rest)	2.07	2.12
Mean Market Share (Top 4)	0.17	0.18
Mean Market Share (Rest)	0.12	0.09
Mean Log Dist. from HQ	9.01	9.07
St. Dev. Market Shares	0.07	0.06
Mean Log No. of Sellers by Market	1.99	1.90
Mean Log Stock of Robots	10.30	10.30

Note: The table reports the data moments targeted by the SMM procedure and the simulated ones implied by the estimated model.

The model also replicates moments not targeted during the SMM procedure, as shown in Table 4. The rows show seller or market-level outcomes, whereas the columns report their values in the data and as implied by the model. As shown by the last column, the null hypothesis of equal means cannot be rejected for any outcome.

Table 4. MODEL FIT ON NON-TARGETED MOMENTS

Description	Data Moments	Simulated Moments	P-value
Log Sales _s	5.87	6.33	0.48
HHI _d	0.33	0.40	0.28
Log GDP per capita _d	10.0	11.4	0.50
Log Export Values _d	10.6	11.2	0.76

Note: Each row contains a seller (*s*) or market-level (*d*) outcome. The first column reports average values in the data. The second column shows model-implied average values for each outcome. Averages are computed across sellers or markets. The last column is the p-value associated with the null hypothesis that data and model-implied moments have equal means.

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 (19) 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 taxing the adoption of robots.

7.1 Design and Implementation

The Ongoing Debate. In 2017, the EU Parliament debated the introduction of a tax on automation technology, including robots, to mitigate its potential adverse effects on exposed workers.¹⁹ Although the proposal was ultimately voted down, discussions about policies regulating the adoption of automation technology continue to pervade the academic and policy debates (Shiller, 2017; Acemoglu and Johnson, 2023).²⁰

The ongoing debate focuses on how a robot tax affects robot-adopting firms and the labor market. Responses from the supply side are largely overlooked. In this section, I contribute to this debate and use the model to evaluate how multinational robot sellers react to a robot tax 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 $d \in \text{EU}$ and 0 otherwise. The new price of robots can be expressed as:

$$r_d = \frac{\beta \bar{t}_d p_d Y_d}{(1 + t_d) R_d}. \quad (29)$$

Wage equalization between robots and routine workers requires $w_d(r) = (1 + t_d)r_d$. Equation (15) can be modified as:

$$R_{sd} = \phi_{sd} r_{sd}^{-\sigma} r_d^{\sigma-1} \frac{\beta \bar{t}_d p_d Y_d}{1 + t_d}. \quad (30)$$

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

¹⁹See 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.

²⁰In a frictionless economy, the first-best policy instrument to deal with robot-induced displacement consists of lump sum transfers from non-routine to routine workers. Scope for direct taxation of robot adoption only arises in economies with frictions (e.g., occupational switching costs, borrowing constraints, government imperfect information about workers' type).

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. 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. All else equal, 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.

I consider a 5% robot tax as the baseline. This tax rate aligns with the short-run optimal tax 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. 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 5.2% increase in robot prices, leading to a 4.8% reduction in robot demand. Accordingly, production costs rise by 1.9% and output decreases by 1.7%. Consumer prices increase by 0.6%. Income inequality is reduced by 4.7%, with routine households experiencing a 3.3% welfare gain and non-routine households experiencing a 1.5% welfare loss due to their different sustainability with robots.

In the second scenario, the tax leads to a 2.2% reduction in the number of robot sellers. Exit induces an endogenous reallocation of market shares among incumbents, generating a 0.2% increase in their average markup, denoted as $\bar{\mu} = \frac{1}{|S_d|} \sum_{s \in S_d} \mu_{sd}$. This increase puts upward pressure on the other prices. Robot prices increase by 5.1% more than in the first scenario, generating a 15.8% stronger reduction in robot adoption. Producer prices increase by 1.3% more than in the first scenario, while output decreases by 31.6% more. Consumer prices also rise by 37.1% more than in the first case. Income inequality is reduced by 6.9% more, with 11.3% smaller welfare gains

Table 5. THE EFFECTS OF AN EU-WIDE ROBOT TAX IN THE EU

Outcome	Variable	First Scenario	Second Scenario	% Change
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	0.000%	-2.287%	
Markups	$\bar{\mu}_d$	0.000%	0.239%	
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	5.247%	5.519%	5.184%
Robot Stock	R_d	-4.898%	-5.675%	15.864%
Producer Price Index	p_d	1.921%	1.947%	1.353%
Output	Y_d	-1.794%	-2.362%	31.661%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.667%	0.915%	37.181%
Welfare Routine	$\mathcal{W}_d(r)$	3.349%	2.968%	-11.377%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-1.573%	-2.290%	45.582%
Income Inequality	$E_d(n)/E_d(r)$	-4.763%	-5.094%	6.949%

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.

for routine households and 45.4% larger welfare losses among non-routine households.

Comparing outcome changes between scenarios suggests that ignoring multinational robot sellers' responses leads to underestimating the aggregate and distributional effects of a tax in the average EU market by about 20%. In terms of policy implications, the results suggest that a welfare-maximizing European Social Planner should set lower robot taxes when robot sellers adjust to it.

The Effects Beyond the EU. Since markets are linked via international trade, a tax also produces effects beyond the EU. Table B.9 shows the effects of a 5% EU-wide value-added tax on robot adoption in the average non-EU market.

An EU-wide robot tax makes EU final goods more expensive, leading EU and non-EU households to shift their expenditures towards non-EU goods. This demand shift prompts non-EU final goods producers to increase output by using more robots. In the first scenario, the average non-EU market sees a 0.8% rise in both robot adoption and output. The consumer price index goes up by 0.6%, resulting in a welfare loss of

0.4% for routine and non-routine households.

In the second scenario, the exit of some robot sellers from the EU generates a 26.4% stronger increase in consumer prices beyond the EU, leading to twice as large welfare losses for all non-EU households compared to the first scenario. Therefore, ignoring multinational robot sellers' responses to a local tax leads to underestimating the ripple effects of a tax also beyond the domestic border.

Robustness. The results presented in this section are robust to alternative tax rates or market structure assumptions. Tables B.10 and B.11 show the effects while considering a 2% or 7% EU-wide robot tax. As the tax rate increases, all changes in outcomes relative to an equilibrium without taxes are amplified. Tables B.12 and B.13 show that the direction of the second-scenario effects are robust to assuming Cournot or monopolistic competition.

7.3 Further Discussion

The Role of Gravity. Table B.2 highlights that reductions in market access induce disproportionately more exit of robot sellers originating from more distant locations. Since an EU-wide robot tax reduces market access in the EU, higher exit rates among Asian robot sellers are expected. Table B.14 provides evidence for this uneven effect. In an equilibrium with a tax, the average Asian seller serves 1.6% fewer EU markets than in an equilibrium without. By contrast, the average EU seller experiences a lower reduction in the number of EU markets served, equal to 0.7%. Therefore, robot sellers' heterogeneous responses effectively make a robot tax a protectionist measure.

The Role of International Trade in Final Goods. Tables B.15 and B.16 compare the second-scenario outcomes in Tables 5 and B.9 with those obtained in a counterfactual economy where bilateral trade costs on final goods are 5% lower. Both tables reveal a complementarity between trade costs and robot sellers' responses: the same robot tax produces larger effects when trade costs are lower. This happens because lower trade costs lead to higher sensitivity of households' import shares in equation (11) to changes in prices.²¹ Consequently, the reallocation of demand for final goods across markets is amplified, and so is the reallocation of robot supply.

²¹This effect should be understood as a local one around the observed trade costs. In the limit case of free trade, final goods prices equalize and households' expenditure shares become fixed.

Unilateral Versus Multilateral Taxation. Table B.17 compares the outcomes in Tables 5 and B.9 with those resulting from a worldwide 5% value-added tax on robot adoption. Compared to a unilateral one, a worldwide tax reduces the number of active robot sellers and output everywhere. All routine households experience welfare gains and all non-routine households face welfare losses. 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. Tables 5 and B.9 refer to 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.18. 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. 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.19 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 B.9.

Additional Margins of Supply-Side Responses. Besides market entry and pricing choices, multinational robot sellers could respond to regulation along additional margins, such as product innovation. If a tax reduces innovation incentives, robot supply contracts even more than in the baseline model, further magnifying outcome differences between models with and without supply-side responses.

The model can be extended to include multi-product robot sellers. For instance, sellers may offer factory-gate robots differentiated in terms of speed and precision. If robot sellers specialize in different products, markets become more segmented, leading to greater concentration. Since robot prices are more sensitive to changes in the number of sellers when there are only a few incumbents (see Figure 3), the exit of robot sellers would cause a stronger increase in markups and prices than in the baseline model.

Therefore, the results presented thus far should be understood as a lower bound to those implied by a richer model that includes additional margins of supply-side responses.

8 Additional Counterfactuals

This section discusses the effects of boosting competition in the robot industry. It is worth noticing that the model can also be used to study a range of additional 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. 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 et al., 2023). These concerns are relevant for the robot industry given its high level of concentration. In light of this debate, I investigate what are the effects of promoting competition in the robot industry.

Counterfactual Scenarios. I evaluate two counterfactual scenarios. In the first, while holding the total number of robot sellers fixed, I simulate the effects of a 25% reduction in the entry costs that robot sellers must pay to serve each market. In the second, while holding entry costs fixed, I simulate the arrival of a new top robot seller with HQ in China, the largest country in the world in terms of robot adoption. In each scenario, I study the implications for competition in the robot industry, final goods producers, and households. Details about the solution algorithm are in Section F.4.

Results. Table B.20 shows the results. I present all outcomes as percentage changes relative to the baseline model equilibrium.

Boosting competition among robot sellers reduces markups and prices in all markets. In the first counterfactual scenario, routine households experience a welfare loss, whereas non-routine households face a welfare increase. In the second counterfactual scenario, where pro-competitive effects are stronger, both types of households are better off. Still, income inequality increases in both scenarios.

These findings suggest that distortions in the robot industry are potentially large but their cost is not evenly borne. If the pro-competitive effects of policy interventions are strong enough, all types of workers can be better off. However, the non-neutrality of robots implies that non-routine workers experience disproportionately larger gains.

9 Conclusions

Automation technology enhances productivity but generates concerns about job displacement, leading to an academic and policy debate about policies to favor or discourage its adoption. The current debate focuses on how policy interventions impact technology adopters. In this paper, I investigate how supply-side responses shape the outcomes of policy changes. I focus on the global market of industrial robots, an industry where a few multinational enterprises dominate production and sales.

I collect new data on the characteristics and global sales of the leading multinational robot sellers worldwide. I then develop and estimate a quantitative multi-country general equilibrium model accounting for the role of multinational sellers in the robot industry. Using the model, I show that multinational robot sellers' market entry and pricing responses to policies targeting robot adoption substantially amplify the aggregate and distributional effects of these interventions. To the extent that markets are linked via international trade and multinational activity, the effects of a local policies transmit beyond local borders.

Overall, this paper conveys two messages. First, any regulation targeting the diffusion of robots should take into account 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

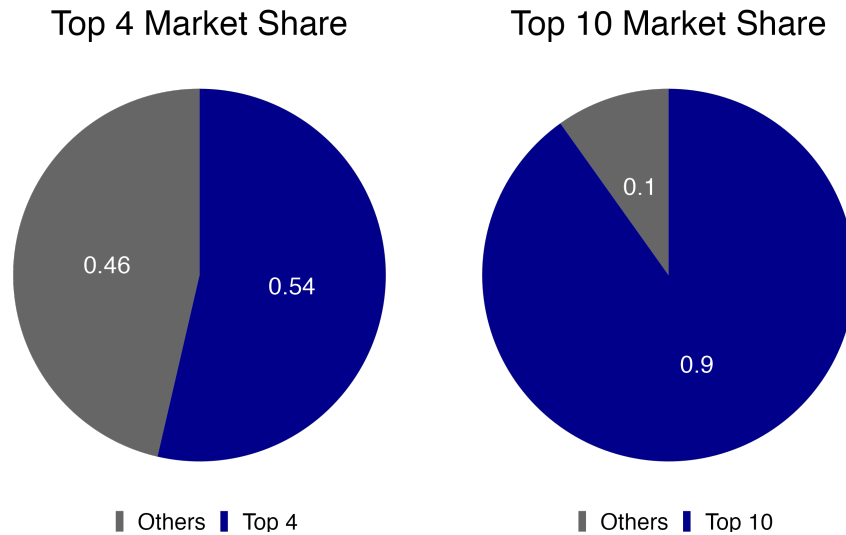
A Figures

Figure A.1. THE SUPPLY CHAIN OF INDUSTRIAL ROBOTS



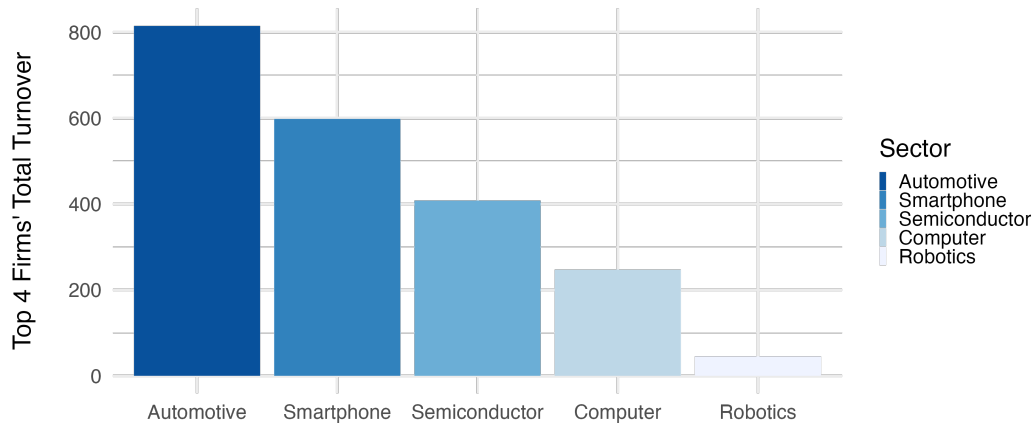
Note: The figure shows the typical supply chain of industrial robots. Nearly half of the world’s production of robots takes place in Japan. During the integration stage, final users purchase robots and “integration services” such as customization, installation, and ongoing maintenance from sellers. Robots 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

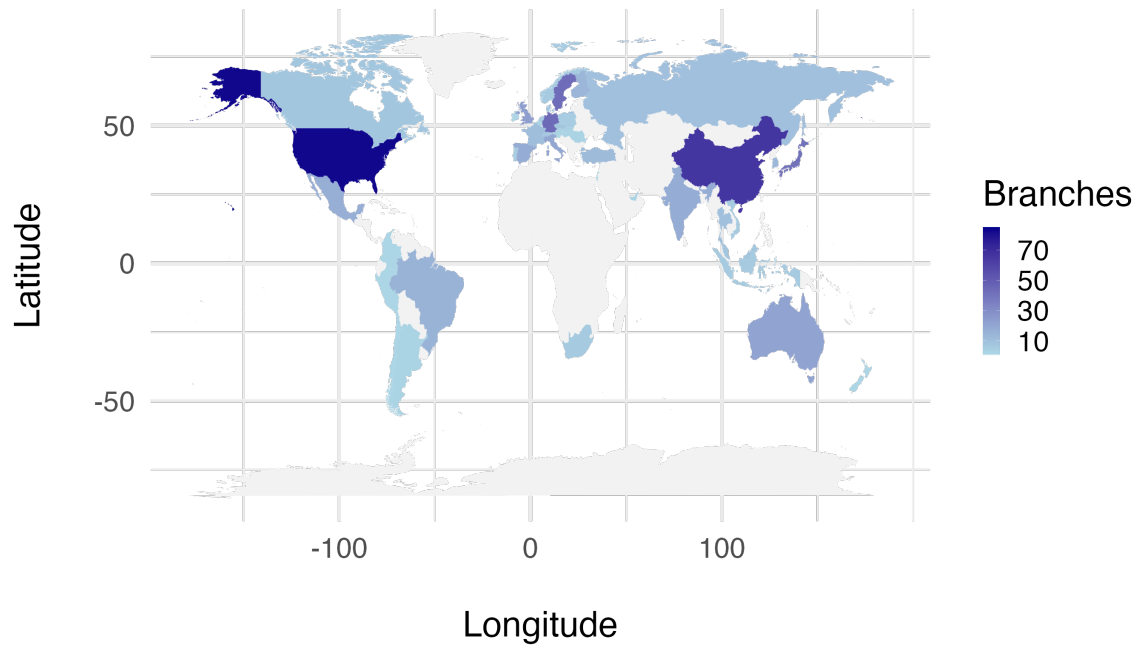
Website: <http://tsrsolutions.co>
Phone: +1 720 480-3484
Email: sales@tsrsolutions.co

List of authorized area

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

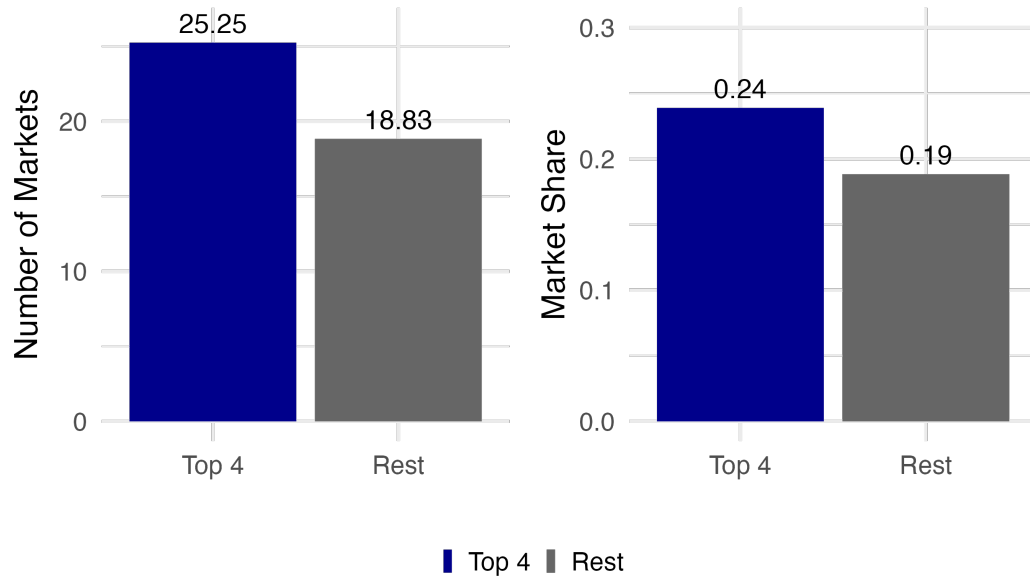
Note: The figure shows an example of a website containing information about robot sales branches. The typical information displayed is the branch name and address, as in Example 1. Sometimes, additional information like the telephone number, web address, list of countries served, and product lines are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

Figure A.5. THE GLOBAL FOOTPRINT OF ROBOT SELLERS



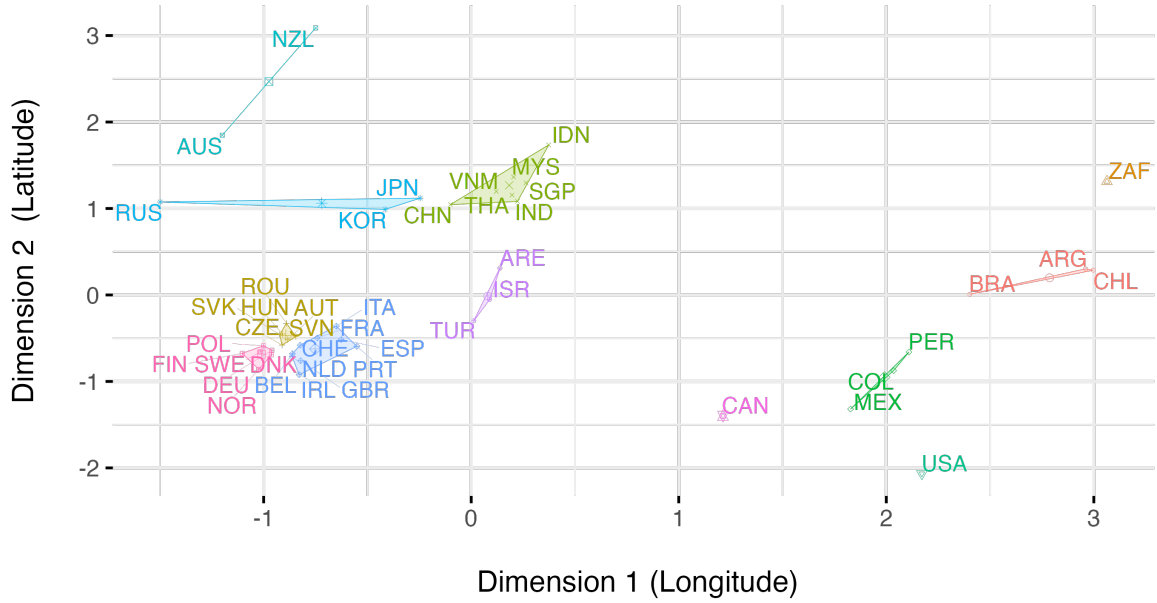
Note: The figure shows the number of branches per country. China, Germany, Japan, South Korea, and the US are the five largest destination countries.

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. GRAVITY IN MARKET ENTRY AND SALES

Dependent Variables:	$Entry_{s(o)d}$ (1)	$Market\ Share_{s(o)d}$ (2)	$Entry_{s(o)d}$ (3)	$Market\ Share_{s(o)d}$ (4)
<i>Log Distance from HQ_{s(o)d}</i>	-0.14*** (0.03)	-0.04*** (0.010)		
<i>Cultural Distance from HQ_{s(o)d}</i>			0.05* (0.03)	0.03*** (0.010)
Seller FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	450	214	450	214
Estimator	OLS	OLS	OLS	OLS

Note: An observation is a robot seller-destination country pair. In the first and third columns, the dependent variable is a binary indicator equal to 1 if seller s from HQ o enters in country d . In the second and fourth columns, the dependent variable is the market share of seller s from HQ o in country d . *Log Distance from HQ_{s(o)d}* is the log of the distance between the two most populated cities of the seller HQ and destination country in kilometers. *Cultural Distance from HQ_{s(o)d}* is a continuous index of linguistic proximity between the seller HQ and the destination country. Both variables are standardized 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 IMPLICATIONS OF GRAVITY

Dependent Variable:	<i>Number of Sellers_{od}</i>	
	(1)	(2)
<i>Log Distance from HQ_{od}</i>	-0.19* (0.11)	-0.41*** (0.12)
<i>Remoteness_d</i>	-0.24** (0.11)	
<i>Log Distance from HQ_{od} × Remoteness_d</i>	-0.11** (0.04)	-0.17** (0.07)
Origin FE	Yes	Yes
Destination FE	No	Yes
Destination Controls	Yes	No
Bilateral Controls	Yes	Yes
Observations	180	180
Estimator	PPML	PPML

Note: An observation is a country pair. In the both columns, the dependent variable is the number of robot sellers from HQ o that have at least one branch in country d . *Log Distance from HQ_{od}* is the log distance between the two most populated cities of the origin and destination countries in kilometers. *Remoteness_d* is the inverse of the market access measure developed by Redding and Venables (2004). Both variables are standardized to have zero mean and unit variance in the sample. Destination controls include the GDP per capita (in 2010 USD PPP), population, and land size of the destination country. Bilateral controls include a binary indicator equal to 1 if o and d belong to the same continent and bilateral cultural proximity. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.3. CONCENTRATION AND MARKET SIZE

Dependent Variables:	<i>Number of Sellers_d</i>	<i>HHI_d</i>	<i>Number of Sellers_d</i>	<i>HHI_d</i>
	(1)	(2)	(3)	(4)
Intercept	4.8*** (0.34)	0.34*** (0.02)	4.8*** (0.21)	0.34*** (0.02)
<i>Log GDP per capita_d</i>			1.0*** (0.23)	-0.02 (0.02)
<i>Log Population_d</i>			2.2*** (0.24)	-0.09*** (0.02)
Observations	45	45	45	45
Estimator	OLS	OLS	OLS	OLS

Note: An observation is a destination country. In the first and third columns, the dependent variable is the number of robot sellers active in country d . In the second and fourth columns, the dependent variable is the HHI in country d . *Log GDP per capita_d* is the log GDP per capita in country d (in 2010 USD PPP), whereas *Log Population_d* is the log total population of country d . I standardize both variables 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.4. ROBOT ADOPTION AND ROBOT SELLERS

Dependent Variables:	<i>Log Number of Sellers_d</i>		<i>Log (1 + New Installments_d)</i>			
	(1)	(2)	(3)	(4)	(5)	(6)
IV_d	2.7*** (0.45)	2.0*** (0.44)				
<i>Log Number of Sellers_d</i>			4.9*** (0.76)	3.9*** (0.96)	6.5*** (0.82)	4.7*** (1.2)
Controls	No	Yes	No	Yes	No	Yes
Observations	45	45	45	45	45	45
KP F-stat					35.8	20.2
Stage	First	First	Second	Second	Second	Second
Estimator	OLS	OLS	OLS	OLS	IV	IV

An observation is a destination country. In the first two columns, the dependent variable is the log number of robot sellers in country d . In the last four columns, the dependent variable is the log of one plus the number of new robot installments in country d . The first two columns show the first-stage OLS estimates. The third and fourth columns report the second-stage OLS estimates. The last two columns report the second-stage IV estimates. $IV_d = \sum_o \frac{1}{\log(dist_{od})}$ is the total inverse log distance in kilometers between the two most populated cities of country d and the robot sellers' HQ countries. *Log Number of Sellers_d* is the log number of robot sellers in country d . Controls include the log GDP per capita (in 2010 USD PPP), population, latitude, and longitude of country d . KP F-stat is the Kleibergen-Paap Wald statistics. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.5. ROBOT ADOPTION AND ROBOT SELLERS - ALTERNATIVE IV

Dependent Variables:	<i>Log Number of Sellers_d</i>	<i>Log (1 + New Installments_d)</i>		
	(1)	(2)	(3)	(4)
<i>IV2_d</i>	0.28*** (0.04)			
<i>IV3_d</i>		0.26*** (0.04)		
<i>Log Number of Sellers_d</i>			3.4*** (1.0)	3.5*** (1.2)
Controls	Yes	Yes	Yes	Yes
Observations	45	45	45	45
KP F-stat			46.1	40.9
Stage	First	First	Second	Second
Estimator	OLS	OLS	IV	IV

An observation is a destination country. In the first two columns, the dependent variable is the log number of robot sellers in country d . In the last two columns, the dependent variable is the log of one plus the number of new robot installments in country d . The first two columns show the first-stage OLS estimates. The last two columns report the second-stage IV estimates. *Log Number of Sellers_d* is the log number of robot sellers in country d . Controls include the log GDP per capita (in 2010 USD PPP), population, latitude, and longitude of country d . $IV2_d = \sum_o IV2_{od}$, where $IV2_{od}$ are the fitted values of a gravity regression of the log number of sellers with HQ in country o with at least one branch in country d on the log distance in kilometers between the two countries. $IV3_d$ is defined as $IV2_d$ but adding to the underlying gravity regression a cultural proximity variable and indicator variables equal to 1 if the country pair belongs to a regional trade agreement, shares a common religion, or has ever been in a colonial relationship. KP F-stat is the Kleibergen-Paap Wald statistics. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.6. ROBOT ADOPTION AND ROBOT SELLERS - ALTERNATIVE SAMPLE

Dependent Variables:	<i>Log Number of Sellers_d</i>		<i>Log (1 + New Installments_d)</i>			
	(1)	(2)	(3)	(4)	(5)	(6)
<i>IV_d</i>	2.4*** (0.42)	1.9*** (0.48)				
<i>Log Number of Sellers_d</i>			4.4*** (0.84)	4.3*** (1.1)	6.6*** (0.91)	5.7*** (1.4)
Controls	No	Yes	No	Yes	No	Yes
Observations	40	40	40	40	40	40
KP F-stat					33.1	15.4
Stage	First	First	Second	Second	Second	Second
Estimator	OLS	OLS	OLS	OLS	IV	IV

This table reproduces Table B.4 but excludes the top five markets for robots (i.e., China, Germany, Japan, South Korea, and the US) from the estimation sample. An observation is a destination country. The dependent variable is the log of one plus the number of new robot installments in country d . *Log Number of Sellers_d* is the log number of robot sellers in country d . The first two columns show the second-stage OLS estimates. The last two columns report the second-stage IV estimates. The instrument $(IV_d = \sum_o \frac{1}{\log(dist_{od})})$ is the total inverse log distance in kilometers between the two most populated cities of country d and the robot sellers' HQ countries. Controls include the log GDP per capita (in 2010 USD PPP), population, latitude, and longitude of country d . KP F-stat is the Kleibergen-Paap Wald statistics. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.7. ROBOT ADOPTION AND ROBOT SELLERS - ALTERNATIVE OUTCOME

Dependent Variable:	<i>Log Robot Imports_d</i>			
	(1)	(2)	(3)	(4)
<i>Log Number of Sellers_d</i>	0.15*** (0.03)	0.10*** (0.03)	0.21*** (0.03)	0.15*** (0.04)
Controls	No	Yes	No	Yes
Observations	45	45	45	45
KP F-stat			35.8	20.2
Stage	Second	Second	Second	Second
Estimator	OLS	OLS	IV	IV

An observation is a destination country. The dependent variable is the log of robot imports (HS 847950) in country d . *Log Number of Sellers_d* is the log number of robot sellers in country d . The first two columns report the second-stage OLS estimates. The last two columns report the second-stage IV estimates. The instrument $(IV_d = \sum_o \frac{1}{\log(dist_{od})})$ is the total inverse log distance in kilometers between the two most populated cities of country d and the robot sellers' HQ countries. Controls include the log GDP per capita (in 2010 USD PPP), population, latitude, and longitude of country d . KP F-stat is the Kleibergen-Paap Wald statistics. Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.8. ROBOT ADOPTION AND ROBOT SELLERS - ALTERNATIVE ESTIMATOR

Dependent Variable:	<i>New Installments_d</i>			
	(1)	(2)	(3)	(4)
<i>Log Number of Sellers_d</i>	3.7*** (0.76)	1.3** (0.58)	3.6*** (0.88)	0.93* (0.55)
Controls	Yes	Yes	Yes	Yes
Observations	45	45	45	45
Stage	Second	Second	Second	Second
Estimator	PPML	PPML	PPML CF	PPML CF

An observation is a destination country. The dependent variable is the number of new robot installments in country d . *Log Number of Sellers_d* is the log number of robot sellers in country d . The first two columns show the second-stage PPML estimates. The first two columns report the second-stage PPML control function (CF) estimates. The instrument $\left(IV_d = \sum_o \frac{1}{\log(dist_{od})}\right)$ is the total inverse log distance in kilometers between the two most populated cities of country d and the robot sellers' HQ countries. Controls include the log GDP per capita (in 2010 USD PPP), population, latitude, and longitude of country d . Heteroscedasticity-robust standard errors in parenthesis. Significance levels: *** 0.01, ** 0.05, * 0.1.

Table B.9. THE EFFECTS OF AN EU-WIDE ROBOT TAX BEYOND THE EU

Outcome	Variable	First Scenario	Second Scenario	% Change
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	0.000%	0.050%	
Markups	$\bar{\mu}_d$	0.000%	-0.003%	
<i>Panel B: Final Goods Producers</i>				
Robot Stock	R_d	0.837%	0.735%	-12.186%
Output	Y_d	0.835%	0.717%	-14.132%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.643%	0.813%	26.439%
Welfare Routine	$\mathcal{W}_d(r)$	-0.418%	-0.978%	133.971%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-0.419%	-0.979%	133.652%
Income Inequality	$E_d(n)/E_d(r)$	0.000%	0.000%	

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.

Table B.10. THE EFFECTS OF AN EU-WIDE ROBOT TAX IN THE EU - ALTERNATIVE TAX RATES

Outcome	Variable	Tax = 2%	Tax = 5%	Tax = 7%
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	-1.895%	-2.287%	-1.308%
Markups	$\bar{\mu}_d$	0.172%	0.239%	0.098%
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	2.284%	5.519%	7.731%
Robot Stock	R_d	-2.459%	-5.675%	-7.585%
Producer Price Index	p_d	0.798%	1.947%	2.854%
Output	Y_d	-1.019%	-2.362%	-3.190%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.374%	0.915%	1.424%
Welfare Routine	$\mathcal{W}_d(r)$	1.261%	2.968%	3.678%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-0.967%	-2.290%	-3.379%
Income Inequality	$E_d(n)/E_d(r)$	-2.193%	-5.094%	-6.793%

Note: The table summarizes the effects of different EU-wide value-added taxes 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.

Table B.11. THE EFFECTS OF AN EU-WIDE ROBOT TAX BEYOND THE EU - ALTERNATIVE TAX RATES

Outcome	Variable	Tax = 2%	Tax = 5%	Tax = 7%
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	0.097%	0.050%	0.033%
Markups	$\bar{\mu}_d$	-0.006%	-0.003%	0.000%
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	0.473%	1.219%	1.661%
Robot Stock	R_d	0.296%	0.735%	1.009%
Producer Price Index	p_d	0.476%	1.218%	1.660%
Output	Y_d	0.286%	0.717%	0.986%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.311%	0.813%	1.086%
Welfare Routine	$\mathcal{W}_d(r)$	-0.369%	-0.978%	-1.254%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-0.365%	-0.979%	-1.256%
Income Inequality	$E_d(n)/E_d(r)$	0.004%	-0.000%	-0.002%

Note: The table summarizes the effects of different EU-wide value-added taxes 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.

Table B.12. THE EFFECTS OF AN EU-WIDE ROBOT TAX IN THE EU - ALTERNATIVE MARKET STRUCTURE

Outcome	Variable	Bertrand	Cournot	Monopolistic Competition
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	-2.287%	-0.178%	-3.318%
Markups	$\bar{\mu}_d$	0.239%	0.030%	0.823%
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	5.519%	5.289%	5.117%
Producer Price Index	p_d	1.947%	1.958%	1.445%
Output	Y_d	-2.362%	-2.068%	-0.286%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.915%	0.986%	0.824%
Welfare Routine	$\mathcal{W}_d(r)$	2.968%	2.563%	2.818%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-2.290%	-2.327%	-2.598%
Income Inequality	$E_d(n)/E_d(r)$	-5.094%	-4.768%	-5.261%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average EU market under alternative market structure assumptions (Bertrand competition, Cournot competition, and monopolistic competition). 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.

Table B.13. THE EFFECTS OF AN EU-WIDE ROBOT TAX BEYOND THE EU - ALTERNATIVE MARKET STRUCTURE

Outcome	Variable	Bertrand	Cournot	Monopolistic Competition
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	0.050%	0.006%	0.078%
Markups	$\bar{\mu}_d$	-0.003%	-0.001%	-0.015%
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	1.219%	1.262%	0.949%
Producer Price Index	p_d	1.218%	1.262%	0.957%
Output	Y_d	0.717%	0.042%	2.238%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.813%	0.737%	0.589%
Welfare Routine	$\mathcal{W}_d(r)$	-0.978%	-0.650%	-0.573%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-0.979%	-0.649%	-0.562%
Income Inequality	$E_d(n)/E_d(r)$	-0.000%	0.000%	0.012%

Note: The table summarizes the effects of a 5% EU-wide value-added tax on robot adoption in the average non-EU market under alternative market structure assumptions (Bertrand competition, Cournot competition, and monopolistic competition). 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.

Table B.14. THE EFFECTS OF AN EU-WIDE ROBOT TAX ON DIFFERENT SELLERS

HQ	Change in the Number of EU Markets
Europe	-0.735%
Asia	-1.667%

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.15. THE COMPLEMENTARITY BETWEEN MARKET STRUCTURE AND TRADE COSTS - AVERAGE EU MARKET

Outcome	Variable	Actual Trade Costs	Low Trade Costs	% Change
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	-2.287%	-2.763%	20.813%
Markups	$\bar{\mu}_d$	0.239%	0.375%	56.904%
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	5.519%	5.547%	0.507%
Robot Stock	R_d	-5.675%	-6.478%	14.150%
Producer Price Index	p_d	1.947%	1.945%	-0.103%
Output	Y_d	-2.362%	-2.492%	5.504%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.915%	0.888%	-2.951%
Welfare Routine	$\mathcal{W}_d(r)$	2.968%	3.072%	3.504%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-2.290%	-2.232%	-2.533%
Income Inequality	$E_d(n)/E_d(r)$	-5.094%	-5.134%	0.785%

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.16. THE COMPLEMENTARITY BETWEEN MARKET STRUCTURE AND TRADE COSTS - AVERAGE NON-EU MARKET

Outcome	Variable	Actual Trade Costs	Low Trade Costs	% Change
<i>Panel A: Robot Sellers</i>				
Number of Sellers	S_d	0.050%	0.051%	2.000%
Markups	$\bar{\mu}_d$	-0.003%	-0.004%	33.333%
<i>Panel B: Final Goods Producers</i>				
Robot Price	r_d	1.219%	1.053%	-13.618%
Robot Stock	R_d	0.735%	0.792%	7.755%
Producer Price Index	p_d	1.218%	1.053%	-13.547%
Output	Y_d	0.717%	0.774%	7.950%
<i>Panel C: Households</i>				
Consumer Price Index	P_d	0.813%	0.653%	-19.680%
Welfare Routine	$\mathcal{W}_d(r)$	-0.978%	-0.670%	-31.493%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-0.979%	-0.670%	-31.563%
Income Inequality	$E_d(n)/E_d(r)$	-0.000%	0.000%	

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.17. AN EU-WIDE VERSUS A WORLDWIDE ROBOT TAX

Outcome	Variable	EU-wide Tax	Worldwide Tax
<i>Panel A: EU</i>			
Number of Sellers	S_d	-2.287%	-0.451%
Markups	$\bar{\mu}_d$	0.239%	0.051%
Robot Price	r_d	5.519%	5.433%
Robot Stock	R_d	-5.675%	-2.046%
Producer Price Index	p_d	1.947%	2.079%
Output	Y_d	-2.362%	1.172%
Consumer Price Index	P_d	0.915%	1.726%
Welfare Routine	$\mathcal{W}_d(r)$	2.968%	0.422%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-2.290%	-4.394%
Income Inequality	$E_d(n)/E_d(r)$	-5.094%	-4.795%
<i>Panel B: Non-EU</i>			
Number of Sellers	S_d	0.050%	-0.407%
Markups	$\bar{\mu}_d$	-0.003%	0.031%
Robot Price	r_d	1.219%	6.010%
Robot Stock	R_d	0.735%	-4.762%
Producer Price Index	p_d	1.218%	2.649%
Output	Y_d	0.717%	-1.636%
Consumer Price Index	P_d	0.813%	1.742%
Welfare Routine	$\mathcal{W}_d(r)$	-0.978%	0.964%
Welfare Non-Routine	$\mathcal{W}_d(n)$	-0.979%	-3.860%
Income Inequality	$E_d(n)/E_d(r)$	-0.000%	-4.778%

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.18. THE EFFECTS OF AN EU-WIDE ROBOT TAX WITHIN EU AND NON-EU MARKETS

Counterfactual	EU	Mean	Q25	Median	Q75
<i>Panel A: Robot Stock, R_d</i>					
First Scenario	0	0.837%	0.000%	0.147%	0.190%
First Scenario	1	-4.898%	-5.056%	-4.346%	-4.091%
Second Scenario	0	0.735%	0.013%	0.101%	0.514%
Second Scenario	1	-5.675%	-6.853%	-5.727%	-5.377%
<i>Panel B: Output, Y_d</i>					
First Scenario	0	0.835%	0.000%	0.147%	0.190%
First Scenario	1	-1.794%	-1.958%	-1.225%	-0.957%
Second Scenario	0	0.717%	0.004%	0.101%	0.375%
Second Scenario	1	-2.362%	-3.062%	-2.651%	-2.224%
<i>Panel C: Welfare Routine, $\mathcal{W}_d(r)$</i>					
First Scenario	0	-0.418%	-0.603%	-0.308%	-0.295%
First Scenario	1	3.349%	2.785%	3.188%	3.798%
Second Scenario	0	-0.978%	-1.281%	-1.164%	-0.961%
Second Scenario	1	2.968%	2.587%	3.453%	4.719%
<i>Panel D: Welfare Non-Routine, $\mathcal{W}_d(n)$</i>					
First Scenario	0	-0.419%	-0.603%	-0.308%	-0.296%
First Scenario	1	-1.573%	-2.111%	-1.726%	-1.145%
Second Scenario	0	-0.979%	-1.285%	-1.149%	-0.962%
Second Scenario	1	-2.290%	-2.399%	-1.474%	-1.391%

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.19. THE EFFECTS OF AN EU-WIDE ROBOT SUBSIDY

Outcome	Variable	Value
<i>Panel A: EU</i>		
Number of Sellers	S_d	0.994%
Markups	$\bar{\mu}_d$	-0.129%
Robot Price	r_d	-5.155%
Robot Stock	R_d	8.233%
Producer Price Index	p_d	-1.856%
Output	Y_d	2.786%
Consumer Price Index	P_d	-0.991%
Welfare Routine	$\mathcal{W}_d(r)$	-1.253%
Welfare Non-Routine	$\mathcal{W}_d(n)$	4.013%
Income Inequality	$E_d(n)/E_d(r)$	5.335%
<i>Panel B: Non-EU</i>		
Number of Sellers	S_d	-0.056%
Markups	$\bar{\mu}_d$	0.005%
Robot Price	r_d	-1.041%
Robot Stock	R_d	-0.135%
Producer Price Index	p_d	-1.042%
Output	Y_d	-0.121%
Consumer Price Index	P_d	-0.670%
Welfare Routine	$\mathcal{W}_d(r)$	1.515%
Welfare Non-Routine	$\mathcal{W}_d(n)$	1.513%
Income Inequality	$E_d(n)/E_d(r)$	-0.002%

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.20. BOOSTING COMPETITION IN THE ROBOT INDUSTRY

Outcome	Variable	Lower Market Entry Costs	New Robot Seller
<i>Panel A: Robot Sellers</i>			
Number of Sellers	S_d	5.111%	5.271%
Markups	$\bar{\mu}_d$	-0.324%	-0.395%
<i>Panel B: Final Goods Producers</i>			
Robot Price	r_d	-0.147%	-16.366%
Producer Price Index	p_d	-0.014%	-15.980%
Output	Y_d	0.068%	17.746%
<i>Panel C: Households</i>			
Consumer Price Index	P_d	-0.000%	-18.489%
Welfare Routine	$\mathcal{W}_d(r)$	-0.142%	1.576%
Welfare Non-Routine	$\mathcal{W}_d(n)$	0.059%	5.228%
Welfare Inequality	$\mathcal{W}_d(n)/\mathcal{W}_d(r)$	0.204%	3.310%

Note: The table summarizes the effects of a 25% worldwide reduction in market-level entry costs and the addition of a new robot seller to the set of potential incumbents. Panel A shows the effects on robot sellers. Panel B shows the effects on final goods producers. Panel C shows the effects on households. All outcome changes are relative to the initial equilibrium with the estimated entry costs and actual number of potential incumbents, respectively.

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`,²² 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.

²²Steven 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.²³ 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 (nine years for the top 10 sellers vs. three years for the others).

²³See <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 its 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 a 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 an 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**,²⁴ 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.

²⁴See <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:	<i>Mkt Share (Sales)_{sd}</i>		<i>Log Sales_{sd}</i>	
	(1)	(2)	(3)	(4)
<i>Mkt Share (Branches)_{sd}</i>	0.83*** (0.07)	0.48** (0.24)		
<i>Log Branches_{sd}</i>			1.1*** (0.19)	0.77*** (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:

$$Robots_d = \alpha + \beta \text{ Branches}_d + \gamma \text{ Controls}_d + \varepsilon_d.$$

$Robots_d$ 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)
$Branches_d$	0.62*** (0.21)	0.63*** (0.21)
Controls	No	Yes
Observations	45	45
R ²	0.56	0.57
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 the GDP per capita (in 2010 USD PPP). 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:

$$Trade\ in\ Robots_{od} = \beta \text{ Branches}_{od} + \gamma \text{ Controls}_{od} + FE_o + FE_d + \varepsilon_{od}.$$

$Trade\ in\ Robots_{od}$ 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*** (3.8)	11.8*** (3.9)	11.3*** (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:	<i>Branch Dummy</i> _{sd}		<i>Branches</i> _{sd}	
	(1)	(2)	(3)	(4)
<i>Subsidiary Dummy</i> _{sd}	0.44*** (0.03)	0.32*** (0.04)		
<i>Subsidiaries</i> _{sd}			0.16*** (0.06)	0.10** (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:

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

Notation follows from equation (9). Combining the first-order conditions of equations (8) and (E.1), the demand faced by each branch can be expressed as:

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

$r_{b(s)d}$ 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:

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

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

$b_{sd}^{1+\frac{1}{\lambda}} / (1+\frac{1}{\lambda})$ 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.²⁵ Hence, the demand function in equation (E.2) can be expressed as:

$$R_{sd} = \phi_{sd} r_{sd}^{-\sigma} b_{sd}^{\frac{\rho-\sigma}{1-\rho}} r_d^{\sigma-1} \beta \bar{t}_d p_d Y_d. \quad (\text{E.5})$$

The sellers' maximization problem can be formulated as:

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

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

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

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

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

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

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:

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

²⁵This 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 (8) from a task-based model as in [Acemoglu and Restrepo \(2018\)](#). Let the production function of final goods producers be, for $\rho > 1$ and $\beta \in (0, 1)$:

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

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

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

being $\gamma_d(\iota)$ and $\psi_d(\iota)$ the productivity of 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:

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

Moreover, equation (E.11) boils down to equation (8). The producer price index in the final good sector is, for $\bar{\beta} = \beta^{-\beta}(1 - \beta)^{\beta-1}$:

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

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 .²⁶ 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:

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

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 (23) 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 (10).

²⁶This 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 3.

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

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

Therefore:

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

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

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

$$\log \check{r} = \frac{1}{1 - \sigma} \log |S| + \log r + \frac{1}{1 - \sigma} \log \phi. \quad (\text{E.19})$$

Therefore:

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

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

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

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

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

Therefore:

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

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 $r_d = w_d(r)$;
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 (21);
5. Find $\bar{\iota}_d$ using equation (22);
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 (16);
 - (b) Compute profits π_{sd} ;
 - (c) If $\pi_{sd} > w_d(n)f$, 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 (16) is only defined for $S \geq 2$. When initializing the inner loop to solve the sellers' problem, I modify equation (16) assuming that the seller behaves as a local monopolist. In this case, the optimal pricing rule can be written as:

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

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 $B = 200$;
2. Guess a vector of parameters Θ ;
3. For each of the B matrices of random shocks:
 - (a) Compute demand shifters using equation (28);
 - (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.²⁷ 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 200 replications.

²⁷This 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 Counterfactual Scenario: Robot Tax

Algorithm. I modify the algorithm in Section F.1 to account for the presence of a tax as follows:

1. Guess a value of $w_d(n)$ and r_d for each market as well as aggregate profits Π and total tax transfers $T_{EU} = \sum_{d \in \mathcal{M}} \mathbf{1}\{d \in EU\} t_d r_d R_d$;
2. Set $r_d = (1 + \tau_d) w_d(r)$;
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 households' disposable income $E_d(i)$ using equation (6);
5. Find Y_d using equation (21);
6. Find $\bar{\iota}_d$ using equation (22);
7. Compute the expenditure on robots $\beta \bar{\iota}_d p_d Y_d$ in each market;
8. Solve the sellers' sequential entry game market-by-market:
 - (a) Let $S = 1$. Use a fixed-point search to find r_{sd} from equation (16);
 - (b) Compute profits π_{sd} ;
 - (c) If $\pi_{sd} > w_d(n)f$, let $S = 2$ and repeat from (7.a);
 - (d) Stop when last entrant would make negative profits.
9. Find a new vector of market-level robot prices r'_d , aggregate profits Π' , and tax transfers T'_{EU} ;
10. Find a new vector of market-level non-routine wages $w_d(n)'$ (up to a numéraire);
11. Iterate until $\|r_d - r'_d\| < tol$, $\|w_d(n) - w_d(n)'\| < tol$, $|\Pi - \Pi'| < tol$ and $|T_{EU} - T'_{EU}| < tol$.

Also in this case, I update prices taking a half step between the old guess and the new one at each iteration. As before, I modify equation (16) assuming that the seller behaves as a local monopolist when $S_d = 1$.

First Scenario. 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 the paragraph at the beginning of Section F.3 but skipping step 8;
 - (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.

Second Scenario. 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 the paragraph at the beginning of Section F.3;
 - (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 $\tau_{EU} = 5\%$).

F.4 Counterfactual Scenario: Competition Policy

I use the algorithm in Section F.1 to solve for the new equilibrium. When reducing entry costs while keeping the number of robot sellers constant, I simply discount the parameter f before solving the model. To simulate the entry of a new Asian robot seller, I add a row to the matrix of demand shifters in equation (28). I assign to this new robot seller ϕ_H as average appeal. The distance from China to each country comes from the data. Error terms are sampled from the $N(0, 1)$ distribution.