

# Collaboration in Technology and Multinational Production

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## Abstract

How does technology sharing affect global production choices? To answer this question, I incorporate technology choices into a structural multinational production model and allow for collaboration in specialized assembly assets across firms when choosing the optimal production locations for their varieties. I find that both the technology choice itself and the potential sharing of it have important effects on the expected cost and profits of firms. Conditional on technology choices, the median firm's cost of serving a market increases by 24.65% compared to traditional models that do not model input technology. On the other hand, allowing for collaboration reduces their cost by 2.9%, with large firm heterogeneity. Importantly, the model allows for analysis not only of trade policy shocks but also of industrial policies. While restricting technology access has limited global effects, it creates significant production consequences for specific firms and countries, highlighting industrial policy as a more targeted tool than trade policy.

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# 1 Introduction

Multinational enterprises (MNEs)<sup>1</sup> are responsible for a large proportion of economic activity and, particularly, international trade (Bernard et al., 2009). Their key role in shaping global production landscapes was first pointed out by Hymer (1960). Building on his insights, the subsequent literature (Caves, 1971; Dunning, 1977; Buckley and Casson, 1976) emphasized the role of specialized assets and technology as a strategic comparative advantage over domestic firms in foreign markets. According to this view, global production choices are shaped by the trade-off between direct investment and licensing of these assets. With the seminal works of Krugman et al. (1980) and Melitz (2003), the new (new) trade theories subsequently formalized a general equilibrium framework of multinational production, introducing product differentiation and firm heterogeneity. A key trade-off for the choice of operating multiple production locations is forgoing increasing returns to scale production at the benefit of economizing on trade costs when serving multiple markets. While important aspects of the early theory were absorbed by the new models, they abstract from explicitly modeling the choice of specific production technologies and the notion of asset specificity. In practice, however, production processes are facilitated by highly specialized technologies in assembly plants.<sup>2</sup> Because (re-) configuring plants is costly, the choice of input technologies limits the firm’s ability to reorganize its production once investments in plants have been made (Michalos et al., 2010). These constraints help to rationalize another phenomenon in MNE activity, commonly found yet little discussed: the sharing of technology and production sites via licensing or joint development and operation. Such collaborations practically allow firms to ease their production constraints by enlarging their sourcing potential. While asset-sharing via licensing was at the heart of the early literature, there is neither an empirical description of the prevalence nor a structural quantification of this effect on the multinational production landscape to date.

Building on these important aspects of multinational production, this paper revisits the original ideas of Hymer (1960). Developing a framework of multinational production that explicitly models the choice of input technology and allows for collaboration, I show that the technology specialization of assembly plants restricts the firms’ production flexibility, increasing variable costs, while collaboration generates heterogeneous efficiency gains. Both the technology choices and the possibility of collaboration thus shape the geography of production.

Using rich data of the global automotive industry by the consultancy S&P Global (formerly IHS Markit), I first contribute to the literature by documenting the prevalence of licensing. While

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<sup>1</sup>A multinational enterprise is a firm operating facilities in more than one country. Its home country is usually defined as the headquarters location of the parent companies.

<sup>2</sup>In fact, there is a whole engineering research field concerned with designing products to facilitate automated assembly processes, ‘Design for Assembly’.

studying a single industry comes with the caveat of limited external validity, the automotive sector is an excellent environment to study such collaborations. First, car manufacturing is a trade-intensive activity, contributing to 6.2% of total world trade in 2021, with the vast majority of production conducted by MNEs (Head and Mayer, 2019). In most advanced economies, the sector is vital for employment, revenues, and innovation.<sup>3</sup> Furthermore, highly disaggregated and detailed data encompassing the universe of models, firms, and locations are available over a long time horizon. The data also provides detailed information on the production processes, including inputs and technology, and information on ownership, which allows to detect inter-firm linkages precisely. Importantly, I show that collaboration through licensing or joint ventures is common and sizable, similar to the pharmaceutical (Simonet, 2002) and IT sector (Vonortas and Kim, 2004). Thus, the implications of this study can be extended to similar manufacturing activities with differentiated varieties produced in highly standardized production processes that involve large development costs and typically many players.

Table 1 documents the number of automotive firms operating with the same assembly technologies and plants or utilizing common supplier relationships. Indeed, production sites are operated by up to eight firms, and input technologies are shared among up to nine different firms. Focusing

**Table 1:** Sharing of Assets per Year

	Mean	SD	Median	Min	Max
# of firms per assembly technologies/year	1.65	1.02	1	1	9
# of firms per plant/year	1.36	0.71	1	1	8
# of firms per engine supplier	2.49	2.23	1	1	10
# of firms per transmission supplier	2.53	3.29	1	1	14
N	676,361				

*Notes:* based on own calculations, source data from S&P Global Sales data set for 2000-2023. Firms are sales groups, defined as the ultimate owners of car models. Assembly technology refers to specific car platforms.

on *automotive platforms* as a key input technology in car assembly, I find that each year, 22% of platforms are licensed among 54% of firms, with large heterogeneity in the reliance on licensing. Moreover, I provide novel evidence linking firms' collaborative behavior to their multinational production choices. In particular, I find that licensing implies cost advantages that grant firms access to new production locations and sales destinations.

The second contribution of the paper is to develop a structural framework that incorporates these novel layers into a standard MP model: the choice of input technology and inter-firm collaboration.

<sup>3</sup>In the OECD, only pharmaceuticals and information technology have more patent applications and R&D spending each year, see OECD, 2025, last retrieved: June 21, 2025.

In the model, firms first select an optimal input technology for each variety they produce. Because production plants operate under fixed, specific configurations, the technology choice conditions the firms' subsequent market entry and assembly sourcing choices, thus affecting global production patterns. Collaboration enters the model by extending the potential technology choice set: Firms can license competitors' technologies against a firm-specific collaboration fixed cost, enlarging the set of potential assemblies. Licensing thus offers an opportunity to reduce variable production costs, at the expense of larger fixed costs.<sup>4</sup>

Third, the detailed and rich data allows to identify the crucial structural parameters of the discrete choice model: an elasticity of substitution between assemblies, market-segment specific demand elasticity, variances of the entry choices, and the elasticity of substitution between platform technologies. Furthermore, I estimate the unobserved platform and collaboration fixed costs that allow me to pin down the gains from collaboration in terms of expected production cost, profits, and resulting market shares. I find that accounting for technology choices is quantitatively important: Compared to models that abstract from these choices, a firm's average costs to serve a market are 25% higher, which results in large reallocation and welfare effects. Collaboration, on the other hand, matters particularly for specific firms. While the average cost advantage is 3%, these benefits can be infinitely large for firms that rely entirely on licensing.

Finally, the structural nature of the model allows to simulate various trade *and* industrial policy scenarios. Motivated by national security and independence concerns, technology-restricting policies have become more fashionable in recent years. In an effort to control and limit the sharing of essential technology with China, in October 2022, the USA, for example, updated its Export Administration Regulations (EAR), exacerbating the rules to both export and license out sensitive technology. Compared to the traditional models, the framework can quantify the global effects of such policies and predict the global reshuffling in technology sharing and production choices. I find that an export ban of US technology increases the average cost of firms on average by 0.75%, with the incidence primarily borne by US firms. This leads to an average production decrease of 4.87% across all firms, with large spatial re-allocations: US production rises by about 20%, mostly at the expense of its neighbors Canada and Mexico, which face output drops of 35-75%. In the reverse scenario, where the US forbids foreign technology imports, the costs are borne mainly by foreign firms producing in the US, which face increases up to 10%, resulting in only minor global production re-allocation overall. Similarly, a US-China technology war, with the two countries constraining the export and import of technologies bilaterally, has detrimental effects on only a handful of firms, with limited spillover to other countries. Comparing this to traditional trade

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<sup>4</sup>Note that firms still forego substantial development fixed costs of the technologies themselves. Modeling the innovation and development of technologies, while playing an essential role, particularly in the dynamic long-run equilibrium, exceeds the scope of this paper and is part of the future research agenda.

policy scenarios shows that while technology-restricting policies can achieve similar global outcomes, the distributional effects are substantially different, with incidence borne by specific firms and countries.

This paper contributes to two distinct strands of literature. First, the paper builds on the large body of work related to global production models that study the sourcing, exporting, or assembly decisions in the presence of multiple frictions and inter-dependencies. This literature has advanced greatly in developing tractable multi-country models adapting a CES heterogeneous firm product market structure as in [Melitz \(2003\)](#) with a constant-elasticity sourcing decision as in [Eaton and Kortum \(2002\)](#) to understand firms' decisions of input sourcing ([Antràs and Helpman \(2004\)](#), [Antràs et al. \(2017\)](#), [Arkolakis et al. \(2023\)](#)) or exporting and offshoring ([Tintelnot \(2017\)](#), [Arkolakis et al. \(2018\)](#), [Castro-Vincenzi \(2022\)](#)). These models typically exhibit complementarities across source and/or destination markets as well as multi-dimensional frictions. In that way, they extend the gravity framework to settings with firm-specific fixed costs to operate in specific countries. Recently, a number of papers have utilized rich micro-level data from the car industry to address these multinational production problems ([Goldberg \(1995\)](#), [Cosar et al. \(2018\)](#), [Head and Mayer \(2019\)](#), [Castro-Vincenzi \(2022\)](#)). The paper closest to this work is [Head and Mayer \(2019\)](#), who build a multi-product structural model of export platform and model entry featuring a double CES (demand and production) structure with external returns to scale. While they allow for a rich set of frictions between headquarters, assemblies, and destination markets, they abstract from the input sourcing decision by assuming inputs are sourced entirely from the MNE's headquarters. The model is estimated using rich data provided by the consultancy S&P Global (formerly IHS Markit), encompassing the entire automobile industry, which is also the prime data source of this paper. While adopting their nested structure of decision-making regarding assembly location and entry, I deviate in several ways from their paper. First, I extend their nested decision model to include the choice of technology for each model. Second, I allow for collaboration in the technologies and show that this has important direct implications for the optimal assembly location choices. In doing so, I connect to the second strand of literature concerned with collaboration and international strategic alliance formation among firms. Much of this research centers on collaboration in R&D and innovation ([Katz \(1986\)](#), [d'Aspremont and Jacquemin \(1988\)](#), [Suzumura \(1992\)](#), [Hernan et al. \(2003\)](#), [König et al. \(2019\)](#)). Additionally, studies have examined collaboration in the context of mergers and acquisitions and competition, emphasizing a resources-based view of firms prevalent in management research ([Wernerfelt \(1984\)](#), with [Nocke and Yeaple \(2007\)](#) being an exception). The international management literature, particularly during the 1990s and 2000s, has concentrated on the pre-agreement phase of such alliances, exploring qualitative determinants for collaboration, joint ventures as strategic choices, partner selection, and contract negotiations ([Doz \(1996\)](#), [Doz et al. \(2000\)](#), [Glaister and Buckley \(1996\)](#)). The determinants influencing firms'

engagement in technology collaboration are multifaceted and have been analyzed from various perspectives. Recurring themes include: 1) *technological knowledge and resource spillover*: joining complementary skills and resources creating new synergies (Berg and Friedman (1977), Tatoglu and Glaister (2000), Contractor et al. (1988), Harrigan (1985)). 2) *innovation and operational risk sharing*: hedging the risk of developing new, expensive technologies (Porter and Fuller (1986), Harrigan (1985), Contractor et al. (1988)). 3) *market access*: facilitating international expansion by economizing on the local market knowledge of partner firms, including host government regulations, e.g., ownership constraints, local content levels, export requirements, etc. (Morris and Hergert (1987), Walters et al. (1994), Glaister and Buckley (1996)). 4) *economies of scale*: reducing the average cost per unit, learning by doing, and using the comparative advantage of each partner while avoiding the uncertainties and difficulties of full-scale merger (Mariti and Smiley (1983), Glaister and Buckley (1996)). This paper investigates an additional advantage of technology collaborations: *access to specialized operational facilities*. Firms that collaborate on input technology are also inclined to share production plants, thereby lowering production costs and, through export linkages, reducing market entry barriers in destination markets.

These benefits must be traded off against certain costs, such as risking product convergence and thus losing uniqueness and cannibalization of profits. Some studies have also shown a loss in innovativeness and hold-up due to the risk of property rights theft (Teece (1986), Kotabe et al. (1996), Antras (2005), Mudambi and Tallman (2010)). Methodologically, most studies develop hypotheses and test them in case studies and surveys of firm behavior. In this way, they can describe firm-specific strategies but lack a more generalizable, comprehensive framework and methodology to speak to mechanisms. A few recent empirical works provide a more micro-based structural insight. For instance, Cai and Szeidl (2017) use a randomized field experiment to show that facilitating inter-firm relationships in China significantly improves business performance through enhanced supplier and customer matching, innovation, and knowledge spillovers. Their work provides causal micro-evidence for the productivity benefits of collaboration, reinforcing the intangible gains that underpin collaborative production and entry decisions in my model. In a related theoretical contribution, Zhang et al. (2021) develop a framework where manufacturers choose between building or joining a resource-sharing platform, balancing control and network externalities. Their model shows that these decisions depend crucially on firm-level capabilities and the extent of complementarities, echoing the endogenous collaboration mechanisms embedded in my structural model. The distinction between owning versus participating in shared infrastructure parallels the choice firms face between independent and joint production technologies in a multinational setting. Moreover, in the context of the Chinese auto industry, Bai et al. (2020) show how joint ventures formed under market-access conditions resulted in technology transfers and quality upgrading among domestic firms. These spillovers enhanced local firm capabilities and allowed them to enter higher-quality

segments, directly validating the argument that technology collaboration can shape production upgrading and market entry. Their empirical evidence provides important support for my model’s emphasis on how collaboration affects not just firm productivity but also the structure and geography of global production.

The remainder of the paper is structured as follows. Section 2 will first describe the data and main concepts, and present key stylized facts that guide the theoretical framework, which is introduced in Section 3. I then turn to the structural identification and present the estimation results in Section 4. Finally, the counterfactual analysis is discussed in Section 5, before concluding in Section 6.

## 2 Collaboration in Technology

### 2.1 Data and Concepts

The data comes from three different sources. First, S&P Global (formerly IHS Markit) offers a comprehensive plant-level dataset of the global automotive industry that captures annual flows of individual car models from assembly plants to final sales locations from 2000-2023. It includes technical information on all models, with details on the assembly technology (platforms) utilized, the body types, programs, and other key features (horsepower, valves, etc.). It also provides the respective firm responsible for sales, design, and engineering of each model and its components.<sup>5</sup> This ownership information will serve as a basis to track inter-firm relationships in technology and plants. Finally, the assembly location of each vehicle at the plant level allows for tracking sales flows between assembly and destination.

Second, since S&P Global reports only the current majority-owner as of 2024, based on the information in the data and web-scraping, I compile a new data set that dynamically tracks ownership of firms, brands, plants, and input technology over time, controlling for M&As, name changes, and minority and cross-firm shareholding. The Swedish car brand Volvo, for example, was reported to be owned by Chinese OEM Geely. This is only true since 2010, however. From 1999 to 2008, Volvo was majority owned by Ford Motor Company. Similarly, German brand Opel underwent several ownership changes (Opel, General Motors, PSA) before becoming a Stellantis brand in 2021. Controlling for these ownership changes is important to correctly trace out collaboration and licensing.

Third, I use several sources to gather the relevant gravity-related information for each country pair

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<sup>5</sup>S&P Global documents these different entities in much detail: the variable ‘sales parent’ refers to the ultimate owner of car brands and models. The ‘manufacturer group’ is the firm operating the manufacturing plant, and the ‘design parent’ specifies the firm responsible for the platform design.

from 2000 to 2023: the CEPII’s gravity data set provides distance measures and information on regional trade agreements; MFN and preferential tariffs are obtained from the UNCTAD WITS tariffs database and information on GDP and population are retrieved from the Worldbank’s World Development Indicator database. Jointly, those data sources allow me to 1) have a precise measure of technology and link it to multinational production decisions and 2) identify collaboration *within* (across different brands of the same firm) and *across* firm boundaries in each year. Table A.1 in Appendix A.2.1 provides an overview of the key concepts relevant to the model and how they are constructed from data. Appendix A.2.2 also describes the data construction and cleaning steps in more detail.

**Key Concepts.** The analysis focuses on *automobile platforms* as a key input technology in car assembly. Platforms are a blueprint of the vehicle chassis, fixing crucial dimensions of the car’s underbody and constraining which and where parts, such as engines and transmission, fit. Their development is typically undertaken by the automobile firms themselves and entails large fixed costs. For example, the development and deployment of the Volkswagen platform ‘MQB’ cost almost 70bn USD.<sup>6</sup> As Table A.2 in Appendix A.2.3 indicates, the median platform is used for roughly 22 years.<sup>7</sup> Over their life-cycle, they are available in 10 plants and serve as a basis for 15 different car models in two market segments. Thus, platforms are mere process technologies, reducing production costs, but without affecting the product competition.

*Collaboration* is defined when the original designer and the user of the platform in the data have no significant cross-ownership ties.<sup>8</sup> Comprehensive firm-level descriptive statistics can be found in Table A.3 in Appendix A.2.3. Using the data and definitions, I next document a few stylized facts on platform collaboration and its link to global production patterns.

For better readability, a note on terminology is in order: In the following, I use the terms collaboration and licensing interchangeably. Moreover, the term *licenser* refers to the owner of the platform, offering it for licensing. The term *licensee* refers to the owner of a car model using a licensed platform.

## 2.2 Stylised Facts

**Fact #1: Inter-firm platform collaboration is common.** Sharing of technology via licensing and joint R&D is a common feature in automotive production. About 22% of all platforms are

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<sup>6</sup><http://www.autocar.co.uk/car-news/industry/vw-could-sell-50bn-mqb-platform>, last retrieved: June 21, 2025.

<sup>7</sup>This is substantially longer than the life-cycle of a model variety, which stays in the market for about seven to eight years on average, indicating the long-lasting effect of platform development.

<sup>8</sup>Following the international accounting standard of the IMF, shareholdings below 10% are considered as equity investments, without giving firms strategic influence that would matter for collaboration choices. The analysis is robust to a strict definition of 0% ownership ties but loses in terms of statistical power.

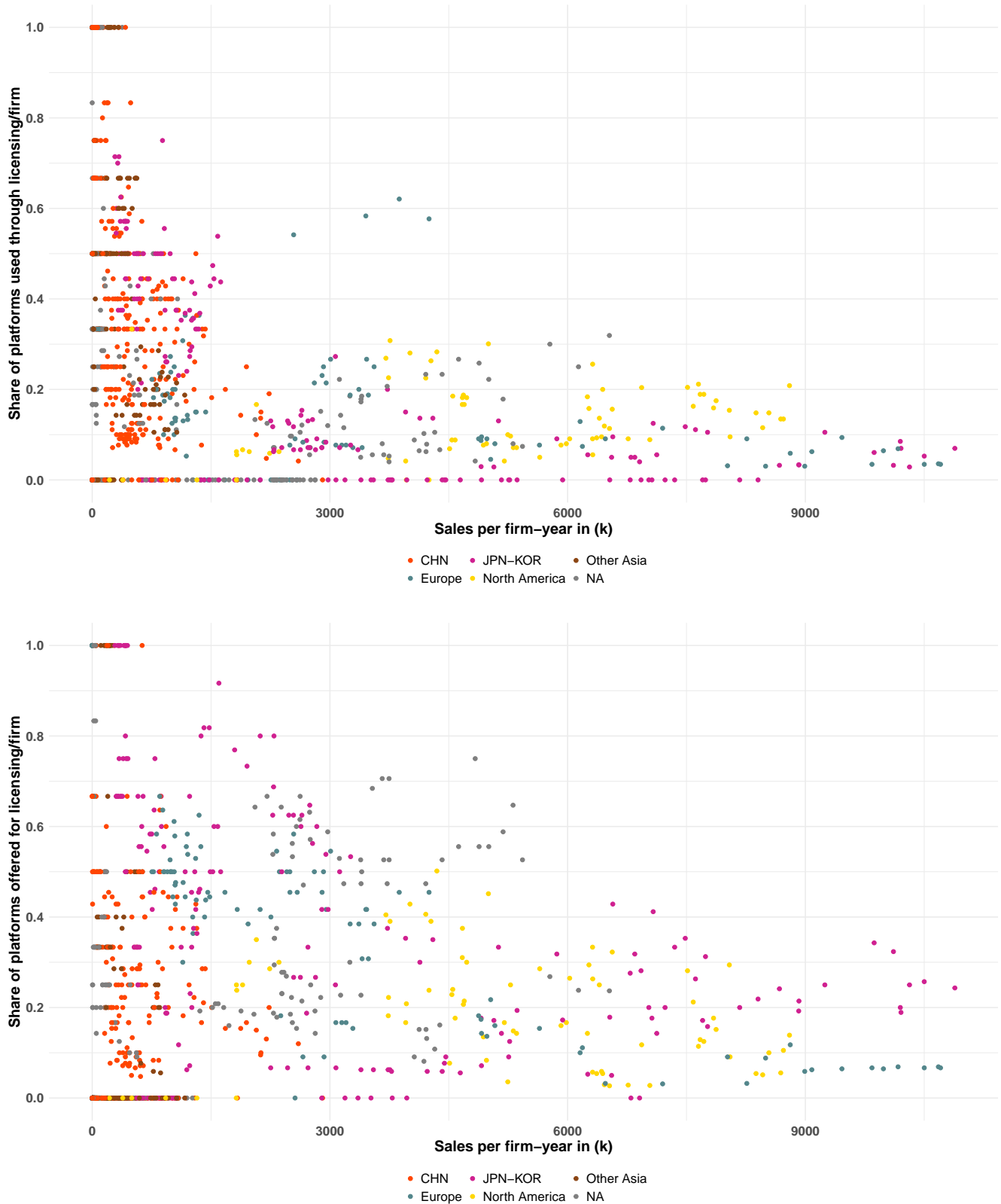
shared collaboratively among at least two different firms, corresponding to about 29% of all vehicle sales.<sup>9</sup> About 54% of all firms lease at least one platform per year, and 39% of platform owners offer at least one platform for licensing. Table A.4 in Appendix A.2.3 summarizes the collaboration in platforms. Notably, firms' reliance on collaboration in their platform technology varies substantially.

**Fact #2: Collaboration is heterogeneous across firms.** The extent to which firms rely on licensing is heterogeneous across firms as suggested by Figure 1. Smaller firms tend to rely more heavily on licensing, while the platform licensors are much more concentrated and larger. This aligns with the fact that legacy automakers from the Western hemisphere are typically larger and offer the most platforms for licensing. The distribution of the average share of licensed platforms per licensee, displayed in Figure A.1 in Appendix A.2.3, indicates that the underlying collaboration strategies overall diverge in two extremes: In a given year, of roughly 200 firms about 92 *never* use a licensed platform, while 35 firms rely *entirely* on other firms' platforms in production. Here, Chinese firms seem to be distinct, as they make up 65% of the never collaborators and 47% of the always collaborators. This might be a reflection of China's JV policy, which allows foreign firms to produce in China only when operating in a joint venture with a Chinese firm, which has led to a lot of technology transfers to Chinese firms. While the policy was abandoned much earlier for all other manufacturing industries, it stayed in place for the non-electric automotive sector until 2021. Lastly, never-collaborating firms are substantially different along many dimensions from collaborators, as indicated by Table A.5: They are smaller in total size, have significantly fewer varieties, and are much less innovative. These observations suggest that the cost to develop and the cost to collaborate differ across firms, a heterogeneity that will be taken into account by the model.

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<sup>9</sup>Note that this is driven in large part by the sales of the owner itself: collaboration accounts for 5% when only considering the sales of the licensee.

**Figure 1: Collaboration and Firm Size**



*Notes:* Share of platforms licensed (top) and offered for licensing (bottom) per firm, by firm size and headquarters region. Own calculations based on S&P Global sales data for 2000-2023. Each dot represents a firm-year observation.

**Fact #3: Collaboration is linked to multinational production choices.** Once a platform is installed in a plant, it is typically operated for more than 17 years there, more than 75% of the median platform life-cycle. Accommodating new platforms in assemblies requires substantial reconfiguration costs.<sup>10</sup> Because of this persistent link of platforms and plants, multinational production can be a motive for technology collaboration, both on the donating and the licensing side. Since developing technology and establishing a production facility entail large investments, donating firms can economize on these fixed costs by sharing the technology and plants. In addition to this scale effect, they might benefit from easier access to new destination markets. While it might be too costly for firms to directly enter a certain destination, by licensing the technology to local firms there, they gain indirect access and learn about demand, local policies and regulations and can decrease the barriers to enter in the future.<sup>11</sup> On the other hand, firms using a licensed technology can not only save on the fixed cost, but additionally benefit from eased access to additional assembly locations, and consequently new export markets, since they can produce wherever the chosen technology is available, including plants of competitors. Thus, through collaboration, both firms enlarge their assembly potential, which reduces their average cost of serving a market with a specific model and, in turn, makes market entry more profitable.

To test whether these two mechanisms play a role in the decision to collaborate, I regress the probability that a firm  $f$  uses a licensed platform  $\rho$  when introducing a *new* variety  $\omega(\rho)$  on indicators of market access and assembly potential. More specifically, in the first specification, I regress the probability to collaborate on a dummy indicating whether the firm enters a new assembly location, interacted with a dummy of whether the local plant is its own. Additionally, I add an indicator of whether the firm enters a new destination market with this new variety:

$$\begin{aligned} \mathbb{P}[\text{col}_{f\omega(\rho)} = 1] = & \beta_0 + \beta_1 \text{new assembly loc}_{f/s/\omega(\rho)} \times \text{plant col}_{f\omega(\rho)} \\ & + \beta_2 \text{new sales market}_{f/s/\omega(\rho)} + \mathbf{FE} + \epsilon_{f\omega(\rho)p} \end{aligned} \quad (1)$$

Where the vector **FE** controls for year, firm, and segment fixed effects. The second specification runs the same specification with the entry dummies specified at the firm-segment level. Lastly, I check at the variety level whether collaboration is more likely when using new platforms when the variety is assembled in a new assembly or enters a new location. Table 2 shows the results of the three specifications in the respective columns.

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<sup>10</sup>In only 7% of cases, a platform is switching away to a different plant within an ongoing model life-cycle. Table A.6 summarizes this platform-plant attachment.

<sup>11</sup>For some firms, the revenues from royalty payments might exceed the expected profits from serving the market themselves entirely.

**Table 2:** Collaboration and Multinational Production

	<i>Dep variables:</i> $\mathbb{P}[\text{col}_{\omega(\rho)} = 1 \mid \text{new } \omega = 1]$	$\mathbb{P}[\text{col}_{\omega(\rho)} = 1 \mid \text{new } \rho(\omega) = 1]$	
<i>Covariates level:</i>	firm	segment	variety
<i>Estimator:</i>	PPML	PPML	PPML
new assembly loc=0 $\times$ plant col=1	2.764*** (0.082)	2.874*** (0.082)	4.038*** (0.122)
new assembly loc=1 $\times$ plant col=0	-0.326 (0.245)	0.098 (0.123)	1.672*** (0.124)
new assembly loc=1 $\times$ plant col=1	3.042*** (0.108)	2.668*** (0.089)	3.686*** (0.123)
new sales market	-0.239* (0.139)	0.121 (0.080)	0.310*** (0.064)
constant	-2.857*** (0.054)	-2.913*** (0.053)	-4.289*** (0.108)
year FE	Yes	Yes	Yes
firm FE	Yes	Yes	Yes
segment FE	Yes	No	Yes
N	17,510	17,510	59,465
Pseudo $R^2$	0.413	0.407	0.360

*Notes:* Standard errors in parentheses, c:  $p < 0.10$ , b:  $p < 0.05$ , a:  $p < 0.01$

The estimate of  $\beta_2$  suggests that platform collaboration and market access are indeed positively correlated. A new variety is 1.12% more likely to use a licensed platform when the firm enters an entirely new market altogether. This increases to 1.35% when conditioning on the model entering a new market. Moreover, there is also a positive association of platform collaboration with increased assembly potential, captured by the  $\beta_1$  estimate. Relative to using an own, already operational plant, collaboration on a platform is about 20.9% more likely if the firm starts producing the variety in a new assembly location that is operated via a plant collaboration. This indicates that platform sharing might be motivated by access to new assemblies that can be jointly operated and are thus more cost-efficient. In contrast to the market access channel, these gains are reaped at each level: firm-segment, and model.

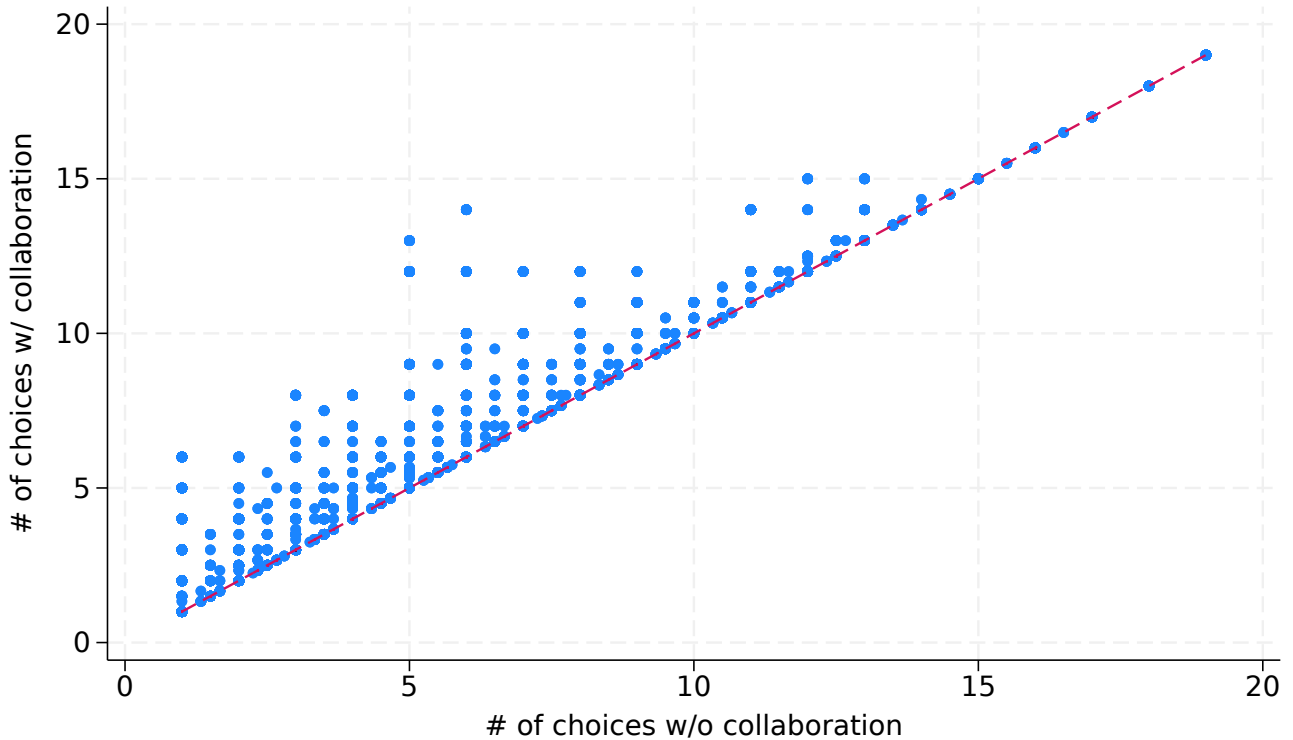
**Fact #4: Collaboration offers greater assembly potential.** The important link between collaboration, technology, and multinational production choices is summarized in Table 3. It

**Table 3:** Assemblies Sourcing Choice Set

	Mean	SD	P25	Median	P75	Max
unconstrained	15.26	9.40	6.00	16	23.00	37
w/ platform, w/o collab	4.80	4.11	1.00	3	7.00	19
w/ platform, w/ collab	5.03	4.15	1.00	4	8.00	19
% difference w/ platform	-42.97	101.81	-83.33	-65.2	-35.71	1,300
% difference w/ collab	9.13	38.83	0.00	0.0	0.00	500
N	49,517					

*Notes:* own calculations based on S&P Global data for 2000-2023.

**Figure 2:** Heterogeneity in Assemblies Sourcing Choice Set Differences



*Notes:* own calculations based on S&P Global data for 2000-2023. Each dot represents a car model-year observation. The 90-degree line indicates no change in the choice set with collaboration compared to without.

displays the number of assembly locations firms can choose from to produce their models under different constraints. The standard MP models would assume that firms can choose among any country where they operate their own assembly, which in the median is 16. However, knowing the specific technological requirements to produce a variety, the platform constrains the choice set to only those plants that have a given platform installed. This reduces the potential assembly set of a given variety on average by 43% to only three production locations. Allowing for collaboration relaxes this constraint. Firms can potentially use *any* assembly that operates with the specific platform, including other firms' plants, which increases their choice set on average by 9% to four. Figure 2 plots the heterogeneity across these choice differences for each variety-year. Figure A.2 in Appendix A.2.3 illustrates this change in sets in the case of the Peugeot 4008 in 2012, which was produced with a Mitsubishi-Daimler platform. However, as all of these choices are highly endogenous, a model is needed to uncover the mechanisms more causally. The following section develops the framework.

### 3 A Multinational Production Model with Technology & Collaboration

Based on the stylized facts above, I developed a structural framework that allows to quantify the multinational scope of introducing specialized technology and collaboration.

#### 3.1 Model Setup

There's a mass of firms  $f$  with a headquarters country  $i(f) \in N$  that sell multiple, symmetrically differentiated varieties  $\omega \in \Omega$ . The Boolean  $\mathbb{1}_{f,\omega}$  indicates whether variety  $\omega$  belongs to firm  $f$ . To allow for more realistic substitution patterns, I group varieties into eight market segments  $s$  according to their primary functions following Goldberg (1995).<sup>12</sup> Each variety  $\omega$  is produced using a single process technology  $\rho \in \mathcal{P}$  (platform), indicated by the  $\omega(\rho)$  notation. Platform technologies map one-to-many into segments. Varieties map uniquely to segments, such that they can be produced only with platforms operating in the same segment.  $\mathbb{1}_{\omega,\rho} = 1$  will denote that variety  $\omega(\rho)$  is produced with  $\rho$ . Given the production technology, varieties  $\omega(\rho)$  can be sold in markets  $n, \in N$ , where  $\mathbb{1}_{\omega(\rho),n} = 1$  when  $\omega(\rho)$  is offered in  $n$ , and are produced in facilities  $\ell, k \in \mathcal{L}_\rho$  that operate with the specific platforms. The installation of platforms in the plants is assumed to be pre-determined and fixed in the short and medium run. For better readability, I am simplifying

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<sup>12</sup>Segments categorize small cars, big cars, SUVs, Vans, multi-purpose vehicles (MPV), Pick-up trucks (PUP), electric vehicles (EVs) and sports cars.

the notation whenever possible. In particular, due to the unique mapping, I drop the subscripts  $s$  from the platforms and  $f$  from the varieties.

### 3.2 Demand

The demand for each variety is derived from the household’s discrete choices across varieties in each segment. Households  $h$  minimize  $p_{h,n}(\omega(\rho))/\psi_h(\omega(\rho))$ , where  $p_{h,n}(\omega(\rho))$  is the price of variety  $\omega(\rho)$  of household  $h$  in market  $n$  and  $\psi_h(\omega(\rho))$  is the quality that household perceives of this variety. Assuming that  $\psi_h(\omega(\rho))$  is Fréchet-distributed with a segment-specific shape parameter  $\eta_s$  (an inverse measure of customer heterogeneity), the quantity of variety  $\omega(\rho)$  demanded in market  $n$  can be expressed as:

$$q_n(\omega(\rho)) = \left( \frac{p_n(\omega(\rho))}{P_{sn}} \right)^{-\eta_s} Q_{sn}, \text{ where } P_{sn} = \left( \sum_{\omega(\rho)} \mathbb{1}_{\omega(\rho),n} p_n(\omega(\rho))^{-\eta_s} \right)^{-1/\eta_s}$$

The delivered price of variety  $\omega(\rho)$  in segment  $s$  in  $n$  under monopolistic competition is a segment-specific, constant markup  $\eta_s / (\eta_s - 1)$  over marginal cost. Substituting this price into the demand curve, a variety’s sales in a given market segment are:

$$q_n(\omega(\rho)) = \left( \frac{\eta_s}{\eta_s - 1} c_n(\omega(\rho)) \right)^{-\eta_s} Q_{sn} P_{sn}^{\eta_s} \quad (2)$$

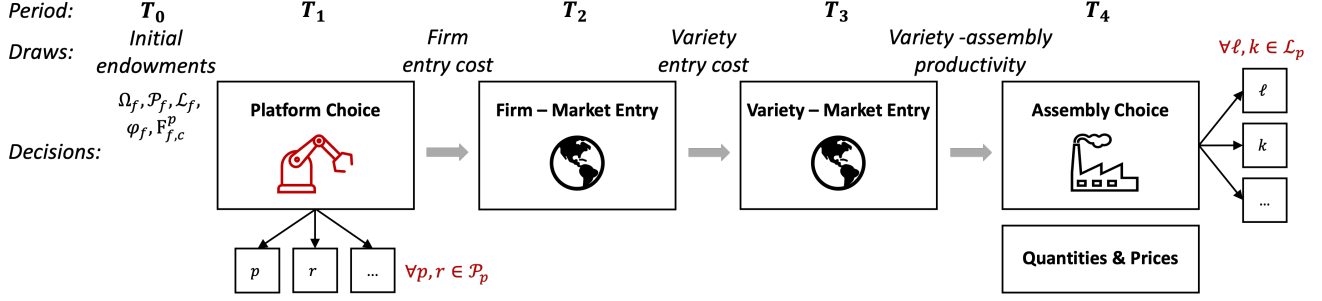
Recent literature has shown the importance of endogenous mark-ups. However, assuming that mark-ups are independent of firm-level market shares is justifiable in this setting as these shares are very small: The median share is less than 1%, and in the 95th percentile it’s only 15.5%. Endogenous mark-ups will thus have only little impact on the results while making the analysis substantially more complex. Note that since platforms are a mere process technology, they are not directly perceived by households (only indirectly through the variety quality) and hence do not enter the household’s problem explicitly.

### 3.3 Supply

**Firm problem.** The model is static. The firm takes four sequential decisions, as depicted in Figure 3. First, firms draw their initial core productivity  $\varphi_f$ , a variety portfolio  $\Omega_f$ , a set of assemblies  $\mathcal{L}_f$ , and their platform technology set  $\mathcal{P}_f$ .<sup>13</sup> After drawing its platform-collaboration

<sup>13</sup>A future extension is in work to endogenize the technology investment choice. For now, there is no investment choice in technologies.

Figure 3: Firm Problem



fixed cost  $F_{f(\rho)}^p$ , the firm selects an optimal platform technology for each variety. In particular, it trades off the expected average profits in all markets against the cost of using a platform. Platforms can be sourced from a firm's own set of technologies or via collaboration from a competitor. The fixed cost of using a specific technology depends on whether the platform is used collaboratively or not and entails an ex-ante unobserved variety-platform-specific cost shock. Having chosen the optimal platform, the firm observes its firm-specific entry fixed cost  $F_{fn}^d$  and chooses in which markets to open distribution networks in order to sell *any* of its varieties. Next, it selects which varieties to offer in each market, conditional on variety-market-specific entry fixed costs  $F_{\omega(\rho)n}^e$ . Lastly, after observing the variety-assembly specific productivity shifter  $z_{\omega(\rho)\ell n}$ , the firm makes the final choice of where to assemble the variety, minimizing unit costs. As firms are considered forward-looking, they solve their problem by backward induction of expectations facing various trade frictions in addition to the fixed cost and random productivity shifters.

Next, I describe the cost structure, which will guide the firm's choice of collaboration, platform, and location.

**Cost and frictions.** The unit cost of firm  $f$  with headquarters  $i(f)$  to produce a variety  $\omega(\rho)$  with platform  $\rho$  in assembly plant  $\ell$  and deliver it to market  $n$  depends on the costs of inputs, trade costs, as well as productivity shifters. Input costs are comprised of some composite factors associated with the assembly and headquarters,  $w_\ell$  and  $w_{i(f)}$ , which are used in Cobb-Douglas proportions  $\alpha$  and  $1 - \alpha$ . As in [Head and Mayer \(2019\)](#), in order to ship inputs from headquarters  $i$  to assembly  $\ell$ , a unit cost  $\gamma_{i(f)\ell} = \tau_{i(f)\ell}^{1-\alpha} \geq 1$ , capturing input tariffs and other trade barriers, must be paid. Similarly, to ship final goods from  $\ell$  to  $n$ , an iceberg trade cost  $\tau_{\ell n} \geq 1$ , representing tariffs and freight, applies. The last friction  $\delta_{i(f)n}$  captures variable marketing costs that need to be incurred for firms in  $i$  when selling to market  $n$ , such as bilateral regulatory requirements (e.g., visa for managers). On the productivity side, the firm-level shifter  $\varphi_f$  captures the overall firm-level productivity. In addition, the variety-destination-assembly-specific random productivity shock,  $z_{\omega(\rho)\ell n}$ , guides the matching of varieties to assemblies and follows a Fréchet - distribution with shape parameter  $\theta$ . As is common in other MP frameworks, there is a notion of complementarity

across choices, implied either through internal or external economies of scale. Here I follow [Head and Mayer \(2019\)](#) specification to incorporate these returns to scale as a power function at the location level,  $q_\ell^\zeta$ , with  $\zeta$  capturing the elasticity of costs with respect to industry size at each location. The unit costs are then given by:

$$c_{\ell i(f)n}(\omega(\rho)) = \frac{w_\ell^\alpha w_{i(f)}^{1-\alpha} \gamma_{i(f)\ell} q_\ell^\zeta}{\varphi_f z_{\omega(\rho)\ell n}} \times \delta_{i(f)n} \tau_{\ell n} \quad (3)$$

Lastly, utilizing a platform entails a fixed cost  $F_{f(\rho)}^\rho = f^\rho + f_f^c + z_{\omega,\rho}$ , which is comprised of a platform cost, paid regardless of the ownership, a collaboration component  $f_f^c > 0$ , paid only if the platform is sourced from outside the firm's technology portfolio, and finally a platform-variety specific cost shifter  $z_{\omega,\rho} \sim \text{Gumbel}(\lambda)$ , which guides the matching of varieties to platforms. This is similar to the random productivity shifters found in the MP literature, except that it varies by platform technology. Compared to existing MP models, the platform-collaboration cost component is a novel element that allows to endogenize input technology and collaboration choices. Next, I solve the resulting firm's cost-minimization problem. Note that the novelty of the model comes in the platform and collaboration stage, with implications for the assembly sourcing stage. The following sections discuss these two stages in depth. The middle stages variety and firm market entry follow methodologically [Head and Mayer \(2019\)](#). For more detailed insights on these stages, readers are referred to the specific sections of that paper.

***Conditional assembly choice.*** Due to the double CES framework, firms choose the optimal assembly location by minimizing the associated unit cost of producing varieties when serving markets. The probability of choosing a location conditional on platform, collaboration, and sales destination is:

$$\begin{aligned} \mathbb{P}[\mathbb{1}_{\omega(\rho),\ell n} = 1 \mid \ell \in \mathcal{L}_\rho] &= \mathbb{P}[c_{\ell i(f)n}(\omega(\rho)) \leq c_{ki(f)n}(\omega(\rho))], \quad \forall k \in \mathcal{L}_\rho \\ &= \mathbb{P}[\zeta \ln q_\ell + \alpha \ln w_\ell + (1 - \alpha) \ln w_{i(f)} + \ln \gamma_{i(f)\ell} + \ln \delta_{i(f)n} + \ln \tau_{\ell n} - \varphi_f - \ln z_{\omega(\rho)\ell n} \\ &\quad \leq \alpha \ln w_k + (1 - \alpha) \ln w_{i(f)} + \ln \gamma_{i(f)k} + \zeta \ln q_k + \ln \delta_{i(f)n} + \ln \tau_{kn} - \varphi_f - \ln z_{\omega(\rho)kn}] \end{aligned} \quad (4)$$

Note that the condition requires that the chosen location operates with the given platform  $\rho$ , thus, the choice set is substantially constrained compared to classical MP frameworks. Given the unit

cost in equation 3 and the distribution of  $z_{\omega(\rho)\ell n}$ , this has the following closed-form solution:

$$\begin{aligned} \mathbb{P}[\mathbb{1}_{\omega(\rho),\ell n} = 1 \mid \ell \in \mathcal{L}_\rho] &= \left( \frac{w_\ell^\alpha q_\ell^\zeta \gamma_{i(f)\ell} \tau_{\ell n}}{\left( \sum_{k \in \mathcal{L}_\rho} \left( w_k^\alpha q_k^\zeta \gamma_{i(f)k} \tau_{kn} \right)^{-\theta} \right)^{-1/\theta}} \right)^{-\theta} \\ &= \left( \frac{q_\ell^\zeta w_\ell^\alpha \gamma_{i(f)\ell} \tau_{\ell n}}{C_{f(\rho)n}} \right)^{-\theta} \end{aligned} \quad (5)$$

Where  $C_{f(\rho)n}$  summarizes the firm's costs of serving market  $n$  using platform  $\rho$  in terms of the potential assemblies these choices entail. Lower-cost locations will get a larger weight in the term, reducing the overall cost. The same mechanism holds for adding more elements to the potential set of choices  $\mathcal{L}_\rho$ . Intuitively, firms get more variety-location-specific productivity draws  $z_{\omega(\rho)\ell n}$  and thus, will have on average more favorable draws resulting in lower marginal unit cost.

This is the key mechanism at play when considering collaboration benefits in multinational production models: Allowing firms to collaborate in technology opens new assembly opportunities and thus lowers their expected cost. Subsequently, this will propagate to expected profits, market shares, and entry choice.  $\theta$  captures the degree of substitutability of assemblies.

**Market shares & variable profits.** From the CES demand in equation 2 and exploiting that there is both single sourcing for varieties and single platform choices per destination markets, the expected market shares for each variety are given by:

$$\mathbb{E}[q_n(\omega(\rho))/Q_{sn}] = \mathbb{1}_{\omega,\rho} \mathbb{1}_{\omega(\rho),n} \left( \frac{\eta_s}{\eta_s - 1} \right)^{-\eta_s} P_{sn}^{\eta_s} \mathbb{E}[c_{li(f)n}(\omega(\rho))^{-\eta_s}] \quad (6)$$

Plugging in the expected cost using the moment conditions derived in Hanemann (1984)<sup>14</sup> yields:

$$\mathbb{E}[q_n(\omega(\rho))/Q_{sn}] = \mathbb{1}_{\omega,\rho} \mathbb{1}_{\omega(\rho),n} \kappa_1 \left( \frac{\varphi_f P_{sn}}{w_{i(f)}^{1-\alpha} \delta_{i(f)n}} \right)^{\eta_s} C_{f(\rho)n}^{-\eta_s} \quad (7)$$

where  $\kappa_1 = \left( \frac{\eta_s}{\eta_s - 1} \right)^{-\eta_s} \Gamma \left( 1 - \frac{\eta_s}{\theta} \right)$  and the country-segment-specific price index is given by  $P_{sn} = \kappa_1^{-1/\eta_s} \left( \sum_f \Omega_{f sn} (\varphi_f / w_{i(f)}^{1-\alpha})^{\eta_s} \delta_{i(f)n}^{-\eta_s} C_{f(\rho)n}^{-\eta_s} \right)^{-1/\eta_s}$ , with  $\Omega_{f sn} = \sum_{\omega(\rho) \in s} \mathbb{1}_{f,\omega(\rho)} \mathbb{1}_{\omega(\rho),n}$ .  $C_{f(\rho)n}$  in equation 7 identifies  $\eta_s$  as an exogenous cost (price) shifter. Using the structural parameters  $\eta_s$  and the cost  $C_{f(\rho)n}$ , I construct the expected variety profits for all potential destination-platform com-

<sup>14</sup>See the derivation in Appendix A.1

binations:

$$\mathbb{E}[\pi_n(\omega(\rho))] = \mathbb{E}[p_n(\omega(\rho))q_n(\omega(\rho))]/\eta_s = \mathbb{E}[p_n(\omega(\rho))^{1-\eta_s}]P_{sn}^{\eta_s}Q_{sn}/\eta_s \quad (8)$$

With  $\mathbb{E}[p_n(\omega(\rho))^{1-\eta_s}] = \left(\frac{\eta_s}{\eta_s-1}\right)^{1-\eta_s} \mathbb{E}[c_{li(f)n}(\omega(\rho))^{1-\eta_s}]$ , the expected variable profits conditional on the platform and firm entry choice are:

$$\mathbb{E}[\pi_n(\omega(\rho))] = \frac{\kappa_2}{\eta_s} \left( \frac{w_{i(f)}^{1-\alpha} \delta_{i(f)n}}{\varphi_f} \right)^{1-\eta_s} C_{f(\rho)n}^{1-\eta_s} P_{sn}^{\eta_s} Q_{sn} \quad (9)$$

$\kappa_2 = \left(\frac{\eta_s}{\eta_s-1}\right)^{1-\eta_s} \Gamma\left(1 + \frac{1-\eta_s}{\theta}\right)$ . Those hypothetical profits will determine the platform and entry choice in the following.

**Conditional variety entry choice.** Conditional on the optimal platform choice, a variety will be sold in a specific destination if the expected variable profits exceed the variety's entry fixed cost:

$$\begin{aligned} \mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1 \mid \mathbb{1}_{f,n} = 1] &= \mathbb{P}[\mathbb{E}[\pi_n(\omega(\rho))] \geq F_{\omega(\rho)n}^e] \\ &= \mathbb{P}\left[\frac{\kappa_2}{\eta_s} \left( \frac{w_{i(f)}^{1-\alpha} \delta_{i(f)n}}{\varphi_f} \right)^{1-\eta_s} C_{f(\rho)n}^{1-\eta_s} P_{sn}^{\eta_s} Q_{sn} \geq F_{\omega(\rho)n}^e\right] \end{aligned} \quad (10)$$

Since  $F_{\omega(\rho)n}^e = w_{i(f)}^\varsigma w_n^{1-\varsigma} \delta_{i(f)n}^e \varepsilon_{\omega(\rho),n}^e$  and  $\varepsilon_{\omega(\rho),n}^e \sim \text{Lognormal}(\mu_n^e + \beta_f^e, \sigma_e)$ , the variety entry probability is given by:

$$\begin{aligned} \mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1 \mid \mathbb{1}_{f,n} = 1] &= \mathbb{P}\left[\mathbb{E}[\pi_n(\omega(\rho))] \geq w_{i(f)}^\varsigma w_n^{1-\varsigma} \delta_{i(f)n}^e \varepsilon_{\omega(\rho),n}^e\right] \\ &= \Phi\left[\left(\ln \mathbb{E}[\pi_n(\omega(\rho))] - \ln(w_{i(f)}^\varsigma w_n^{1-\varsigma}) - \ln \delta_{i(f)n}^e - \mu_n^e - \beta_f^e\right)/\sigma_e\right] \\ &= \Phi\left[\left(\ln \kappa_2 - \ln \eta_s + (\eta_s - 1) \ln(\varphi_f/w_{i(f)}^{1-\alpha}) - (\eta_s - 1) \ln \delta_{i(f)n} - (\eta_s - 1) \ln C_{f(\rho)n}\right.\right. \\ &\quad \left.\left.+ \eta_s \ln P_{sn} + \eta_s \ln Q_{sn} - \ln w_{i(f)}^\varsigma - \ln w_n^{1-\varsigma} - \ln \delta_{i(f)n}^e - \beta_f^e - \mu_n^e\right)/\sigma_e\right] \end{aligned} \quad (11)$$

Here, friction between a firm's headquarters and the final sales market will be important, both at the intensive margin (via the expected profits) as well as the extensive margin (model entry fixed cost). To simplify, denote  $\Theta_{f(\rho)n} = \left(\ln \mathbb{E}[\pi_n(\omega(\rho))] - \ln(w_{i(f)}^\varsigma w_n^{1-\varsigma}) - \ln \delta_{i(f)n}^e - \mu_n^e - \beta_f^e\right)/\sigma_e$

**Conditional firm entry choice.** Conditional on the optimal platform choice, a firm will enter to sell in a specific destination if the expected variable profits in this market exceed the firm's

entry fixed cost:

$$\mathbb{P}[\mathbb{1}_{f,n} = 1] = \mathbb{P} \left[ \mathbb{E}[\pi_n(f)] \geq F_{fn}^d \right] \quad (12)$$

Let  $\Omega_{fs} = \sum_{\omega(\rho) \in s} \mathbb{1}_{f,\omega(\rho)}$  denote the total number of varieties per firm in each segment, then the expected firm profits in each market are the sum of net variety profits in each segment:

$$\begin{aligned} \mathbb{E}[\pi_n(f)] &= \sum_s \Omega_{fs} \times \mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1] \times \left( \mathbb{E}[\pi_n(\omega(\rho))] - \mathbb{E}[F_{\omega(\rho)n}^e \mid \mathbb{1}_{\omega(\rho),n} = 1] \right) \quad (13) \\ &= \sum_s \Omega_{fs} \times \Phi \left[ \left( \ln \mathbb{E}[\pi_n(\omega(\rho))] - \ln(w_{i(f)}^\zeta w_n^{1-\zeta}) - \ln \delta_{i(f)n}^e - \mu_n^e - \beta_f^e \right) / \sigma_e \right] \\ &\quad \times \left( \mathbb{E}[\pi_n(\omega(\rho))] - \exp \left[ \ln(w_{i(f)}^\zeta w_n^{1-\zeta}) + \ln \delta_{i(f)n}^e + \mu_n^e + \beta_f^e + 0.5\sigma_e^2 \right] \right) \\ &\quad \times \frac{\Phi \left( \left( \left( \ln \mathbb{E}[\pi_n(\omega(\rho))] - \ln(w_{i(f)}^\zeta w_n^{1-\zeta}) - \ln \delta_{i(f)n}^e - \mu_n^e - \beta_f^e \right) / \sigma_e \right) - \sigma_e \right)}{\Phi \left( \left( \ln \mathbb{E}[\pi_n(\omega(\rho))] - \ln(w_{i(f)}^\zeta w_n^{1-\zeta}) - \ln \delta_{i(f)n}^e - \mu_n^e - \beta_f^e \right) / \sigma_e \right)} \quad (14) \end{aligned}$$

Note that since  $\mathbb{P}[\mathbb{1}_{\omega(\rho),n}] = \Phi(\Theta_{f(\rho)n})$ , the expression can be simplified:

$$\begin{aligned} \mathbb{E}[\pi_n(f)] &= \sum_s \Omega_{fs} \times \Phi(\Theta_{f(\rho)n}) \\ &\quad \times \left( \mathbb{E}[\pi_n(\omega(\rho))] - \exp \left[ \ln(w_{i(f)}^\zeta w_n^{1-\zeta}) + \ln \delta_{i(f)n}^e + \mu_n^e + \beta_f^e + 0.5\sigma_e^2 \right] \right) \\ &\quad \times \frac{\Phi(\Theta_{f(\rho)n} - \sigma_e)}{\Phi(\Theta_{f(\rho)n})} \quad (15) \end{aligned}$$

Thus, with  $F_{fn}^d = w_{i(f)}^\zeta w_n^{1-\zeta} \delta_{i(f)n}^d \varepsilon_{f,n}^d$  and  $\varepsilon_{f,n}^d \sim \text{Lognormal}(\mu_n^d + \beta_f^d, \sigma_d)$ , the firm's entry probability is given by:

$$\begin{aligned} \mathbb{P}[\mathbb{1}_{f,n} = 1] &= \mathbb{P} \left[ \mathbb{E}[\pi_n(f)] \geq F_{fn}^d \right] \\ &= \Phi \left[ \frac{\mathbb{E}[\pi_n(f)] - \ln(w_{i(f)}^\zeta w_n^{1-\zeta}) - \ln \delta_{i(f)n}^d - \mu_n^d - \beta_f^d}{\sigma_d} \right] \quad (16) \end{aligned}$$

**Platform & collaboration choice.** Up to this point, platform technology has entered the firm's problem only by conditioning the set of assemblies that firms can choose from, affecting their cost of serving a market, and hence their expected profits. Now, those expected profits, aggregated across all markets, will be traded off against the cost of using the platform  $F_{f(\rho)}^\rho = f^\rho + f_f^c + z_{\omega,\rho}$  to determine the platform and collaboration choice.  $f^\rho$  summarizes the cost associated with the

platform itself and will be captured by measures of platform productivity, platform age, and the number of plants and destination countries it serves.  $f_f^c$  denotes the firm's cost associated with using the platform. It is costless to use one's own platforms, but collaboration requires a licensing fixed cost. This will be captured by the number of partners a firm has and a fixed effect.  $z_{\omega,\rho} \sim \text{Gumbel}(\lambda)$  captures an unobserved cost-shifter at the variety-platform level, which guides the mapping of platforms to varieties. Hence, the gross profits of choosing a platform are:

$$\begin{aligned} \mathbb{E}[\Pi(\omega(\rho))] &= \mathbb{E}[\pi(\omega(\rho))] - F_{f(\rho)}^\rho \\ &= \sum_n (\mathbb{P}[\mathbb{1}_{f,n} = 1] \times \mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1] \times \mathbb{E}[\pi_n(\omega(\rho))]) - F_{f(\rho)}^\rho \end{aligned} \quad (17)$$

Then, the firm's maximization problem of choosing the optimal platform  $\rho$  for its variety  $\omega(\rho)$  is the following multinomial logit:

$$\begin{aligned} \mathbb{P}[\mathbb{1}_{\omega,\rho} = 1] &= \mathbb{P} \left[ \mathbb{E}[\pi(\omega(\rho))] - F_{\omega(\rho)}^\rho \geq \mathbb{E}[\pi(\omega(r))] - F_{\omega(r)}^\rho, \forall r \neq \rho \in \mathcal{P} \right] \\ &= \frac{\exp \left[ \lambda \left( \mathbb{E}[\pi(\omega(\rho))] - f^\rho - f_f^c \right) \right]}{\sum_{r \neq \rho} \exp \left[ \lambda \left( \mathbb{E}[\pi(\omega(r))] - f^r - f_f^c \right) \right]} \\ &= \exp \left[ \lambda \left( \mathbb{E}[\pi(\omega(\rho))] - f^\rho - f_f^c \right) - IU(\omega(\rho)) \right] \end{aligned} \quad (18)$$

where the log-sum term  $IU(\omega(\rho)) = \ln \sum_{r \neq \rho} \exp \left[ \lambda \left( \mathbb{E}[\pi(\omega(r))] - f^r - f_f^c \right) \right]$  is the inclusive utility of variety  $\omega(\rho)$ , summarizing the utility of all alternative platforms  $r$  in terms of net profits. Firms gain from collaboration by being able to choose from a larger set of platforms, which improves their cost to serve a market  $C_{f(\rho)n}$  and thus increases expected profits. Additionally, the chosen platforms might be lower in the cost of using ( $f_\rho$ ) compared to the platforms owned by the firm itself. If the firm then has sufficiently low collaboration costs, it is going to benefit from collaboration. The exact gains are determined by comparing the expected profits under the utility-maximizing choice under collaboration to those without.

Note that the large set of platforms to choose from is computationally demanding and requires some constraining assumptions to achieve tractability.

### 3.4 Discussion of Assumptions

The tractability of the model comes at the expense of abstracting from several potentially important aspects.

First, I am agnostic to any strategic considerations, such as the bilateral negotiations underlying the licensing agreements. Solving this type of entry game requires more information on prices

and contracts, and adds considerable complexity to the already complicated framework. As the primary goal of this paper is to understand how firms’ production choices are driven by technology and collaboration choices, I consider the long-term collaboration strategies fixed at the firm level. As such, I assume that firms will offer their technologies to *any* firm willing to pay the fixed collaboration price, not considering who the recipient is.

Second, the sequentiality of the model relies on the assumption that, conditional on the observables (e.g., distances and tariffs), any shocks in the upper-level choices (ie., market entry costs) are uncorrelated with each other and with the productivity shock  $z_{\omega(\rho)\ell n}$ .

Third, the lack of detailed variety-level price data prevents me from estimating demand systems with richer substitution patterns and variable mark-ups. As alluded to before, the observed market shares are sufficiently small to deem the assumption of CES monopolistic competition justifiable. Additionally, [Head and Mayer \(2023\)](#) shows that CES models can fit standard IO demand system-based predictions closely. While acknowledging that the decision to collaborate bears strategic elements for the MNEs, the CES framework still provides valuable new insights in a tractable way and allows for comparability to the MP literature.

Third, I take the existing production infrastructure in each period as pre-determinedly given. Modeling plant location and platform equipment choices endogenously creates a significantly complicated combinatorial problem with profit functions that are locally both sub- and supermodular due to these additional complementarities. Without further assumptions that force the profit functions to be only one of the two, this is intractable for a large set of plants and firms using standard methods ([Antràs et al., 2022](#); [Arkolakis et al., 2023](#)). An ongoing literature ([Arkolakis et al., 2023](#); [Antràs et al., 2024](#); [Head et al., 2024](#); [Kulesza, 2024](#)) is currently developing novel methods that might be applied in a future extension of this paper. As both the opening of new plants and the reconfiguration of existing plants with new platforms are much less frequent than the choices modeled in the paper (on average every 17 years, see Section 2), this assumption seems reasonable. As such, the model can be viewed as a medium-run analysis of firm choices and market equilibria, abstracting from the more strategic long-run dimensions.

Lastly, in the model, platforms require only fixed cost investments and affect marginal production cost only indirectly via the multinational cost index  $C_{f(\rho)n}$ . This shuts down a potential channel of increasing returns to scale at the individual platform level. A direct impact on marginal cost would be an important source of efficiency gains from collaboration. Unfortunately, the variation of the data is insufficient to structurally identify the variable cost shifter at the platform level, which is why the fixed cost approach is chosen.

I now turn to describe the empirical estimation of the four stages and the identification of the structural parameters in detail.

## 4 Structural Estimation

To identify the structural parameters  $\theta$ ,  $\eta_s$ ,  $\sigma_e$ ,  $\sigma_d$  and  $\lambda$ , the distribution parameters of the entry fixed cost, as well as the components of the platform fixed costs  $f^\rho$  and  $f_f^c$ , the theoretical moments need to be transformed into their empirical counterparts. Because the estimation uses the complete time series from 2000-2023 to exploit time variations, a subscript  $t$  is added to the time-varying variables to indicate the respective year.

**Friction determinants.** The trade frictions  $\gamma$ ,  $\tau$ , and  $\delta$  are captured by several observable, bilateral gravity variables, such that:

$$\tau_{\ell nt} = \exp[\mathbf{X}'_{knt} \mathbf{b}], \quad \gamma_{i\ell t} = \exp[\mathbf{X}'_{i(f)kt} \mathbf{g}], \quad \delta_{i(f)nt} = \exp[\mathbf{X}'_{i(f)nt} \mathbf{d}] \quad (19)$$

The parameters on the vector  $\mathbf{X}$  capture the coefficients of underlying observables that are standard in the gravity literature: home, distance, common language, and whether the countries are part of a deep regional trade agreement. The parameterization of  $\tau_{\ell nt}$  additionally controls for tariffs imposed on fully finished vehicles<sup>15</sup> ( $\log(1+\text{tariffs})$ ), which are obtained from the WITS database for 2000-2023. The input frictions  $\gamma_{i(f)\ell t}$  are supplemented by controls for the average car-parts tariffs between headquarters  $i(f)$  and assemblies  $\ell$ . The marketing frictions  $\delta_{i(f)n}$ , while not controlling for tariffs no goods are transferred), guard additional regulatory differences, such as RTAs, and the development status of countries, which correlates with their respective protectiveness.

### 4.1 Assembly Choice Estimation

For the estimation of the conditional probability in equation 5, the choice of the optimal location can be aggregated into a count variable, summing over the varieties within segment  $s$  owned by  $f$  using  $\rho$  that are assembled in  $\ell$ :  $\Omega_{f(\rho)\ell nt} = \sum_{\omega(\rho)} \mathbb{1}_{f,\omega(\rho)} \mathbb{1}_{\omega(\rho),\ell n}$ . This is because the probability that a firm produces in  $\ell$  when serving consumers in  $n$  depends on the marginal cost, which is constant for varieties within the same segment and platform. Equation 5 can therefore be estimated using Pseudo Poisson Maximum Likelihood (PPML) as follows:

$$\mathbb{E}[\Omega_{f(\rho)\ell nt} \mid \ell \in \mathcal{L}_{\rho t}] = \exp \left[ \underbrace{\text{FE}_\ell - \mathbf{W}'_{\ell t} \mathbf{v}_1 - \tilde{\zeta} \ln q_{\ell t}}_{\text{Assembly cost determinants}} - \underbrace{\mathbf{X}'_{\ell nt} \tilde{\mathbf{b}}}_{\tau\text{-frictions}} - \underbrace{\mathbf{X}'_{i(f)nt} \tilde{\mathbf{g}}}_{\gamma\text{-frictions}} + \underbrace{\text{FE}_{f(\rho)nt}}_{-C_{f(\rho)n}} \right] \quad (20)$$

<sup>15</sup>These tariffs are computed as the average of the applied tariffs of each 6-digit HS code belonging to the sub-header groups "8703" (vehicles) and "8704" (pick up trucks).

Where the fixed effects have structural interpretation as  $FE_\ell = -\alpha\theta \ln w_{\ell T}$  and  $\mathbf{W}'_\ell \mathbf{v}_1 = \alpha\theta(\ln w_{\ell t} - \ln w_{\ell T})$ ,  $T$  referring to the last year in the data, 2023, which is used to normalize the wage-level index. The second high-dimensional fixed effect  $FE_{f(\rho)nt}$  captures the denominator of equation 5 and thus represents the inclusive value of firm  $f$  to serve market  $n$  with platform  $\rho$ ,  $C_{f(\rho)n}$ , multiplied by -1:

$$FE_{f(\rho)nt} = -\ln \sum_{k \in \mathcal{L}_{\rho t}} \exp \left[ (FE_k - \mathbf{W}'_{kt} \mathbf{v}_1 - \theta \zeta \ln q_{kt} - \theta \mathbf{X}'_{knt} \mathbf{b} - \theta \mathbf{X}'_{i(f)kt} \mathbf{g}) \right]$$

The tilde-denoted coefficients from the regression in equation 20 also have structural interpretation:  $-\mathbf{b}\theta$ ,  $-\mathbf{g}\theta$ , and  $-\zeta\theta$ . Because the car tariff enters with a unitary coefficient as a direct cost-shifter in equation 3, it directly identifies  $\theta$ , the critical elasticity of substitution between assemblies. Local wages, input tariffs, and the location size only have a partial impact on the unit cost, and thus their coefficient estimates are the true coefficient values scaled by the nesting parameter. They are recouped by dividing them by  $-\theta$ . Thus, the headquarters input cost share  $1 - \alpha$  is given by the elasticity estimate on the car part tariffs in the  $\gamma$  component, scaled by  $\theta$ .

**Results.** Table 4 displays the estimation results of the conditional assembly choice. As expected and in line with the gravity model, choosing assembly  $\ell$  to produce variety  $\omega(\rho)$  for market  $n$  is more likely if assembly  $\ell$  and destination  $n$  are closer together, there are lower car tariffs between  $\ell$  and  $n$  and lower parts tariffs between  $i$  and  $\ell$ . The likelihood also increases if  $i$  and  $\ell$  share the same language (the effect is negligible for trade between  $n$  and  $\ell$ ), a regional trade agreement, or are within the same country.  $\theta$ , the coefficient on the car tariffs, is large (-9.36) and considerably larger than the -7.7 estimate in [Head and Mayer \(2019\)](#). This difference is explained simply by the longer time horizon and the fact that I include Vans and pick-ups, both of which display higher tariffs on average. The elasticity of cost to local productivity  $\zeta = \tilde{\zeta}/\theta = -.022$  indicates that firms are more likely to operate in  $\ell$  if there is a higher overall output. All estimates are well within the range of other MP production models, such as [Head and Mayer \(2019\)](#) and [Cosar et al. \(2018\)](#).

Using the parameters estimated in the first stage,  $C_{f(\rho)n}$  is constructed for all *potential platform-destination combinations* at time  $t$ , not just the realized ones, and then used to estimate subsequent choices.

**Table 4:** Assembly Choice Regression

<i>Step:</i>	<b>Assembly Sourcing</b>
<i>Dep. variable:</i>	$\mathbb{E}[\Omega_{f(\rho)\ell nt} \mid \ell \in \mathcal{L}_{\rho t}]$
<i>Method:</i>	PPML
home $_{\ell n}$	1.239a (0.268)
ln dist $_{\ell n}$	-0.383a (0.072)
language $_{\ell n}$	-0.007 (0.124)
ln (1+ car tariff $_{\ell n}$ )	-9.359a (0.662)
Deep RTA $_{\ell n}$	0.199b (0.088)
home $_{i(f)\ell}$	1.061b (0.422)
ln dist $_{i(f)\ell}$	0.007 (0.080)
language $_{i(f)\ell}$	0.333 (0.208)
ln (1+ parts tariff $_{i(f)\ell}$ )	-3.306b (1.619)
Deep RTA $_{i(f)\ell}$	0.469c (0.243)
ln $q_{\ell}$	0.205b (0.082)
N	1,977,392
(Pseudo) $R^2$	0.338

*Notes:* Standard errors in parenthesis.  $c : p < 0.1, b : p < 0.05, a : p < 0.01$ .  $R^2$  is the squared correlation of fitted and true dependent variables. Controls for income and price level of the assembly country included.

## 4.2 Market Shares Estimation

To identify the second structural parameter  $\eta_s$ , the market shares equation in equation 7 is estimated for each segment separately. Because all covariates only vary at the firm-segment-platform level, I aggregate sales at that level:  $q_{f(\rho)n} = \sum_{\omega(\rho)} q_n(\omega(\rho))$ . The firm's market shares are then given by:

$$\mathbb{E}[q_{f(\rho)n}/Q_{sn} \mid \mathbb{1}_{f,n} = 1] = \sum_{\omega(\rho)} \mathbb{1}_{f,\omega(\rho)} \mathbb{1}_{\omega,\rho} \mathbb{E}[q_n(\omega(\rho))/Q_{sn}] = \Omega_{f(\rho)n} \kappa_1 \left( \frac{\varphi_f P_{sn}}{w_{i(f)}^{1-\alpha} \delta_{i(f)n}} \right)^{\eta_s} C_{f(\rho)n}^{-\eta_s} \quad (21)$$

Where  $\Omega_{f(\rho)n} = \sum_{\omega(\rho)} \mathbb{1}_{f,\omega(\rho)} \mathbb{1}_{\omega,\rho} \mathbb{1}_{\omega(\rho),n}$  denotes the count of varieties  $\omega(\rho)$  offered by a firm in a market-segment  $s - n$ . Taking this endogenous variable to the left-hand side, the average firm market share can be estimated for each segment using PPML:

$$\mathbb{E}[q_{f(\rho)n}/\Omega_{f(\rho)n} Q_{snt}] = \exp(\text{FE}_f - \mathbf{W}'_{i(f)t} \mathbf{v}_{2s} + \text{FE}_{snt} - \eta_s \mathbf{X}'_{i(f)nt} \mathbf{d}_s - \eta_s \ln C_{f(\rho)n}) \quad (22)$$

Where  $\delta_{i(f)nt} = \exp(\mathbf{X}'_{i(f)nt} \mathbf{d}_s)$ ,  $\mathbf{W}'_{i(f)t} \mathbf{v}_2 = \eta(1 - \alpha)(\ln w_{i(f)t} - \ln w_{i(f)T})$ ,  $\text{FE}_{snt} = \ln \kappa_1 + \eta \ln P_{snt}$  and  $\text{FE}_f = \eta_s \ln \varphi_f - \eta(1 - \alpha) \ln w_{i(f)T}$ .  $C_{f(\rho)n}$ , the expected variable cost, will identify  $\eta_s$  as a direct price shifter.

**Results.** Table 5 shows the results of the market shares regression for each segment. As with the assembly choice, gravity matters for market shares: consumers value domestic models higher and strongly penalize cars of physically more distant firms. The home market effect is less pronounced and even negative for the big cars and pick-up segment (insignificant and small for the latter one). Sharing a common language implies lower marketing frictions, and expectedly increases the market share of a model on average by a quarter compared to destinations where consumers speak a different language. The effect of deep RTAs is ambiguous; for big cars, MPVs, SUVs, PUPs, and EVs it is estimated negatively, but with varying magnitude and precision. Overall, such trade agreements seem to matter more at the sourcing and firm entry margin, and less at the model-platform entry and market shares level. The demand elasticity estimated from the cost shifter  $C_{f(\rho)n}$ , while significant and negative throughout, varies substantially in magnitude across segments. Higher elasticities are found for the big car (7.9) segment, while SUV (3.8), small cars (3.2), Vans (2.3), and MPVs (2.2) display lower responsiveness to price changes. Pick-up trucks (PUP), sports car, and EV estimates are out of bounds (-1.6, -0.9, and -0.8), implying nearly inelastic demand by consumers and thus infinite markups.<sup>16</sup> For the well-estimated segments, the elasticities translate into mark-ups ranging from 14.7% in the big car segment to 83.3% in the MPV segment. The average elasticity over all segments is 3.6, an estimate at the lower end of

<sup>16</sup>I will drop those segments from the subsequent analysis.

**Table 5:** Market Shares Regression

<i>Step:</i>	<b>Market Shares</b>								
<i>Dep. variable:</i>	$\mathbb{E}[q_n(\omega(\rho))/\Omega_{f(\rho)n}Q_{sn}]$								
<i>Method:</i>	PPML								
<i>Segment:</i>	Small cars	Big cars	MPV	SUV	PUP	Van	Sport	EV	All
home <sub>i(f)n</sub>	0.139c (0.075)	-0.448a (0.083)	0.118 (0.092)	0.074 (0.068)	-0.100 (0.133)	0.084 (0.079)	0.868a (0.089)	0.955a (0.202)	0.064 (0.039)
home <sub>i(f)n</sub> × LDC <sub>n</sub>	0.779a (0.100)	-1.151a (0.168)	-0.175 (0.163)	0.424a (0.090)	1.657a (0.187)	1.276a (0.139)	-0.537b (0.266)	-1.329a (0.315)	0.383a (0.058)
ln dist <sub>i(f)n</sub>	-0.277a (0.016)	-0.056a (0.021)	-0.398a (0.021)	-0.192a (0.017)	-0.174a (0.030)	-0.469a (0.020)	-0.097a (0.020)	-0.061 (0.045)	-0.295a (0.009)
language <sub>i(f)n</sub>	0.087b (0.038)	0.293a (0.041)	0.192a (0.046)	0.372a (0.034)	0.237a (0.047)	0.232a (0.041)	0.256a (0.045)	0.350a (0.101)	0.244a (0.019)
Deep RTA <sub>i(f)n</sub>	0.077a (0.025)	-0.319a (0.035)	-0.066c (0.037)	-0.027 (0.026)	-0.482a (0.051)	0.055 (0.035)	0.036 (0.038)	-0.088 (0.080)	-0.040b (0.016)
ln C <sub>f(ρ)n</sub>	-3.229a (0.096)	-7.889a (0.206)	-2.217a (0.140)	-3.783a (0.115)	-1.605a (0.125)	-2.296a (0.135)	-0.918a (0.129)	-0.784c (0.437)	-3.596a (0.074)
N	77,881	58,890	43,371	88,697	17,603	44,461	31,638	7,417	265,304
<i>R</i> <sup>2</sup>	0.314	0.371	0.304	0.322	0.375	0.285	0.439	0.539	0.327

*Notes:* Standard errors in parenthesis.  $c : p < 0.1, b : p < 0.05, a : p < 0.01$ .  $R^2$  is the squared correlation of fitted and true dependent variables.

other studies of the automotive sector (Cosar et al. (2018), Head and Mayer (2019)), yielding a mark-up of  $\sim 38.4\%$ .

### 4.3 Model-Market Entry Estimation

Because all costs are symmetric at the firm-segment-platform destination level for each firm, the variety entry probability in  $n$  is equivalent to the expected share of models with the same platform offered by each firm in a given market:  $\mathbb{E}[\Omega_{f(\rho)n}/\Omega_{f,\rho}]$ , where  $\Omega_{f(\rho)n} = \sum_{\omega(\rho)} \mathbb{1}_{f,\omega(\rho)} \mathbb{1}_{\omega(\rho),n}$  and  $\Omega_{f(\rho)} = \sum_{\omega(\rho)} \mathbb{1}_{f,\omega(\rho)}$ . Equation 11 is then estimated as a fractional probit for each segment:

$$\begin{aligned}
 \mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1] &= \mathbb{E}[\Omega_{f(\rho)n}/\Omega_{f(\rho)}] \\
 &= \Phi \left[ \text{CST}_s + \mathbf{X}'_{i(f)nt} \mathbf{e}_s - \mathbf{W}'_{i(f)t} \mathbf{v}_{3s} - (\eta_s - 1) \ln C_{f(\rho)nt} + \text{FE}_f + \text{FE}_{snt} \right]
 \end{aligned} \tag{23}$$

Where the components have the following structural interpretation:

$$\begin{aligned}
\delta_{i(f)nt} &= \exp(\mathbf{X}'_{i(f)nt} \mathbf{e}_s), \quad \text{with } \mathbf{e}_s = -[(\eta_s - 1)\mathbf{d} + \mathbf{f}^e]/\sigma_e \\
CST_s &= (\ln \kappa_2 - \ln \eta_s)/\sigma_e \\
\mathbf{W}'_{i(f)t} \mathbf{v}_3 &= (((1 - \alpha)(\eta_s - 1) + \zeta)/\sigma_e)(\ln w_{i(f)t} - \ln w_{i(f)T}) \\
FE_{fs} &= [(\eta_s - 1) \ln \varphi_f - (((1 - \alpha)(\eta_s - 1) + \zeta)/\sigma_e) \ln w_{i(f)T} - \beta_f^e] \\
FE_{snt} &= [\ln Q_{snt} + \eta_s \ln P_{sn} - (1 - \zeta) \ln w_{nt} - \mu_n^e]/\sigma_e
\end{aligned}$$

**Results.** The results of the model entry regressions are shown in Table 6. There is more variability both in terms of signs and significance across segments. It seems that the gravity forces are stronger at the sourcing and firm entry choice. For model entry, expected profits seem to matter most, which is indicated by a very strong negative effect of expected higher variable cost  $C_{f(\rho)nt}$ . While greater distance reduces entry probabilities (mostly), a shared language increases them - these gravity forces are, however, much smaller and more imprecisely estimated than in the previous stages. The home-market effect and RTAs again are mixed and seemingly irrelevant for this stage. The structural parameter associated with this stage is the variance of the entry fixed cost,  $\sigma_e$ , which can be obtained by dividing  $\eta_s - 1$  by the coefficient on  $C_{f(\rho)nt}$ . Note that since the coefficients on the cost-shifter  $C_{f(\rho)nt}$  is high, the entry variance is very low, in particular, compared with the estimates of [Head and Mayer \(2019\)](#). Column (4) of Table 11 displays the estimated model entry cost variance for each segment. Given that my model, by controlling for technologies, offers a richer structure, the lower variance is a sign that it can capture more of the underlying mechanisms, which MP models, agnostic to technology choices, only capture as noise. Moreover, headquarters-destination frictions seem to play a less important role at the model entry stage, indicated by the largely insignificant estimates on the gravity covariates. This suggests that model entry is determined mostly by the expected variable cost of serving a market, and variable marketing frictions might matter more at the firm entry level than the model entry level.

**Table 6:** Variety Entry Regression

<i>Step:</i>	<b>Model-Market Entry</b>								
<i>Dep. variable:</i>	$\mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1] = \mathbb{E}[\Omega_{f(\rho)n}/\Omega_{f(\rho)}]$								
<i>Method:</i>	Fractional Probit								
<i>Segment:</i>	Small cars	Big cars	MPV	SUV	PUP	Van	Sport	EV	All
home <sub><i>i(f)n</i></sub>	-0.214a (0.071)	-0.179 (0.122)	0.057 (0.084)	-0.086 (0.166)	0.477a (0.167)	0.134 (0.152)	-0.247c (0.148)	-0.088 (0.305)	-0.050 (0.063)
home <sub><i>i(f)n</i></sub> × LDC <sub><i>n</i></sub>	0.147 (0.156)	-0.471a (0.155)	-0.509b (0.235)	0.133 (0.167)	-0.407 (0.266)	-0.260 (0.206)	0.414 (0.252)	0.204 (0.341)	0.023 (0.102)
ln dist <sub><i>i(f)n</i></sub>	-0.069a (0.024)	0.078a (0.024)	-0.174a (0.043)	-0.018 (0.023)	0.041 (0.055)	-0.086c (0.049)	0.063 (0.039)	-0.057 (0.063)	-0.039c (0.020)
language <sub><i>i(f)n</i></sub>	0.059 (0.040)	0.100c (0.060)	-0.016 (0.066)	0.040 (0.035)	0.113b (0.052)	-0.029 (0.051)	0.024 (0.083)	-0.026 (0.081)	0.037 (0.024)
Deep RTA <sub><i>i(f)n</i></sub>	-0.087 (0.063)	-0.061 (0.045)	-0.063 (0.087)	0.017 (0.071)	0.017 (0.051)	-0.011 (0.076)	-0.171a (0.058)	-0.346a (0.124)	-0.048 (0.043)
ln $C_{f(\rho)n}$	-2.983a (0.331)	-4.166a (0.393)	-3.103a (0.399)	-3.338a (0.305)	-2.171a (0.488)	-3.174a (0.495)	-3.017a (0.740)	-3.601b (1.453)	-3.095a (0.243)
N	132,970	90,263	60,592	117,058	25,956	59,711	33,361	7,251	460,594
$R^2$	0.320	0.356	0.390	0.395	0.341	0.311	0.329	0.560	0.327

*Notes:* Standard errors in parenthesis.  $c : p < 0.1, b : p < 0.05, a : p < 0.01$ .  $R^2$  is the squared correlation of fitted and true dependent variables.

#### 4.4 Firm-Market Entry Estimation

While the market shares and model entry equations are estimated segment-wise, the resulting expectations are aggregated across segments to the firm level to determine its global entry decisions into markets. Thus, the firm entry regression in equation 16 can be estimated as a probit, taking the underlying segmentation of the car market only implicitly into account:

$$\mathbb{P}[\mathbb{1}_{f,n} = 1] = \Phi \left[ \frac{1}{\sigma_d} \ln \mathbb{E}[\pi_{f,nt}] - \mathbf{X}'_{i(f)nt} \mathbf{f}^d / \sigma_d - \mathbf{W}'_{i(f)t} \mathbf{v}_4 + FE_f + FE_{nt} \right] \quad (24)$$

With the structural correspondence:

$$\begin{aligned} \mathbf{W}'_{i(f)t} \mathbf{v}_4 &= (\zeta / \sigma_d) (\ln w_{i(f)t} - \ln \ln w_{i(f)T}) \\ \delta_{i(f)nt} &= \mathbf{X}'_{i(f)nt} \mathbf{f}^d \\ FE_f &= - (\beta_f^d + \zeta \ln w_{i(f)T}) / \sigma_d \\ FE_{nt} &= \left( \mu_n^d + \ln w_{nt}^{1-\zeta} \right) \end{aligned}$$

**Results.** Table 7 suggests a strong presence of headquarter-destination frictions. The home market effect is strong and significantly larger than in all previous stages. The coefficient of 2.1

implies that a firm’s entry probability increases by about 25% if the country is your home market. Moreover, higher spatial proximity and the existence of RTAs increase the firms’ entry probability, suggesting significant bilateral entry costs. The coefficient on the expected firm profit is positive and significant, its inverse yielding the firm’s entry cost variance of  $\sigma_d = 2$ . This estimate compares well to the estimator of [Head and Mayer \(2019\)](#), naturally given that the estimation is done at the same level of aggregation, thus averaging across the technology conditioning in the levels below. Intuitively, platform choices condition the allocation of assembly and models within a given firm’s activity space.

**Table 7:** Firm Entry Regression

<i>Step:</i>	<b>Firm Entry</b>
<i>Dep. variable:</i>	$\mathbb{P}[\mathbb{1}_{f,n} = 1]$
<i>Method:</i>	Probit
$\text{home}_{i(f)n}$	2.0884b (0.812)
$\text{home}_{i(f)n} \times \text{LDC}_n$	0.7207 (0.963)
$\ln \text{dist}_{i(f)n}$	-0.2675a (0.104)
$\text{language}_{i(f)n}$	0.0952 (0.188)
$\text{Deep RTA}_{i(f)n}$	0.3966a (0.127)
$\ln \mathbb{E}[\pi_{f,n}]$	0.4915a (0.070)
N	105,270
$R^2$	0.6687

*Notes:* Standard errors in parenthesis.  $c : p < 0.1, b : p < 0.05, a : p < 0.01$ .  $R^2$  is the squared correlation of fitted and true dependent variables.

## 4.5 Platform & Collaboration Choice Estimation

Finally, I can use the previous results to compute the expected profits of each platform for each model,

$$\mathbb{E}[\pi(\omega(\rho))] = \sum_n (\mathbb{P}[\mathbb{1}_{f,n} = 1] \times \mathbb{P}[\mathbb{1}_{\omega(\rho),n} = 1] \times \mathbb{E}[\pi_n(\omega(\rho))]), \quad (25)$$

which is constructed for all *possible* model-platform combinations using the structural estimates from the previous stages. Since on average, varieties can match with 105 platforms per segment in each year, the estimation for the more than 1250 varieties is high-dimensional and requires further assumptions to be feasible. Table A.7 in the Appendix A.3 displays the average number of platforms available for each model by segment in an unconstrained and two constrained scenarios. In the first constraint, I include only platforms that are at least two years in the market before being available for licensing. Furthermore, platforms are added to other firms' choice sets only if they belong to firms that follow a general 'collaboration-friendly' strategy, i.e., they license out platforms at least once in the whole period. By excluding never-collaborator platforms from the choice set of other firms, I make sure not to inflate their choice sets by de facto unavailable platforms. This reduces the average choice set per segment by about 15 platforms. The second constraint goes further and requires a 'collaboration-friendly' strategy at the platform level: A platform can only be included in the choice set of other firms if it was used collaboratively in the previous periods up to the present at least once. This reduces the potential choice sets by an additional 51 platforms on average.

Based on these choice sets for each model, I compute each variety's expected profit using any platform,  $\mathbb{E}[\pi(\omega(\rho))]$ . Conditional on the platform and the segment, however, the utility is symmetric across varieties of a firm. Thus, following [Guimaraes et al. \(2003\)](#), I again aggregate  $\mathbb{E}[\pi(f(\rho))] = \sum_{\omega} \mathbb{E}[\pi(\omega(\rho))]$ , summarizing the utility of a platform at the firm-segment level constructed from the previous stages. The dependent choice variable is similarly turned into a count variable  $\Omega_{f,\rho} = \sum_{\omega} \mathbb{1}_{f,\omega} \mathbb{1}_{\omega,\rho}$ , referring to the number of times the firm chooses  $\rho$  for any of its models within a segment  $s$ . Then, the equation can be consistently estimated using PPML:

$$\mathbb{E}[\Omega_{f,\rho}] = \exp [\lambda \mathbb{E}[\pi(f(\rho))] + \text{FE}_{s\rho} + \text{FE}_{fc} + \text{FE}_{fst}] \quad (26)$$

accounting for  $\text{FE}_{s\rho}^{17} = -\lambda f^{\rho(s)}$ ,  $\text{FE}_{fc} = -\lambda f_f^c$  and  $\text{FE}_{fst} = -\text{IU}_{f(s)}$ , the firm-segment-specific inclusive utility  $\text{IU}_{f(s)} = -\ln \sum_{r \neq \rho} \exp [\lambda (\mathbb{E}[\pi(f(r))] - f^r - f_f^c)]$ . A second specification uses a parametric approach to model the collaboration fixed cost. In particular, the vector of bilateral frictions between the headquarters of the user and the platform owner,  $\mathbf{X}\beta$ , captures gravity-like bilateral collaboration costs associated with distance, language and trade agreements that impact the likelihood of a collaboration between firms in  $i(f)$  and  $i(\rho)$ .

$$\mathbb{E}[\Omega_{f,\rho}] = \exp [\lambda \mathbb{E}[\pi(f(\rho))] + \mathbf{X}\beta + \text{FE}_{\rho s} + \text{FE}_{fc} + \text{FE}_{fst}] \quad (27)$$

Note that the specification 27 has the advantage of being less demanding on identifying variation

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<sup>17</sup>I am allowing the fixed cost of using the platform to depend on a segment

compared to specification 26. The latter adds three high-dimensional fixed effects. Platform fixed effects cannot be identified for platforms that are chosen only once, or chosen by only one firm-segment while being installed in only one assembly location. This results in 41 of 858 non-identified platform effects. In order to identify the firm-specific collaboration fixed effects, firms need to (i) engage in collaboration and non-collaboration at least once, (ii) be active in more than one year. Due to these restrictions, 27 of the 103 firm-specific collaboration fixed effects cannot be identified. In specification 27, instead of adding high-dimensional firm-specific collaboration cost, I parametrize the cost by headquarter-specific bilateral cost and a general collaboration dummy. This less restrictive identification helps to shed some light on the underlying mechanisms that drive firms' choices of technology. In the counterfactual analysis, I will, however, work with the firm-specific estimates.

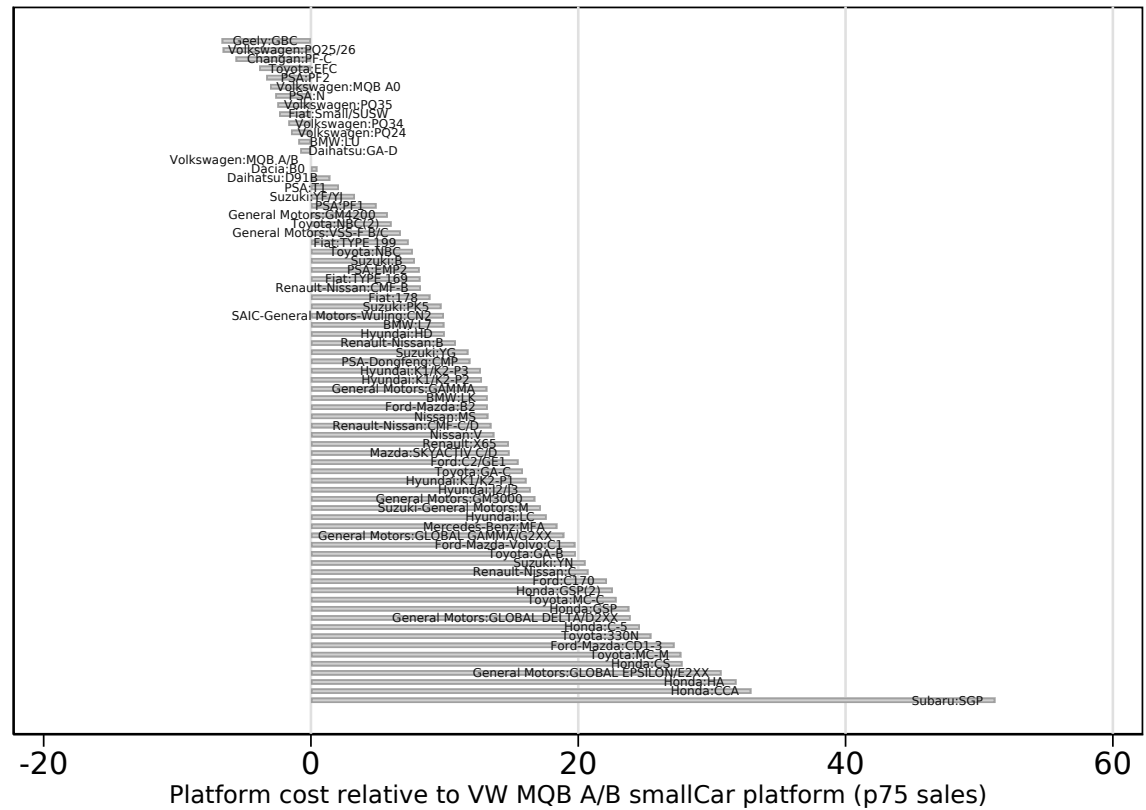
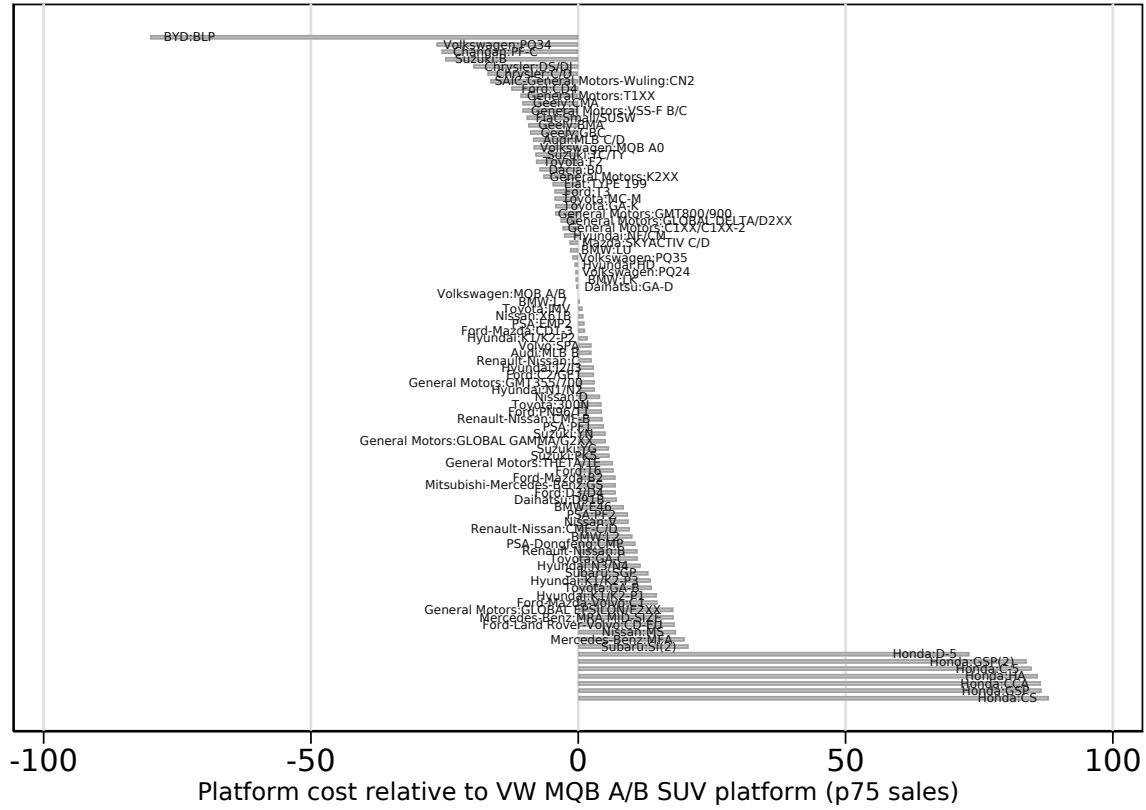
**Results.** The results of the regressions under constraint 2 are displayed in Table 8. Column (1) shows the results of the specification with only fixed effects, while column (2) displays the results with parametric specifications of the platform fixed cost. The positive coefficient on the expected profits per firm-segment-platform,  $\mathbb{E}[\pi(f(\rho))]$  of 0.107 implies that a higher expected profit increases the choice probability of a given platform only marginally. Its structural interpretation as the parameter  $\lambda$  implies that there is only limited substitutability across platforms and that the fixed cost of a platform and collaboration seem to matter strongly. I recover these fixed costs by rescaling the fixed effect estimates by  $\lambda$ . The resulting ranking of the estimated platform fixed costs is plotted in Figure 4 for the big car and small car platforms with sales shares in the 75th percentile. These costs are normalized relative to one platform that serves all included segments ('VW MQB A/B'). These figures and the summarized normalized cost estimates displayed in Table 9 indicate a very large dispersion of fixed costs.

**Table 8:** Platform Choice Regression

<i>Step:</i>	<b>Platform choice</b>	
<i>Dep. variable:</i>	$\mathbb{E}[\Omega_{f(s),\rho}]$	
<i>Method:</i>	PPML	
$\mathbb{E}[\pi_{f(\rho)}]$	0.107a (0.007)	0.056a (0.007)
$\ln \text{dist}_{i(f)i(\rho)}$		-0.729a (0.148)
$\text{language}_{i(f)i(\rho)}$		1.125 (0.724)
$\text{deep RTA}_{i(f)i(\rho)}$		-1.224a (0.349)
$\text{home}_{i(f)i(\rho)}$		-0.580 (0.758)
# firms/platform (lag)		0.072a (0.026)
# assemblies/platform (lag)		0.027a (0.007)
# sales destinations/platform (lag)		0.007a (0.001)
$\ln \text{av. productivity/platform (lag)}$		0.046a (0.008)
collab=1		-3.242a (0.124)
$\text{FE}_{\rho s}$	Yes	Yes
$\text{FE}_{fc}$	Yes	No
$\text{FE}_{fst}$	Yes	Yes
N	226,810	175,728
$R^2$	0.675	0.790

*Notes:* Standard errors in parenthesis.  $c : p < 0.1, b : p < 0.05, a : p < 0.01$ .  $R^2$  is the squared correlation of fitted and true dependent variables.

Figure 4: Distribution of Estimated Platform Fixed Cost



Notes: Estimated platform fixed cost for platforms with sales above the 75th percentile, normalized relative to Volkswagen's 'MQB:A-B'-platform, which serves all segments. Big car (top) & small cars (bottom) segment.

**Table 9:** Estimated Platform Cost by Segments

	Mean	SD	P25	P50	P75
MPV	0.40	22.98	2.09	10.81	17.16
SPORT	1.14	14.58	1.11	7.84	14.47
SUV	-0.61	25.78	-5.57	2.31	10.17
Van	0.15	19.37	-5.90	5.52	15.23
bigCar	1.02	15.37	9.16	17.19	24.36
smallCar	-2.18	22.09	2.60	10.95	19.15
Total	-0.22	21.79	-0.20	8.49	17.06

*Notes:* Estimated platform fixed cost, normalized relative to Volkswagen’s ‘MQB:A-B’-platform, which serves all segments.

Obtaining the collaboration fixed cost from the estimated fixed effects is more involved. For each firm, I estimate a collab fixed effect  $FE_{f1}$  and a no-collab fixed effect  $FE_{f0}$ , the normalization is relative to one firm in one of these cases. Thus, I first normalize both fixed effects relative to one firm (Volkswagen):  $FE_{f0}^{norm} = FE_{f0} - FE_{f0}^{VW}$  and  $FE_{f1}^{norm} = FE_{f1} - FE_{f0}^{VW}$ . Then, the firm-specific collaboration costs are given as the difference between these normalized fixed effects, scaled by  $\lambda$ :  $f_f^c = (-FE_{f1}^{norm}/\lambda) - (-FE_{f0}^{norm}/\lambda)$ . I summarize the resulting collaboration cost in Table 10 and plot the ranking in Figure 5. Again, the distribution is very dispersed, with the maximum collaboration cost being 18 times higher than the minimum one. Column (2) of Table 8 sheds

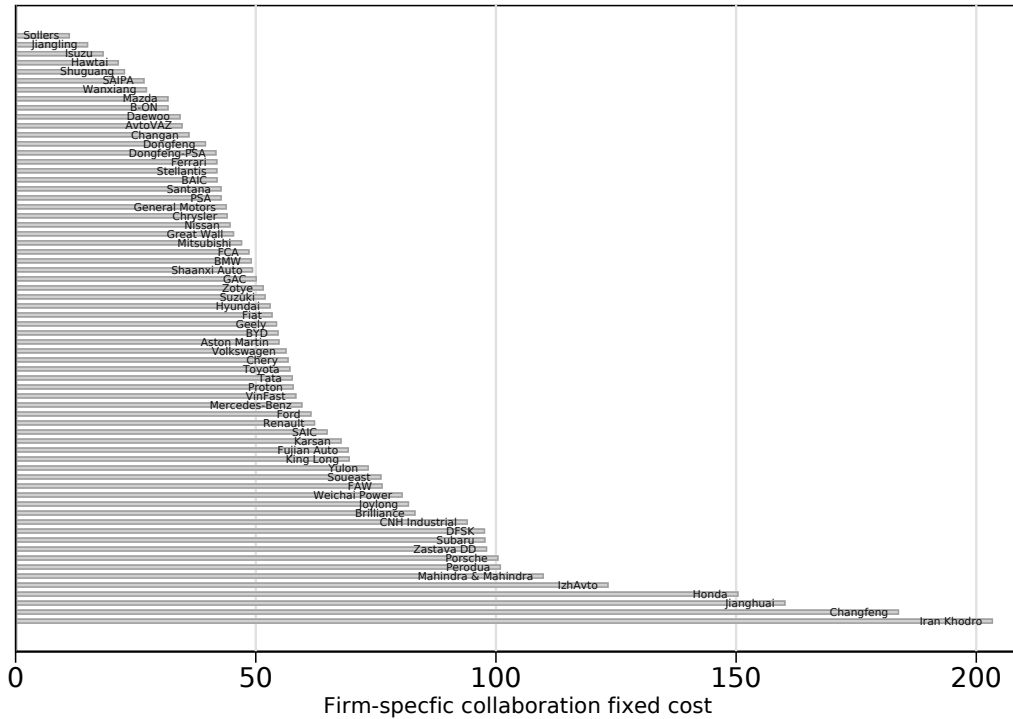
**Table 10:** Estimated Collaboration Fixed Cost  $f_f^c$ 

	Mean	SD	Min	P50	P75	Max
Normalised firm cost (collab=0)	-13.2594	21.43	-153.1478	-8.3333	-2.5702	2.0893
Normalised firm cost (collab=1)	49.3162	32.49	-3.2416	45.8075	59.5526	172.7103
Firm-collab cost	62.5755	37.86	-5.3309	54.4895	76.1770	203.5055
N	67					

*Notes:* Estimated firm-specific fixed cost, normalised relative to Volkswagen w/o collaboration cost.

some more light on what underlies these collaboration costs. Platforms that are previously used by more firms had larger output, and were available in more locations or sold in more markets, are more likely to be chosen. I interpret this as corresponding to lower platform cost  $f^p$ . With respect to the firm-specific collaboration fixed cost, gravity seems to play a role in reducing the cost of firms to choose a platform: firms are more likely to select platforms from owners whose headquarters are closer and with whom they share a common language. Interestingly, the same headquarters location and trade agreements are less important and enter with negative signs. One reason might be that trade agreements are not relevant when negotiating licensing agreements. Furthermore,

**Figure 5:** Distribution of Estimated Collaboration Fixed Cost  $f_f^c$



*Notes:* Estimated firm-specific collaboration fixed cost, normalised relative to Volkswagen w/o collaboration cost.

since there is a market access component to choosing platforms, the home market effect is less relevant. Overall, collaboration is more costly than using an own platform, as indicated by the large negative and significant coefficient of the dummy.

The final goal is to use these estimates to conduct counterfactuals that simulate what happens when firms gain or lose access to specific technologies. As geopolitical tensions intensify globally, and countries compete in industrial policies for competitiveness, multinational production is not only threatened by increased protectionist trade policy but also by policies affecting the global mobility of technology. The framework developed here can give insights into the substitutional patterns of precisely such policies and inform the reshuffling of the global production landscape.

**Table 11:** Segment-specific Structural Parameter Estimates

<i>Step:</i>	Assembly	Market Shares	Model Entry	Firm Entry	Platform Choice
<i>Parameter:</i>	$\theta$	$\eta_s$	$\sigma_e$	$\sigma_d$	$\lambda$
<b>Total</b>	9.36	3.59	0.84	2.04	0.11
<b>Segment</b>					
EV	9.36	0.784	-0.060	2.035	0.107
MPV	$\vdots$	2.217	0.392	$\vdots$	$\vdots$
PUP		1.605	0.279		
SUV		3.783	0.834		
Vans		2.296	0.408		
sport cars		0.918	-0.027		
big cars		7.889	1.654		
small cars		3.229	0.747		

## 5 Counterfactual Analysis

How important are location-specific technology choices and collaboration in shaping the global landscape? To address this research question, I leverage the structural nature of the framework to simulate various counterfactual scenarios that quantify the gains and losses associated with these factors.

### 5.1 Counterfactual Scenarios

I conduct five counterfactual scenarios to evaluate the impact of technology (dis-) integration, collaboration, and technology-targeted industrial policies in MP frameworks. These scenarios function through the key mechanism of the model: adjustments in the available assembly sourcing options  $\mathcal{L}$ , which influence the expected cost of serving a market  $C_{f,n}$ . Specifically, the choice sets are defined as follows:

#### Platform counterfactuals:

- *No platform constraint CF:*  $\mathcal{L}_f$  (standard MP)
- *No collaboration CF:*  $\mathcal{L}_{f(\rho)}$

#### Industrial policy counterfactuals:

- *US technology export ban:*  $\mathcal{L}_\rho$  if  $\ell = \text{USA}$ , otherwise  $\mathcal{L}_{\rho \setminus \rho^{US}}$
- *US technology import ban:*  $\mathcal{L}_\rho$  if  $\ell \neq \text{USA}$ , otherwise  $\mathcal{L}_{\rho^{US}}$

- *China-US technology war*:  $\mathcal{L}_{\rho \setminus \rho^{CHN}}$  if  $\ell = \text{USA}$ ,  $\mathcal{L}_{\rho \setminus \rho^{US}}$  if  $\ell = \text{China}$ , otherwise  $\mathcal{L}_{\rho}$

Intuitively, in the no-platform scenario, firms can assemble varieties in all *own* locations, regardless of their platform choice. This corresponds to the standard MP framework, which does not account for underlying location-specific technology requirements. In the no-collaboration scenario, firms can select from all *own* plants, provided that the platform technology is available, but they cannot utilize competitors’ platforms. The final three scenarios are motivated by the recent rise in geopolitical tensions and the corresponding competition in industrial policy. Such policies significantly impact the global production landscape by shifting multinationals’ incentives regarding production locations. Most MP frameworks fail to explicitly assess these implications. My model allows for industrial policy thought experiments, where certain technology access is restricted. Specifically, I simulate a US technology export ban, restricting US-owned platforms to US territory. Conversely, a US import ban prohibits foreign-owned technology deployment within US territory.<sup>18</sup> The last industrial policy counterfactual examines the effect of a US-China ‘technology war,’ where the two nations impose reciprocal technology bans while third countries retain access. Finally, to compare these technology-related scenarios with trade policy counterfactuals, I run three recent scenarios of escalating trade conflicts under ‘Trump 2.0’, which each levy an additional 25% bilateral tariffs on both cars and car parts.

**Trade policy counterfactuals:**

- *US-NAFTA trade war*:  $\tau_{\ell n}$  and  $\gamma_{i(f)\ell} \uparrow 25\%$  btw USA and Canada, Mexico
- *US-EU trade war*:  $\tau_{\ell n}$  and  $\gamma_{i(f)\ell} \uparrow 25\%$  btw USA and EU27
- *US-main partner trade war*:  $\tau_{\ell n}$  and  $\gamma_{i(f)\ell} \uparrow 25\%$  btw USA and NAFTA, EU, Japan, Korea, UK

## 5.2 Methodology

To conduct these counterfactual analyses, I first solve the model under the observed, factual frictions using the unconstrained, technology-specific choice set  $\mathcal{L}_{\rho}$ . Subsequently, I re-solve the model for each counterfactual scenario using the new choice sets and compute the changes relative to the factual outcomes. This ‘Difference in Expected Values’ (DEV) approach (as employed by [Head and Mayer \(2019\)](#)) requires more parameters and estimation time compared to the more widely used ‘Exact Hat Algebra’ by [Dekle et al. \(2007\)](#), which computes percentage changes relative to observed initial levels only. The latter approach is unsuitable here as it does not permit firms

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<sup>18</sup>A real-world example includes the ban on Huawei’s 5G technology.

to switch technologies, explore new assembly sources, or enter new markets—factors crucial for evaluating the counterfactual scenarios. The solution algorithm employs a four-level nested fixed-point iteration, akin to [Head and Mayer \(2019\)](#), with two main differences. First, everything is conditional on platform technologies, meaning the choice set in assembly sourcing probabilities determines available options. Second, an outer-level nest iterates over expected sourcing, market shares, and entry choices to optimize platform selection for each firm model within a segment. To underscore interdependence through increasing returns to scale at the location level,  $q_{\ell}^{\zeta}$ , I conduct simulations both with and without this effect. The estimated factor of  $\zeta\theta = 0.205 < 1$  ensures a unique solution ([Kucheryavyy et al., 2023](#)) to the fixed-point iteration under IRS. To ensure that the results are not driven by the entry fixed cost draws, I present the averages of 100 Monte-Carlo simulations.

### 5.3 Counterfactual Results

*Sample selection & model fit.* Simulations are based on the final year of data, 2023, with constant total expenditures in each market-segment,  $Q_{sn}$ , and fixed plant and technology locations. I exclude the three segments for which the estimates were out of bounds (EV, PUP, and sports cars) and all firms and countries with unidentified fixed effects, resulting in a final sample of 35 origin countries, 55 destinations (213 market-segments), and 48 firms. How well does the model match observed data? The model fit is satisfactory for the three nested moments of price index, production quantities, and firm entry choices. The model best replicates aggregated production quantities and aggregated trade flows (correlations of 0.92 and 0.7, respectively). Market-segment price level fits with 0.7-0.95%. The firm-level trade flows show room for improvement in model fit (0.58). The binary firm-entry choices match at an 80% rate, with an estimated entry average of 32% compared to the observed rate of 52%. Figure A.3 in Appendix A.3 shows the model fit for a representative simulation run. Given these preliminary results, further sensitivity analysis is necessary.

Table 12 summarizes the results of the different counterfactual scenarios without platform re-adjustment, for the case with increasing returns to scale. The first five columns refer to changes in firms’ expected costs for serving markets  $n$ , columns 6-10 describe the resulting aggregated production adjustments in locations  $\ell$ , and the last five columns summarize the changes in consumer surplus, measured as segment-weighted price index changes. The results without increasing returns to scale are reported in Table A.8 in the Appendix A.3.

**Table 12: Counterfactual Results**

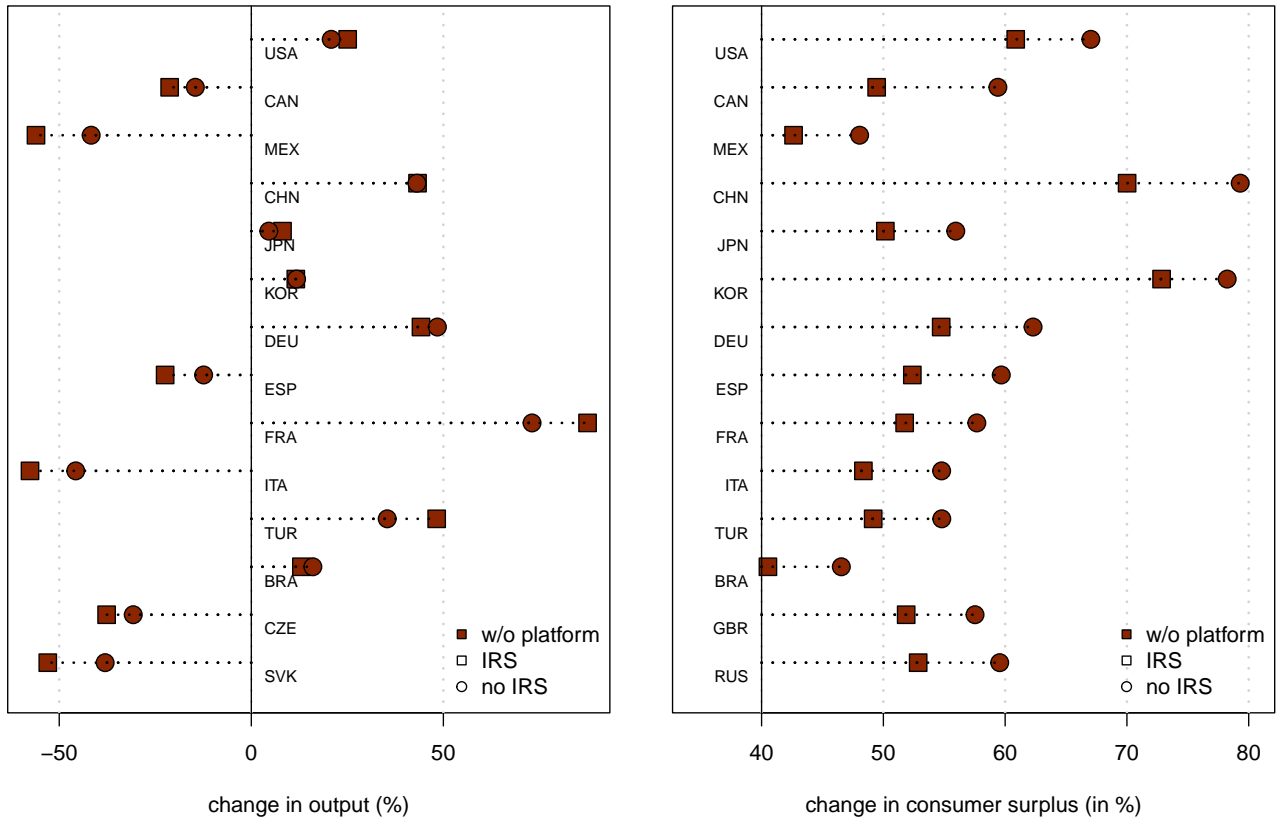
	% $\Delta C_{f,n}$					% $\Delta Q_\ell$					% $\Delta CS_n$				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
<b>Platform CF</b>															
w/o platform constraint	-24.65	1.46	-25.33	-24.86	-24.69	-9.08	59.79	-57.61	-8.47	15.25	44.53	11.94	38.66	46.59	50.16
w/o collaboration	2.90	1.19	2.44	2.58	2.88	-1.66	8.46	-1.45	0.04	1.46	-0.57	1.12	-0.97	-0.75	-0.36
<b>IP policy CF</b>															
US tech export ban	0.75	0.26	0.56	0.80	0.89	-4.87	20.74	-4.21	3.21	5.54	-0.96	0.72	-1.32	-1.08	-0.44
US tech import ban	0.03	0.15	-0.02	-0.02	0.02	4.56	12.65	1.61	2.72	4.42	-0.05	0.91	-0.34	-0.16	-0.08
US-China tech war	0.05	0.03	0.03	0.04	0.05	0.52	0.99	0.07	0.26	0.62	-0.23	0.42	-0.16	-0.02	-0.01
<b>Trade policy CF</b>															
US-NAFTA trade war	0.05	0.14	0.00	0.01	0.02	-0.89	12.40	0.63	1.61	2.64	-0.24	0.65	-0.18	-0.05	-0.01
US-EU trade war	0.13	0.20	0.04	0.09	0.17	-0.12	8.02	-5.79	1.50	4.05	-0.04	0.99	-0.47	-0.31	-0.02
US-ROW trade war	0.42	1.18	0.14	0.24	0.29	5.92	23.07	-4.12	2.96	14.33	-0.64	0.96	-0.67	-0.52	-0.16

*Notes:* Counterfactual percentage changes in firm’s expected cost to serve a market  $C_{f,n}$ , total production per location  $Q_\ell$ , and consumer surplus,  $CS_n$ , measured as the change in the country-segment aggregate price index. Results are the average of 100 Monte-Carlo simulations, including IRS.

***Effect of technology constraint.*** The first row highlights the significant impact of technology on a firm’s cost evaluation. MP models that do not account for platform differences underestimate firms’ costs to serve a market by 24.65% on average. The large variation in production levels across countries is a direct consequence of this: since costs neglect a crucial determinant in selecting assembly locations, local production factors and trade frictions become the primary drivers of production allocation, with increasing returns to scale (IRS) further amplifying the mismatch.

The left panel of Figure 6 illustrates the counterfactual changes for the largest production locations, showing that production levels in many markets are largely overstated when platform dimensions are ignored. China, Germany, Turkey, and especially France appear to be ‘overly’ attractive. For the European countries, this comes from the fact that they are headquarters of several of the largest firms, and the headquarters frictions will push sourcing closer to home, all else equal. Similarly, the large demand in China gravitates production close. Turkey has favorable production conditions to serve many of the largest consumer markets as well, and thus attracts more production when ignoring technology availability. Consequently, as indicated by Table 12 and the left panel of Figure 6, consumer surplus is significantly overstated due to mismeasured production costs affecting price indexes. These results underscore the importance of controlling for location-specific technologies to accurately capture the global production landscape.

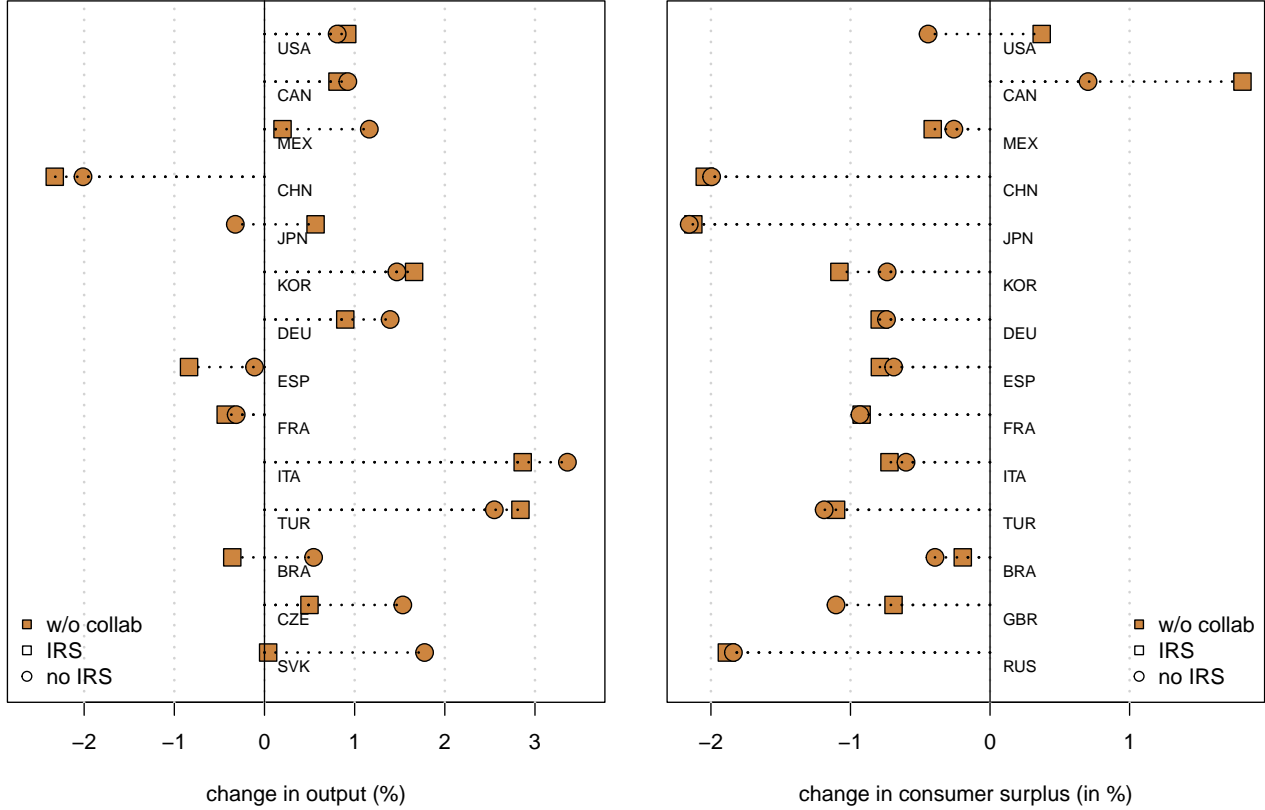
**Figure 6:** Technology Constraint Counterfactual



*Notes:* Percentage changes in country-level total production (left),  $Q_\ell$ , and change in consumer surplus (right), measured as the average change in the aggregate country-segment price index. Counterfactuals simulate the usage of *any* location, irrespective of platform availability. Results are the average of 100 Monte-Carlo simulations, including IRS.

***Effect of collaboration.*** Collaboration alleviates firms’ technology constraints, as evidenced by increased average costs when collaboration is prohibited. The second row of Table 12 suggests this results in a 2.9% average cost increase, with some firms experiencing cost increases in some markets of up to 70%, such as Chinese producers BAIC and Changan. Figure A.4 in the Appendix A.3 indicates that the benefits of collaboration are more pronounced for firms with smaller platform sets, which typically rely more on licensing. Regarding aggregate production, the reallocation across countries is less pronounced than in the first scenario, with production shrinking by 1.66% on average. As Figure 7 shows, Russia (-11%), Malaysia (-7.68%), UK (-3.85%), and China (-2.33%) see the largest declines when collaboration is prohibited, while Italy (2.86%) and Turkey (2.83%) would benefit slightly from a reallocation of production. Consequently, consumer surpluses are adversely affected, as collaboration reduces firms’ costs to serve specific markets.

**Figure 7:** Restricting Collaboration Counterfactual



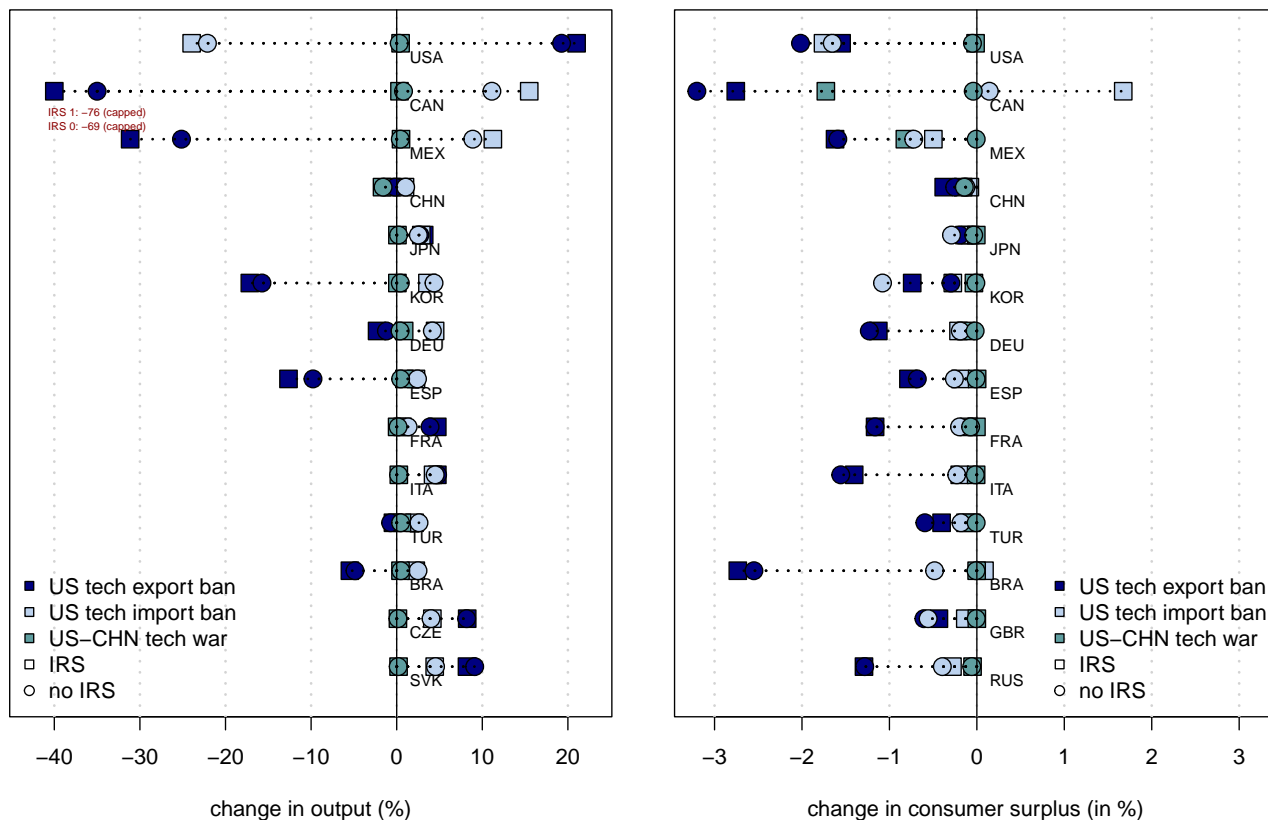
*Notes:* Percentage changes in country-level total production (left),  $Q_{\ell}$ , and change in consumer surplus (right), measured as the average change in the aggregate country-segment price index. Counterfactuals simulate the forced usage of only *own* platforms. Results are the average of 100 Monte-Carlo simulations, including IRS.

**Effect of industrial policies.** The industrial policy scenarios yield relatively moderate effects, however, with large heterogeneity across firms and countries. This is because only a small subset of firms and countries is directly affected, and the spillover effects through IRS are negligible.<sup>19</sup> In 2023, of the 55 US-owned platforms, 34 belonging to Tesla, Ford, and General Motors are installed in 24 countries outside the USA. At the same time, there are 52 platforms, owned by only 13 firms from five different countries, that are installed in the US. Hence, for the US technology export ban, the primary burden falls on firms utilizing US platforms outside the US, particularly GM and Ford, producing in Canada, Korea, and Mexico. For example, GM’s expected cost to serve the Korean market increases by 36% in this policy experiment. Conversely, as Figure 8 shows, production in these countries declines the most, up to 76% in Canada. Notably, the reduction in production is not fully offset by increased US output due to the higher costs associated with models produced using US platforms. Instead, consumer demand shifts toward other models, leading to increased production elsewhere, i.e., the Czech Republic, Slovakia, and France. However, the higher

<sup>19</sup>Throughout the analysis, results with and without IRS are only marginally different

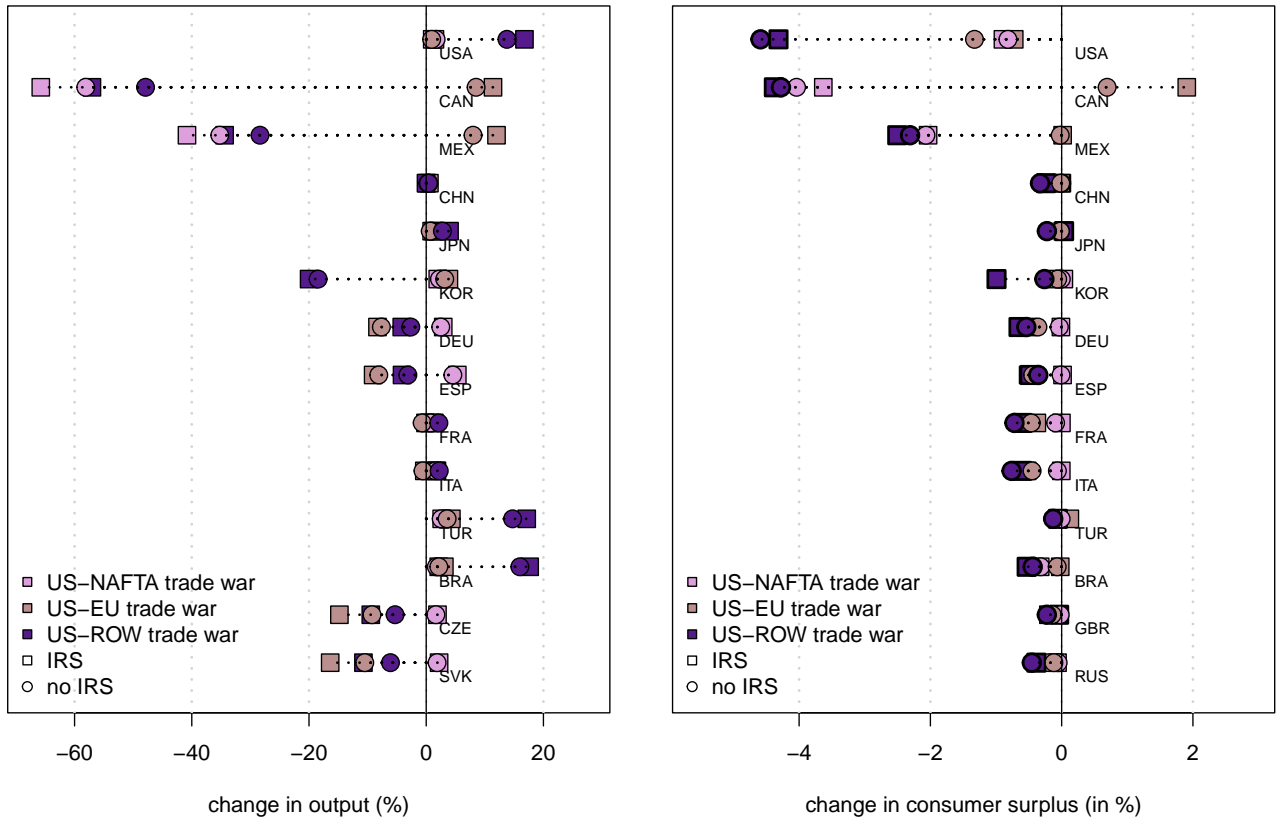
production costs translate into higher consumer prices, ultimately reducing consumer welfare in all countries. In the case of the US import ban, the costs are borne entirely by foreign firms producing in the USA. Subaru and Honda, for example, experience an expected delivered cost increase of 6.5% for the US market. Canada and Mexico, as the closest substitutes, benefit from increased production of 12-17%. Consequently, the welfare losses, measured by consumer surplus, are most pronounced in the US but relatively moderate elsewhere. A potential US-China technology war has almost no global impact, as the number of affected firms is minimal. Ford and GM experience a 4% cost increase when selling in China. Geely, the owner of Volvo, is most hurt when selling to the US, as it sees costs increase by 6%. Therefore, while the overall implications are minimal, such technology restrictions can serve as precise tools to target single firms or countries, enlarging the policy space of governments compared to traditional trade policies. The effects of a similar technology war between Europe, NAFTA, and the US would naturally have much larger impacts and severely disrupt the global production landscape, with high costs borne by both sides.

**Figure 8:** Industrial Policy Counterfactuals



*Notes:* Percentage changes in country-level total production (left),  $Q_\ell$ , and change in consumer surplus (right), measured as the average change in the aggregate country-segment price index. Counterfactuals simulated the restricted access to specific technology, based on the HQ country of the platform owner. Results are the average of 100 Monte-Carlo simulations, including IRS.

**Figure 9: Trade Policy Counterfactuals**



*Notes:* Percentage changes in country-level total production (left),  $Q_\ell$ , and change in consumer surplus (right), measured as the average change in the aggregate country-segment price index. Counterfactuals simulate a 25% tariff bilateral increase on cars and car parts (with leveled retaliation)

**Comparison with trade policies.** So far, I have outlined the effects of technology-restricting industrial policies. Since technology choices and collaboration have a clear multinational dimension, they can serve as alternative tools to trade policy. In order to assess the substitutability of both policies, I run several trade policy experiments that increase bilateral tariffs for cars and inputs between the US and the other NAFTA members, as well as the EU and its major trade partners. Similar to the technology-restricting policy experiments, the overall global impacts are moderate. A NAFTA trade war would affect firms' costs on average by 0.05%, GM and Ford, however, see their cost to serve Mexico and Canada rise by 6-10%. In terms of quantities, Canada and Mexico are hit in similar magnitudes compared to the US tech export ban - the reason is simple: the majority of production in those countries comes from US firms, thus, a US technology export ban has the same effect as raising the cost of production in those countries through tariffs. A major difference is that the US output is not increasing at all - this is due to the retaliation effects. Instead, production shifts to Germany and Spain, which can increase the production of platforms for GM and Ford more easily. Unsurprisingly, consumer surplus is negatively affected

in all of NAFTA. From a trade escalation between the US and the EU, Canada and Mexico stand to gain the most. Finally, a full-blown multilateral dispute between the US and its major trade partners reduces output of all involved parties, but the effects in terms of output are dampened compared to the bilateral trade escalations simply because the respective closer substitutes are also hit and thus reallocation is not lucrative. The same logic makes the consumer surplus worse off in this scenario.

Note that the reallocation of production is overall more limited compared to the trade policy counterfactuals in [Head and Mayer \(2019\)](#). This is because in all of the above counterfactuals, the production patterns are still contingent on the platform choice. Hence, production can only move locations conditionally based on the availability of the chosen platforms. This explains why Japan and Korea are not benefiting as much from the trade policy disputes between the US and NAFTA or the EU.

Overall, these results emphasize that multinational production models that ignore technology choices and collaboration are likely to suffer from omitted variable bias in the allocation of production. Additionally, the gains from collaboration appear to be unevenly distributed across firms and regions. Thus, industrial policies restricting technology access can serve as a targeted alternative to trade policies.

## 6 Conclusion

This paper examines the impact of inter-firm collaboration in technology on multinational production. Using a unique dataset on the global automotive industry that accounts for ownership links, I demonstrate that firms extensively share key input technologies. In particular, I document that more than 70% of firms use at least one production technology (platform) they do not own, although reliance on such collaborations varies significantly. While firms in principle engage in collaboration for multiple reasons, for example, innovation cost savings and knowledge spillovers, I show that this type of asset sharing furthermore has an important multinational production dimension. In particular, I show that the likelihood of collaboration in technology correlates with improved market access and the sharing of assembly plants. To account for these patterns, I build and estimate a structural model that incorporates the novel layers of input technology choices and collaboration in a multinational production framework. Using the estimated parameters of the model, I simulate counterfactual scenarios of trade and technology-restricting industrial policies. I find that both technology choice and platform sharing significantly affect costs and, consequently, production allocation and consumer welfare across countries. Specifically, not accounting for input technology choices underestimates firms' costs by 24.65%. Collaboration in technology, in

turn, eases a firm's sourcing constraints, reducing the average costs of serving a market by 2.9%. Comparing policy experiments that restrict access to specific assembly technology with traditional trade policies shows that industrial policy in the form of restricting technology can serve as a substitute for trade policy. While achieving similar global reallocation, such industrial policies can be employed to target specific firms and countries and potentially manipulate domestic firms' comparative advantages, a practice that needs more attention and regulation in order to maintain a fair global production and trade landscape. Overall, these findings highlight the necessity for MP models to incorporate underlying production processes when modeling spatial production allocation and estimating gains from trade. Furthermore, modeling endogenous collaboration choices within a nested logit framework that considers both platform and assembly decisions enhances our understanding of market structures, thereby informing trade and industrial policy.

## References

- Pol Antras. Property rights and the international organization of production. *American economic review*, 95(2):25–32, 2005.
- Pol Antràs and Elhanan Helpman. Global sourcing. *Journal of political Economy*, 112(3):552–580, 2004.
- Pol Antràs, Teresa C Fort, and Felix Tintelnot. The margins of global sourcing: Theory and evidence from us firms. *American Economic Review*, 107(9):2514–2564, 2017.
- Pol Antràs, Evgenii Fadeev, Teresa C Fort, and Felix Tintelnot. Global sourcing and multinational activity: A unified approach. Technical report, National Bureau of Economic Research, 2022.
- Pol Antràs, Evgenii Fadeev, Teresa C Fort, and Felix Tintelnot. Exporting, global sourcing, and multinational activity: Theory and evidence from the united states. *Review of Economics and Statistics*, pages 1–48, 2024.
- Costas Arkolakis, Natalia Ramondo, Andrés Rodríguez-Clare, and Stephen Yeaple. Innovation and production in the global economy. *American Economic Review*, 108(8):2128–2173, 2018.
- Costas Arkolakis, Fabian Eckert, and Rowan Shi. Combinatorial discrete choice: A quantitative model of multinational location decisions. Technical report, National Bureau of Economic Research, 2023.
- Jie Bai, Panle Jia Barwick, Shengmao Cao, and Shanjun Li. Quid pro quo, knowledge spillover, and industrial quality upgrading: Evidence from the chinese auto industry. Technical report, National Bureau of Economic Research, 2020.
- Sanford V Berg and Philip Friedman. Joint ventures, competition, and technological complementarities: Evidence from chemicals. *Southern Economic Journal*, pages 1330–1337, 1977.
- Andrew B Bernard, J Bradford Jensen, Stephen J Redding, and Peter K Schott. The margins of us trade. *American Economic Review*, 99(2):487–493, 2009.
- Peter J. Buckley and Mark Casson. *The Future of the Multinational Enterprise*. Macmillan, London, 1976.
- Jing Cai and Adam Szeidl. Interfirm relationships and business performance\*. *The Quarterly Journal of Economics*, 133(3):1229–1282, 12 2017. ISSN 0033-5533. doi: 10.1093/qje/qjx049. URL <https://doi.org/10.1093/qje/qjx049>.

- Juanma Castro-Vincenzi. Climate hazards and resilience in the global car industry. *Princeton University manuscript*, 2022.
- Richard E Caves. International corporations: The industrial economics of foreign investment. *Economica*, 38(149):1–27, 1971.
- Farok J Contractor, Peter Lorange, et al. Why should firms cooperate? the strategy and economics basis for cooperative ventures. *Cooperative strategies in international business*, 1:3–30, 1988.
- A. Kerem Cosar, Paul L.E. Grieco, Shengyu Li, and Felix Tintelnot. What drives home market advantage? *Journal of International Economics*, 110:135–150, 2018. ISSN 0022-1996. doi: <https://doi.org/10.1016/j.jinteco.2017.11.001>. URL <https://www.sciencedirect.com/science/article/pii/S0022199617301356>.
- Claude d’Aspremont and Alexis Jacquemin. Cooperative and noncooperative r & d in duopoly with spillovers. *The American Economic Review*, 78(5):1133–1137, 1988.
- Robert Dekle, Jonathan Eaton, and Samuel Kortum. Unbalanced trade. *American Economic Review*, 97(2):351–355, 2007.
- Yves L Doz. The evolution of cooperation in strategic alliances: initial conditions or learning processes? *Strategic management journal*, 17(S1):55–83, 1996.
- Yves L Doz, Paul M Olk, and Peter Smith Ring. Formation processes of r&d consortia: Which path to take? where does it lead? *Strategic management journal*, 21(3):239–266, 2000.
- John H Dunning. Trade, location of economic activity and the mne: A search for an eclectic approach. In *The international allocation of economic activity: proceedings of a Nobel Symposium held at Stockholm*, pages 395–418. Springer, 1977.
- Jonathan Eaton and Samuel Kortum. Technology, geography, and trade. *Econometrica*, 70(5): 1741–1779, 2002.
- Keith W Glaister and Peter J Buckley. Strategic motives for international alliance formation. *Journal of Management studies*, 33(3):301–332, 1996.
- Pinelopi Koujianou Goldberg. Product differentiation and oligopoly in international markets: The case of the us automobile industry. *Econometrica: Journal of the Econometric Society*, pages 891–951, 1995.
- Paulo Guimaraes, Octávio Figueirido, and Douglas Woodward. A tractable approach to the firm location decision problem. *Review of Economics and Statistics*, 85(1):201–204, 2003.

- W Michael Hanemann. Discrete/continuous models of consumer demand. *Econometrica: Journal of the Econometric Society*, pages 541–561, 1984.
- Kathryn Rudie Harrigan. Vertical integration and corporate strategy. *Academy of Management journal*, 28(2):397–425, 1985.
- Keith Head and Thierry Mayer. Brands in motion: How frictions shape multinational production. *American Economic Review*, 109(9):3073–3124, 2019.
- Keith Head and Thierry Mayer. Poor substitutes? counterfactual methods in io and trade compared. *Review of Economics and Statistics*, pages 1–51, 2023.
- Keith Head, Thierry Mayer, Marc Melitz, and Chenying Yang. Industrial policies for multi-stage production: The battle for battery-powered vehicles. *Working Paper*, 2024.
- Roberto Hernan, Pedro L Marin, and Georges Siotis. An empirical evaluation of the determinants of research joint venture formation. *The Journal of Industrial Economics*, 51(1):75–89, 2003.
- Stephen H Hymer. *The international operations of national firms, a study of direct foreign investment*. PhD thesis, Massachusetts Institute of Technology, 1960.
- Michael L Katz. An analysis of cooperative research and development. *The RAND Journal of Economics*, pages 527–543, 1986.
- Michael D König, Xiaodong Liu, and Yves Zenou. R&d networks: Theory, empirics, and policy implications. *Review of Economics and Statistics*, 101(3):476–491, 2019.
- Masaaki Kotabe, Arvind Sahay, and Preet S Aulakh. Emerging role of technology licensing in the development of global product strategy: Conceptual framework and research propositions. *Journal of Marketing*, 60(1):73–88, 1996.
- Paul Krugman et al. Scale economies, product differentiation, and the pattern of trade. *American economic review*, 70(5):950–959, 1980.
- Konstantin Kucheryavy, Gary Lyn, and Andrés Rodríguez-Clare. Grounded by gravity: A well-behaved trade model with industry-level economies of scale. *American Economic Journal: Macroeconomics*, 15(2):372–412, 2023.
- Adrian Kulesza. Combinatorial discrete choice with deep reinforcement learning, 2024.
- Paolo Mariti and Robert H Smiley. Co-operative agreements and the organization of industry. *The Journal of industrial economics*, 31(4):437–451, 1983.

- Marc J Melitz. The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725, 2003.
- George Michalos, Sotiris Makris, Nikolaos Papakostas, Dimitris Mourtzis, and George Chrysolouris. Automotive assembly technologies review: challenges and outlook for a flexible and adaptive approach. *CIRP Journal of Manufacturing Science and Technology*, 2(2):81–91, 2010.
- Deigan Morris and Michael Hergert. Trends in international collaborative agreements. *Columbia Journal of World Business*, 22(2):15–21, 1987.
- Susan M. Mudambi and Stephen Tallman. Make, buy or ally? theoretical perspectives on knowledge process outsourcing through alliances. *Journal of Management Studies*, 47(8):1434–1456, 2010. doi: <https://doi.org/10.1111/j.1467-6486.2010.00944.x>. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-6486.2010.00944.x>.
- Volker Nocke and Stephen Yeaple. Cross-border mergers and acquisitions vs. greenfield foreign direct investment: The role of firm heterogeneity. *Journal of International Economics*, 72(2):336–365, 2007.
- Michael E Porter and Mark B Fuller. Coalitions and global strategy. *Competition in global industries*, 1(10):315–343, 1986.
- Daniel Simonet. Licensing agreements in the pharmaceutical industry. *Journal of Medical Marketing*, 2(4):329–341, 2002.
- Kotaro Suzumura. Cooperative and noncooperative r&d in an oligopoly with spillovers. *The American Economic Review*, pages 1307–1320, 1992.
- Ekrem Tatoglu and Keith W Glaister. Strategic motives and partner selection criteria in international joint ventures in turkey: Perspectives of western firms and turkish firms. *Journal of Global Marketing*, 13(3):53–92, 2000.
- David J Teece. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research policy*, 15(6):285–305, 1986.
- Felix Tintelnot. Global production with export platforms. *The Quarterly Journal of Economics*, 132(1):157–209, 2017.
- Nicholas Vonortas and YoungJun Kim. Technology licensing. *Patents, innovation and economic performance*, pages 181–199, 2004.

Bruce A Walters, Steve Peters, and Gregory G Dess. Strategic alliances and joint ventures: making them work. *Business Horizons*, 37(4):5–11, 1994.

Birger Wernerfelt. A resource-based view of the firm. *Strategic management journal*, 5(2):171–180, 1984.

Yu Zhang, Min Huang, Lin Tian, Delong Jin, and Gangshu(George) Cai. Build or join a sharing platform? the choice of manufacturer’s sharing mode. *International Journal of Production Economics*, 231:107811, 2021. ISSN 0925-5273. doi: <https://doi.org/10.1016/j.ijpe.2020.107811>. URL <https://www.sciencedirect.com/science/article/pii/S0925527320301857>.

## A Appendix

### A.1 Derivation of Moment Conditions

In the following, [Hanemann \(1984\)](#) moment conditions for a discrete choice model with an extreme value distribution are derived. Let  $\pi_j$  denote the probability that good  $j$  is the preferred choice, i.e. the good with the lowest quality  $\psi_j$  adjusted price  $p_j$ :

$$\begin{aligned}\pi_j &= \Pr [\ln p_j - \ln \psi_j \leq \ln p_i - \ln \psi_i, \forall i] \\ &= \Pr \left[ \varepsilon_j + \alpha_j + \sum_k \gamma_k b_{jk} - \ln p_j \geq \varepsilon_i + \alpha_i + \sum_k \gamma_k b_{ik} - \ln p_i, \forall i \right].\end{aligned}$$

This has the general form:

$$\pi_j = \Pr [\varepsilon_j + \lambda_j \geq \varepsilon_i + \lambda_i, \forall i],$$

where the  $\lambda_i$ ’s contain all the non-stochastic components of the  $\psi_i$ ’s. Let  $F'_j(\cdot)$  denote the derivative of  $F(\cdot)$  with respect to the  $j$ th argument.

$$\pi_j = \int_{-\infty}^{\infty} F'_j(t + \lambda_j - \lambda_1, \dots, t + \lambda_j - \lambda_N) dt.$$

For the EV distribution,

$$F'_j(t + \lambda_j - \lambda_1, \dots, t + \lambda_j - \lambda_N) = \frac{e^{-t/\mu} \exp[-\beta_j e^{-t/\mu}]}{\mu},$$

where

$$\beta_j = e^{-\lambda_j/\mu} \sum_{i=1}^N e^{\lambda_i/\mu}.$$

$$\begin{aligned} \pi_j &= \int_{-\infty}^{\infty} \frac{e^{-t/\mu} \exp[-\beta_j e^{-t/\mu}]}{\mu} dt \\ &= \beta_j^{-1} \\ &= \exp \left[ \bar{\alpha}_j + \sum_k \bar{\gamma}_k b_{jk} - \frac{1}{\mu} \ln p_j \right] / \sum_i \exp \left[ \bar{\alpha}_i + \sum_k \bar{\gamma}_k b_{ik} - \frac{1}{\mu} \ln p_i \right], \end{aligned}$$

where  $\bar{\alpha}_j \equiv \alpha_j/\mu$  and  $\bar{\gamma}_k \equiv \gamma_k/\mu$ , which is a logit model of discrete choice. With a univariate extreme value distribution with scale parameter  $\mu$ , the moment generating function is then given by:

$$\mathbb{E}[e^{t\epsilon_j}] = ((\mathbb{P}[\epsilon_j])^{-1})^{t\mu} \Gamma(1 - t\mu)$$

In order to derive the expected market shares in the model, we need to derive:

$$\mathbb{E}[c_{\ell i(f)n}(\omega(\rho))^{-\eta}] = \left( \varphi_f^{-1} w_\ell^\alpha w_{i(f)}^{1-\alpha} \gamma_{i(f)\ell} q_\ell^\zeta \delta_{i(f)n} \tau_{\ell n} \right)^{-\eta} \mathbb{E}[z_{\omega(\rho)\ell n}^\eta]$$

This has the same form as the [Hanemann](#) formula, with  $t = \eta$  and  $\mu = 1/\theta$ . Thus,

$$\begin{aligned} \mathbb{E} [c_{\ell i(f)n}(\omega(\rho))^{-\eta}] &= \left( \varphi_f^{-1} w_\ell^\alpha w_{i(f)}^{1-\alpha} \gamma_{i(f)\ell} q_\ell^\zeta \delta_{i(f)n} \tau_{\ell n} \right)^{-\eta} \\ &\quad \times \left( [\mathbb{P}(\mathbb{1}_{\omega(\rho), \ell n} = 1 \mid \ell \in \mathcal{L}_\rho)]^{-1} \right)^{\frac{\eta}{\theta}} \Gamma \left( 1 - \frac{\eta}{\theta} \right) \\ &= \left( \varphi_f^{-1} w_\ell^\alpha w_{i(f)}^{1-\alpha} \gamma_{i(f)\ell} q_\ell^\zeta \delta_{i(f)n} \tau_{\ell n} \right)^{-\eta} \\ &\quad \times \left( \left( \frac{q_\ell^\zeta w_\ell^\alpha \gamma_{i(f)\ell} \tau_{\ell n}}{C_{f(\rho)n}} \right)^{-\theta} \right)^{\frac{\eta}{\theta}} \Gamma \left( 1 - \frac{\eta}{\theta} \right) \\ &= \left( \frac{\varphi_f}{w_{i(f)}^{1-\alpha} \delta_{i(f)n}} \right)^\eta C_{f(\rho)n}^{-\eta} \Gamma \left( 1 - \frac{\eta}{\theta} \right) \end{aligned}$$

Then, the expected market shares can be derived by plugging in the expected unit cost:

$$\mathbb{E}[q_{\omega(s), n|p(s)}/Q_n] = \mathbb{1}_{\omega(s), n|p(s)} \kappa_1 \left( \frac{\varphi_f P_n}{w_{i(f)}^{1-\alpha} \delta_{i(f)n}} \right)^\eta C_{f(\rho)n}^{-\eta}$$

## A.2 Data

### A.2.1 Key Concepts

**Table A.1:** Key Concepts

Concept	Definition	Example
Firm (=OEM)	‘Original equipment manufacturer’, <i>owner of brands and varieties</i> → Decision maker	Volkswagen AG
Brand	Brand belonging to OEM at time t	VW, Seat, Skoda, Audi
Variety	Combination of brand, model and bodytype	VW Golf Hatchback
Platform	Set of critical shared dimensions between the front axle centerline, the cowl, and the driver’s hip-point which fixes the placement of the car’s hardware = production blueprint of chassis → defines assembly line layout	VW MQB
Platform Owner	Firm responsible for the original design of the vehicle platform	Volkswagen AG
Collaboration	Firm uses a platform or plant owned by another OEM, with whom it has no majority ownership ties (< 10%)	

### A.2.2 Data Cleaning Steps

#### *S&P Global sales data.*

The raw data comes from the ”S&P Light Vehicle Sales Forecast” from October 2023. There are a few steps taken to clean this raw data:

- observations with unknown brand or assembly country are dropped. I also exclude destinations for which more than 90% of the sales come from unknown/unspecified brands
- market segments are defined as follows:
  - I classify the segments SUV, MPV, PUP, SPORT, Van based on the variable ”function”
  - I split the function ”Car” into two segments: bigCar and smallCar based on the weight classification (below or above size category ‘C’ on the scale A-F)
  - I group all the models that use a purely electric form of propulsion in the segment ”EV”. This information is provided for all the model in a separate S&P Global data set provided by Thierry Mayer
  - there are 8 final market segments: EV, smallCar, bigCar, SUV, MPV, PUP, SPORT and Van

- because I cannot identify segment-specific entry variances, I drop PUP, SPORT and Van from the counterfactual analysis
- in order to identify collaboration accurately in each year, tracking ownership of **brands** over time involved the following steps:
  - the "sales group" and "sales parent" variables provide information on the latest ultimate owners of brands and models. I collect data on all the mergers and acquisitions of brands in the automotive industry and generate a dynamic brand ownership variable. Opel, for example, changes owner first from General Motors to PSA and then to Stellantis in the data.
  - I also add the headquarter of each of those highest owners.
  - the list of brands and owners matching over time is available upon request
- in order to identify collaboration accurately in each year, tracking ownership of **platforms** over time involved the following steps:
  - the "design parent" and "engineering group" variables provide information on the latest owners of platforms in the data. I collect data on all the mergers and acquisitions of these firms and generate a dynamic platform ownership variable. Additionally, I research manually the original developers, which are often engineering groups of brands (i.e. Porsche or Audi within the Volkswagen group). For some platforms, in particular Chinese reported ones, the name of the platform is just a small alteration of the original platform of the joint venture partner (e.g. "S-") in this case the wikipedia pages of the models indicate clearly whether the models in questions were build using an inherited joint venture technology, in which case I change the name of the platform reported to the original one. An example is the "S-UCR145" platform reported by Chinese producer Jianling for the Landwind X6, which is built on Isuzus "UCR145" platform
  - thus I create a constant variable for the original developer of the platform. The name of the developer and the platform will serve as a unique platform identifier in the panel. In addition, I create a dynamic platform owner variable that allows to trace collaboration.
  - there are 22 of about 900 platforms that were developed jointly by two or three firms. This is accounted for when considering collaboration
  - the list of platforms and their developer and owners matching over time is available upon request
- in order to identify collaboration accurately in each year, tracking ownership of **plants** over time involved the following steps:

- the "manufacturer" and "manufacturer group" variables likewise serve to identify the firms responsible for the operation of the assembly plant. I trace the ownership of these manufacturers similar to the platform and brands, since some of them are majority owned by OEMs
- there are more JV plants, due to country-specific policies, and I account for the percentage of JV ownerships
- the list of platforms and their developer and owners matching over time, is available upon request
- based on these three variables, I identify collaboration between brand, platform, and plant owners accurately in each year as follows:
  - at each point in time, I compare the cross-ownership holdings between any two pairs of owners of brands vs. owners of plants/platforms as defined above
  - I define collaboration=1 whenever I observe a brand owner operate in a plant or use a platform of an owner with whom it has < 10% ownership ties

***Other data sources: gravity variables, tariffs and RTAs.***

- distance, home, contiguity, common language and RTAs come from the CEPII gravity data set (version 2023). I use the arithmetic weighted distance variable.
- GDP per cap comes from the WDI 2024 database
- tariffs are drawn from Worldbank WITS database:
  - car tariffs are averages of the simple AHS tariff under the HS heading 8703. For the PUP segment, I use the HS heading 8704.
  - car part tariffs are the averages of the simple AHS tariff for the HS codes: 840733, 840734, 840820, 840991, 840999, 850760, 850650, 850790, 870600, 870710, 870790, 870810, 870821, 870829, 870830, 870831, 870839, 870840, 870850, 870860, 870870, 870880, 870891, 870892, 870893, 870894, 870895, 870899, which are the main car components, engines and transmissions.
  - missing tariffs are filled via linear interpolation. When tariffs are missing in the most recent years, the last available year is used.
  - when a preferential tariff exists, it is used. For all other missing tariffs, the MFN tariff, inclusive of the AVE of specific tariffs, is applied
- I follow [Head and Mayer \(2019\)](#) in correcting and controlling for the most recent updates in RTAs, based on the WTO RTA sheets

### A.2.3 Summary Statistics

**Table A.2:** Descriptive Statistics on Platforms

	Mean	SD	P25	Median	P75	Max
# of platform per year	514	63.34	451	535	558	612
# of platform owner per year	98	14.16	84	100	106	121
# of platforms used per firm/year	24	11.64	15	22	31	54
# of platforms owned per firm/year	21	9.52	13	21	30	40
Total # of varieties per platform	19	14.98	8	15	25	96
# of platforms per plant/year	3	2.18	2	2	4	35
# of plants per platform/year	9	7.10	3	7	12	35
# years platform in market	23	7.94	18	22	26	67
# of new platform per year	28	7.48	22	29	35	40
# of new platform owned per firm/year	0.68	0.84	0.00	0.00	1.00	5.00
Rate of process innovation	0.05	0.01	0.05	0.05	0.06	0.08
Rate of process innovation per firm	0.03	0.05	0.00	0.00	0.06	1.00
N	676,361					

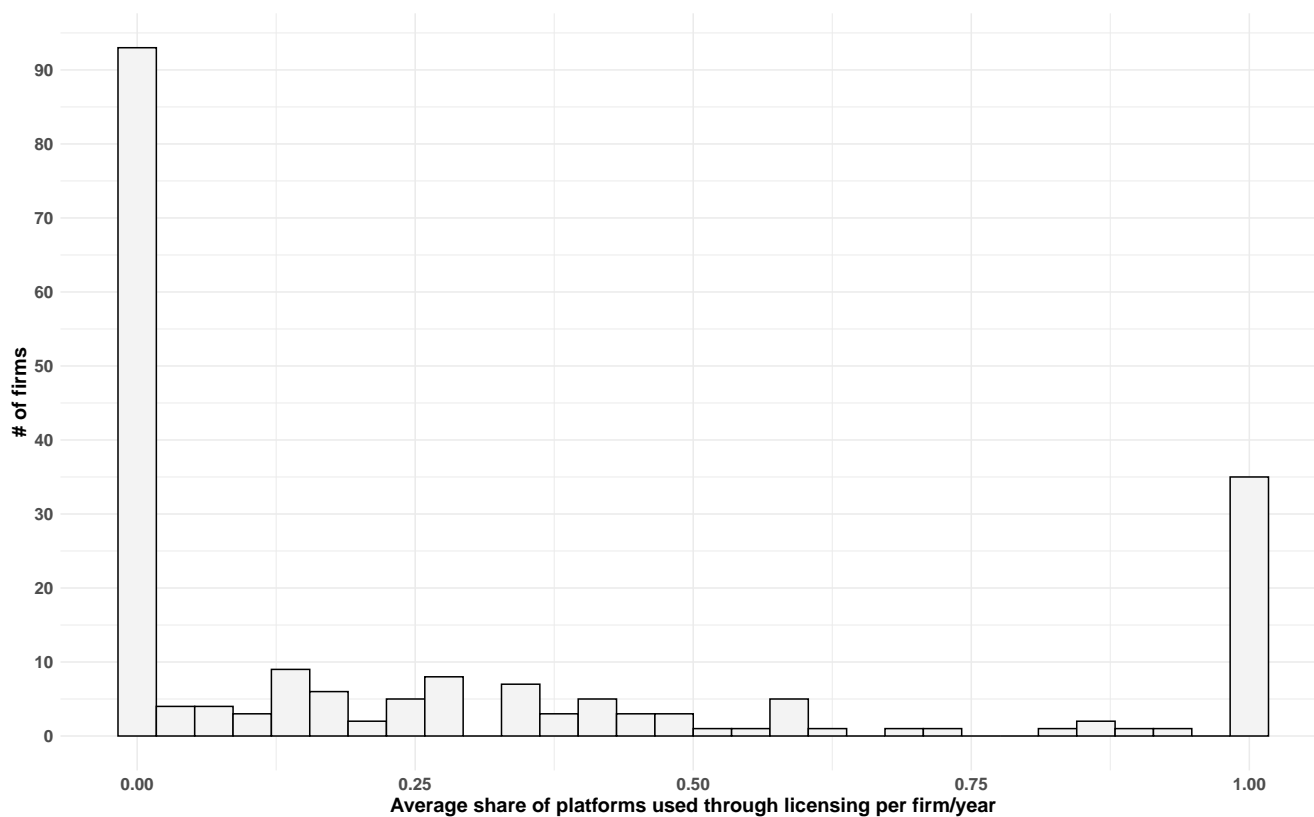
**Table A.3:** Firm-Level Summary Statistics 2000-2023

	Mean	P50	SD	P25	Max
Firm sales/year (in 10k)	437.79	367.95	298.94	207.20	1,088.68
# of brands per firm/year	5	4	3.24	2	15
# of models per firm/year	97	87	56.16	54	277
# of platforms used per firm/year	24	22	11.64	15	54
# of platforms owned per firm/year	18	17	10.52	10	38
# of destinations per firm/year	69	73	13.02	68	78
# of assembly countries per firm/year	19	19	7.67	14	38
# of plants used per firm/year	41	40	22.46	25	105
# of plants owned per firm/year	26	23	17.26	13	67
# of segments per firm/year	7	7	1.40	6	8

**Table A.4:** Collaboration in Platforms

	Mean	SD	P50	Min	Max
Share of sales with shared platform/year	0.29	0.05	0.27	0.24	0.40
Share of sales with collab/year	0.05	0.01	0.05	0.03	0.07
Share of sales with shared platform per firm/year	0.28	0.27	0.21	0.00	1.00
Share of firm sales with collab/year	0.04	0.11	0.01	0.00	1.00
# of shared platforms/year	111	12.22	115	83	133
Share of shared platforms/year	0.22	0.02	0.22	0.18	0.26
# of shared platforms by firm/year	7	5.04	5	0	23
Share of shared platforms by firm/year	0.30	0.21	0.29	0.00	1.00
# of firms offering platform leasing/year	38	4.63	38	29	45
Share of firms offering platform leasing/year	0.39	0.05	0.40	0.28	0.46
# of firms using leased platform/year	57	4.12	57	51	65
Share of firms using leased platform/year	0.54	0.06	0.57	0.42	0.63
# of firms never using leasing	31	9.70	30	19	54
# of platforms never leased	320	57.66	323	241	431
# of years of platform collab bw. brand and platform owner	12.45	7.51	13.00	1.00	24.00
# of years of platform collab bw. brand and platform owner per platform	10.62	6.14	9.00	1.00	24.00
# of partners per firm/year	2	1.99	2	0	9
N	676,361				

**Figure A.1:** Distribution of Firm Reliance on Platform Sharing



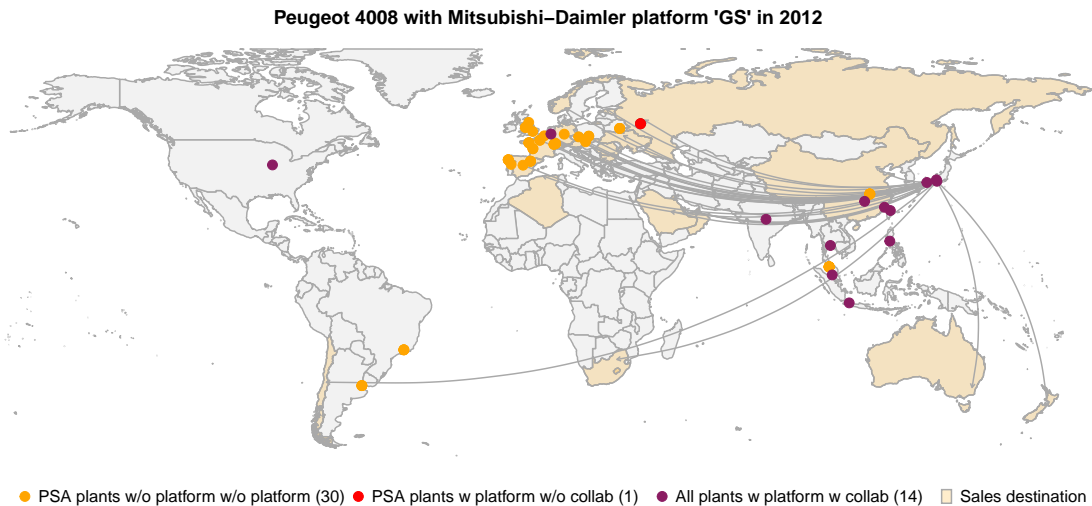
**Table A.5:** Comparison of Collaborators and Never-Collaborators

	Mean			Max		
	Collab	No collab	Total	Collab	No collab	Total
Vehicle sales (in k) per firm/year	1,099.64	50.65	575.14	1,543.36	191.56	1,543.36
No of brands per firm/year	2.44	1.10	1.77	3.00	1.34	3.00
No of segments per firm/year	3.31	1.41	2.36	3.91	1.54	3.91
No of models per firm/year	30.92	2.97	16.94	39.70	6.00	39.70
No of destination countries per firm/year	27.18	5.25	16.21	32.56	9.63	32.56
No of assembly countries per firm/year	6.19	1.28	3.73	7.32	1.77	7.32
No of platforms used by firm/year	9.13	1.76	5.44	10.88	2.22	10.88
No of platforms owned by firm/year	7.17	1.45	4.31	8.77	2.15	8.77
No of leased platforms used by firm/year	2.17	0.00	1.09	2.60	0.00	2.60
Share of leased platforms per firm/year	0.50	0.00	0.25	0.58	0.00	0.58
No of platforms offered for leasing by firm/year	1.73	0.00	0.87	2.09	0.00	2.09
Share of donated platforms per firm/year	0.17	0.00	0.09	0.21	0.00	0.21
No of partners per firm/year	1.59	0.00	0.80	1.86	0.00	1.86

**Table A.6:** Platform-Plant Linkages

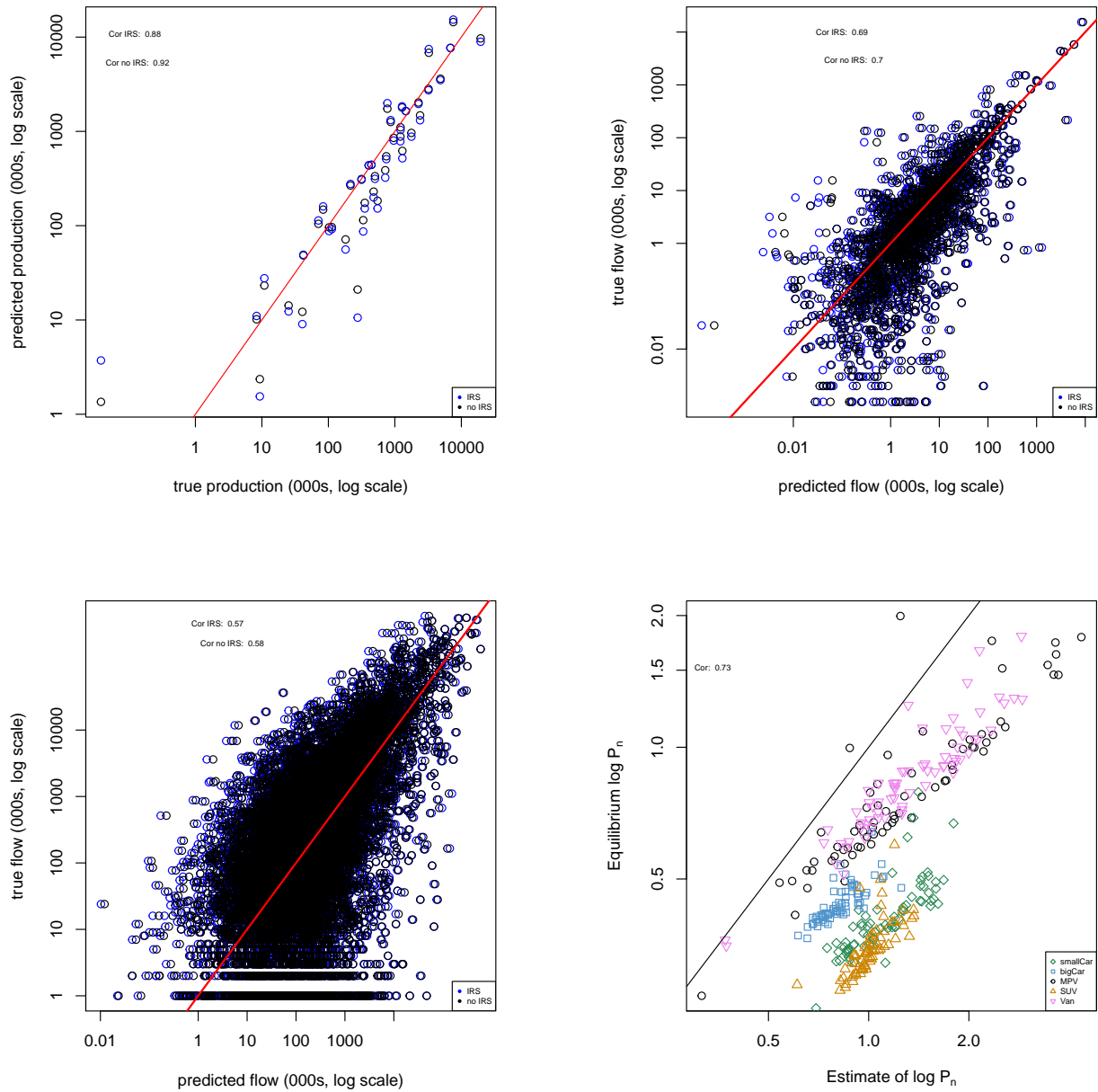
	Mean	SD	P25	Median	P75	Max
# of plants per platform	12.55	9.68	1	10	18	38
# of plants per platform/year	8.08	6.75	1	6	12	35
# years platform in market	18.03	8.35	1.00	17.00	22.00	61.00
# years platform in plant	18.96	8.45	1.00	17.00	23.00	67.00
Share of platforms switching to new plants/variety	0.07	0.25	0.00	0.00	0.00	1.00
N	216,333					

**Figure A.2:** Peugeot 4008 with Mitsubishi-Daimler Platform GS in 2012



## A.3 Additional Results

Figure A.3: Model Fit



**Table A.7:** Average Number of Platforms per Segment

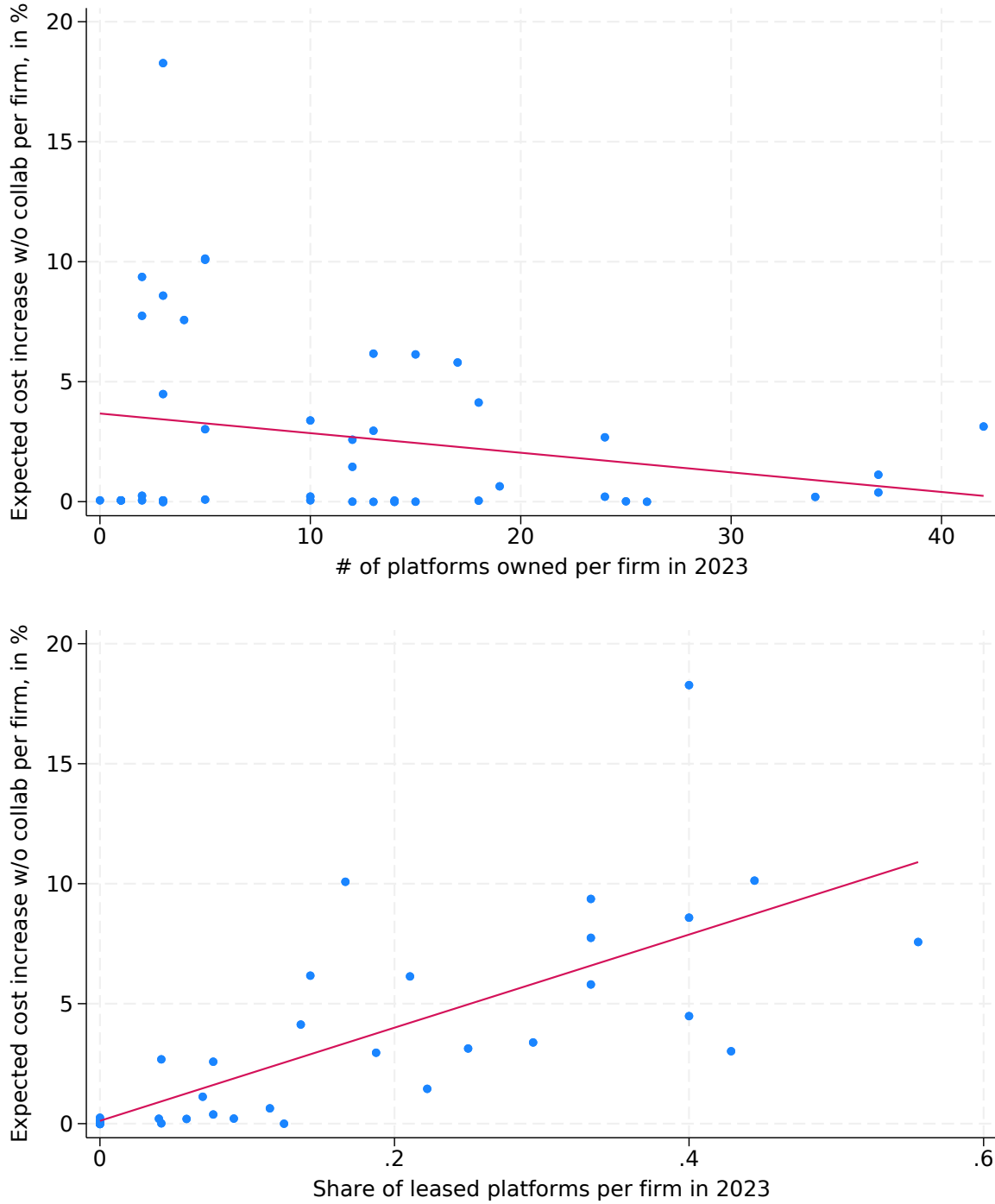
	unconstrained	constraint 1	constraint 2
EV	105	75	34
MPV	103	95	45
PUP	50	44	18
Sport	53	48	16
SUV	166	139	56
Van	131	111	51
Big cars	94	87	34
Small cars	139	124	57
Total	105	90	39

**Table A.8:** Counterfactual Changes, w/o IRS

	% $\Delta C_{f,n}$					% $\Delta Q_\ell$					% $\Delta CS_n$				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
<b>Platform CF</b>															
w/o platform constraint	-28.64	1.26	-29.27	-28.77	-28.64	-5.55	49.46	-43.68	-12.41	16.02	50.59	13.43	44.37	52.80	57.53
w/o collaboration	2.76	1.13	2.32	2.45	2.71	-0.16	4.90	-0.50	1.16	1.78	-0.71	0.67	-0.91	-0.72	-0.39
<b>IP policy CF</b>															
US tech export ban	0.70	0.25	0.52	0.75	0.83	-3.52	18.90	-1.68	3.37	4.85	-0.69	1.29	-1.28	-0.78	-0.28
US tech import ban	0.08	0.15	0.03	0.03	0.07	3.94	9.16	1.72	2.64	4.17	-0.37	0.56	-0.48	-0.25	-0.19
US-China tech war	0.04	0.04	0.02	0.03	0.04	0.46	0.88	0.16	0.22	0.42	-0.03	0.07	-0.04	-0.01	-0.01
<b>Trade policy CF</b>															
US-NAFTA trade war	0.06	0.13	0.01	0.02	0.02	-0.69	10.90	0.68	1.59	2.26	-0.18	0.72	-0.09	-0.03	-0.01
US-EU trade war	0.13	0.20	0.06	0.10	0.16	-0.26	5.95	-6.94	1.04	3.58	-0.23	0.33	-0.42	-0.23	-0.07
US-ROW trade war	0.43	1.19	0.16	0.25	0.28	6.01	18.53	-3.13	3.02	13.77	-0.58	0.97	-0.58	-0.38	-0.22

*Notes:* Counterfactual percentage changes in firm's expected cost to serve a market  $C_{f,n}$ , total production per location  $Q_\ell$ , and consumer surplus,  $CS_n$ , measured as the change in the country-segment aggregate price index. Results are the average of 100 Monte-Carlo simulations, without IRS.

**Figure A.4:** Correlation of % change in  $C_{f,n}$  w/o Collaboration and Reliance on Collaboration



*Notes:* Counterfactual percentage changes in firm-average expected cost to serve a market  $C_{f,n}$  when restricting collaboration (y-axis) and # (top) / share (bottom) of licensed platforms in 2023 (X-axis). Counterfactual changes are the average of 100 Monte-Carlo simulations, without IRS.