Industrial policies for multi-stage production: The battle for battery-powered vehicles*

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Abstract

Many countries have implemented policies to promote transition from combustion engines to electric vehicles (EVs). As batteries constitute about one third of the cost of EVs, firms need to establish low-cost battery supply chains in order to make EVs attractive to consumers. At the same time, governments increasingly use tax and subsidy schemes to induce firms to place more stages of the supply chain within their jurisdictions. We specify a multi-stage supply chain for EVs from battery cell production to vehicle distribution. Each car producer selects where to open facilities at each stage considering production costs, trade costs, and subsidies. This is a difficult combinatorial choice problem that cannot be solved using existing "squeezing" algorithms that have been used in the recent literature analyzing global supply chain location choices. Instead, we use a mixed integer linear program formulation that drastically reduces computation times. We estimate the parameters of our model—which include the variable production costs and fixed plant/model activation costs—using observed sourcing decisions for all production stages over the period 2021 to 2023. We then investigate counterfactual simulations for different types of industrial and trade policies and describe how those affect the production location choices across the global chains for EVs and the trade patterns from battery through assembly to final consumption destinations.

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1 Introduction

Industrial policies are increasingly being used to reshape the plant location patterns of industries characterized by multi-stage production and economies of scale. Such industries feature complex interdependencies. At any given stage, different locations substitute for each other. However, because of various trade costs, upstream and downstream production sites are complementary. Costs of production differ, and final demand is spread in a highly uneven manner. These factors imply that there is no obvious way to structure the firm's value chain across space. Furthermore, when the government inserts itself into the profit maximization problem by offering subsidies or imposing tariffs, the results are hard to predict. These challenges are relevant for industries such as semiconductors, solar panels, aluminum, and electric vehicles (EVs), all of which have been the subject of recent policy interventions, most recently when the Biden administration lifted its tariffs on China on each product.[1]

This paper develops a quantitative method to analyze industrial polices for multi-stage production and applies it to the EV industry. The application to EVs follows from data availability and policy relevance. The 2022 US Inflation Reduction Act (IRA) awards consumer and production subsidies that do not extend to Asian and European-made cars. European governments are considering measures to counter US policies and have imposed tariffs on Chinese EV imports. Canada, meanwhile has promised to match US IRA production subsidies for factories that Volkswagen and Stellantis are constructing in Ontario. Deputy Prime Minister Freeland defended the Canadian government's decision to spend roughly $30 billion on production subsidies, saying "Our government is absolutely determined that Canada gets its fair share of those green jobs."

The value chain for EVs is economically interesting because of countervailing forces at work. First, there are China's cost advantages in all stages of the EV value chain from refining of minerals to final assembly. The IRA contains a provision that prevents subsidies from being applied to vehicles containing Chinese minerals and other components. Second, there are large transport costs because batteries are heavy, bulky once arranged in packs, and the EVs themselves are challenging to transport because of their weight and fire risk. Finally, there are the subsidies and protectionist rules designed to pull EV and battery production into the consuming countries. With large fixed costs for each new facility, these forces interact in complex ways to determine the equilibrium locations of production and the distribution of sales.

[1] https://www.federalregister.gov/documents/2024/09/18/2024-21217/notice-of-modification-chinas-acts-policies-and-practices-related-to-technology-transfer

This paper studies how firms endogenously form supply chains over space and how these chains shape the spatial distribution of the EV industry. Firms decide where to build plants and from whom to source inputs at every stage along a supply chain. Characterizing such allocation of production stages to countries is a challenging computational problem for even moderate number of alternative locations. Even with just one stage of production, the facility location problem (as it is referred to in the operations research literature) is already known to be an "NP-hard" problem. Loosely speaking, this means that there are no algorithms guaranteed to solve it in polynomial time, or put more simply the problem-solving time blows up as the number of locations increases. The difficulty is compounded under multi-stage production because the optimal location of a given stage is not only a function of the marginal cost and fixed cost at that production stage, but is also shaped by the proximity of that location to the desired locations of production of the upstream and downstream stages. One contribution of this paper is to adapt techniques from operations research (OR) to solve for the geography of global supply chains with fixed costs. We extend the multi-stage production cost minimization problem considered in OR to allow for endogenous demand and market entry by multi-product firms.

We show in simulations that the way firms respond to government policies depends in complex ways on the geographic structure and parameter choices. Various types of industrial policy can be effective, ineffective, or even counterproductive. Therefore, one cannot make policy recommendations without bringing in detailed data on the costs of distance, borders, and trade agreements. Variable and fixed costs of production need to be estimated. We propose a methodology to do so that uses different decisions the firms make to extract the implied parameters.

Once the model is quantified through data and estimation, we perform counterfactual exercises to determine how various industry policies currently in use are predicted to affect the extent to which various countries participate in domestic, regional, or global supply chains. We also quantify the welfare consequences of these policies. Specifically, we examine policies inspired by the US Inflation Reduction Act (IRA) which subsidize the US-assembled EVs with batteries sourced from its trade partners. The conditions to qualify for the EV tax credit have raised concerns from major battery makers, including those in China, Japan, South Korea and the EU. In response, the European Union is also considering loosening its rules to allow governments to provide more subsidies for EV manufacturers, leading to a subsidy war that may potentially be wasteful. In addition, the restrictions on cheap input sources also increase the cost of US car manufacturers, leading to a potential welfare loss.

US government officials argue that the transformation of green technology and the global urgency of decarbonization imply that the more subsidies—on both sides of the Atlantic—the better.[2]

The paper is organized as follows. Section 2 positions this paper within the literature on multi-stage production and the role of fixed costs in location choices and sourcing along the value chain. Section 3 describes three key facts about the EV industry that inform core assumptions in the model. Section 4 presents the model of multi-stage production market entry, and equilibrium. In section 5, we verify the computational feasibility and illustrate how policies work within a stripped down model with a single firm. We specify the variable profits associated with each potential path in section 6. The next step is to use discrete choice estimation to quantify the path-level profits. Section 7 develops the estimation framework, with the estimates shown and discussed in section 8. Section 9 carries out counterfactual policy exercises. Section 10 concludes.

2 Literature

This paper is positioned methodologically at the confluence of two streams in the literature. The first is the modelling of global value chains (GVCs) which we refer to in this paper as multi-stage production. The second literature considers the role of interdependencies in sourcing/location choices at a given stage of production.

Global value chains with constant returns The pioneering papers in the modern GVC literature are Yi (2003) and Yi (2010). With recent important contributions by Antràs and De Gortari (2020), Tyazhelnikov (2022), and Johnson and Moxnes (2023), this literature tackles a first type of interdependence: the presence of trade costs makes production stages interdependent such that simple stage-by-stage minimization of costs does not solve the global problem. These papers all consider multi-stage production with transport costs and comparative advantage and develop recursive methods to find the optimal assignment solution, where cost minimization at one stage accounts for the fact that all preceding stages have already made optimal choices. Those methods work with a constant-returns assumption. Opening a new factory implies some form of fixed cost, and therefore of increasing returns. Hence, to allow for optimal location of factories along the value chain, one needs to tackle a new spatial interdependence *within* each stage.

[2] The *Financial Times* (Feb. 24, 2023) quotes Biden's senior clean energy adviser John Podesta saying "The challenge of dealing with the climate crisis requires ... a transformation of the global economy on a size and scale that's never occurred in human history, so there's plenty of room for everybody to participate in that."

Plant location/sourcing with fixed costs Tintelnot (2017) pioneers work on multinational location choice with fixed costs. Antràs et al. (2017) consider a sourcing decision but the fixed cost of adding a new supplier country as a source is not so different from the fixed cost of adding a supplier plant in a new country. Given our emphasis on fixed costs, we focus on that literature. However, in the short run there is a second form of interdependence that can be very important. Castro-Vincenzi (2024) shows how to solve single-stage location models with capacity constraints. This is important in their empirical application: floods that shut down factories. Our paper is oriented towards long run impacts and does not incorporate capacity constraints. We will present evidence to justify this approach in our context.

Plant location with fixed costs is a hard combinatorial problem as the number of potential locations (N) grows. Even with just a single production stage, brute force requires evaluating 2^N alternative solutions. Jia (2008) pioneered using supermodularity of the profit function to reduce computational difficulty. Antràs et al. (2017) pointed out that the global sourcing problem can be supermodular or submodular depending on the relative magnitudes of the key demand and supply parameters, σ and θ. With σ denoting the elasticity of substitution between varieties in the demand function, and θ denoting the Frechet shape parameter on the supply side, supermodularity obtains if and only if $\sigma > 1+\theta$. This restriction holds in Antràs et al. (2017): $\sigma = 3.9$, $\theta = 1.8$. However, Arkolakis et al. (2023) find $\sigma = 4$, $\theta = 4.5$ implying submodularity. They extend the Jia (2008) method to exploit submodularity with a "generalized squeezing" algorithm. Arkolakis et al. (2023) propose a solution that covers cases that are either sub or super-modular *globally*.[3]

Our structure requires a different approach because one mechanism for submodularity and two mechanisms pushing for supermodularity. The submodularity mechanism is that plants at the same stage k substitute for each other. The supermodularity mechanism is that active upstream or downstream production facilities at stages $k \leq K$ complement each other. Furthermore, activated distribution ($K + 1$) facilities increase the profitability of adding production plants. We do not think parametric restrictions to ensure global sub- or super- exist for this setup. One attractive feature of our approach is that it is not necessary to rely on them.

Combining multi-stage production with fixed costs is a challenging problem and there have so far been only a few attempts. de Gortari (2020) and Antràs et al. (2024b) stand out in this respect. The first paper proposes an algorithm for solving GVC models with fixed

[3]Oberfield et al. (2024) reduce considerably the computational burden by developing a limit solution where firms choose a density of plants over continuous space rather than making discrete plant location decisions. This limit approach is however more relevant for retail/services where firms have many "plants" serving small catchment areas.

costs. The proposed solution is elegant and fast, but limits the analysis to a single final good sold in a single destination, reducing considerably the extent of interdependencies. The presence of fixed costs makes it impossible to separate the computation of equilibrium for each product-market combination: The problem must be considered globally to account for the interdependencies. Antràs et al. (2024b) extend Antràs et al. (2017) to allow for many markets to be served by the firm with its potentially many plants. Firms choose three global strategies associated with three *firm-level fixed costs:* one for assembly plants, one for sourcing plants and one for marketing. This enables rich interdependencies *between* each of those margins. However, the authors impose a strong parametric restriction that neutralizes the interdependencies *within* each margin. [4]

Our methodological contribution is to adapt techniques from operations research to solve for the geography of global supply chains with fixed costs, allowing for a range of interdependencies substantially wider than the existing literature. To be very precise, we extend the Multi-level Uncapacitated Facility Location Problem (MUFLP), (Ortiz-Astorquiza et al., 2018, provide a comprehensive survey.) to allow for endogenous demand, multi-product firms and market entry.

3 Facts

This section describes our data and presents some useful facts about the battery EV industry.

3.1 Data on batteries and electric vehicles

We use three main sources of data in this project.

1. The first one is a dataset on the value chain of batteries for electric vehicles produced by the consultancy firm IHS-Markit (now part of S&P). For each vehicle produced in a given assembly plant, the dataset provides the source of the cells, modules, pack with associated respective plants and suppliers (LG, CATL, Panasonic etc.). Additional details are provided regarding the shape of the cell (prismatic, pouch or cylinder), the detailed chemistry (various forms of two main types: NMC and LFP), and the battery capacity in KWh. This is production-based data (years 2015

[4] A recent paper by the same set of co-authors (Antràs et al., 2024a) relax that restriction, allowing for richer interdependencies, but do not propose a method to solve for the firm's optimal strategy. The three papers de Gortari (2020), Antràs et al. (2024b) and (Antràs et al., 2024a) consider a setup in which firms only produce one variety per assembly plant, which sidesteps the thorny question of optimal sharing of production facilities by multi-product firms.

to 2022), with total volumes of cars assembled associated battery elements, but no information on where the cars are sold.

2. The second source is the updated version of the sales data (also from IHS-Markit) used in Head and Mayer (2019). It provides bilateral volumes at the car model level for each of 75 markets, and providing information on the plant of assembly. It also provides information on the manufacturing firm at that assembly plant (which can differ from the brand name, i.e. GM vs Chevrolet). Importantly, the car model information does not include fuel type: when a flow of Hyundai Konas appears in a dataset, it sums all fuel types, Gas, Diesel, Hybrid, Plug-in hybrid and BEVs in that case. This is not an issue for models that are only produced as BEVs (the Nissan Leaf for instance), but there is no way to identify those in this source.

3. The third source, still produced by IHS-Markit is called New Registration. This is a destination-based dataset available for 24 markets, where sales (registrations) are reported, with more detail on the car model but no information on the assembly plant. We use the fuel type indicator to identify i) models that are only BEVs, which means that the allocation of production in data source 1) can be safely done with data source 2), ii) models that have mixed fuel types, for which we compute a share of BEVs in total sales over the markets in order to allocate production of the BEV version.

The combination of those three sources help us construct a novel type of micro-level GVC dataset where we can track where the final product is sold (and how much), where it is assembled, and where do the elements of its core value chain (the battery pack) are themselves produced. All plants along the value chain have been geocoded with latitude and longitude. The data is available for the quasi universe of the nascent BEV industry (none of the major destinations or countries of production are missing), over the period 2015–2022. Frictions that will be used in estimation stages use the usual sources in this literature (CEPII gravity data for distance and RTAs), WITS for tariffs.

3.2 Main markets of BEVs

Table 1 shows the top 15 markets for BEVs in 2023. China is by far the largest market in all dimensions except the share of EVs. Relative to the US it has more than double the number of active firms and almost four times as many models. Many major ICE vehicle-making countries (US, Japan, Canada, Italy) have EV shares under 10%. In the

Table 1: The 15 top markets of BEVs in 2023

Rank	Country	# Models	# Firms	Sales (000′)	EV share (%)
1	China	206	38	5353.0	21.0
2	United States	57	16	1264.3	8.1
3	Germany	124	25	625.8	20.2
4	United Kingdom	104	20	389.7	17.3
5	France	108	20	383.6	17.9
6	South Korea	48	10	181.8	10.7
7	Canada	53	15	160.3	9.4
8	Netherlands	120	24	147.3	33.3
9	Sweden	111	23	143.7	43.1
10	Norway	113	26	132.0	83.7
11	Belgium	111	21	109.4	20.0
12	Japan	49	13	101.0	2.1
13	Australia	51	16	99.8	8.4
14	Italy	105	18	90.5	5.1
15	Thailand	30	13	80.8	10.7
16	Rest Of World	38	11	743.6	7.2

Note: Rest of world row reports averages across 59 countries for numbers of models and EV share and the sum for Sales.

model it will be important to capture both market size in terms of car buyers and pro-EV policies (Three countries with high EV shares—Norway, Sweden, and China—offered early aggressive inducements for buyers to switch to EVs).

3.3 Location of plants and sourcing along the value chain

Figures 1, 2, and 3 show the impressive growth in the numbers of plants for cells, packs, and vehicles from 2015 to 2022—in all the main regions. The size of plant symbols corresponds to total output in gigawatt-hours for cells and packs and total sales for vehicles.

East Asia remains dominant in cell production but the number of plants in the US and Europe grow by factors of three and two respectively and the capacity in GWH rises by two orders of magnitude. While the growth of cells is impressive, it is also worth noting that many of countries in Figure 3 with multiple vehicle plants (Italy, Spain, Portugal, and Turkey) lack local cell production.

Figure 2 shows packs are intermediate: there are more pack plants than cell plants in every region in both years but fewer pack plants than vehicle plants. We will see that this "fanning out" is a natural feature of the multi-stage production model and does not rely on differences in either transport costs or fixed costs across stages.

Figure 1: Cell plants in the major regions

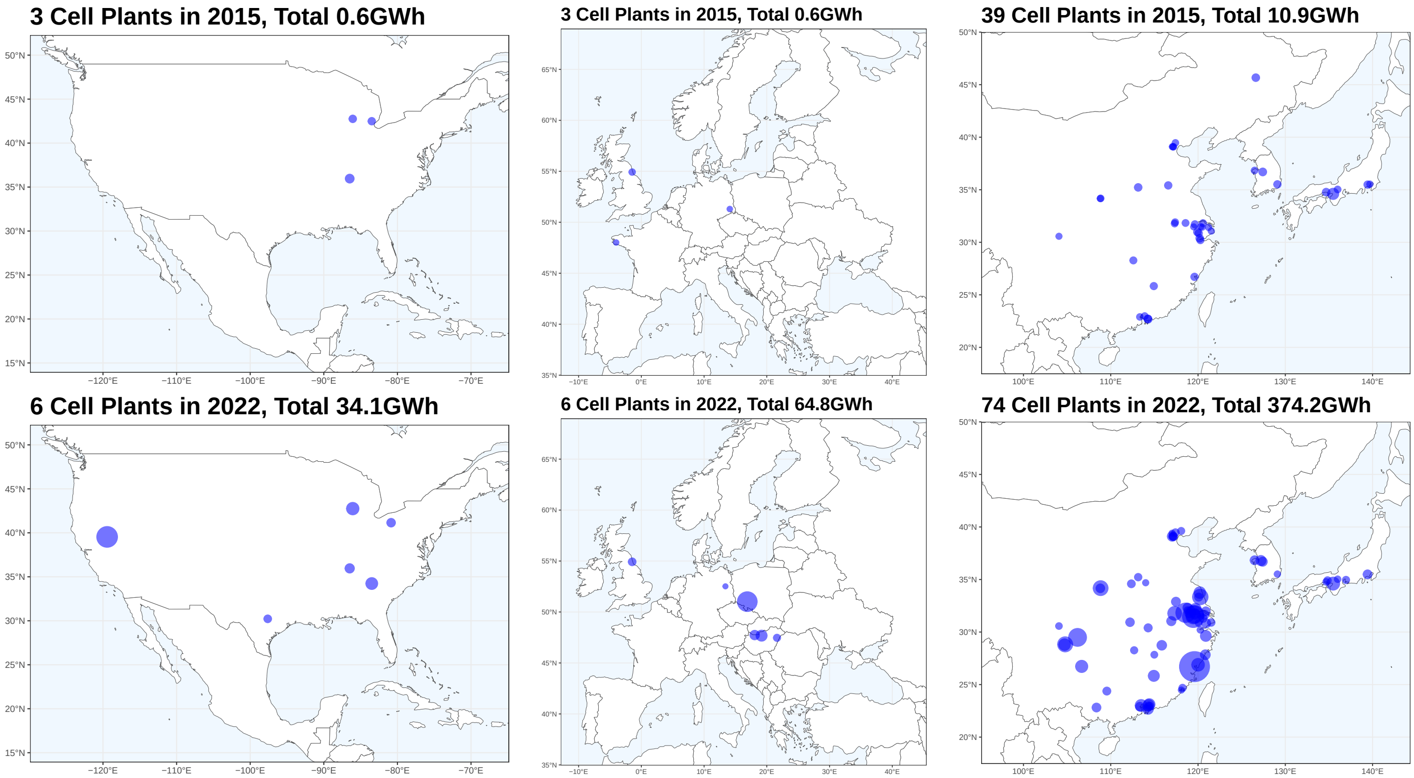


Figure 2: Pack plants in the major regions

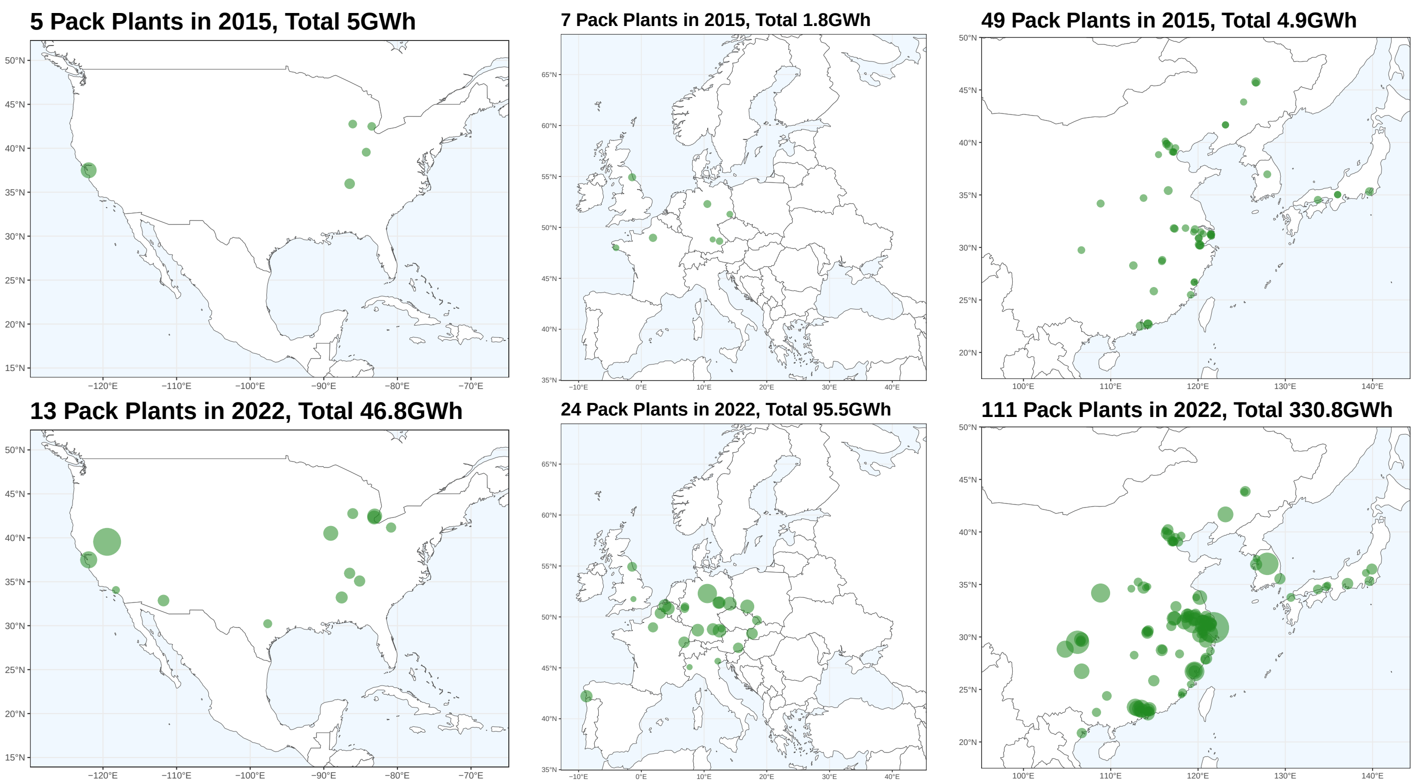


Figure 3: EV plants in the major regions

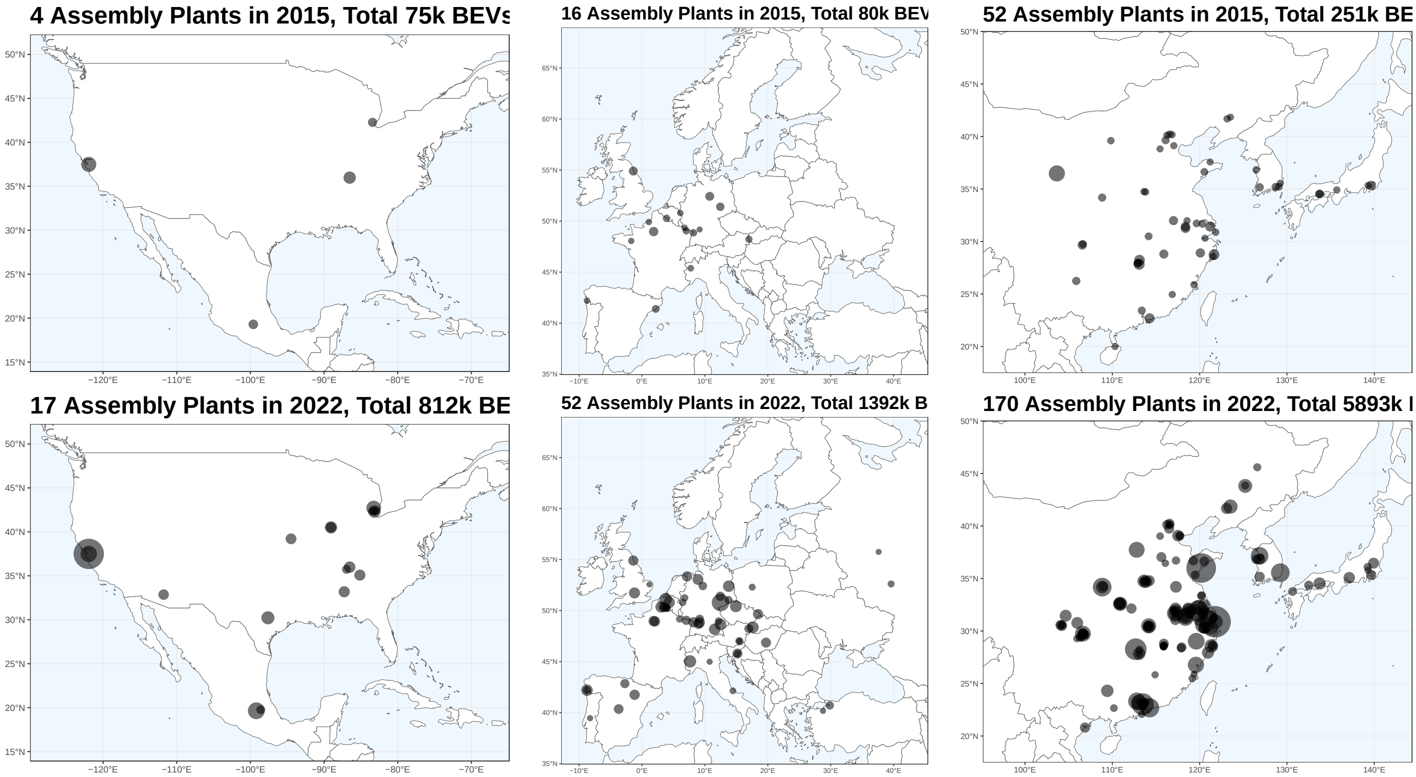
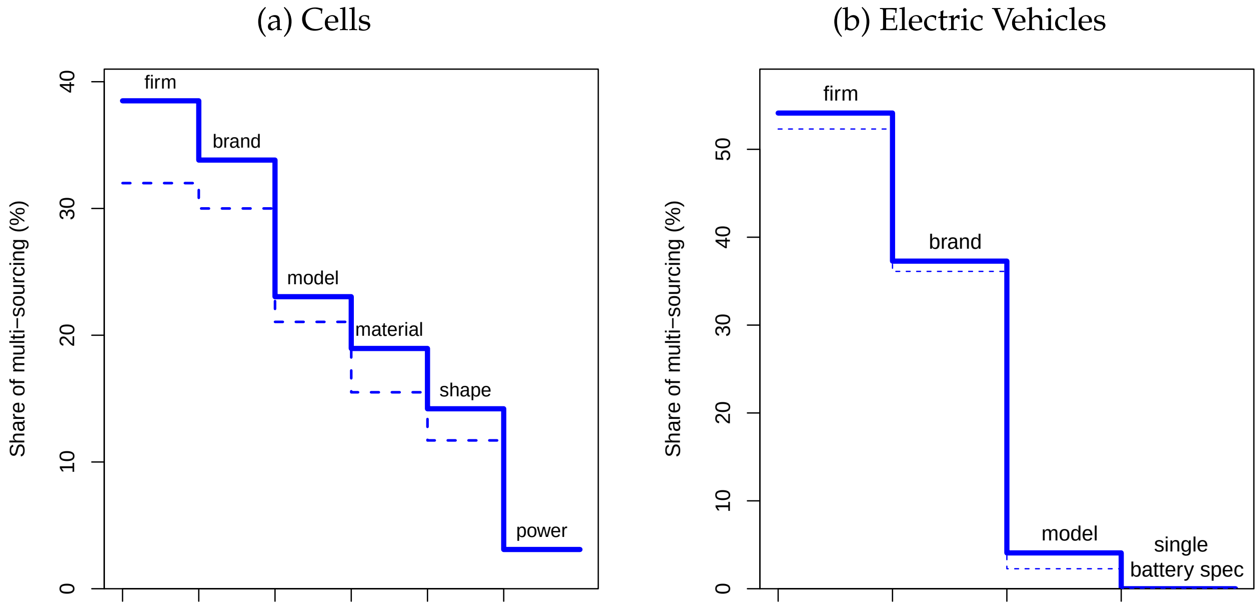


Table 2: How much do components travel?

Link	Year	Distance in km median	Distance in km mean
Battery Electric Vehicle			
Pack to Assembly	2015	299	819
	2022	215	641
Module to Pack	2015	1	994
	2022	1	830
Cell to Module	2015	13	1782
	2022	1	477
Internal Combustion Engine Vehicle			
Engine to Assembly	2018	133	1034
Transmission to Assembly	2018	681	2184

Figure 4: Multi-sourcing is rare for both cells and EVs (2022)



The maps show the geographic dispersion of plants but they do not tell us which plants trade with which. Table 2 provides some insight into the distances that components travel. By showing medians and means we see the huge skewness in the distribution of distances that the output of a stage travels before becoming an input. For comparison purposes we also show distance for two of the most important parts of the ICE vehicle: the engine and the transmission. The finding that over 50% of modules travel 1km reflects our decision to code intra-plant distances as 1 to make them easy to recognize. Of the modules that travel long distances a very large share of them are put together in the Cell factory. Also many cells skip the module stage and go straight into packs. For this reason, we will omit modules from our representation of the value chain.

Figure 4(a) shows that when we disaggregate as much as the data allow, cells are almost always single-sourced. This is not the case at more aggregate levels of models, brands or firms. The reason is that there are different types of battery components and a purchaser may obtain one type of cell from one plant and a different type from another plant. The share of cell multi-sourcing is about 38% for firms and falls regularly to 3% at the most detailed level, which account for the shape, material, and power of the cell. The dashed lines are accounting for multi-sourcing which are not transitory, i.e. which last more than 3 years, and are all systematically lower. Even at the final assembly stage, reported in the panel (b), we see that market countries tend to single source, with a narrowly defined vehicle only coming from two different plants 4.07% of the cases. In this respect, EVs do not differ notably from traditional vehicles. Head and Mayer (2019) find multi-sourcing (measured in terms of countries of origin rather than plants) for 2.3% of all model-market years from 2000 to 2016. This residual multi-sourcing for EVs certainly hides further detail that we do not observe fully in the flows. Indeed, we observe the flows detailed for a model, but not for its detailed specifications which often involve different batteries. When this battery specification is defined in terms of material and total power of the pack, we observe that car models with a single battery specification available are never multi-sourced.

This fact is very important for thinking about how to formalize the firm's profit maximization problem. It is common in the trade literature that is applied to more aggregate data to think of each source country as supplying a distinct variety (Armington assumption) with firms using a CES aggregator to combine them. This is not appropriate at the detailed micro level. Instead, our setup realistically assumes that firms choose the lowest cost source for a narrowly defined component or final vehicle.

The last three columns of Table **??** examine a related but different pattern of the data regarding the frequency of multi-supplying inside a region. For instance, the third column reports that around half of the firms have more than one plant supplying cells, packs and vehicles inside a region (defined as Asia, North America and Europe). This should not be surprising, since even a recently born firm like Tesla has two assembly plants in the US, and uses two cell plants in each of the regions.[5] The figures drop drastically at the car model level. For instance, Renault has 3 plants assembling electric cars in Europe, but each of them supplies the whole of European markets with a different car model.[6] Overall only 2.4 % of EVs are assembled in more than one plant inside a region (the Tesla Model Y in both Fremont and Austin for North America being an example). At the most detailed level (spec accounting notably for battery material), the pattern is the same for cells and packs: Debrecen is the only plant supplying prismatic LMFP cells, and Berlin the only plant supplying cylinder NCM cells intended for two different versions of the battery pack that can equip the German-made Tesla Model Y. Regional multi-supplying is extremely rare at this level of detail.

There is another explanation for multi-sourcing/supplying which is also important to consider in setting up the firm's profit maximization problem: capacity constraints. We might see multi-sourcing/supplying not because of the love of variety common in trade models but simply because the preferred source is unable to meet the demand. In Ap-

[5] Austin and Sparks in North America, Nanjing and Shanghai in Asia, Berlin and Debrecen in Europe.

[6] The Zoe is supplied by Flins, The Twingo by Novo-Mesto, and the Megane by Douai.

pendix D.1, we present some examples suggesting that capacity constraints do not seem to be a major concern in our case. Between 2015 and 2023, figure D4 shows that the Tesla factory in Fremont multiplied its output by 10 (from about 50 thousand vehicles to around 500). On top of that, the Shanghai factory was able to add more than a 150 thousand vehicles on its first year in 2020, and reached 950 thousands in 2023). Continuing on the Tesla example, one can investigate cases of multi-sourcing. In figure D5 in the same appendix takes the example of the four Tesla models sold in Germany. The Model 3 is sourced both from Fremont and Shanghai in 2020, but this turns out to be a transition, since Fremont was the only source until 2019, and Shanghai becomes the sole supplier of Model 3 to Germany starting in 2021. The story is very similar with the Model Y, which starts to get imported from Shanghai in 2021. Then Germany also sources from the Berlin factory when it opens in 2022. In 2023, Berlin becomes dominant, while imports from Shanghai fall and are predicted by IHS to go to 0 in 2024. Panel (b) of the same figure shows that those are not isolated examples. The Volkswagen ID.4 SUV is sold in the United States and Canada in 2021 from the German factory of Mosel. In 2022, The American plant in Chattanooga starts to produce the car, and both sources co-exist for one year, before the imports from Germany are stopped in 2023.

In line with those data patterns, we employ an uncapacitated model in this paper.

3.4 Investment costs

The development of the EV industry has generated staggering levels of capital investment in new plants along the value chain. There are no official statistics on these investments, but we have collected everything we could find from news reports. Unfortunately, most articles tend to refer to battery plants without differentiating between cell and pack plants. Also, some reports lump investments in the assembly factories together with the battery investments.

Table 3: Investment costs for battery and EV plants

	Cost ($US bn)		Articles
Stage	Mean	Std. Dev.	Count
Cells	2.53	2.60	83
Packs	0.67	0.71	20
Vehicle Assembly	0.79	0.94	198
Battery and Vehicle	4.09	3.54	13

Source: Authors' calculations based on collected news articles.

Table 3 reports, based on hundreds of news articles, that on average EV assembly plants involve a \$0.79 billion investment and battery plants require \$1.85 billion. There is substantial heterogeneity as captured by standard deviations that are similar to the means.

Taking the "Battery" investment costs as including both the fixed costs of the cell and pack facilities allows us to produce a ballpark estimate of total investment. There are 234 EV assembly plants and 145 pack plants in the IHS EV supply chain data set. Multiplying by the reported means, total EV investment from 2015 to 2022 amounts to \$452 billion.

These massive investment costs strongly suggest that there are indivisible fixed costs that we need to incorporate into the model because they are core features of industry. Firms face a fundamental dilemma regarding activating more plants or incurring higher distance and border costs. The fixed costs relevant for the static model described in the next section differ from these investment costs in two main respects. First, the investments lead to long-lived plants, so we need to multiply by the capital cost (interest plus depreciation) to obtain annual fixed costs. Second, governments have often given large subsidies to these firms. From the firm's point of view the relevant fixed costs are the ones net of subsidies.

4 Multi-product, Multi-stage, Multinational Production

A firm is characterized by a set of models (varieties), $\{m : m \in M_f\}$.[7] A global value chain for a given model has levels of production $\{1, ..., K\}$, where level 1 is the furthest production stage from consumers and level K the closest stage. The set of potential locations where firms can open facilities, $\mathbf{L}$ is partitioned into K levels: $\mathbf{L} \equiv \{L_1, ..., L_K\}$. A particular production location at level k is denoted as ℓ_k. A complete path of production (or value chain) is denoted $\boldsymbol{\ell} \equiv \{\ell_1, \ell_2, \ldots, \ell_K\}$. Final consumption happens at level $K+1$, with the location of final consumers (which we also refer to as markets) denoted $n \in N$. Therefore, a path for a specific market n for model m is given by $\boldsymbol{\ell}_{mn} \equiv \{\ell_1, ..., \ell_K\}_{mn}$.

4.1 The firm's problem

Our model has two types of decisions that a firm must take. The first decision we refer to as an *activation* problem. As in the OR literature firm chooses where to open facilities at each level from $k = 1$ to K. In our framework, the set of clients for the facilities is also another kind of activation decision in which firms decide which models to offer in which

[7] We do not consider adding or dropping products in this paper.

markets (stage $K+1$). The sets of nodes at each stage which paths can follow is given by $\boldsymbol{\mathcal{L}}_f = \{\mathcal{L}_1(f), ..., \mathcal{L}_K(f)\}$. Because of fixed costs, firms do not open facilities in every element of L_k nor serve all markets in N. Constrained by the active facilities and markets, the firm takes its second type of decision: choosing *paths* for each car model from cells to final consumers. We refer to this as the *assignment* problem. The chosen path $\boldsymbol{\ell}_{mn}$ for model m sold in n is constrained by $\boldsymbol{\mathcal{L}}_f$.

Figure 5: Schematic of a supply chain with $K = 2$

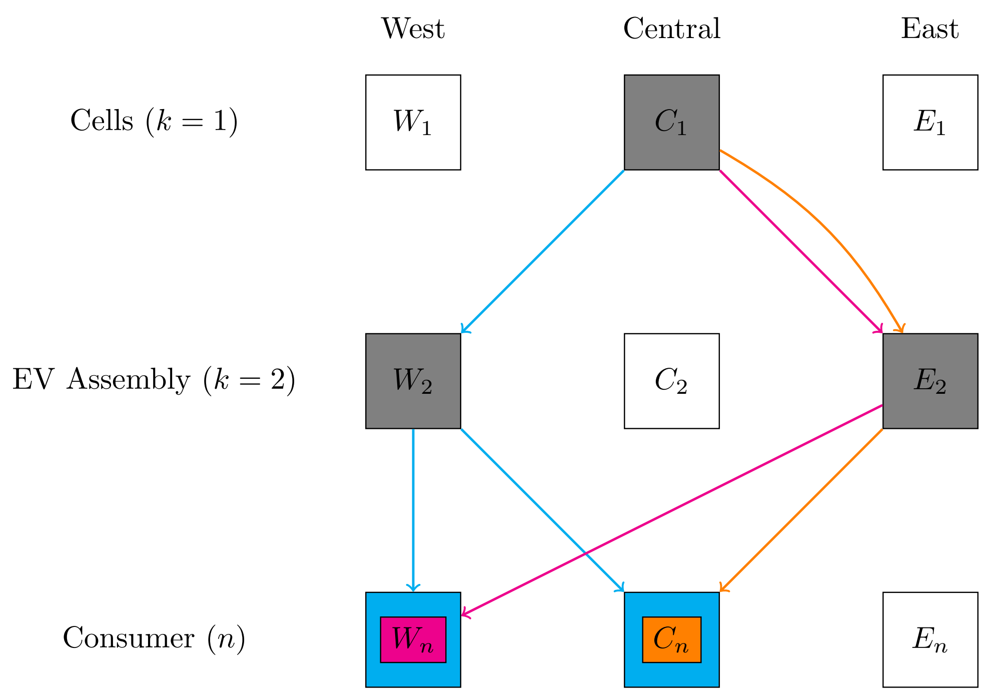


Figure 5 depicts a simplified version of our model to clarify the decisions we are modeling. As in our application, we have $K = 2$, that is two stages of production. In addition, there is the decision to enter a consumer market. The schematic portrays a single firm that makes three models (identified by the colors Cyan, Magenta, and Orange). There are three potential locations: East, Central, and West. In figure 5, Cyan is offered in West and Central; Magenta and Orange are only offered in Central. No model was profitable to offer in East. The firm simultaneously decides the locations of facilities along the value chain. In this example, only one location (Central) has an active cell plant; there are two assembly plants (Central is not activated at $k = 2$). In our model, once a firm activates a production facility, it can be used by more than one model, as we see for E_2. The decisions of which plants and markets to activate depend on quantities, which are in turn determined by the marginal costs incurred at each node and along each edge.

The firm's problem is to maximize variable profits net of activation costs. Our method relies on the following assumption that ensures that the firm's variable profits are determined by the path it selects.

Assumption 1. *The choice of path $\boldsymbol{\ell}_{mn}$, combined with a market-level aggregator of the paths of its competitors, A_n, are sufficient to determine the variable profits of model m in market n.*

Here the path enters profits via the variable cost function, $c(\boldsymbol{\ell}_{mn})$, so variable profits can be expressed as $\pi(c(\boldsymbol{\ell}_{mn}), A_n)$.[8] Aggregators, often specified as price indexes, exist for linear, logit, and CES demand curves under monopolistic competition. Note that it is also possible to extend this model to oligopoly. [9] Furthermore, the path could affect variable profits through channels such as demand (if consumers care directly about sourcing).

For a chosen path $\boldsymbol{\ell}_{mn}$, the firm also incurs fixed costs $\phi_{\ell k}$ in location ℓ for each stage of production k (presumably, a substantial portion of these are sunk once a facility is open). Note that these fixed costs are not indexed by model: Once a facility is open in ℓ for production stage k, we assume that it can accommodate any of the firm's models. We denote this facility location choice with a binary variable $y_{\ell_k} \in \{0, 1\}$ (the firm identifier f is suppressed to simplify notation).

Let ϕ_{mn} be the fixed market entry cost of selling model m in market n. This includes the cost of marketing, sales training, and space for display. The firm will then sell all models for which the variable profit $\pi(c(\boldsymbol{\ell}_{mn}), A_n)$ exceeds this cost. We denote those market entry choices with binary variables $z_{mn} \in \{0, 1\}$. Firm's total profits sums variable profits over all of its models m and served markets n, and subtracts the fixed costs of activating facilities and entering markets.

In the following section, we describe how the firm maximizes global profits by finding an optimal set of paths $\boldsymbol{\ell}_{mn}$, together with determining all the binary $y_{\ell k}$ facility location choices and z_{mn} market entry choices.

4.2 Mixed integer linear programming formulation

The problem of the firm described in the previous subsection can be expressed as a linear optimization problem with integer constraints, for which the Operations Research (OR) literature has developed very efficient algorithms. More precisely, the OR framework closest to ours is the Multi-level Uncapacitated Facility Location Problem (MUFLP),[10] to

[8]For simplicity, we express profits as a function of costs only. Later on we will add a model-market mn demand shifter, but its impact on variable profits will be isomorphic to a cost shifter.

[9]In this case, markups become a function of the market share which depends on the paths of all other models sold in market n.

[10]We draw on the Ortiz-Astorquiza et al. (2018) survey of MUFLP formulations.

which we add two features: multi-product firms and endogenous choice of market entry. In a typical MUFLP, there are two types of decisions involved. One is the facility location decision y_{ℓ_k} at each level of production. The other is the assignment of chosen paths across those locations and stages of production for a given product to a given set of clients. In the optimized decision, $x_{mn\boldsymbol{\ell}}$ equals one for the path $\boldsymbol{\ell} = \{\ell_1, \ell_2, \ldots, \ell_K\}$ chosen for model m to market n and is zero for all alternative paths. If there are L_k potential locations with production stages $k = 1...K$, then there are a total of $L_1 \times ... \times L_K$ indicator variables $x_{mn\boldsymbol{\ell}}$ for a given product m and location n. Multiplying by the number of products and number of locations yields the total number of x variables.[11] On top of considering multiple products for each firm, we further adapt this optimization problem to incorporate the market entry decisions z_{mn}. Because our problem has Multi-stage, Multi-product and Multi-national features we refer to it as MMM-UFLP. Setting $K = 3$ as in our application, profit maximization for a given firm f can be written as the following mixed integer linear program:

$$\max \sum_{m \in M_f} \sum_{n \in N} \sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} \pi(c(\boldsymbol{\ell}_{mn}), A_n) x_{mn\ell_1\ell_2} - \sum_{k=1}^{2} \sum_{\ell_k \in L_k} \phi_{\ell_k} y_{\ell_k} - \sum_{m \in M_f} \sum_{n} \phi_{mn} z_{mn} \tag{1}$$

subject to

$$\begin{aligned}
\sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} x_{mn\ell_1\ell_2} &\leq z_{mn}, \;\; n \in N, m \in M_f & (2)\\
\sum_{\ell_1 \in L_1} x_{mn\ell_1\ell_2} &\leq y_{\ell_2}, \;\; n \in N, m \in M_f, \ell_2 \in L_2 & (3)\\
\sum_{\ell_2 \in L_2} x_{mn\ell_1\ell_2} &\leq y_{\ell_1}, \;\; n \in N, m \in M_f, \ell_1 \in L_1 & (4)\\
x_{mn\ell_1\ell_2} &\geq 0, \;\; n \in N, m \in M_f, \ell_k \in L_k, k = 1, 2 & (5)\\
y_{\ell_k} &\in \{0, 1\}, \;\; \ell_k \in L_k, k = 1, 2 & (6)\\
z_{mn} &\in \{0, 1\}, \;\; n \in N, m \in M_f. & (7)
\end{aligned}$$

The inequalities defined in (2) are *activity constraints* that govern market entry: the left-hand-side sum will be equal to one if the model m is sold in market n (only a single $x_{mn\ell_1\ell_2\ell_3}$ path is set to one at the optimum), or will be equal to zero otherwise (all

[11]The operations research literature refers to this MUFLP formulation as a path-based optimization problem. There is also an alternative arc-based formulation, which defines the x variables for "arcs" from one stage k to stage $k + 1$. We use the path-based formulation as this delivers a linear optimization problem in the x and y variables, even when the variable profit is non-linear in delivered marginal cost $c(\boldsymbol{\ell}_{mn})$ and aggregator A_n.

the $x_{mn\ell_1\ell_2\ell_3}$ paths are set to zero). In the standard OR formulation of MUFLP with cost minimization and no market entry, these constraints are defined with an equal sign and named as flow-conservation constraint, meaning that the outflow (unit demand) of each model to a market must equal to its inflow via supply chains. However, in our setting of profit maximization, the equality constraints can be relaxed as inequalities because if the firm has paid the fixed market entry cost, i.e., $z_{mn} = 1$, it is only profit maximizing to actually produce and sell this model in the market via some supply chains to gain variable profit, even if the firm has the option to not do so. The inequality formulation improves speed, as explained in Appendix A.

The inequalities (3) and (4) are *activity constraints* that govern whether a given facility is open: the left-hand side sum equals one if a path through a facility in ℓ_k is used (only a single $x_{mn\ell_1\ell_2\ell_3}$ path is set to 1 at the optimum), or equals zero otherwise (all the $x_{mn\ell_1\ell_2\ell_3}$ paths are set to 0). These constraints guarantee that a facility must be active to be used in supply chains.

Equations (6) and (7) restrict facility activation and market entry to be binary. Some statements of the uncapacitated FLP explicitly constrain the $x_{mn\ell_1\ell_2\ell_3}$ to be binary. However, this is not needed here. The x need to be non-negative to ensure that paths with negative variable profits would not be chosen. Given the other constraints, it is sufficient in equation (5) to restrict the assignment variables to be positive. While fractional assignments are not explicitly excluded, the x are binary at the optimum.[12]

5 Single-model Policy Simulation

We simulate a production chain of a single firm with one car model. There are three stages of production (cell, pack, vehicle assembly for concreteness) in a world of 40 locations[13] (production and consumption sites). The coordinates of each site are randomly drawn from the unit interval. Demand for the representative model is Logit (with an outside good: ICE vehicles). The number of vehicle buyers in each consumption location rises with the square root of latitude, thus the further north the more buyers.

To make costs observable in the maps we draw, the delivered marginal cost of the final good is given by its Euclidean distance from stage 1 to the final consumer: $c(\boldsymbol{\ell}_{mn}) = \tilde{d}_{\ell_1,\ell_2} + \tilde{d}_{\ell_2,\ell_3} + \tilde{d}_{\ell_3,n}$, where $\tilde{d}_{ab} = [(\text{lat}_a - \text{lat}_b)^2 + (\text{lat}_a - \text{lat}_b)^2]^{1/2}$. Fixed costs of establishing plants at any stage are set to be the same for all locations and stages. Fixed costs of market

[12] Intuitively, it makes no sense under constant marginal costs to source from a high (delivered) cost plant when a lower cost plant is available. Formally the assignment problem is *totally unimodular*.

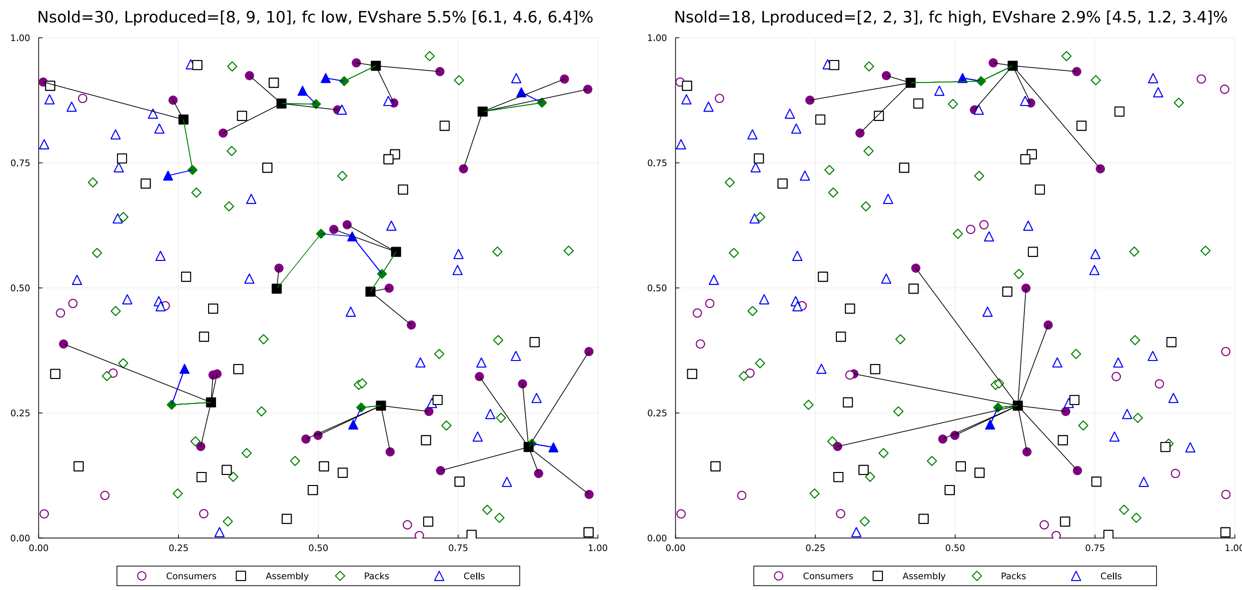
[13] As of 2021, 38 countries are involved in one or multiple stages of the production of EVs.

access are drawn randomly from a uniform distribution.

The low and high fixed costs to revenue ratios implied by the parameter settings in the simulation are 6.2% and 16%. Converting the up-front investments from Table 3 into fixed costs per year at rates or 5% or 10%, we compute fixed cost to revenue ratios for the EV industry as 6% to 11%. Our revenue calculation assumes an average price of $50,000 per EV for the 8.1 million EVs assembled worldwide in 2022. These "back of the envelope" calculations suggest that the fixed cost to revenue ratios in the simulation are in the right ballpark.

Each of the mapped simulation below takes about 20–40 seconds to solve the firm's location problem, depending on the computer and the levels of fixed costs and subsidies. This establishes that the mixed integer programming solver can handle realistically sized problems in a reasonable amount of time.[14]

Figure 6: Simulation: no policy interventions



(a) Low fixed costs

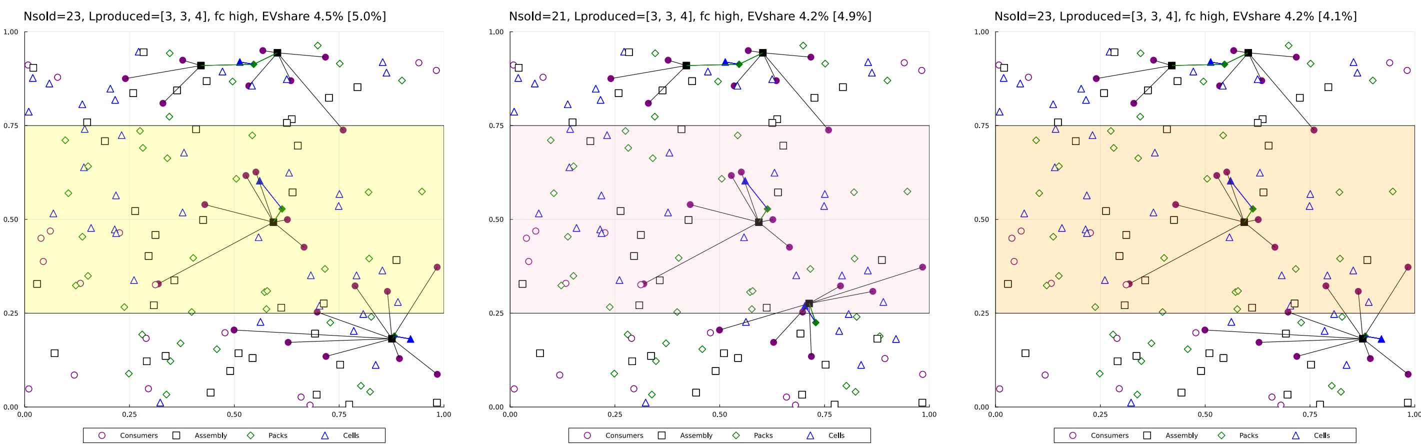
(b) High fixed costs

We begin the investigation of the MUFLP by simulating the model without any subsidies for EVs. The left panel of Figure 6 shows the case of low fixed costs. We see the three key features of the model: (i) there are more plants in the North, reflecting the higher demand, (ii) for any given latitude, plants tend to be central to be closer to more consumers,

[14]The code, which will be made available online when it is finalized, is written in Julia using the JuMP package to interface with the solver.

(iii) peripheral and southern consumers are less likely to be served (one quarter of the consumers do not have sufficient demand to justify the fixed costs of serving them). In the right panel, we multiply fixed costs by five. This reduces the number of cell plants by a factor of four and the number of assembly plants by a factor of three. The greater distances from assembly to consumer lower the number markets served from 30 to 18. The combination of higher marginal costs and reduced number of markets lowers the share of EVs in the market from 5.5% to 2.9%.

Figure 7: Simulation: $5,000 subsidies in Middle



(a) Unconditional subsidy (b) Final-assembly (c) Full-path

Figure 7 brings consumer subsidies into the picture, continuing the high fixed cost case from Figure 6. The three frames correspond to three different types of rules for which vehicles qualify for the subsidy. In panel (a) any consumer in the designated region—shown in yellow—qualifies for the $5,000 dollar subsidy. This resembles the way credits are allocated in Canada and many European countries. In panel (b), the subsidy is only available for vehicles assembled in the region. This is similar to the situations in China and the US where there are consumer subsidies coupled with large tariffs on imported EVs. Panel (c) takes its inspiration from the IRA provisions requiring the whole value chain of batteries to come from countries with whom the US has a free trade agreement.

The unconditional subsidy in Middle (panel a) leads to a new assembly plant being opened in the South, and the existing plant in the Middle is replaced by a more centrally located plant. Five new consumer sites are activated, and the EV share rises from 2.9% to 4.5%. Making the subsidy eligible only to regionally produced vehicles leads assembly site serving Southern consumers to be relocated to the lower part of Middle. Two markets in the South are closed due to higher marginal costs. The EV share falls to 4.2%. Panel (c) makes qualification rules even stricter. The pack plant used in panel (b) would disqualify vehicle sales from the plant in the southern part of Middle. It is replaced by a new plant in the South, which leads to reactivating two Southern consumers. There are conflicting effects on affordability that leave the overall market share of EVs unchanged. This case illustrates the Laffer curve effect identified by Head et al. (2024): stricter rules can be counterproductive in terms of domestic production. As in that paper the point where Laffer curve effects kick in depends on the size of the subsidy.

The takeaway from this series of simulations is that in a world where fixed costs are important, subsidies can reshape the geography of production but do so in ways that are not easy to predict, either quantitatively or even qualitatively. To obtain a better idea of the effects of the gamut of recent policies, we are going to need parameter estimates grounded in the data.

6 Mapping paths to profits

The MMM-UFLP setup from section 4 is very general but we need to make more specific modelling choices before we can estimate the parameters and conduct realistic policy simulations.

One important simplification we make for estimation is to reduce it to just the two most important stages of production: cell manufacture and vehicle assembly. While we have seen in flat-world that MILP is fully capable of solving three-stage production problems, estimation of simulated moments via a global solver (TikTak) requires us to solve the problem over and over again. Another initial simplification we make here is to take model entry (z) as given by the data. We will endogenize the model-market entry decision in a future version.

6.1 Demand

While much of the literature on the car industry uses nested logit or mixed logit demands, we use a constant elasticity of substitution (CES) form. The main difference between the two is that while logit demand has price responsiveness α parameter that multiplies price, CES has an elasticity η that multiplies log price. In the discrete choice derivation of logit demand, α corresponds to the marginal utility of income and $1/\alpha$ is the limiting value of the *additive* markup as market shares become small. There are two problems with this here: first, poorer countries should have higher marginal utilities of income and second markups of say \$10,000 seem reasonable for a Tesla priced at \$50,000 but not for Chinese model priced at \$15,000. These issues could be addressed with a household-specific α

as is common in mixed logit models, but we would lose the tractability needed for our facility-location problem. One convenient feature of CES is that the average own-price elasticity is widely reported in the literature. Table C2 provides 18 different estimates, taken mainly from the Industrial Organization literature. We calibrate $-\eta$ to the median of these estimates.

Each country spends R_n^{EV} on battery-powered EVs, with R_n^{EV} determined by *inter alia* charging stations, local regulations regarding emissions, gas prices, etc. Market shares of model m depend on the ratio of the model's quality-adjusted price p_{mn}/ξ_{mn} to the price index for EVs, P_n^{EV}.[15] The price of model m in country n is adjusted to incorporate any tariffs or consumer subsidies (such as tax credits). The resulting demand is given by

$$q_{mn} = R_n^{\mathrm{EV}} \left(P_n^{\mathrm{EV}}\right)^{\eta-1} \xi_{mn}^{\eta-1} p_{mn}^{-\eta}, \tag{8}$$

where P_n^{EV} is a CES index of firm-level quality-adjusted price index of models offered in n (models for which an entry dummy z_{mn} turns 1):

$$P_n^{\mathrm{EV}} = \left(\sum_f \left(P_{fn}^{\mathrm{EV}}\right)^{1-\eta}\right)^{1/(1-\eta)}, \text{ with } P_{fn}^{\mathrm{EV}} \equiv \left(\sum_{m\in M_f} z_{mn}(p_{mn}/\xi_{mn})^{1-\eta}\right)^{1/(1-\eta)}. \tag{9}$$

Assume that ICE varieties substitute for EV varieties using the same CES η as other EV varieties. Then we have

$$\frac{R_n^{\mathrm{EV}}}{R_n} = \left[\frac{P_n^{\mathrm{EV}}}{P_n}\right]^{1-\eta} \quad \text{where} \quad P_n \equiv [(P_n^{\mathrm{EV}})^{1-\eta} + (P_n^{\mathrm{ICE}})^{1-\eta}]^{1/(1-\eta)}, \tag{10}$$

and R_n is total spending on vehicles of all fuel types and is treated as exogenous and P_n^{ICE} is the price index for ICE vehicles, defined analogously to P_n^{EV}.

Under monopolistic competition, each firm is sufficiently small that it takes the aggregator, P_n to be unaffected by its price (which itself depends on the choice of path). With CES demand (8), firms apply a constant markup $\mu_{mn} = \mu = \eta/(\eta-1),\ \forall\ n, m$ to their delivered marginal cost $c(\boldsymbol{\ell}_{mn})$ for all their models: $p_{mn} = \mu c(\boldsymbol{\ell}_{mn})$. The resulting variable profit for each model is given by

$$\pi_{mn} = \frac{c(\boldsymbol{\ell}_{mn})q_{mn}}{\eta-1}, \tag{11}$$

where q_{mn} is defined in (8) as a function of $c(\boldsymbol{\ell}_{mn})$ and P_n^{EV}. This completes the specifica-

[15] We show how to calibrate the ξ_{mn} in section 8.3.

tion of $\pi(c(\boldsymbol{\ell}_{mn}), P_n)$ and establishes that variable profits depend on only the path and the aggregator ($A_n = P_n$), thus complying with Assumption 1. The next step is to flesh out the cost function $c(\boldsymbol{\ell}_{mn})$.

6.2 Path costs

Going back to the general specification of the firm's problem, our first step is to choose functional forms for the costs that will determine assignment and location decisions. Any production function that gives final costs as function of the chosen path can work for the firm's optimization problem. Leontief and Cobb-Douglas yield cost functions that are readily suitable for estimation by discrete choice sourcing regressions because of their separability. These cases can be seen as first-order approximations for more general cost (or log cost in the case of Cobb-Douglas) functions. We follow Yi (2003), Yi (2010), Antràs and De Gortari (2020), and Johnson and Moxnes (2023) in using Cobb-Douglas across stages here, but the appendix shows the Leontief version. We prefer Cobb-Douglas because it estimates cost differences as percentages, and it works well with *ad valorem* duties (Leontief's additive structure is more compatible with specific duties).[16]

The variable costs for a particular chain depend on three key aspects: (i) a location-stage production cost shifter, $w^k_{\ell_k}$, comprising wages and other local material costs, (ii) trade costs $\tau_{\ell_K n}$ between consumers and assembly, and $\tau_{\ell_k \ell_{k+1}}$ between two adjacent levels of production, (iii) model-specific cost shocks attributable to bilateral locations $\varepsilon^k_{m\ell_k\ell_{k+1}}$.[17]

In this specification with $K = 2$ stages of production, the marginal cost of cells (produced in ℓ_1, delivered to ℓ_2) and of vehicles (assembled in ℓ_2, delivered to n) are given by

$$\text{Cells:} \quad c^1_{m\ell_1\ell_2} = w^1_{\ell_1} \tau^1_{\ell_1\ell_2} \varepsilon^1_{m\ell_1\ell_2}, \tag{12}$$

$$\text{Vehicles:} \quad c(\boldsymbol{\ell}_{mn}) = \left(w^2_{\ell_2}\right)^{\alpha_{22}} \left(c^1_{m\ell_1\ell_2}\right)^{\alpha_{12}} \tau^2_{\ell_2 n} \varepsilon^2_{m\ell_2 n}, \tag{13}$$

where $\alpha_{k2} \in (0, 1)$ denotes the cost share of stage $k = 1, 2$ factors in final assembly ($k =$

[16] Leontief would seem the natural choice when combining stages of production. Thus, each car needs two axles and four wheels. Cobb-Douglas allows for labor at an upstream stage to substitute for labor at a downstream stage. One way to justify this is in terms of subassemblies. In our case cells are usually combined into modules that are then combined into packs. The module and packs stage could occur at the cell factory, at some intermediate location, or the vehicle factory. The former case would increase labor input upstream relative to the last case which requires more labor at the assembly factory. Cobb-Douglas also implies constant cost shares across stages. This is appealing for the case of BEVs because as the size, power and range of a vehicle rises, its battery capacity requirements increase proportionately.

[17] The subscript m appears in the shock term and explains why sourcing decisions vary across models. We will provide parametric assumptions for the ε later when we estimate these cost equations using discrete choice.

2). The above costs consider those incurred at production facilities and along transport edges. Costs at the final consumption stage—sales taxes, buyer subsidies, variable costs of distribution—can be incorporated in $\tau^2_{\ell_2 n}$.

We can also extend these marginal cost determinants to include the costs of other inputs that come from other locations (other than cell production and vehicle assembly). A key assumption is that the trade costs of those inputs to the cell or assembly locations are negligible. In this case, those additional input costs are subsumed into an additive constant term (for log costs) in the sourcing regressions in the next section. We do not explicitly incorporate those additional input costs for notational simplicity.

Equation (11) translates an estimate of path costs—derived from (13)—into profits, which is the key requirement of the MUFLP. The drawback of this formulation of the profit equation is that it also depends on a price index P_n. If we calibrated P_n with actual prices, it would be in different units from the path costs (which are only identified up to a scalar since they are based on differences in log costs). We substitute path costs into equation (9) to express the price index in terms of an index of the path costs of all competing models:

$$P_n^{\text{EV}} = \mu C_n^{\text{EV}}, \quad \text{where} \quad C_n^{\text{EV}} \equiv \left(\sum_{m' \in \text{EV}_n} [c(\boldsymbol{\ell}_{m'n})/\xi_{m'n}]^{1-\eta} \right)^{1/(1-\eta)}, \tag{14}$$

where EV_n is the set of EV models sold in market n (that is: all m such that $z_{mn} = 1$). Now profits can be expressed as a function of the cost index:

$$\pi(c(\boldsymbol{\ell}_{mn}), P_n) = \left(\frac{c(\boldsymbol{\ell}_{mn})/\xi_{mn}}{P_n/\mu} \right)^{1-\eta} \frac{R_n}{\eta} = \left(\frac{c(\boldsymbol{\ell}_{mn})/\xi_{mn}}{C_n^{\text{EV}}} \right)^{1-\eta} \frac{R_n^{\text{EV}}}{\eta}. \tag{15}$$

The factor R_n^{EV}/η represents EV industry variable profits in market n. The fraction in front of it shows how relative quality-adjusted cost determines each EV model's market share. The unidentified scalar cancels out in this fraction.

In the next section, we delineate a method to estimate the parameters for variable costs in equations (12)–(13). Applying a system of sourcing regressions, we can get the estimates of $w^k_{\ell_k}$ and $\tau^k_{\ell_k \ell_{k+1}}$ for all locations at each level of production (up to a normalization), and estimates of the parameters driving the distribution of the random cost terms ε^k. These estimates for $k = 1, ..., K$ will be used, together with simulated ε draws, to construct equation (15), and then solve the optimal GVC for each firm-model-consumer, given guesses of fixed costs.

7 Estimation method

To estimate the parameters of the model we divide the problem into two main pieces. First, we use the assignment (or sourcing) decisions in the data (which are conditional on open markets and facilities) to estimate the variable costs of production. The second stage estimates a parsimonious set of fixed-cost parameters to match moments in the MMM-UFLP solution to corresponding moments in the data. Our focus here is the cost-side of the firm's problem, so we calibrate the demand side shifters to fit the sales data, drawing on the literature for the own-price elasticity. While our MMM-UFLP solution method allows for endogenizing market entry, z_{mn}, this version of the paper takes the observed z_{mn} as given. We want to establish the ability to generate reasonable fixed cost estimates that can rationalize observed facility location decisions.

7.1 Conditional choice estimation of variable costs

Taking logs and substituting upstream cost into the next stage's cost equation, the cost of the complete production path is

$$\ln c(\boldsymbol{\ell}_{mn}) = \alpha_{22} \ln w^2_{\ell_2} + \ln \tau^2_{\ell_2 n} + \alpha_{12}(\ln w^1_{\ell_1} + \ln \tau^1_{\ell_1 \ell_2}) + u(\boldsymbol{\ell}_{mn}), \tag{16}$$

where $u(\boldsymbol{\ell}_{mn}) = \alpha_{12} \ln \varepsilon^1_{\ell_1 \ell_2} + \ln \varepsilon^2_{\ell_2 \ell_3}$ is the structural interpretation of the error term. The probability of choosing path $\boldsymbol{\ell}_{mn}$ is given by the product of the conditional probabilities at each stage:

$$\mathbb{P}(\boldsymbol{\ell}_{mn}) = \mathbb{P}_{\ell_1|\ell_2} \times \mathbb{P}_{\ell_2|n}.$$

Breaking down the probability into these logarithmically separable probabilities greatly facilitates estimation.

The literature has taken three approaches to deriving the choice probabilities at each stage. The most straightforward approach is to ignore the common components in the path-level error and model $u(\boldsymbol{\ell}_{mn})$ as the log of a Fréchet shock, as in Antràs and De Gortari (2020) and Allen and Arkolakis (2022). The best known method is based on McFadden (1978), modelling $u(\boldsymbol{\ell}_{mn})$ as single shock with a generalized extreme value distribution that allows for correlated errors. Finally, one can model the components of $u(\boldsymbol{\ell}_{mn})$ directly. Cardell (1997) and (Ben-Akiva and Lerman, 1985, p. 287) take this approach, and it was also adopted by Berry (1994). Regardless of which set of error term assumptions we use, the stage-level choice probabilities can be expressed using the same functional forms that we show below.

7.1.1 Estimating equations

Conditional on the set of level-1 facilities established by a firm, $\mathcal{L}_1(f)$, it chooses for each model the location with the lowest cost to serve ℓ_2 (due to constant returns to scale in the variable costs of production). We can therefore use equation (12) to derive the conditional probability of ℓ_1 being the cost-minimizing location of supplying to ℓ_2 as

$$\mathbb{P}^1_{\ell_1|\ell_2} = \frac{\left(w^1_{\ell_1}\tau^1_{\ell_1\ell_2}\right)^{-\theta_1}}{\Phi^1_{\ell_2}}, \text{ with } \Phi^1_{\ell_2} = \sum_{\ell_1\in\mathcal{L}_1(f)} \left(w^1_{\ell_1}\tau^1_{\ell_1\ell_2}\right)^{-\theta_1}. \tag{17}$$

Our estimating equation is

$$\mathbb{P}^1_{\ell_1|\ell_2} = \exp\left[\text{FE}^1_{\ell_1} + \text{FE}^1_{\ell_2} + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right], \tag{18}$$

where $D_{\ell_1\ell_2}$ is a measure of bilateral "distance" (any observable bilateral friction), $t^1_{\ell_1\ell_2}$ is the bilateral tariff for stage 1, with β^1_D and β^1_t being their respective regression coefficients. The term $\text{FE}^1_{\ell_1}$ is a source ℓ_1 fixed effect (but in our estimation we assume all plants in a given country share a common fixed effect). The second fixed effect is specific to the *chooser* ℓ_2 and is given by

$$\text{FE}^1_{\ell_2} = -\ln\left\{\sum_{\ell_1\in\mathcal{L}_1(f)} \exp\left[\text{FE}^1_{\ell_1} + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right]\right\}.$$

This chooser fixed effect is more specific than the assembly plant location as the chooser in our estimation corresponds to a plant, firm, model and the power and chemistry of the battery being sourced.[18]. The correspondence between estimated coefficients and structural variables is

$$\begin{aligned}
w^1_{\ell_1} &= \exp\left[-\text{FE}^1_{\ell_1}/\theta_1\right] \\
\tau^1_{\ell_1\ell_2} &= \exp\left\{-\left[\beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right]/\theta_1\right\} \\
\Phi^1_{\ell_2} &= \exp\left[-\text{FE}^1_{\ell_2}\right]
\end{aligned}$$

Note that since tariffs are direct cost shifters, they can be used to provide a direct estimate of θ_1 (as in Head and Mayer, 2019). Here, we do not restrict β^1_t to be equal to $-\theta_1$, a flexibility allowing for unobserved bilateral trade costs. The tariff coefficient, β^1_t, incorporates variation in those unmeasured trade costs that are correlated with the tariff $t^1_{\ell_1\ell_2}$. We will

[18] These narrow definitions of choosers ensure single-sourcing in almost all cases as we saw in table **??**

obtain θ_1 in a second stage simulated method of moments (SMM) estimation.

An important component of the nesting approach to estimating production costs along the value chain is the integration of the cost of upstream parts in downstream decisions. The Nested Logit approach implied from the assumptions of Ben-Akiva and Lerman (1985) replaces the actual cost of cells (which includes the error term) with the expected cost of the optimal source of the cells. With extreme value distributions, this expected cell cost for assembly plant ℓ_2 is

$$\mathcal{E}c^1_{\cdot,\ell_2} = \left(\Phi^1_{\ell_2}\right)^{-1/\theta_1}. \tag{19}$$

We refer to this term as the *inclusive cost* which depends on the sourcing potential of ℓ_2 and differs across firms due to various choice sets $\mathcal{L}_1(f)$.

The second decision to consider is the one made by a market n when sourcing the EV from an assembly plant. Using (13), the probability that ℓ_2 is selected as the location of assembly is

$$\mathbb{P}^2_{\ell_2|n} = \frac{\left[\left(w^2_{\ell_2}\right)^{\alpha_{22}}\left(\mathcal{E}c^1_{\cdot,\ell_2}\right)^{\alpha_{12}}\tau^2_{\ell_2 n}\right]^{-\theta_2}}{\Phi^2_n}, \text{ with } \Phi^2_n = \sum_{\ell_2\in\mathcal{L}_2(f)}\left[\left(w^2_{\ell_2}\right)^{\alpha_{22}}\left(\mathcal{E}c^1_{\cdot,\ell_2}\right)^{\alpha_{12}}\tau^2_{\ell_2 n}\right]^{-\theta_2}. \tag{20}$$

The estimating equation for destination markets when choosing among potential vehicle assembly facilities is

$$\mathbb{P}^2_{\ell_2|n} = \exp\left[\mathrm{FE}^2_{\ell_2} + \mathrm{FE}^2_n + \beta^2_D \ln D_{\ell_2 n} + \beta^2_t \ln\left(1 + t^2_{\ell_2 n}\right) + \beta^2_\Phi \mathrm{FE}^1_{\ell_2}\right], \tag{21}$$

where $\mathrm{FE}^1_{\ell_2}$ was estimated in equation (18), and accounts for determinants of the upstream (cells) costs. The correspondence between the estimated coefficients and structural parameters is

$$\begin{aligned}
\left(w^2_{\ell_2}\right)^{\alpha_{22}} &= \exp\left(-\mathrm{FE}^2_{\ell_2}/\theta_2\right) \\
\tau^2_{\ell_2 n} &= \exp\left\{-\left[\beta^2_D \ln D_{\ell_2 n} + \beta^2_t \ln\left(1 + t^2_{\ell_2 n}\right)\right]/\theta_2\right\} \\
\alpha_{12} &= -\theta_1 \beta^2_\Phi/\theta_2 \\
\Phi^2_n &= \exp\left[-\mathrm{FE}^2_n\right]
\end{aligned}$$

Again, note that we do not restrict β^2_t to be equal to θ_2 due to unmeasured bilateral trade costs that are potentially correlated with the tariff $t^2_{\ell_2 n}$.

The Antràs and De Gortari (2020) approach of a single independent path-shock would imply $\theta_1 = \theta_2$ in the two probability equations.[19] As we estimate the two equations separately, we do not impose this coefficient restriction. It would be difficult to test in any case due to the unknown α parameters that go into the β_Φ estimates. We use the equivalence (in terms of likelihood functions) between Poisson (with fixed effects) and multinomial logit estimators (Guimaraes et al., 2003), which enables us to estimate equations (18) and (21) as high-dimensional fixed effects PPML regressions.

Define a vector $\boldsymbol{\kappa} = \{\kappa_1, \kappa_2\}$. We can express the log variable costs of the full path as

$$\begin{aligned}\ln c(\boldsymbol{\ell}_{mn}) = &- \kappa_2 \Big\{ \mathrm{FE}^2_{\ell_2} + \beta^2_D \ln D_{\ell_2\ell_3} + \beta^2_t \ln\left(1 + t^2_{\ell_2\ell_3}\right) \\ &+ \kappa_1 \left[\mathrm{FE}^1_{\ell_1} + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right] \Big\} + u(\boldsymbol{\ell}_{mn}).\end{aligned} \tag{22}$$

Parameter κ_2 scales up and down the relative importance of observed determinants of marginal costs relative to fixed costs and it also determines the variance of the u shocks. κ_1 provides the weights to use on the cell stage relative to vehicle assembly. The model implies $\kappa_1 = -\beta^2_\Phi = \alpha_{12}\,(\theta_2/\theta_1)$. Thus, we can obtain κ_1 from the sourcing estimation as the coefficient on the inclusive cost of cells, β^2_Φ. For reasons outlined Ben-Akiva and Lerman (1985), our prior is that $\theta_2 \leq \theta_1$. Consequently, $-\beta^2_\Phi$ is a lower bound of the α_{12} cost share.

8 Estimation sample and results

Estimation proceeds in two stages. First we estimate equations (18) and (21) to get the variable costs of production. We then use these estimates to construct the cost of the full path using equation (22), which is known up to the κ parameters. The second stage estimates the κ parameters using simulated method of moments (SMM). The second stage also estimates the parameters governing the distribution of the fixed costs of opening cell and assembly facilities.

8.1 Filters applied before estimation

The SMM is computationally intensive because each iteration of the estimation requires the computation of multiple solutions of the MUFLP. It is also necessary to use a global minimizer, which necessitates even more iterations. To keep the time manageable (less

[19] As noted in the appendix of Antràs and De Gortari (2020) the IID path shock also implies that the product of each stage's conditional probability collapses to a single conditional logit formula, referred to as the joint logit in Ben-Akiva and Lerman (1985).

Table 4: 15 top firms in 2022

No.	Manufacturer	# Markets	# Models	Sales Cum. Share (%)	Sales-exCHN Cum. Shr (%)
1	Tesla	23	4	20.5	28.0
2	Volkswagen	24	23	30.0	42.4
3	Hyundai	23	15	35.6	54.1
4	Stellantis	18	19	40.3	63.7
5	BMW	24	7	44.0	69.7
6	Renault	19	6	46.7	75.3
7	Mercedes-Benz	24	9	49.3	80.0
8	Geely	24	15	55.6	84.4
9	Ford	22	4	57.5	88.3
10	Nissan-Mitsubishi	23	8	60.1	91.9
11	SAIC	17	21	72.8	95.0
12	General Motors	7	7	74.1	96.6
13	Toyota	23	8	74.9	97.8
14	Rivian	3	3	75.3	98.6
15	BYD	10	14	89.6	98.9

Note: Market shares defined over 24 countries used in simulations.

than 24 hours), we estimate the model on a subset of the data.

1. Restrict to 15 large multinationals. We discuss impact of this restriction below.
2. Restrict to 24 countries that have good data on EV sales and prices. This is needed for calibrating demand parameters.
3. Aggregate potential plant locations to the GAUL1 administrative level (states, provinces, and their equivalents).[20]
4. Restrict to 139 models offered by the 15 large firms, with price data available in 2022. This eliminates some light trucks for which we lack price data.
5. Restrict estimation to 2021–2023, the most recent years we have complete data.

The first filter of keeping only the top 15 firms retains a large share of the world's sales. This is because it mainly removes Chinese firms that serve the Chinese market only. In our data there are 50 firms that assemble EVs in 2022 for whom we have sales by market. Of those, 12 sell exclusively in China. Table 4 shows that the top 15 firms—ranked by number of sales destinations—account for 99% of all EVs sold outside China (but inside

[20] Castro-Vincenzi (2024) also works at the GAUL1 level.

the 24 countries used in the simulation, which account for 97% of world sales). Because the Chinese market is so large, these firms account for a smaller share (90%) of the 24-country world. Other than GM, Rivian, and BYD, the top firms sell in 17 or more of the 24 countries in the filtered sample.

8.2 Sourcing estimation results

Table 5 combines estimation results for the two stages considered in our estimation of cost parameters for the BEV industry: battery cells and assembly.[21] These estimates show variable costs of production and delivery of cells to assembly sites, and of assembled vehicles to dealerships in the 24 markets.

Table 5: Combined sourcing regression results

Stage:	(1) Cells	(2) Vehicle
border	-0.746^b	-0.426^a
	(0.347)	(0.139)
log distance	-0.287^b	0.099
	(0.121)	(0.062)
intraplant	0.129	
	(1.02)	
Inclusive cost of cells		-0.217^a
		(0.083)
log(1+tariff)	-5.45^b	-10.3^a
	(2.15)	(1.65)
cross-continent	-1.35^b	-0.634^a
	(0.571)	(0.192)
log GDP per capita	0.594^a	0.116
	(0.179)	(0.079)
Squared Correlation	0.165	0.080
Pseudo R^2	0.156	0.095

Note: EC(cells) are the expected costs of cells for assemblers, $\mathcal{E}c^1_{\cdot,\ell_2}$, defined in equation (19). Log GDP per capita is measured at the sub-national level.

Geographic proximity matters a great deal for sourcing of both cells and vehicles. We see this in the large border effects and cross-continent effects. Distance (measured using

[21] Additional specifications that vary the control variables for each stage are shown in the appendix tables D4 and D3. Those estimations also consider the whole sample available without the restriction imposed here on major countries and firms.

the great circle formula) influences cell sourcing but has no significant effect on vehicle sourcing. This last result contrasts with the ones obtained with vehicles of all fuel types (and therefore mostly ICEs) from Head and Mayer (2019), where distance effects were stronger. BEVs therefore seem to be less sensitive to physical distance once assembled.[22] We code distance for cell and vehicle factories less than 1 km apart as a distance of 1km and add an intra-plant dummy for such cases. It is small and insignificant.

Tariffs strongly influence sourcing decisions at both stages. The tariff elasticities are 5.45 and 10.3 for cells and vehicles, respectively. One way to make sense of the larger stage-2 elasticity is that there is higher correlation with unmeasured trade costs at that stage. The cross-continent dummy suggests that there are additional barriers not captured in distance and tariffs. One factor is that this variable corrects for using great circle distances which differ more from actual distances traveled for intercontinental trade (polar cap, canals). The other potential explanation is that continents impose some common non-tariff barriers to trade.

As we detailed above the coefficient on the inclusive cost of cells in the vehicle sourcing regression (Column 2) has a special meaning. It provides the weight, denoted κ_1 to use on the cell stage in equation (22). We can use the coefficient to determine the implied cost share of cells: $\alpha_{12} = -\theta_1 \beta^2_\Phi / \theta_2$ As $\beta^2_\Phi = -0.217$, if $\theta_1 = \theta_2$, the implied cost share of cells is 22%. AlixPartners (2021) computes the share of batteries including packs and the battery management system as 8,000 EUR or 34% of the car they studied. Cells accounted for 75% of that cost, or 25.5% of the vehicle cost. This estimate is remarkably close to our estimate but we need to add the caveat that the coefficient on the inclusive cost of cells varies across specifications (as seen in the appendix).

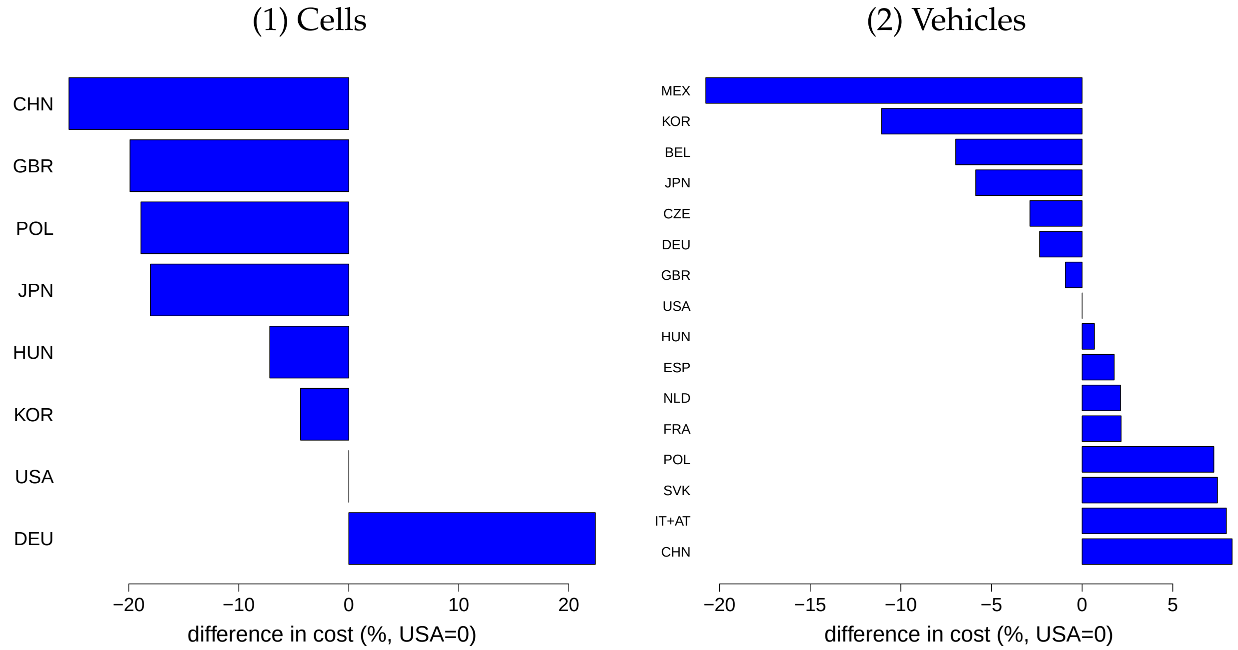
The regressions include source country fixed effects that we display and discuss below. We capture intra-national variation in costs using log GDP per capita measured at the GAUL1 administrative level (States and provinces in North America). This productivity variable is more significant for cells than for vehicles.[23]

Figure 8 uses the estimates of country fixed effects to reveal relative costs for each stage. This is obtained as $w_{\ell_k} = -\mathrm{FE}_{\ell_k}/\theta_k$, and normalized with respect to the USA in each k. The competitiveness of China is visible for cells. Mexico, Korea, and Belgium are identified as very good places for EV assembly as opposed to China, which is revealed as the least cost competitive country for EV assembly. The low costs attributed to Belgium

[22] An important distinction between the two studies is that the present one is much more granular, being able to geo-locate all plants, rather than to simply assign them to countries.

[23] Sub-national productivity has a stronger and more significant effect on sourcing decisions for vehicles in column (3) of table D4 where we use the whole universe rather than the filtered data as in columns (4) and (5).

Figure 8: Relative costs in the value chain of BEVs



reflect the fact that the electric Volvos and Audis assembled in Belgium sell in many places in the world (not only EU). In contrast, most Chinese-assembled EVs are sold locally.

In 2022, the Volkswagen electric SUV ID.4 is produced in 4 plants: 2 in Germany, 1 in the USA, 2 in China. Each of the German plants serves at least 29 markets, the US plant 2 markets, and the 2 Chinese plants serve only China. Those FE estimates reflect those patterns: while the situation is evolving rapidly for China, in our 2021–2023 sample most of the Chinese plants still serve only China. Other consumers in the world prefer to source their BEVs from alternative plants, which translates into high estimated costs.

8.3 Calibration of demand parameters

We calibrate the demand parameters using an estimate of η from the literature. The calibration of ξ_{mn} demand shifters uses IHS model-level car prices in each market, as well as the sales of EV and ICE cars.

The following inversion[24] gives us ξ_{mn} as a ratio of appeal relative to the geometric mean of EV models (as always in this paper we exclude plug-in hybrids) in market n.

[24]Our approach here is closest to Hottman et al. (2016). It is an intellectual descendant of the Berry (1994) inversion but here we used quantities relative to an inside good. Khandelwal (2010) also backs out appeal in a logit demand, but he uses a regression approach with instruments for prices. Khandelwal et al. (2013) imposes a price responsiveness parameter as we do, but then estimates appeal across markets as a residual from a fixed-effects regression.

Let $\tilde{p}_n$ and $\tilde{q}_n$ denote the geometric means of EV prices and quantities in market n. Then inversion of (8) yields:

$$\breve{\xi}_{mn} \equiv \frac{\xi_{mn}}{\tilde{\xi}_n} = \left(\frac{p_{mn}}{\tilde{p}_n}\right)^{\frac{\eta}{\eta-1}} \left(\frac{q_{mn}}{\tilde{q}_n}\right)^{\frac{1}{\eta-1}}. \tag{23}$$

With an estimate of η, we can then compute the relative appeal, $\breve{\xi}_{mn}$ of each EV model in each market. Table C2 provides a number of average elasticities from a set of papers that estimate demand for cars. The left column gives figures for papers focusing on EVs, while the right column does not distinguish between EVs and traditional gas-powered vehicles, and therefore mostly covers ICEs. In table C2, we see that several recent papers estimate price elasticities. The median over all 18 studies is 4.

We can now back out C_n^{EV} from the data using the $c(\boldsymbol{\ell}_{mn})$ obtained from the sourcing regressions. We plug in the $\breve{\xi}_{mn} \equiv \xi_{mn}/\tilde{\xi}_n$ into equation (14) and divide by $\tilde{\xi}_n$. Along with our estimates of the $c(\boldsymbol{\ell}_{mn})$ costs and η, we can now compute variable profits for every potential path: $\pi(c(\boldsymbol{\ell}_{mn}), C_n^{\mathrm{EV}})$.

8.4 SMM estimation of fixed facility costs

In this section, we estimate fixed costs parameters $\boldsymbol{\rho}$. This is a vector of eight parameters. The first six specify means of log fixed costs at the continent-stage level, e.g. Europe-cells. The last two $\boldsymbol{\rho}$ parameters are the elasticities of log fixed costs with respect to distance from headquarters. We parameterize fixed costs of plant activation as draws from log normal distributions, $\phi_{\ell_k} \sim \mathrm{LN}(\boldsymbol{\rho}, \hat{\sigma}_k)$ We currently use the empirical distribution of investment costs from the collected news articles as our estimate of the standard deviation of log fixed costs at each stages of production.

This section also incorporates estimation of the relative marginal cost parameters $\boldsymbol{\kappa} = \{\kappa_1, \kappa_2\}$ as in equation (22).

We draw u shocks and fixed costs $S = 100$ times. For each set of draws, we can compute the objective function of MMM-UFLP in its estimable version, $\Pi_f(\boldsymbol{\kappa}, \boldsymbol{\rho})$, given estimated and calibrated parameters from previous steps indexed by $\hat{}$ and normalized variables indexed by $\breve{}$. Inside $\Pi_f(\boldsymbol{\kappa}, \boldsymbol{\rho})$, the variable profit component is

$$\pi_{mn\boldsymbol{\ell}}(\boldsymbol{\kappa}) = \left(\frac{\breve{c}_{mn\boldsymbol{\ell}}/\xi_{mn}}{\breve{C}_n^{\mathrm{EV}}}\right)^{1-\eta} \frac{R_n^{\mathrm{EV}}}{\eta}, \tag{24}$$

where $\breve{c}_{mn\boldsymbol{\ell}}$, the array of estimated variable costs for each path with a path shock added on, is given by

$$\breve{c}_{mn\boldsymbol{\ell}} = \exp\Bigg[\kappa_2\Big\{\Big[\widehat{\mathrm{FE}}^2_{\ell_2} + \widehat{\beta}^2_D \ln D_{\ell_2\ell_3} + \widehat{\beta}^2_t \ln\left(1 + t^2_{\ell_2\ell_3}\right)\Big] \\ + \kappa_1\Big[\widehat{\mathrm{FE}}^1_{\ell_1} + \widehat{\beta}^1_D \ln D_{\ell_1\ell_2} + \widehat{\beta}^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\Big]\Big\} + u_{mn\boldsymbol{\ell}}\Bigg] \tag{25}$$

$$\breve{C}^{\mathrm{EV}}_n \equiv \left(\sum_f [\breve{C}^{\mathrm{EV}}_{fn}]^{1-\eta}\right)^{1/(1-\eta)} \tag{26}$$

$$\breve{C}^{\mathrm{EV}}_{fn} \equiv \left(\sum_{m' \in M_f} z_{m'n}[\breve{c}_{m'n\boldsymbol{\ell}}/\xi_{m'n}]^{1-\eta}\right)^{1/(1-\eta)}, \tag{27}$$

and $z_{m'n}$ uses *observed entry* of models sold in destination markets, R^{EV}_n also from observed data, and $\eta = 4$. The tariff by market n is m-specific because passenger vehicle and light commercial vehicles can have different tariffs. However, all passenger cars with the same ξ_{mn} and the same origin country will use identical supply chains.

For one set of parameter guess $\{\boldsymbol{\kappa}, \boldsymbol{\rho}, \alpha_c\}$, we solve MMM-UFLP S times and obtain a simulated estimate of the model outcome. Stacking them into a vector of $g(\boldsymbol{\kappa}, \boldsymbol{\rho}, \alpha_c)$, these moments are distances between the respective model outcome and the observed outcome in the data. The calibration's objective is to

$$\min_{\boldsymbol{\kappa}, \boldsymbol{\rho}, \alpha_c} g(\boldsymbol{\kappa}, \boldsymbol{\rho}, \alpha_c)' g(\boldsymbol{\kappa}, \boldsymbol{\rho}, \alpha_c). \tag{28}$$

To identify $\boldsymbol{\kappa}$ which are determined by the ratio of trade elasticities across stages, we match the share of models traded between regions at each stage. At the cell stage, it is the share of BEV models assembled in each region that used cells produced from respective regions. At the car stage, it is the share of BEVs sold in each region that are assembled from respective regions. To identify the overall magnitude of fixed costs $\boldsymbol{\rho}$, we match the share of production lines installed at each region and stage over observed number of production lines worldwide. A production line is defined as a plant-vehicle model combination. Lastly, the elasticity of cost with respect to quality is helped to pin down by the share of world sales by models with quality below the median. A model's quality is calculated by the geometric mean of $\breve{\xi}_{mn}$ across all markets n.

As the discrete choice decisions makes the objective function non-smooth and the firm's problem not globally convex, solving SMM typically suffers from multiple local optima. To address this issue, we implemented a multi-start global optimization algorithm, TikTak, explained and benchmarked by Arnoud et al. (2019). The algorithm starts with a uniform exploration of the (parameter) space and uses the information it accumulates to increasingly focus the search on the most promising region. An important advantage of TikTak is that it is fully parallelizable.[25]

Table 6: SMM Parameter estimates

Parameter	Description	Estimate
$\kappa = 1/\theta$	Variable cost (VC) weight	0.19
ρ_1 (Asia)	Fixed cost of cell plant	0.17
ρ_1 (Europe)	(by continent)	0.13
ρ_1 (Americas)		0.42
ρ_2 (Asia)	Fixed cost of assembly plant	0.16
ρ_2 (Europe)	(by continent)	0.18
ρ_2 (Americas)		0.45
ρ_1 (HQ)	FC HQ-dist. elas. (cells)	0.26
ρ_2 (HQ)	FC HQ-dist. elas. (assembly)	0.56
α_c	Cost elasticity of quality	0.85

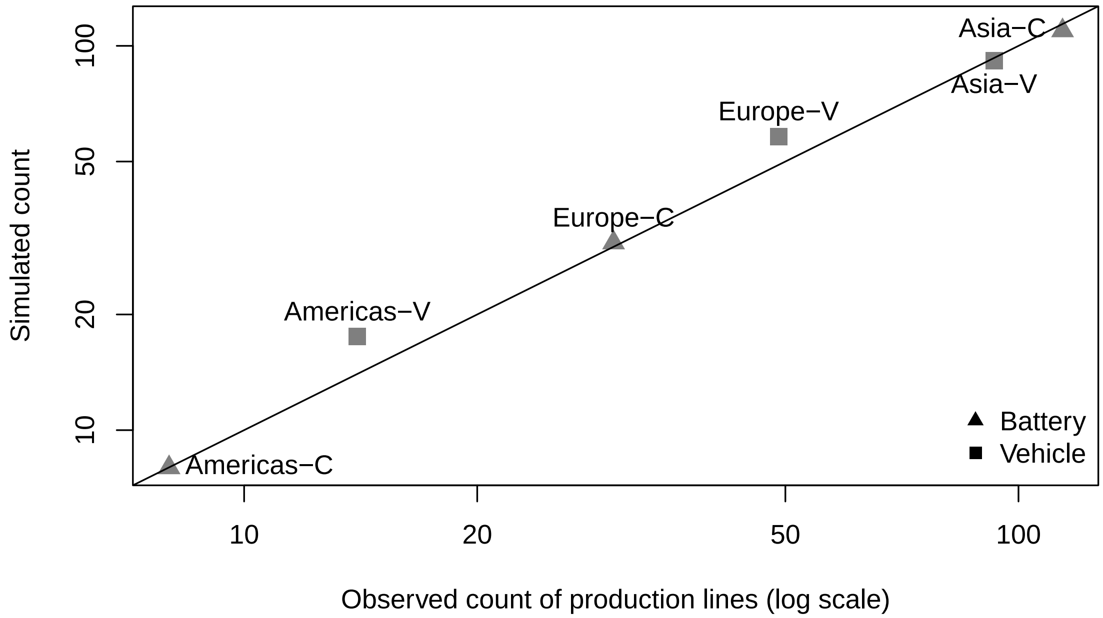
Table 6 shows the results of the SMM estimation. We constrain κ_1 to the range implied by the coefficient on the inclusive value (0.217) and the consulting estimate (0.255). The best fit estimate is 0.255. The weight on observed variable costs relative to the unobserved "u-shocks," is $\hat{\kappa}_2 = 0.18$. This implies a θ_2 of 5.56. This magnitude less than the 10.3 implied from the tariff elasticity of -10.3 in Table 5, column (2), suggesting omitted non-tariff barriers for vehicles. On the other hand it is very close to the θ_1 implied by the cell-sourcing equation, 5.45.

The ρ parameters determine the mean of the log fixed cost draws. We estimate the fixed costs to be about three times larger in the Americas than in Asia or Europe. Fixed costs have similar means for cells and assembly, contrary to our expectation from Table 3. Both sets of fixed costs rise by substantial amounts as firms build plants further from their headquarters. The coefficient of 0.33 implies that doubling distance from HQ raises fixed costs by 26%.

Figures 9 and 10 display the within-sample performance of the SMM estimation for the three moments we target. Figure 9 shows the count of production lines on each continent in the data (horizontal axis) and in the model (vertical axis). Recall that production lines are defined here as combinations of EV model and production location. Thus, cells for

[25]We implement TikTak with 100 random starts. The algorithm retains the 10 parameter vectors with the best objective function values and augment this set with a "prepend" parameter vector (based on priors or past estimation result).

Figure 9: Fit of the estimated model: production lines by continent

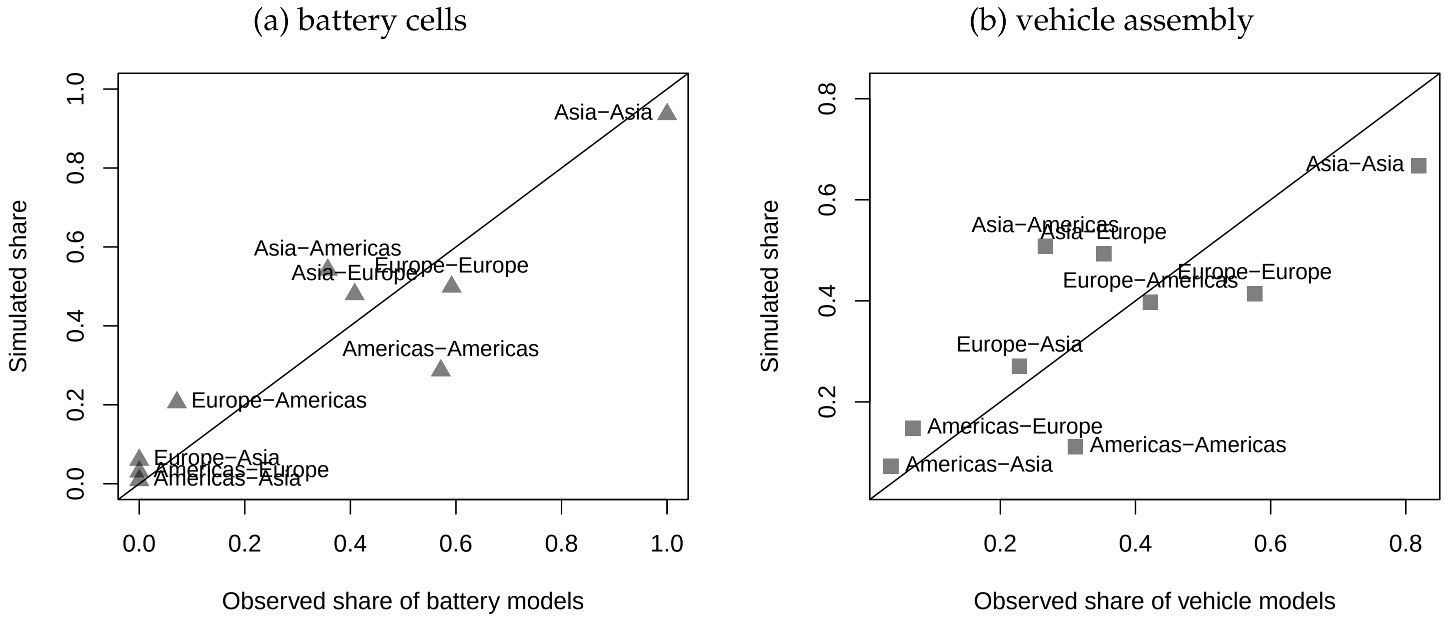


Note: A production line is defined as a combination of EV model and production location.

Tesla Y and sells for Tesla 3 produced in separate factories would be two production lines, as would both models produced in the same factory. The log difference between these vectors is one of our targeted moments, so it is not surprising that the model does a good job of matching the data in this figure.

The second important type of fit targeted in the SMM is between the share of models chosen from each origin continent to serve the markets in each destination continent. This is shown in Figure 10. Panel (a) shows the share of cells sourced from each continent to serve each destination continent. Panel (b) shows the same for vehicle assembly. The simulation fits cell sourcing patterns very closely, except for American producers share of their own continental market. The fit is not as close for vehicle sourcing, with the America-Americas share again underpredicted in the simulation. Asia to Americas is correspondingly overpredicted but Europe to Americas is quite close. This pattern warrants addition exploration. The model correctly predicts that Americas will be the source for few cell or vehicle models in other continents and that Asia cell and vehicle makers will dominate their own continent.

Figure 10: Fit of the estimated model: origin-destination model sourcing



Notes: The SMM estimation targets the share of models each continent sources from the others, for both cells and vehicles.

9 Counterfactuals

Many policies currently incentivize EV purchases and production at home or at least in friendly countries. We currently consider the same three policies we investigated in the more stylized "flat world." Recall that those policies are

1. **Subsidy to North American EV buyers** The policy we consider is a 20% subsidy to buyers (the government rebates 20% of the cost of the car). These credits apply to all consumers from a given continent, and are available for all vehicles regardless of the locations of assembly and battery manufacture.

2. **Subsidy conditional on domestic assembly** Only cars assembled in the same continent as the buyer are eligible for the subsidy.

3. **Subsidy conditional on domestic cell-vehicle supply chain** To qualify both cell production and vehicle assembly must be in the same continent as the buyer.

4. **Production subsidies for US-made cells** Appendix E shows the results for these 20% subsidies as a standalone policy and in combination with the value-chain conditional subsidy as "3+4".

5. **Tariffs on Chinese imported cells and vehicles**. We impose a 20% tariff on cells

and vehicles imported from China as policy 5, restrict the tariff to vehicles as 5V and add it on to the value-chain conditional subsidy as "5+3" in the appendix.

All these policies are set at a level of 20% to make it easy to compare them. Other than this magnitude, they are designed to reflect different aspects of US policy towards EVs under the IRA (and also as carried out in tariffs under the Trump and Biden administrations). Policy 1 resembles the status quo before the IRA when subsidies were not contingent on production locations.[26] Policy 2 add the "buy American" requirement at the assembly level. We impose this at the continental level, which is similar to the requirement that the IRA includes FTA partners Canada and Mexico. Policy 3 mirrors the IRA policies regulating the input sources of EVs to be eligible for the subsidy. Beginning in 2023, 40% of an EV battery's minerals and 50% of the components must come from the US or Free Trade Agreement (FTA) partners. In 2027 and 2029, this requirement will increase to 80% for minerals and 100% for components. In our simulation, the rule is that only cells produced inside the Americas are eligible for the consumer subsidy.

9.1 Policy Simulation Results

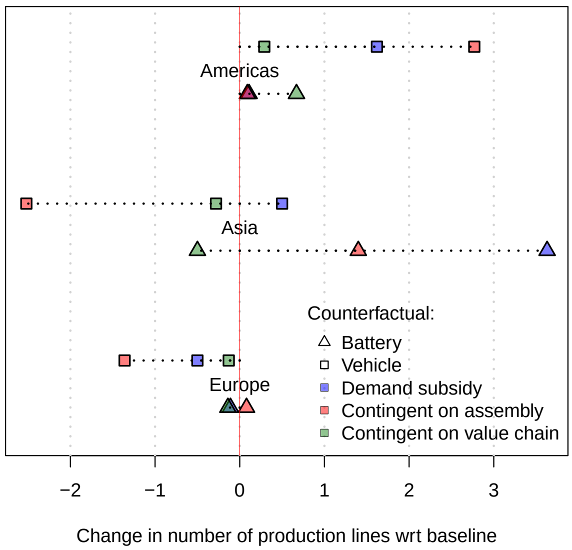
The primary outcome variables are the number of production lines activated in each continent and total expenditures on EVs. The former is our proxy for production and employment, and we treat the latter as a proxy for emissions reductions. We do not model directly how CO2 emissions from internal combustion engines change in response to our policies. The presumption is that rises in EV sales come in large part from reductions in gas engine vehicles. In the US and Europe, Figure ES.1 in Bieker (2021) shows that battery EVs emit 60–69% less CO2 over their lifetime than gas cars.

Figure 11(a) provides the continental summary of our y plant activation indicators. Blue squares (EVs) triangles (cells) correspond to the change in the number of production lines for each continent in response to the 20% reduction in the purchase price to all buyers in North America. We see that this activates an average of about two production lines for assembly but has a negligible effect on in cell-making lines in the Americas. Presumably this is due to the high estimated fixed costs for cell making in the Americas. Instead, we see assembly plants in the Americas sourcing more cell-lines from Asia. The rise in the number of Vehicles assembled in the Americas comes partly at the expense of Europe where V production lines fall by two. Thus, a subsidy that is ostensibly neutral in its application—because it is not contingent on the value chain locations—actually moves production around the three continents.

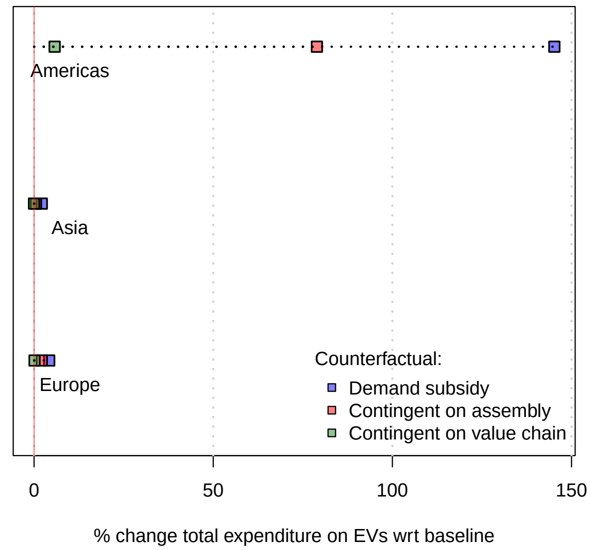
[26] There were other restrictions on eligibility that we do not build in here.

Figure 11: Counterfactual results with 20% subsidy by continent

(a) Continental production lines



(b) Expenditures on EVs



Insisting on domestic final assembly ("Buy American" generalized to include Canada and Mexico) raises production lines by four compared to the baseline and two compared to the non-contingent subsidy. This hurts Asian assembly relative to the baseline and particularly compared to the non-contingent subsidy. Surprisingly European assembly is less adversely affected by the buy-American subsidy. We suspect this is because the buy-American subsidy actually reduces assembly in Asia. The dyadic figures in Figure 12 show the assembly-contingent subsidy promotes cell exports from Asia to the Americas, while lowering vehicle exports. The complementarity between assembly and cell production does not seem very evident in these results, probably because we estimated fixed costs of cell production to be very high in the Americas.

While successful as protection, figure 11(b) shows that Policy 2 lowers expenditures on EVs and thus is not appealing as an environmental policy—although EV expenditure is still much higher than the baseline of no interventions.

Policy 3 is far worse from an environmental perspective, nearly as bad as no intervention. This is because very few EVs sold in the Americas end up qualifying for the subsidy when it is contingent on American cell sourcing. Table 7 shows that only 2.6% of the paths are eligible. Among the small number who do draw low enough fixed costs in the Americas to source cells within the region, there are 15.5% decreases in variable costs and a five-fold increase in revenues. Policy 3 manages to be worse than non-intervention from the point of EV production in both Asia and Europe, while increasing EV production in the Americas by far less than the other two policies. In the appendix table E5 we

Table 7: Contributions to cost changes (in %) in Americas

Policy	Share Elig.	Cost index redn. subsidy	costs	total	Tot. Exp. increase
1: Unconditional	100.0	20	5.8	24.6	145.2
2: Continental V	14.7	8.2	4.4	12.4	78.9
3: Continental V+C	2.6	1.6	-0.2	1.5	5.7

Policies defined in paper. All numbers in percent. Cost changes from subsidy is $(\sum_{m\in\text{EV}}\sum_{n\in\text{Am}} r_{mn}(1-\mathbb{I}_{mn}s)^{1-\eta})^{1/(1-\eta)}$, where $\mathbb{I}_{mn}$ indicates m is eligible for the subsidy of $s = 20\%$ offered in market n, $\mathbb{I}_{mn} = 1$ for policy 1 for $n \in$ Am. r_{mn} is the baseline simulation (no policy). Elig. is the average of $\mathbb{I}_{mn}$. Production cost reductions are $(\sum_{m\in\text{EV}}\sum_{n\in\text{Am}} r_{mn}(\hat{c}_{mn})^{1-\eta})^{1/(1-\eta)}$ result new paths chosen due to new plant activations closer to market n. The "total" cost reduction includes both $s\mathbb{I}$ and $\hat{c}$ effects. All changes average across 100 simulations.

see that augmenting policy 3 with either a cell production subsidy or a tariff on imported cells and vehicles would add vehicle production lines relative to policy 3 alone, but it is less effective even as industrial policy than the other two policies. Policy 3+4 does maximize the number of cell production lines in the Americas, so if that goal is sufficiently important for non-environmental reasons, it could have a justification.

Appendix section E presents the numbers underlying the visualizations in Figures 11 and 12 in Tables E5,E6, and E7.

10 Conclusion

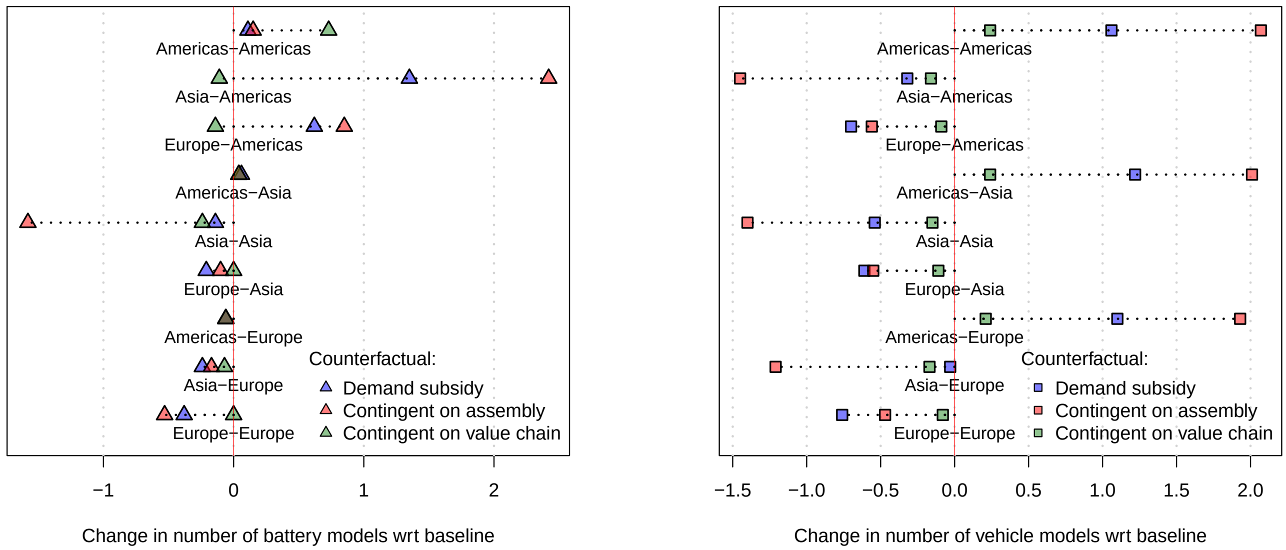
The battery and electric vehicle industry is an important example of a value chain where optimal location conditions are determined in a complex way balancing trade costs, fixed costs, and a mix of substitution and complementarity effects. Just solving the multi-stage problem computationally has been a challenge, leading most researchers to leave out fixed costs. However, fixed costs are important because they lead to increasing returns, which themselves make policy consequences much harder to predict.

Our main contributions are 1) to apply integer programming methods to this problem and show it can solve for optimal locations with fixed costs very quickly and 2) to devise a two-step estimation procedure to estimate the parameters governing variable and fixed costs. Our current best estimates imply that contingent subsidies work as protectionist

Figure 12: Counterfactual results with 20% subsidy: by origin-destination

(1) Battery Cells

(2) Vehicle assembly



measures, especially when applied to the final stage. But they impede the environmental goals of the government relative to non-contingent subsidies.

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A Computational performance of the algorithm

In this section, we evaluate the computational performance of the mixed integer linear programming solution to combinatorial discrete choice problems using a set of simulations.[27] We conduct three different speed tests, each highlighting different aspects of the algorithm.

A.1 Single-stage UFLP compared with AES squeezing algorithm

To make a fair comparison we need a problem that can be solved using both AES and MILP. AES requires $K = 1$ and MILP requires single sourcing. A simplified version of the problem considered by Arkolakis et al. (2023) is stated in Box A.1.

Box A.1: Special case of AES single-stage UFLP formulation

The firm's variable profit selling to market n is a function of its set of potential sourcing locations, denoted $\mathcal{L}$. With iso-elastic demand proportional to $p^{-\eta}$, the variable profit in market n is $\pi_n(\mathcal{L}) = kc_n(\mathcal{L})^{1-\eta}$, where $\mu = \eta/(\eta - 1)$ is the optimal markup and $k = (\eta - 1)^{\eta-1}\eta^{-\eta}$. The firm chooses $\mathcal{L} \subset L$ to maximize profit net of fixed costs ϕ incurred in each activated plant:

$$\mathcal{L}^* = \arg\max_{\mathcal{L}} \left\{ \sum_n \pi_n(\mathcal{L}) - \sum_{\ell \in \mathcal{L}} \phi_\ell \right\}.$$

With a continuum of inputs as in Tintelnot (2017), the cost function is

$$c_n(\mathcal{L}) = \left[\sum_{\ell \in \mathcal{L}} c_{\ell n}^{-\theta} \right]^{-1/\theta}, \quad \text{where} \quad c_{\ell n} = w_\ell \tau_{\ell n}/z_\ell.$$

For finite θ, the cost minimizing solution entails multi-sourcing (the supplier's optimal sourcing shares lie between 0 and 1 for all members of the choice set). The limiting case as $\theta \to \infty$ is given by $c_n(\mathcal{L}) = \min_{\mathcal{L}} c_{\ell n}$. Perfect substitution implies single-sourcing from the least-cost $\ell \in \mathcal{L}$. Randomness arises from firm-location productivity shocks (z_ℓ) and the locations of producers and consumers, both drawn from a uniform distribution on a unit square. The Euclidean distances between locations determine $\tau_{\ell n}$.

[27] Computational performance tests are run on author's MacBook Pro with Apple M2 Max chip and 64GB memory via serial processing.

In the first test, we compare how long it takes to solve for the optimal set of facility locations comparing three methods:

1. formulating firm's total profit as mixed integer linear programming (MILP)
2. using the squeezing algorithm proposed by Arkolakis et al. (2023) (AES)
3. "brute-force": computing the profit associated with every possible configuration, then sorting to find the maximum profit configuration (BF)

The comparable setting between MILP and AES is a single-stage combinatorial discrete choice problem by a single-product firm whose market entry is exogenous. The AES method converges on this problem as their $\theta \to \infty$, that is, as the different location choices become perfect substitutes.

Box A.2 shows the formulation of the single-stage UFLP as a MILP.

Box A.2: Single-stage UFLP formulation as a MILP

$$\max \sum_{n \in N} \sum_{\ell \in L} \pi(c_{\ell n}) x_{\ell n} - \sum_{\ell \in L} \phi_\ell y_\ell \quad \text{subject to}$$

$$\sum_{\ell \in L} x_{\ell n} = 1, \quad n \in N \tag{A.1}$$

$$x_{\ell n} \leq y_\ell, \quad n \in N, \ell \in L \tag{A.2}$$

$$x_{\ell n} \geq 0, \quad n \in N, \ell \in L \tag{A.3}$$

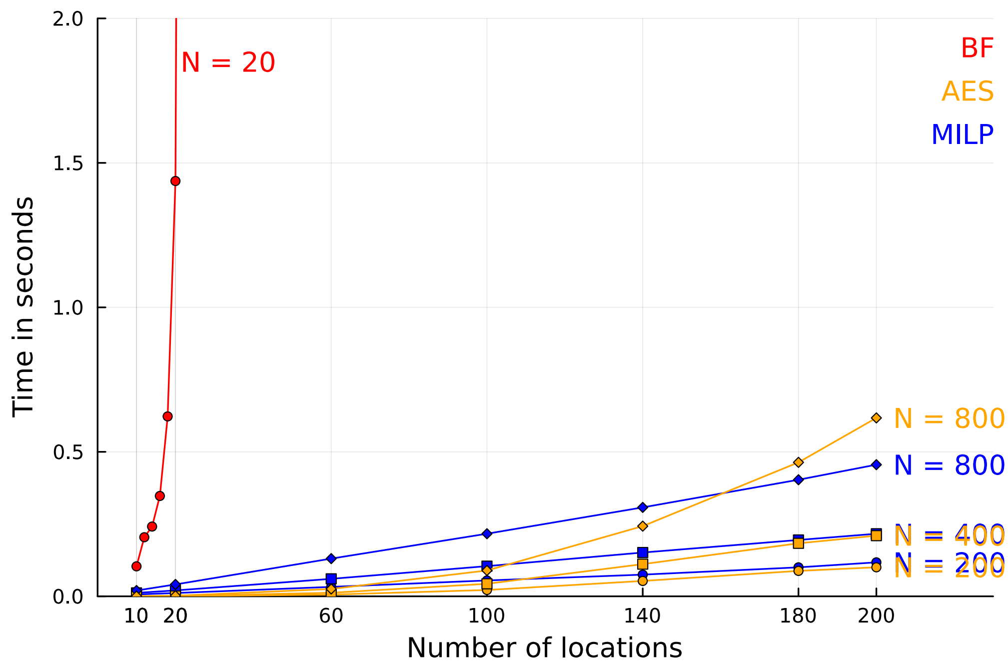
$$y_\ell \in \{0, 1\}, \quad \ell \in L \tag{A.4}$$

We generate data by randomly drawing L potential production locations and N markets on a unit square. The firm is assumed to sell its product in every market. The number of locations L varies within $\{10, 20, 60, 100, 140, 180, 200\}$, and the number of markets varies within $\{200, 400, 800\}$. We found that brute-force demands too much memory to be applied for more than 22 locations and markets.[28] For brute-force, we restrict $L \in \{10, 12, 14, 16, 18, 20, 22\}$ and $N = 20$. The data is simulated 100 times to compute the average algorithm's run time.

Figure A1 shows that the run times (seconds) for MILP and AES are comparable at low number of potential locations, with AES being slightly faster. As the number of locations increases, the computational performance between these two algorithms start to diverge

[28]The memory requirement is proportional to 2^L, so we can project the memory needed for $L = 25$ to be almost 200GB.

Figure A1: Three ways to solve a single-stage UFLP



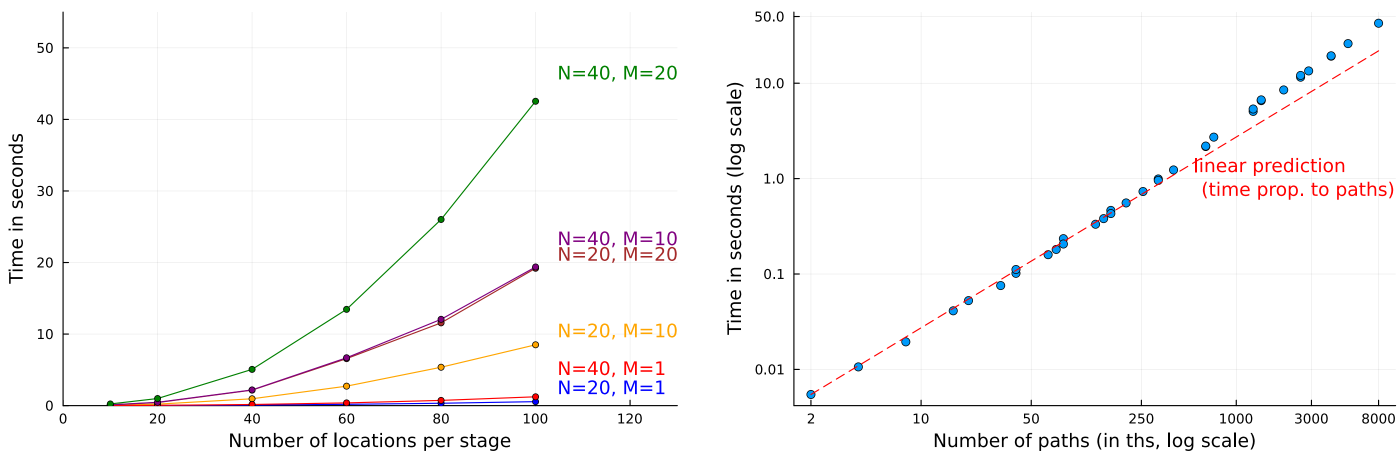
and MILP dominates. The reason is that for a single-stage uncapacitated facility location problem, the possible assignment for each market is L, and thus the computation time of MILP increases with locations at a linear rate (conditional on the number of markets). Nevertheless, both algorithms drastically reduce the run time compared to brute force, and extend our capability of solving combinatorial discrete choice problem in real world applications. Panel (a) of Table A1 provides more details of the average run time for each parameter setting.

A.2 Times for multi-stage UFLP

Here we evaluate the computational speed solving a two-stage supply chain for MILP alone because introducing more than one stage of production violates single crossing difference condition required to use AES. We also relax other restrictions in the first test by allowing for multi-product firm, represented by $M > 1$, and endogenous market entry. We vary the number of locations $L \in \{10, 20, 40, 60, 80, 100\}$, the number of markets $N \in \{20, 40\}$, and the number of products $M \in \{1, 10, 20\}$, and simulate 40 repetitions.

When $K = 2$, there are L^2 number of potential assignments for each product-market. For this reason time is convex in the number of locations in Panel (a) of Figure A2. Moreover, because the number of products and the number of markets are isomorphic in determining the size of the problem, only the product $N \times M$ matters and we observe almost

Figure A2: Computational Performance of MILP



(a) Two stages: MILP only

(b) Time as a function of $L_1 \times L_2 \times N \times M$

equal computation time for $N = 40, M = 10$ and $N = 20, M = 20$.[29] Panel (b) of Table A1 shows how the time scales with the size of the problem. The "size" can be thought of as the number of variables and the number of constraints. However, it turns out that the number of paths is what varies the most. The plot in panel (b) of Figure A2 shows that time is very close to linear in $L_1 \times L_2 \times N \times M$. The log-log regression has a coefficient of 1.1, where 1.0 would correspond to perfect linearity.

In the last test, we add one more stage in the supply chain by having $K = 3$. The three-stage problem is formulated as a MILP in section B. The number of potential assignments for each product-market increases to L^3. Therefore, we limit the potential locations to 30, and only use 10 repetitions. The run time increases more for each location increments in Panel (c) compared to Panel (a) in Table A1.

A.3 Explanation for strong performance of MILP formulation

1. The role of the LP relaxation: integral solutions avoid long branch-and-bound searches.

2. Dual Simplex method

As noted in the main text, we formulate the market entry condition as an inequality even though in the solution, it holds with equality. Gurobi handles inequality constraints more efficiently because it invokes a "sifting" algorithm which can be effective on problems with many more variables than equations. Sifting solves a sequence of LP

[29]The slight difference between column (3) and column (5) shown in Panel (a) of Table A1 is due to simulation error.

Table A1: Average computation time in seconds

Panel (a): $K = 1$

L_k	N = 200		N = 400		N = 800	
	MILP	AES	MILP	AES	MILP	AES
10	0.01	0.0	0.01	0.0	0.02	0.0
20	0.01	0.0	0.02	0.0	0.04	0.0
60	0.03	0.01	0.06	0.01	0.13	0.03
100	0.05	0.02	0.1	0.04	0.22	0.09
140	0.08	0.05	0.15	0.11	0.31	0.24
180	0.1	0.09	0.2	0.18	0.4	0.46
200	0.12	0.1	0.22	0.21	0.46	0.62

Panel (b): $K = 2$

L_k	N = 20			N = 40		
	M =1	M =10	M =20	M =1	M =10	M =20
10	0.01	0.05	0.1	0.01	0.11	0.23
20	0.02	0.21	0.43	0.04	0.46	0.99
40	0.08	0.96	2.17	0.16	2.19	5.07
60	0.18	2.72	6.57	0.38	6.69	13.46
80	0.33	5.37	11.57	0.73	12.06	26.02
100	0.56	8.5	19.2	1.23	19.38	42.54

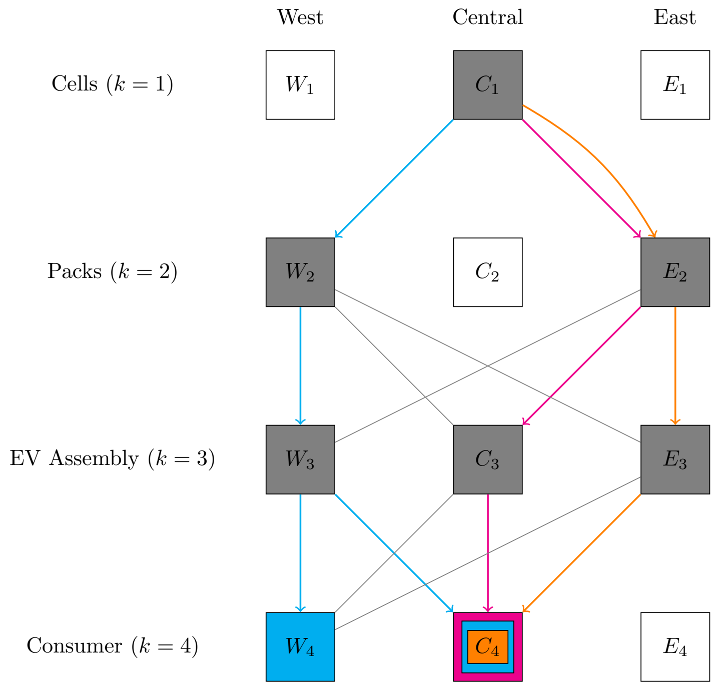
Panel (c): $K = 3$

L_k	N = 20			N = 40		
	M =1	M =10	M =20	M =1	M =10	M =20
10	0.05	0.62	1.39	0.11	1.45	3.03
20	1.69	24.45	53.75	3.7	50.96	115.57
30	5.98	81.33	174.8	13.4	164.8	367.5

sub-problems where the results from one sub-problem are used to select columns from the original model for inclusion in the next sub-problem.

B Three-stage MMM-UFLP formulation

Figure B3: Schematic of a supply chain with $K = 2$



$$\max \sum_{m \in M_f} \sum_{n \in N} \sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} \sum_{\ell_3 \in L_3} \pi(c(\boldsymbol{\ell}_{mn}), A_n) x_{mn\ell_1\ell_2\ell_3} - \sum_{k=1}^{3} \sum_{\ell_k \in L_k} \phi_{\ell_k} y_{\ell_k} - \sum_{m \in M_f} \sum_{n} \phi_{mn} z_{mn} \tag{B.5}$$

subject to

$$
\begin{aligned}
\sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} \sum_{\ell_3 \in L_3} x_{mn\ell_1\ell_2\ell_3} &\leq z_{mn}, \;\; n \in N, m \in M_f && \text{(B.6)}\\
\sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} x_{mn\ell_1\ell_2\ell_3} &\leq y_{\ell_3}, \;\; n \in N, m \in M_f, \ell_3 \in L_3 && \text{(B.7)}\\
\sum_{\ell_1 \in L_1} \sum_{\ell_3 \in L_3} x_{mn\ell_1\ell_2\ell_3} &\leq y_{\ell_2}, \;\; n \in N, m \in M_f, \ell_2 \in L_2 && \text{(B.8)}\\
\sum_{\ell_2 \in L_2} \sum_{\ell_3 \in L_3} x_{mn\ell_1\ell_2\ell_3} &\leq y_{\ell_1}, \;\; n \in N, m \in M_f, \ell_1 \in L_1 && \text{(B.9)}\\
x_{mn\ell_1\ell_2\ell_3} &\geq 0, \;\; n \in N, m \in M_f, \ell_k \in L_k, k = 1, 2, 3 && \text{(B.10)}\\
y_{\ell_k} &\in \{0, 1\}, \;\; \ell_k \in L_k, k = 1, 2, 3 && \text{(B.11)}\\
z_{mn} &\in \{0, 1\}, \;\; n \in N, m \in M_f. && \text{(B.12)}
\end{aligned}
$$

The inequalities (B.7)–(B.9) are *activity constraints* that govern whether a given facility is open: the left hand side sum will be equal to 1 if a path through a facility in ℓ_k is used (only a single $x_{mn\ell_1\ell_2\ell_3}$ path is set to 1 at the optimum), or will be equal to 0 otherwise (all the $x_{mn\ell_1\ell_2\ell_3}$ paths are set to 0). These constraints guarantee that a facility must be active to be used in supply chains.

C Data Appendix

The first three data sets are all proprietary data sets sold to us by IHS Markit. The other data used in the paper are publicly available.

C.1 IHS HVBD

The High Voltage Battery Data (HVBD) module provides value chain data by light vehicle model. We use only Battery Electric Vehicles (BEVs) in our analysis, excluding hybrids, defined here as all vehicles with combustion engines. The data show configurations of brand models, showing the supplier firm and plant location for each cell, module, pack, and battery management system used in a car or light truck. The location and owner of the vehicle assembly plant is also shown, but not the destination market where the vehicle is sold. Quantities for each configuration are provided from 2015 to 2024. However, the last year is currently a projection.

C.2 IHS Sales

The Sales module provides plant of production and destination market for each model sold. The sales quantities are available from 2015 to 2024 (again 2024 is currently a projection). This data set lacks detail on the battery. Furthermore, it does not distinguish BEVs, hybrid, and internal combustion versions with the same nameplate (model name). For that we must combine information from the New Registrations data set.

C.3 IHS New Registrations (NRQ,NRP)

We can obtain ξ_{mn} only for models with prices (the NRP data). The raw data from IHS often express model names slightly differently from the HVBD and Sales data. After some effort to match the model names across IHS modules, we have the merged data has 99% overlap in sales for the set of 15 big firms. Another problem is that some models in the NRQ have Model recorded as the brand name with "Unspecified" as the model name. There are also some Brand names (Make) that are unspecified. Collectively, these cases account for very small shares of the total sales in NRQ, under 2% in all markets in 2022, and 0.5% in all markets except China and Germany. These observations are dropped.

C.4 Sub-national per capita GDP

C.5 Tariff data

The primary source of tariffs is WITS, a database maintained by the World Bank. The rates reported are ad-valorem, and at the HS6 digits level of detail. For battery cells, we take the rates reported for HS 850790. For vehicles, we apply the rates of 870380 for passenger cars, and 870490 for commercial vehicles. Note that 870380 is the HS for electric-only vehicle since the major revision of 2017. We use 870390 until the country declares 870380. For both stages we use the data provided by Fajgelbaum et al. (2020) to adjust the rates following the wave of Trump tariffs against China. Regarding the frequent missing values in WITS raw data, we follow the same method as in Head and Mayer (2019): we fill the holes with linear interpolation, and when the missing data is for the latest years, we replace it with the latest available for this pair of countries and this HS.

C.6 Geography

Distances are calculated from plant to plant for cells to assembly, using latitude and longitude data and exploiting the R **geosphere** package for great circle distances. For distance from the assembly plant to consumer market, we use the **world.cities** data set contained in the R **maps** package. It contains latitude and longitude of close to 1000 cities for France, Japan, Germany, the USA, and Italy, over 500 cities for most countries, with Sweden having the fewest cities at 104. We average the **geosphere**::distGeo distances for each plant-city pair to obtain plant-market distances. To allow discontinuities associated with intercontinental trade, we define continents based on by the R **countrycode** package, which also provides iso codes for each of the countries named in the IHS data sets.

C.7 Demand elasticity estimates

Table C2: Price responsiveness of car demand from recent literature

EV-only	**elas.**	**Mainly ICEV**	**elas.**
Barwick et al. (2024)	4.2	Beresteanu and Li (2011)	8.4
Kwon (2023)	4.4	Castro-Vincenzi (2024)	4.3
Li et al. (2022)	3.7	Colon and Gortmaker (2020)	3.9
Li (2023)	3.7	Coşar et al. (2018)	14.9
Li et al. (2017)	1.3	Goldberg (1995)	3.3
Linn (2022)	5.3	Goldberg and Verboven (2001)	5.2
Muehlegger and Rapson (2022)	2.1	Grieco et al. (2024)	5.4
Springel (2021)	1.8	Head and Mayer (2019)	3.9
Xing et al. (2021)	2.8	Li (2018)	9.5
Median	3.7	**Median**	5.2
Overall Median	4.0		

D Additional empirical results

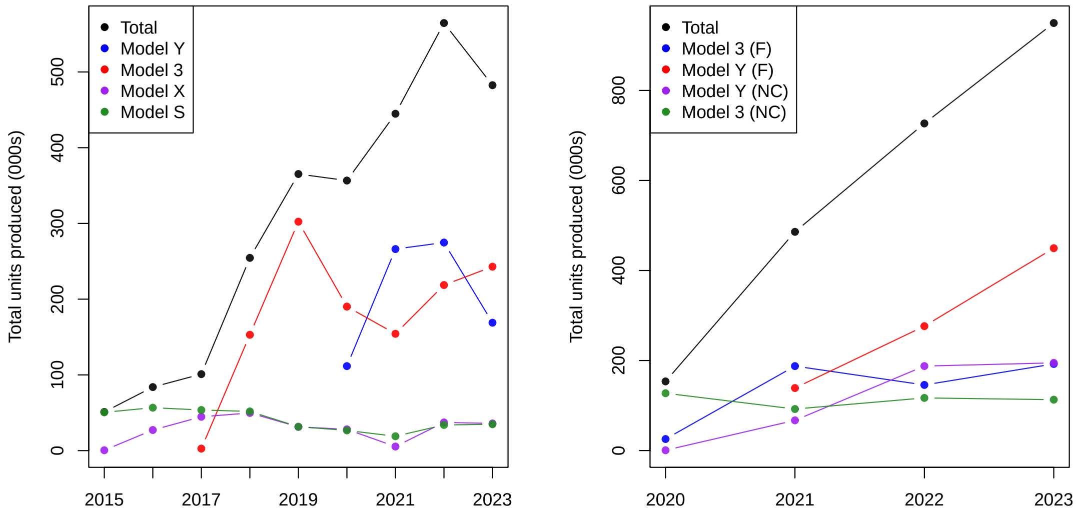
D.1 Evidence on multi-sourcing and capacity increases

D.2 Stage-level regression results

D.3 Results for all source countries

Consider two examples of countries that have high estimated variable costs in regressions that include all source countries. The Hyundai electric Kona produced in India is sold only in India, when the Korean-made one is sold in 59 destinations, and the figure for the Czech-made one in 39. The case of Malaysia is also quite telling since it assembles electric

Figure D4: Tesla's production increases in Fremont and Shanghai



(a) Tesla-Fremont (b) Tesla-Shanghai

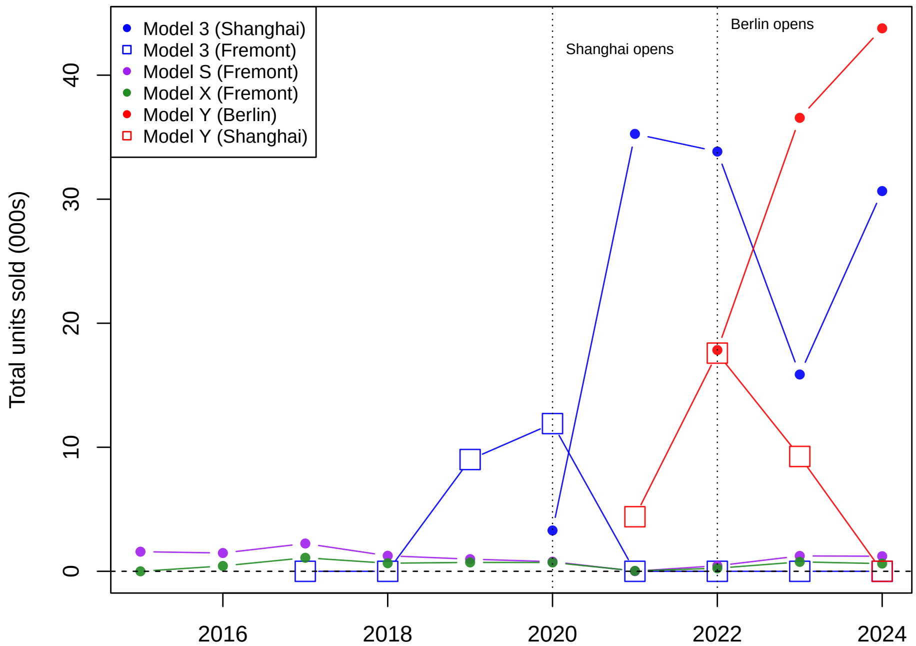
Table D3: Cell Sourcing decision

Dependent Variable:	Cell sourcing decision					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
border	-0.973[a]	-0.662[b]	-0.642[b]	-0.741[a]	-0.709[b]	-0.746[b]
	(0.300)	(0.270)	(0.270)	(0.273)	(0.281)	(0.347)
log distance	-0.281[a]	-0.184[a]	-0.191[a]	-0.185[a]	-0.156[a]	-0.287[b]
	(0.051)	(0.036)	(0.037)	(0.042)	(0.045)	(0.121)
intraplant		0.849[c]	0.841[c]	0.812	1.11[b]	0.129
		(0.498)	(0.501)	(0.530)	(0.470)	(1.02)
cross-continent		-1.68[a]	-1.70[a]	-1.51[a]	-1.52[a]	-1.35[b]
		(0.392)	(0.394)	(0.429)	(0.447)	(0.571)
log GDP per capita			0.257[a]	0.425[a]	0.498[a]	0.594[a]
			(0.069)	(0.055)	(0.064)	(0.179)
log(1+tariff)	-6.47[b]	-4.48[b]	-4.55[b]	-3.71[c]	-6.32[a]	-5.45[b]
	(2.58)	(2.03)	(2.04)	(2.16)	(2.33)	(2.15)
Observations	18,429	18,429	18,429	14,092	13,311	6,688
Squared Correlation	0.187	0.196	0.196	0.174	0.186	0.165

Column (4) constrains the set of choosers to be car models with positive sales (strictly defined). Column (5) adds the constraint that the choice set comprises plants already producing the required cell in terms of chemistry/material (NCM vs LFP). Column (6) adds the constraint that the sample only includes the set of 24 major countries, 15 major firms with their 138 major models. Clustered (dyad) standard-errors in parentheses, Signif. Codes: a: 0.01, b: 0.05, c: 0.1.

Figure D5: Examples of transitory multi-sourcing in 2022

(a) Tesla models sold in Germany



(b) VW ID.4 sold in North America

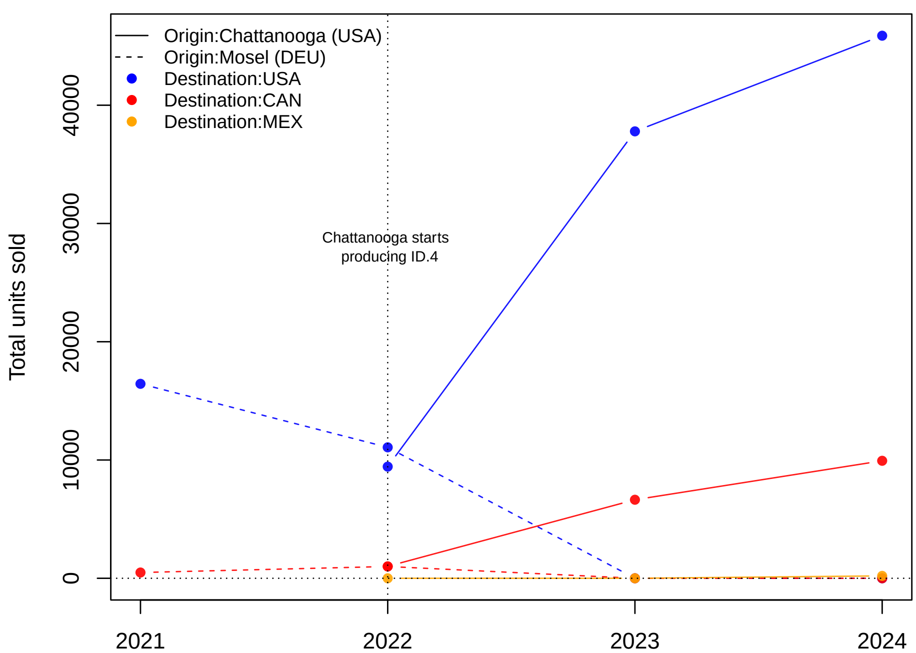


Table D4: BEV Sourcing decision

Dependent Variable:	BEV sourcing decision				
Model:	(1)	(2)	(3)	(4)	(5)
Border	-1.32[a]	-0.674[b]	-0.813[a]	-0.426[a]	-0.835[a]
	(0.358)	(0.263)	(0.263)	(0.139)	(0.222)
log distance	-0.060	-0.083[b]	0.084	0.099	0.073
	(0.044)	(0.042)	(0.062)	(0.062)	(0.059)
RTA	0.641[a]				0.492[b]
	(0.144)				(0.211)
EC(cells)		-0.348[a]	-0.293[a]	-0.217[a]	-0.227[a]
		(0.066)	(0.068)	(0.083)	(0.085)
log(1+tariff)		-5.25[a]	-4.29[a]	-10.3[a]	-7.93[a]
		(1.52)	(1.38)	(1.65)	(1.72)
cross-continent			-0.511[a]	-0.634[a]	-0.465[b]
			(0.108)	(0.192)	(0.201)
log GDP per capita			0.262[a]	0.116	0.113
			(0.095)	(0.079)	(0.078)
Observations	59,355	59,355	59,355	34,776	34,776
Squared Correlation	0.077	0.080	0.081	0.080	0.081
Sample	all	all	all	Majors	Majors

Clustered (dyad) standard-errors in parentheses, Signif. Codes: a: 0.01, b: 0.05, c: 0.1. All specifications include origin country fixed effects. "Majors" sample imposes all the filters detailed in section 8.1.

Volvos (the same as in Belgium) since 2022 that are sold only in Malaysia, and a few in Thailand.[30]

[30] https://paultan.org/2023/02/03/ “Volvo Car Malaysia to begin exporting...”

E Complete counterfactual results

The main text of section 9 presents the results graphically for a subset of the policies we investigated. Here we present the complete set of results in tabular form.

Table E5: Production lines† by policy

Receiving continent	Policy* 0	1	2	3	4	3+4	5V	5	3+5
					Vehicles				
Americas	17.5	19.1	20.3	17.8	17.9	18.4	17.5	16.5	16.8
Asia	91.5	92.0	89.0	91.2	91.2	90.6	91.4	91.9	91.4
Europe	58.1	57.6	56.7	58.0	58.2	58.0	58.2	58.7	58.6
					Cells				
Americas	8.0	8.1	8.1	8.7	9.4	10.3	8.0	8.0	8.6
Asia	109.6	113.2	111.0	109.1	108.5	107.7	109.6	108.6	108.1
Europe	30.7	30.6	30.8	30.6	30.3	30.1	30.7	31.0	30.8

† Production lines are defined as model-plant combinations.

* Policies defined in section 9. Policy 0 is the baseline with all existing 2022 policies absorbed in the estimated path costs. 3+4 is the sum of the expenditures under policies 3 and 4. 3+5 is the sum of the expenditures under policies 3 and 5. 5V is the expenditure under policy 5 for vehicles only.

Table E6: Count of models imported by origin-destination continent

Origin–Destination	Policy 0	1	2	3	4	3+4	5V	5	3+5
					Vehicles				
Americas-Americas	5	6.1	7.1	5.2	5.0	5.5	5.0	4.7	5.0
Asia-Americas	22.9	22.5	21.4	22.7	22.9	22.5	22.7	23.0	22.7
Europe-Americas	17.9	17.2	17.3	17.8	17.8	17.7	17.9	18.0	18.0
Americas-Asia	7.7	8.9	9.7	7.9	7.8	8.2	7.7	7.1	7.5
Asia-Asia	70.1	69.6	68.7	70.0	70.0	69.7	70.0	70.3	70.0
Europe-Asia	28.4	27.8	27.9	28.3	28.4	28.3	28.5	28.7	28.7
Americas-Europe	12.6	13.7	14.5	12.8	12.9	13.3	12.6	11.7	11.9
Asia-Europe	42.0	41.9	40.8	41.8	41.7	41.4	41.9	42.2	41.9
Europe-Europe	35.2	34.5	34.8	35.1	35.3	35.1	35.2	35.5	35.5
					Cells				
Americas-Americas	5.8	5.9	5.9	6.5	6.6	7.7	5.8	5.8	6.5
Asia-Americas	9.1	10.4	11.5	9.0	8.9	8.7	9.1	7.8	7.6
Europe-Americas	3.3	3.9	4.2	3.2	3.0	2.8	3.3	3.5	3.4
Americas-Asia	0.7	0.8	0.8	0.8	0.9	0.8	0.7	0.7	0.7
Asia-Asia	75.7	75.6	74.1	75.5	75.3	75.0	75.6	76.0	75.7
Europe-Asia	5.2	4.9	5.0	5.2	5.2	5.2	5.2	5.2	5.2
Americas-Europe	1.5	1.5	1.5	1.5	2.0	1.9	1.5	1.5	1.5
Asia-Europe	21.5	21.2	21.3	21.4	21.2	21.2	21.5	21.9	21.9
Europe-Europe	22.0	21.6	21.5	22.0	21.8	21.8	22.0	22.0	22.0

* Policies defined in section 9, Policy 0 is the baseline.

Table E7: Expenditures on EVs by policy*

Receiving continent	Policy 1	2	3	4	3+4	5V	5	3+5
Americas	145.2	78.9	5.7	0.2	16.5	-0.1	-2.9	3.6
Asia	2.1	0.5	-0.0	0.2	0.3	-0.0	-0.4	-0.5
Europe	4.2	2.2	0.1	1.4	1.8	0.0	-1.5	-1.5

* Policies defined in section 9, with combinations explained in the notes to table E5.

Table E8: Contributions to cost changes (in %) in Europe and Asia

Policy	Share Elig.	Cost index redn. subsidy	costs	total	Tot. Exp. increase
		Europe			
1: Unconditional	0	0	1.3	1.3	4.2
2: Continental V	0	0	0.7	0.7	2.2
3: Continental V+C	0	0	0.0	0.0	0.1
		Asia			
1: Unconditional	0	0	0.7	0.7	2.1
2: Continental V	0	0	0.2	0.2	0.5
3: Continental V+C	0	0	-0.0	-0.0	-0.0

See note from previous table.