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

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Online Appendix

Abstract

We model a multi-stage supply chain for EVs from battery production to vehicle distribution. Given industrial policies, firms select where to open facilities at each stage. This is a difficult combinatorial choice problem that we solve with a fast mixed integer linear programming formulation. We estimate the variable and fixed costs parameters using SMM. Counterfactual simulations reveal a tension between boosting EV adoption and promoting domestic supply chains. Due to increasing returns, even unconditional subsidies boost the number of factories in the subsidizing region—by about 16% for EVs and 7% for cells in North America, and even more in Europe. Theoretically, local assembly requirements can push down delivered marginal costs relative to unconditional subsidies. Empirically, local content requirements quadruple the boost in cells in America, but they increase costs and decrease subsidy uptake, undoing more than half of the EV adoption stimulus coming from pure buyer subsidies.

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 spatial interdependencies: At any given stage, different locations substitute for each other. However, 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, industrial policies such as subsidies or trade restrictions induce firms to re-organize their global supply chains in complex ways. 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.

This paper develops a quantitative method to analyze those 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. Canada 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 in July 2023 "Our government is absolutely determined that Canada gets its fair share of those green jobs." In 2024, the European Union imposed tariffs on Chinese EV imports and France limited its EV subsidy to cars with batteries from countries with a clean energy mix. With large fixed costs for each new facility across production stages, these industrial policies have the potential to induce a complex process of production relocations across those production stages.

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 this 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.[1] We extend the multi-stage production cost minimization problem considered in OR to allow for

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[1]"Squeezing" algorithms following the contribution of Jia (2008) cannot accommodate our multi-stage framework with fixed costs. We discuss this in further detail below.

endogenous demand and market entry by multi-product firms.

Estimation of the model proceeds in two stages. Data constructed by the S&P Mobility consultancy (formerly IHS Markit) lists the configuration of the battery electric vehicles (BEV) sold in all the major markets of the world. From this data, we observe for every car model sold in a given country, the factory where that car was assembled. We call this the vehicle sourcing decision. The data further reports the location where the cells were manufactured, which we call the cell sourcing decision. Our focus on cells comes from the fact that they represent around three quarters of the overall battery cost (AlixPartners, 2021). Conditional on the location of the cell and assembly facilities, the determinants of these sourcing decisions can be estimated using nested discrete choice. We take advantage of this feature to reduce the number of parameters to be estimated in the computationally demanding second estimation stage. The first stage provides variable costs as a parametric function of dyadic variables (borders, distance, trade agreements and tariffs) along each potential path (cell-location, assembly-location, consumer country). The tariff elasticity, a crucial parameter, is estimated to be about -8.5 at both stages.

The first stage estimation takes the open facilities as given, so fixed costs must be obtained in a second stage that solves the firms' full optimization problem—including the facility activation decisions. We estimate the parameters governing the distribution of fixed costs via simulated method of moments (SMM) solved using a constrained optimization approach, mathematical program with equilibrium constraints (MPEC) to account for endogenous market demand. The estimated fixed costs increase in distance to headquarters and the quality of the vehicle, and much lower in Asia (China, Japan, Korea) than in North America or Europe.

With the complete set of parameter estimates, we can turn to the primary objective of the paper, quantifying the impact of industrial policies on the location of the value chain and on the extent of clean vehicle adoption. We conduct counterfactuals on the main types of policy that governments have contemplated or implemented in recent years. Our main focus is on consumer subsidies that impose varying requirements on the location of different production stages. Given the large fixed costs, subsidies can induce changes in production locations that reduce the delivered cost to consumers (not including the subsidy). When the new open facility is in the subsidizing region, this delivers a "win-win" outcome for industrial policy: lower costs and higher employment. In some cases, adding local content requirements are needed to induce the relocation of a facility to the subsidizing region. Thus, a protectionist element can theoretically deliver such a win-win outcome. However, one of our key takeaways is that, empirically, those requirements do not deliver cost gains relative to unconditional subsidies and therefore impede EV adoption.[2]

In both North America and Europe, we find that the most effective way to expand EV purchases is to offer consumers the subsidy regardless of where the car and its battery is produced. For North America, this generates a 5% variable cost reduction associated with the production relocation choices. If the subsidy requires North American production, the EV adoption stimulus

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[2]In Appendix A.2, we develop a simple theoretical example highlighting how subsidies and content requirements can generate those cost savings.

declines from 86% to 71% (assembly only) to 32% (assembly and cells). This latter conditioning drastically affects the associated variable cost change and reversing the cost reduction into a 2% cost *increase*. It also delivers a mixed protectionist outcome for North America. Although it delivers a 20% increase in cell plants, that is offset by 7% fewer assembly plants—relative to the unconditional subsidy. On the other hand, the same policy for Europe achieves an unambiguous protectionist goal of raising both cell and vehicle production (21% for cells and 7% for vehicles).

The paper is organized as follows. Section 2 positions this paper within the literatures on sourcing across the value chain as well as the emerging work on EVs. Section 3 describes the data on the global EV industry we use, and illustrates important features of the two major stages of production of this sector (cell manufacturing and vehicle assembly). Section 4 documents a set of key facts about the EV industry that inform core assumptions in the model. Section 5 presents the model of multi-stage production market entry, and equilibrium. Section 6 estimates the parameters governing sourcing conditional on existing plants. The method of obtaining variable profits associated with each potential path is developed in section 7. We use simulated method of moments (SMM) to estimate the remaining set of structural parameters in Section 8. With all parameters estimates, Section 9 reaches the end goal of simulating the effects of a menu of industrial policies drawn from recent approaches taken in North America and Europe. Section 10 concludes.

2 Literature

This paper is positioned methodologically at the confluence of three 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. The third literature evaluates recent industrial policies directed at the EV industry.

Global value chains with constant returns: The GVC literature starting with Yi (2003, 2010) and more recently Antràs and De Gortari (2020), Tyazhelnikov (2022), and Johnson and Moxnes (2023) 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. However, those methods work with a constant-returns assumption. Yet, the location choice typically involves opening facilities, which require fixed costs and generate increasing returns to scale. More generally, non-constant returns to scale induce interdependencies between locations at each stage.

Plant location/sourcing with interdependencies: An early analytical treatment of those interdependencies is Yeaple (2003), who focuses on a three-country case, where 2 "Northern" countries trade-off horizontal and vertical motives for foreign direct investment. Tintelnot (2017) pioneers work on multinational location choice with many countries, heterogeneous firms, and 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 the empirical application of this paper: 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. Researchers have developed two approaches to this computational challenge. One path taken by Oberfield et al. (2024) uses 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. The other path pioneered by Jia (2008) uses supermodularity of the profit function to reduce the computational burden. Antràs et al. (2017) point out that the global sourcing problem can be either supermodular or submodular depending on the relative magnitudes of the key demand and supply parameters. 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. Their solution covers cases that are either sub or supermodular *globally*.

Our structure requires a different approach because it combines both submodularity and supermodularity forces: 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 (product entry) increase the profitability of adding production plants. Thus, there is no realistic way of imposing either global sub- or super-modularity to our application. A critical feature of our approach is that we do not need either one to hold.

Combining *multi-stage production with fixed costs* is a challenging problem and there have so far been only a few attempts. Antràs et al. (2024), de Gortari (2020), and Castro-Vincenzi et al. (2025) stand out in this respect. Antràs et al. (2024) 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

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plants and one for marketing. This enables rich interdependencies *between* each of those margins. However, the authors make strong parametric assumptions that restrict the firm-level problem to be supermodular.

A note by de Gortari (2020) proposes an algorithm for solving GVC models with fixed 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. In our framework with multi-market and multi-product firms, the facility fixed costs make it impossible to separate the computation of the equilibrium by product-market: Those problems are all interconnected and must be solved globally for the firm, along with the industry equilibrium in each market. Castro-Vincenzi et al. (2025) also develop a model with multiple markets and products. They extend the Arkolakis et al. (2023) squeezing algorithm for problems that are neither globally sub- or supermodular. The squeezing algorithm then leads to bounds on the firm's optimal choices. In their application to the auto industry, they recover bounds for the fixed location and market entry costs.

Our methodological contribution to this combinatorial discrete choice literature is to adapt mixed-integer linear programming (MILP) methods from operations research to obtain unique solutions to global supply chain location choices that combine sub- and super-modularity forces (complementarity across stages and substitution across facilities within stages). More precisely, 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.

Comparison to recent work on industrial policy towards EVs: Barwick et al. (2024) document that EV-oriented industrial policies now account for almost half of all industrial policies worldwide. Two recent working papers examine the application of industrial policies to the Electric Vehicle industry: Allcott et al. (2024) and Barwick et al. (2025). While there are several areas where our papers overlap with these two, the crucial difference is our focus on the endogenous location of factories.

Allcott et al. (2024) stands out for its careful treatment of the institutional features of the IRA, including the leasing loophole and the detailed treatment of subsidy eligibility over time. The policy simulations in our paper are inspired by the IRA provisions of making subsidies contingent on the value chain, but are not intended to evaluate the IRA's effects. Barwick et al. (2025) investigate how subsidies (consumption and production related) affect learning-by-doing in the EV battery industry in a model where oligopolistic EV assemblers and battery manufacturers bargain over the final battery prices. This results in an estimation equation that accounts for both vehicle and battery equilibrium markups (obtained from the bargaining equilibrium) in the formation of vehicle's price, together with marginal costs. In our framework, producers maximize total profits over the whole value chain. The implicit assumption is that bargaining between cell producers and assemblers leads to efficient production decisions where their relative bargaining power determines

lump-sum transfers.[3] This joint optimization determines the endogenous location choices for both battery production and vehicle assembly—whereas Barwick et al. (2025) take facility locations as given. In our case, industrial policy potentially reduces marginal costs via adding plants closer to downstream purchasers, rather than through achieving cost reductions via learning by doing as in their paper.

3 Description of the global battery-EV industry

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

3.1 Data on batteries and electric vehicles

Our analysis makes use of three data sets provided by the consultancy IHS-Markit, which was recently integrated within S&P Mobility.

The first one is the **High Voltage Battery (HVB)** dataset. For each electric vehicle produced in a given assembly plant, HVB provides the source of the battery cells (production plant location and supplier). Additional details are provided regarding the shape of the cell (prismatic, pouch or cylinder), the detailed chemistry, and the battery capacity in KWh. We aggregate the detailed into two main material categories: NMC (Nickel-Manganese-Cobalt) and LFP (Lithium-Ferrous-Phosphate). We calculate the power of the cells as the ratio of battery capacity to number of cells. This is production-based data (years 2015 to 2023). For each battery specification, HVB provides the total volumes of cars by assembly location. However, HVB does not include the sales destination by those detailed specifications.

The second source is the **Global Sales** dataset, which is an updated version of the data used in Head and Mayer (2019). For every light vehicle sold in 75 destination countries, we observe the vehicle model and assembly plant. For each model, Global Sales records the brand (e.g. Chevrolet; Audi), the brand owner (e.g. GM; VW), and the production platform (e.g. "GEN III" for Tesla Model 3 and Model Y; "MEB" for VW ID.4, ID.3, Audi Q4, and Skoda Enyaq). Platforms establish the architecture of core vehicle systems (e.g. steering, chassis) and dictate the placement of their components. They require a specific organization of the assembly line and its machine tools.

Some models are produced both as EVs but also with internal combustion engines (ICE).[4] For those models, Global Sales does not provide the sales destinations by fuel type. In those cases, we use a third dataset to recover the EV production-destination flows. This third source is **New Registration and Prices (NRP)** dataset. This is a destination-based dataset reporting sales (registrations) for 24 major markets by detailed model characteristic. The latter includes the fuel

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[3]In a few important cases such as BYD and Tesla, cell production is integrated by the assembler. In many other cases, cell production by a separate firm is set up as a joint-venture with the assembler. We provide additional supporting evidence for this simplifying assumption of joint optimization by cell producers and assemblers in section 4.2.

[4]For example, the Hyundai Kona is produced with many fuel types: Gas, Diesel, Hybrid, Plug-in hybrid, as well as EV.

type, which we use to recover the production-destination flows for all EVs. Another characteristic is the vehicle price, which we will also use in our analysis.

Combining these three sources, we construct a novel type of micro-level GVC dataset that tracks the production paths from battery cells to assembly to final sales destination for all EV models sold in those 24 major markets from 2015 to 2023. We geocode all production locations across those two stages by latitude and longitude, which we use to compute distances for every production path from battery cell to assembly and from assembly to final destination. For the latter, we use major cities as destinations and compute a population weighted average of the distances. We add a binary Regional Trade Agreement (RTA) indicator from the CEPII gravity data and tariff from WITS for the two segments along every path.[5]

3.2 The geography of the global BEV industry

We use the above datasets to describe the basic features of where BEVs are purchased and the spatial organization of their production.

Table 1: The 10 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	Rest Of World	40	12	1225.2	7.4

Note: Rest Of World row reports averages across 64 countries for numbers of models and EV share and the sum for Sales.

Table 1 shows the top 10 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 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).

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[5]We correct for missing data following the procedures in Head and Mayer (2019).

3.3 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 hundreds of news reports for those investments. Unfortunately, most articles tend to refer to battery plants without differentiating between cell and pack plants.[6] Also, some reports lump investments in the assembly factories together with the battery investments.

Table 2: Investment costs for battery and EV plants

Stage	Mean Cost ($US bn)	Std. Dev. ($US bn)	Std. Dev (logs)	Article Count
Cells	1.85	2.02	1.50	160
Vehicles	0.66	1.03	1.62	281
Vehicles + Cells	3.88	3.37	1.11	16

Source: Authors' calculations based on collected news articles.

Table 2 reports that on average EV assembly plants involve a $660 million investment and battery plants require $1.85 billion. There is substantial heterogeneity as captured by standard deviations that are similar to the means. The standard deviation in logs will be a target for standard deviations of realized fixed costs for cell manufacturing and vehicle assembly in our simulated method of moments estimation in section 8.

We take these massive investment costs as evidence for indivisible fixed costs that need to be incorporated into the model because they are core features of this 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.

3.4 Location of plants and sourcing along the value chain

Figures 1 and 2 show the impressive growth in the numbers of plants for cells and vehicles from 2015 to 2023—in all the main regions. The size of plant symbols corresponds to total output in gigawatt-hours for cells 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 countrieswith multiple vehicle plants in Figure 2 (Italy, Spain, Portugal, and Turkey) lack local cell production.

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[6]The most usual configuration of an EV battery is that cells are assembled into modules, themselves grouped into a pack, which includes a battery management system notably regulating the cooling system. The pack is what is usually

Figure 1: Cell plants in the major regions

3 Cell Plants in 2015, Total 0.6GWh

3 Cell Plants in 2015, Total 0.6GWh

39 Cell Plants in 2015, Total 9.8GWh

8 Cell Plants in 2023, Total 63.9GWh

7 Cell Plants in 2023, Total 76.5GWh

90 Cell Plants in 2023, Total 517.7GWh
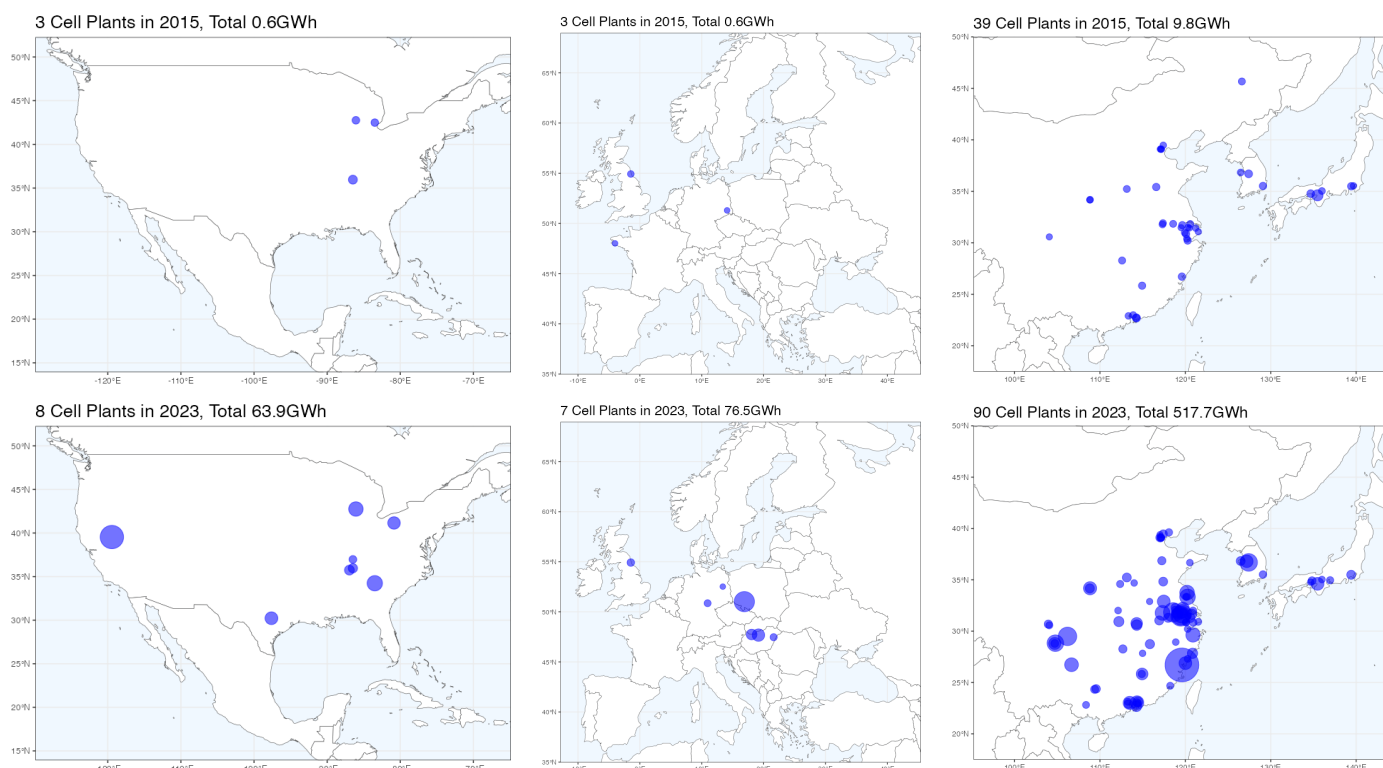
Figure 2: EV plants in the major regions

4 Assembly Plants in 2015, Total 75k BEVs

16 Assembly Plants in 2015, Total 80k BEVs

52 Assembly Plants in 2015, Total 175k BEVs

24 Assembly Plants in 2023, Total 1154k BEVs

62 Assembly Plants in 2023, Total 1954k BEVs

191 Assembly Plants in 2023, Total 7431k BEVs
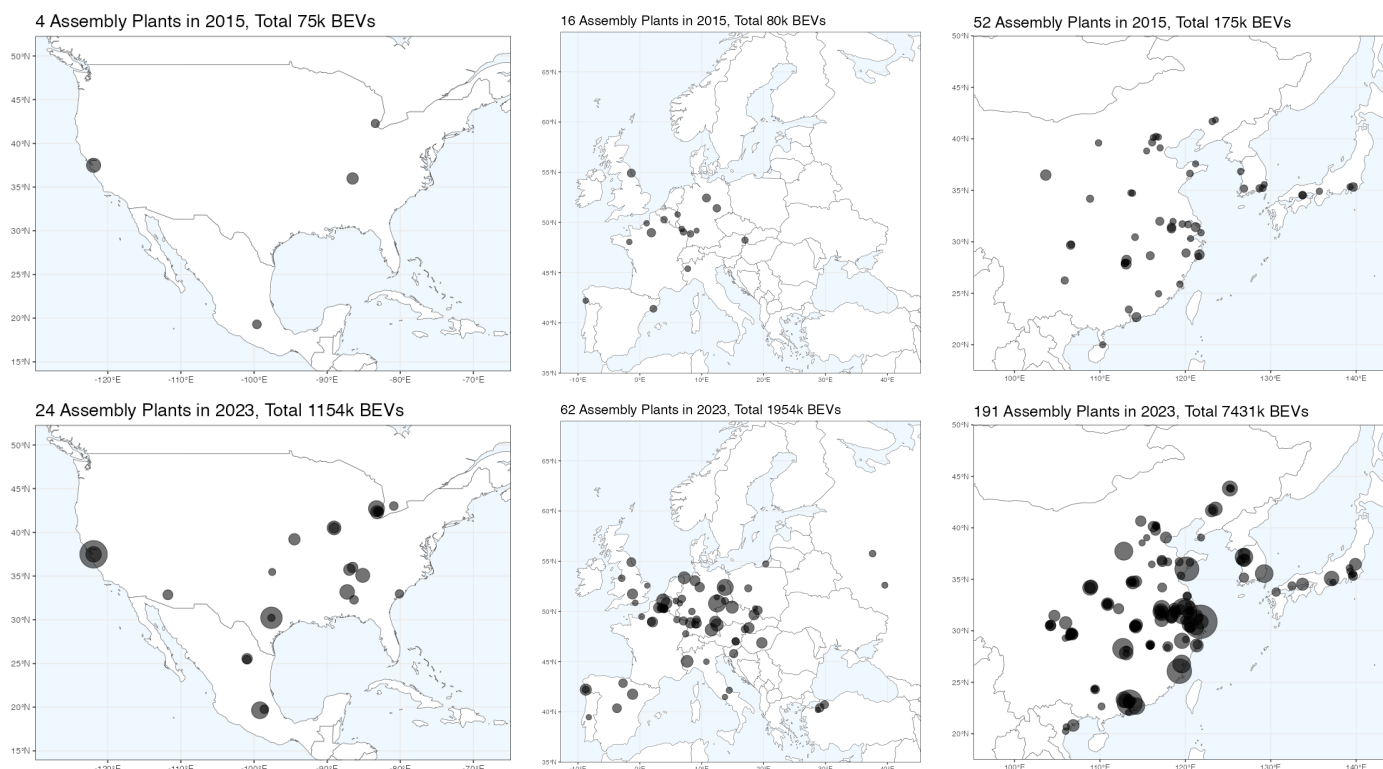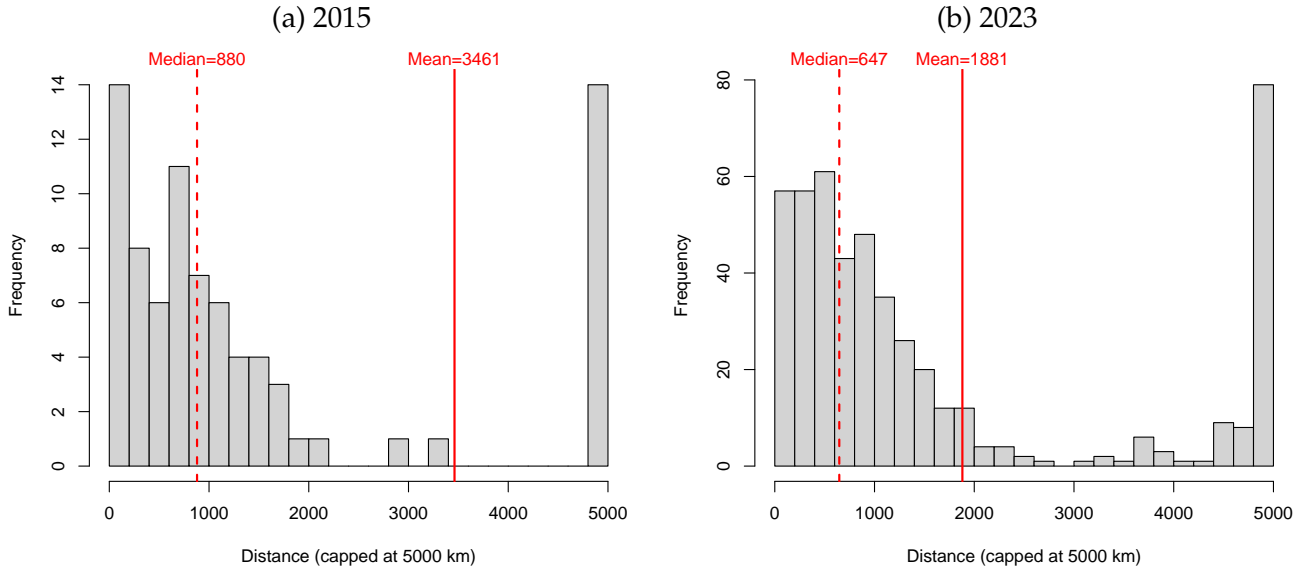
Figure 3: Distances between cell manufacture and vehicle assembly are shortening

(a) 2015

(b) 2023

The maps show the geographic dispersion of plants but they do not tell us which plants trade with which. Figure 3 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. Comparing the two panels of the figure also shows that the distance actually traveled fell substantially between 2015 and 2023, reflecting the fact that the new plants are primarily driven by the desire to serve local/regional markets.

4   Facts guiding our theory

We now turn to features of the data which determine modeling choices made in the next sections.

4.1   Single sourcing of cells and BEVs

In our model, we assume constant marginal costs of production in both stages, with the increasing returns induced by fixed costs for uncapacitated production facilities. This implies that firms choose a single optimal path for a given EV model sold in a given market. In other words, there is single sourcing, conditional of the set of activated plants. On the other hand, decreasing returns generated by either increasing marginal costs or facility capacity constraints would induce firms to multi-source: Sourcing a model sold in a given market from different assembly locations, or sourcing a battery used at a given assembly location from different cell production facilities.

Figure 4 shows that when we disaggregate the data to the car model and battery type level, single-sourcing almost always holds. Data availability at this level of disaggregation is key in assessing this pattern. Data at more aggregated levels appear to support multi-sourcing. Consider

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referred to as the battery.

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

(a) Cells

(b) Electric Vehicles
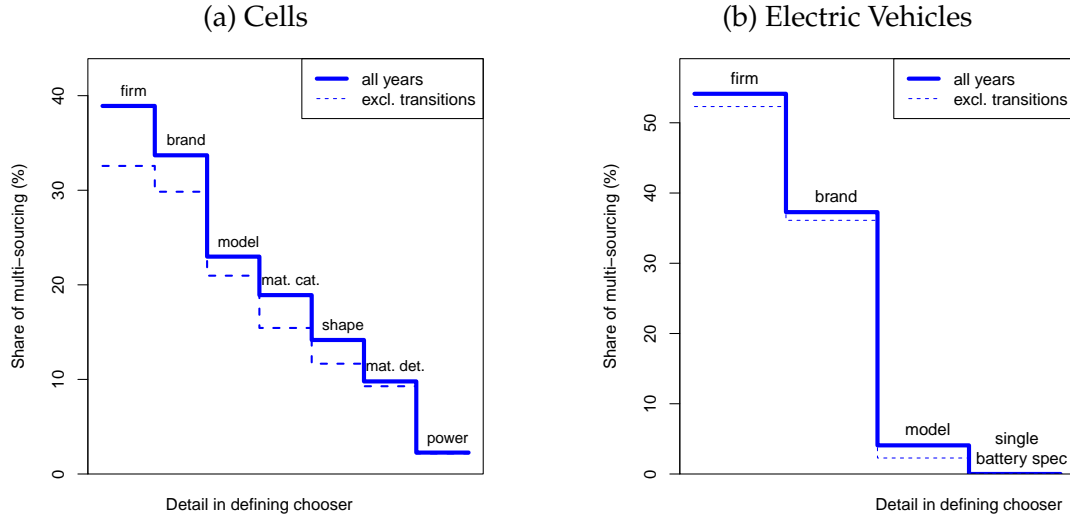
Note: The shares represent the number of choosers which decide to source from multiple options. In panel (a), the chooser goes from a firm-assembly plant-year to a brand-model-battery specification (shape, material and power)-assembly plant-year combination. The options are the different cell plants. In panel (b), the chooser goes from a firm-destination-year to a brand-model-destination-year combination. The options are the different assembly plants.

the case of battery cells in panel (a): An assembly plant may purchase one type of cell from one plant and a different type from another plant. This apparent share of multi-sourcing for cells is about 38% at the most aggregated level of a firm-assembly plant purchaser. However, this multi-sourcing share drops as the data is disaggregated, first by the vehicle type that the battery is purchased for (car brand and model), then by the battery type (shape, material, and power). At the most disaggregated level, the share of multi-sourcing is 3%. The dashed lines drop multi-sourcing that is transitory, which we define as lasting less than 3 years.

A similar pattern holds for the sourcing of vehicles for delivery to a given market in panel (b). A market-destination often sources vehicles produced by a given firm from multiple destinations. Indeed, this happens in more than half of the cases. But this multi-sourcing share drops to 4.07% of the cases for the sourcing of a particular car model.[7] And this residual multi-sourcing hides further model details that we do not fully observe in our flow data of vehicles from assembly to final destination. EV models are also differentiated by their battery type. Using our most detailed measure of battery type available, we find that car models with a single available battery specification are never multi-sourced.[8]

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[7]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.

[8]In Appendix Figure D3, we show an example of apparent multi-sourcing that is related to models differentiated by battery type. Panel (a) shows the sourcing of VW ID.4s sold in Sweden from two different German assembly plants. This multi-sourcing arises because the ID.4 assembled in Mosel use pouch cells whereas those assembled in Emden use prismatic cells.

This single-sourcing pattern is very important for thinking about how to formalize the firm's profit maximization problem. It is common in the supply-chain literature reviewed in Antràs and Chor (2022)—based on more limited/aggregated data—to model part differentiation at the level of the supplying countries and broad product categories. This entails a very different modeling approach that captures those sourcing shares. Instead, firms in our model choose the lowest cost source for a narrowly defined component or final vehicle—as we observe in our more disaggregated data.

There is another explanation for multi-sourcing which is also important to consider in setting up the firm's profit maximization problem: capacity constraints. We might see multi-sourcing not because of the love of variety common in trade models but simply because the preferred source is unable to meet the demand. In Appendix D.1, we present some examples suggesting that persistent capacity constraints do not seem to be a major concern in our case. Between 2015 and 2023, appendix 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 with the Tesla example, Figure D2 in the same appendix shows the sourcing volumes 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 transitory: Fremont was the only available source until 2019, when the Shanghai assembly facility opens. Shanghai then transitions to become the sole supplier for the Model 3 to Germany starting in 2021. The story is very similar with the Model Y, which is uniquely sourced from Shanghai in 2021. When the Berlin factory opens in 2022, sourcing for the model Y transitions to Berlin. In 2023, Berlin becomes the dominant supplier; and sourcing from Shanghai ceases in 2024.

Figure D3 shows that this pattern is not particular to Tesla. Panel (b) shows the case of Volkswagen ID.4 SUV. In 2021, the United States and Canada both uniquely source that vehicle from the German factory in Mosel. When the American plant in Chattanooga opens in 2022, sourcing to both North American countries transitions to that factory. By 2023, sourcing from Germany ceases. In line with these data patterns, we employ the uncapacitated version of the mixed integer linear programming model for facility location problems in this paper.

4.2 Single clients for cell plants

We model a single "lead" firm as in Antràs and De Gortari (2020) who optimizes over the whole supply chain and chooses the lowest cost paths along with the endogenous set of open production facilities. As we previously mentioned, these "lead" firms often take the form of a joint venture between an assembler and cell producer (when those firms are not integrated). This rules out the case of a cell producer paying a single fixed cost for production of battery cells that are sold to multiple assemblers. We show that this kind of multi-clienting is exceedingly rare once we condition on all the observable characteristics of the battery cell.

Figure 5: Single clients served by a battery plant for a type of battery
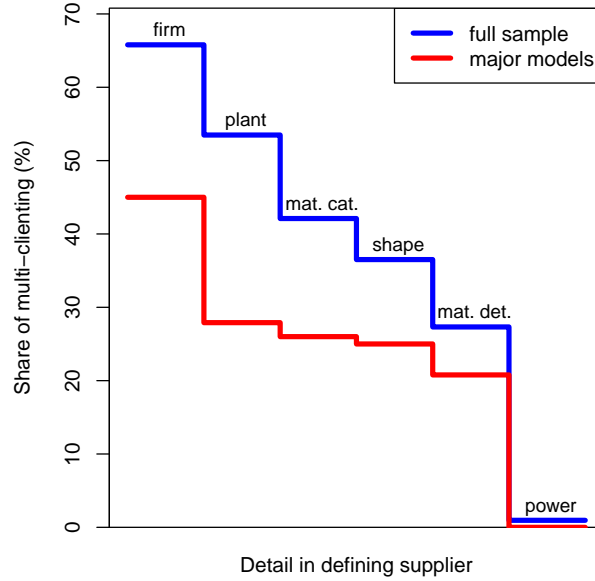
Note: The shares represent the number of battery plants (for a particular battery material, shape and power) that supply multiple car makers in 2022.

Figure 5 shows the share of cell plants with multiple clients as we increase the detail of the battery characteristics. The first step of the blue curve shows that more than 65% of cell plants serve more than one assembly firm. This share falls by more than 10 p.p. when the client is an assembly plant. We then separate out those relationships according to the characteristics of the battery cell. At the detailed material and shape of the cell, the share of multi-clienting is around 30%. The largest drop occurs when we differentiate by the power of the cell: the share of multi-clienting is then negligible. For the major models that we will use in our estimation, the share of multi-clienting is even lower (red curve). This suggests that in almost all cases battery manufacturers produce a specific cell for a single car assembler, rather than supplying a generic type of cell to several buyers.

4.3 Aggregation Levels for Fixed Costs

Our integer programming approach for open/close facilities allows substantial flexibility in defining the scope of a facility that incurs a fixed cost. For vehicle assembly, the fixed cost could be incurred at different aggregation levels across models from trims to firms. And similarly for cell producers, the fixed cost could be incurred at different aggregation levels for battery types. Guided by the data, we define a fixed cost group at the platform level for vehicles and at the combination of material category and shape for cells.

Figure 6 shows the 2022 relationship between the size of cell or vehicle plant and the number

of groups it produces. In panel (a) we see that almost two thirds of the cell plants produce a single shape/material category. Plants that make two different groups are half as frequent and on average about twice as large. This is what we would expect if adding a second group entailed an additional fixed cost. Plants that produce three or more groups are very rare and are much larger. A similar pattern is shown in panel (b) for vehicles. Only one in five assembly plants uses more than one platform, and they tend to be more than twice as large as the single-platform plants. Taken as a whole, Figure 6 suggests that adding a new group entails large fixed costs at both stages, which requires a larger scale of production to be profitable.

Figure 6: Size of plant and count of groups in 2022

(a) Cell plants   (b) Vehicle plants
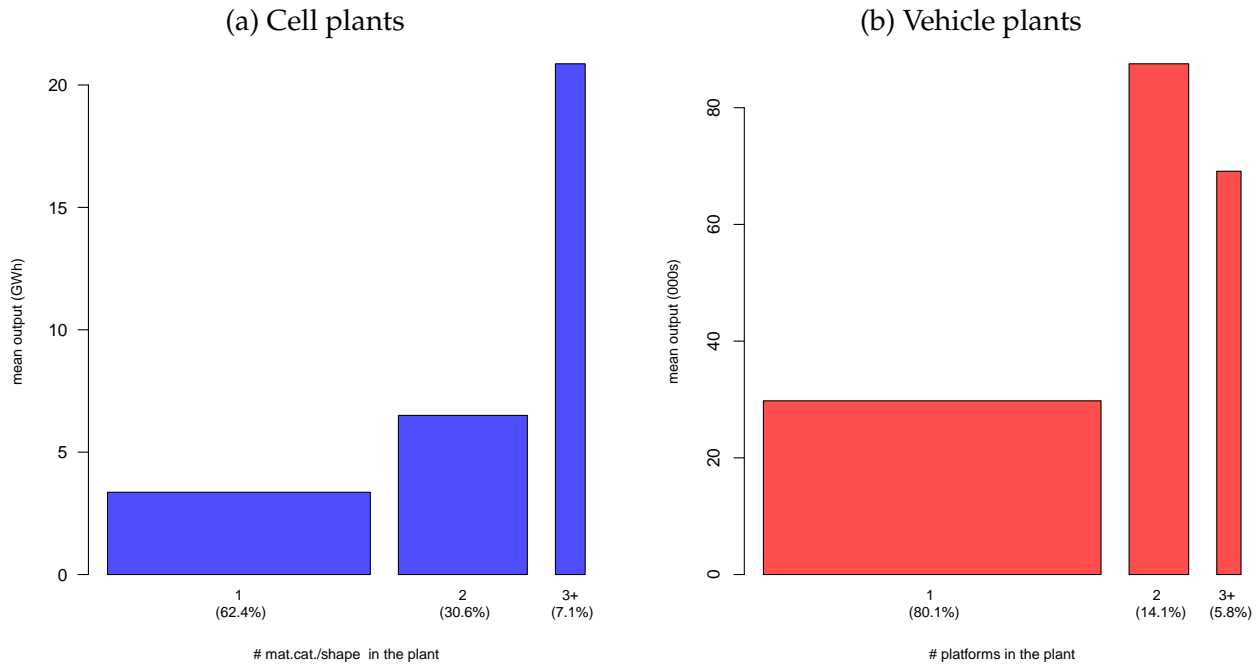
5 Multi-product, Multi-stage, Multinational Production

Guided by the facts in the previous section, we now specify of model of multinational firms' plant location and sourcing decisions. A firm is characterized by a set of models (varieties), $\{m : m \in M_f\}$, and a headquarters location. The models have a vector of "appeal" in each market n. While the firm chooses which models to offer where, they cannot add new models. 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: $\mathbf{L} \equiv \{L_1, ..., L_K\}$. The index ℓ_k represents a particular production location at level 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 market n for

model m is given by $\boldsymbol{\ell}_{mn} \equiv \{\ell_1, ..., \ell_K\}_{mn}$.

5.1 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. A firm chooses where to open facilities at each level from $k = 1$ to K. Firms also decide which models to offer in which markets (stage $K+1$). The sets of nodes at each stage which paths can follow is given by $\mathcal{L}_f = \{\mathcal{L}_1(f), ..., \mathcal{L}_K(f)\}$. Because of fixed costs, firms do not open facilities in every element of L_k nor serve all markets in N. The payment of fixed costs activates a location for groups of models that share common characteristics. The grouping mapping at each stage is given by the matrices Γ^k. Firms can add extra models at a given location for no additional fixed cost payment, so long as they share a common grouping, that is $\Gamma^k_{mg_k} = 1$ for all m that use group g_k at stage k.[9] 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 $\mathcal{L}_f$.

Figure 7: Schematic of a supply chain with $K = 2$
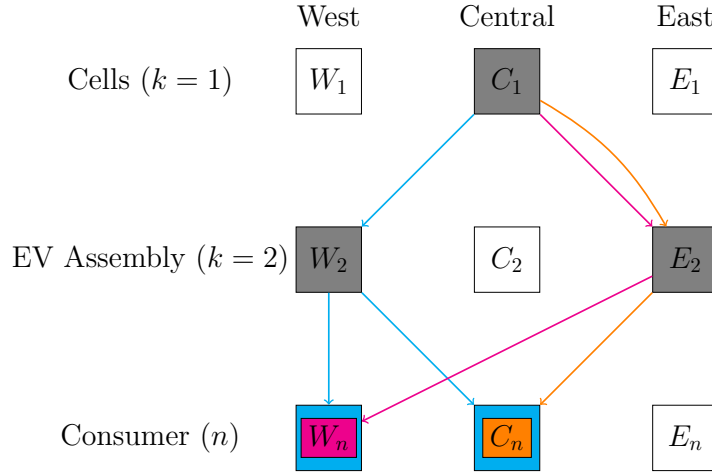
Figure 7 depicts a simplified version of our model to clarify the decisions we are modeling. As in our application, we set $K = 2$ stages of production for cell manufacture and vehicle assembly.[10] In addition, there is the decision to enter a consumer market. The schematic portrays a single firm that makes three models. All three models here share a common stage 1 group. At stage 2, the Magenta and Orange models have a common group, but the Cyan model is in a different group. There are three potential locations: East, Central, and West.

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[9]We describe the groupings for our empirical application in Section 4.3; but our solution methods apply to arbitrary groupings of models at each stage of production.

[10]Our solution method can handle additional production stages subject to the memory requirement associated with keeping track of every potential path assignment. Another important consideration is speed, given that our simulations methods require us to run the optimization algorithm millions of times.

In figure 7, 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, 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 $\pi(c(\boldsymbol{\ell}_{mn}), A_n)$.[11] Aggregators, often specified as price indexes, exist for linear, logit, and CES demand curves under monopolistic competition. 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 $\phi_{fg_k\ell_k}$ in location ℓ_k for a plant to produce type g_k inputs (or final assembly for $k = K$). We denote this facility location choice with a binary variable $y_{fg_k\ell_k} \in \{0, 1\}$. 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 determining all the binary $y_{fg_k\ell_k}$ facility location choices and z_{mn} market entry choices; and assigning paths $x_{mn\ell}$ through the open facilities for all activated markets.

5.2 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).[12] We add three features to that framework: multi-product firms, endogenous choice of market entry, and endogenous quantities. This leads to the following mixed-integer linear programming (MILP) formulation:

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[11] 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.

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

$$\max_{\mathbf{x},\mathbf{y},\mathbf{z}} \quad \sum_{m \in M_f} \sum_{n \in N} \sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} \pi(c(\boldsymbol{\ell}_{mn}), A_n) x_{mn\ell_1\ell_2}$$

$$- \sum_{g_1 \in G_1} \sum_{\ell_1 \in L_1} \phi_{fg_1\ell_1} y_{fg_1\ell_1} - \sum_{g_2 \in G_2} \sum_{\ell_2 \in L_2} \phi_{fg_2\ell_2} y_{fg_2\ell_2} - \sum_{m \in M_f} \sum_{n} \phi_{mn} z_{mn} \qquad (1)$$

subject to

$$\sum_{\ell_1 \in L_1} \sum_{\ell_2 \in L_2} x_{mn\ell_1\ell_2} \quad \leq \quad z_{mn}, \;\; n \in N, m \in M_f \qquad (2)$$

$$\sum_{\ell_1 \in L_1} x_{mn\ell_1\ell_2} \quad \leq \quad \sum_{g_2 \in G_2} \Gamma^2_{mg_2} y_{fg_2\ell_2}, \;\; n \in N, m \in \mathcal{M}_f, \ell_2 \in L_2 \qquad (3)$$

$$\sum_{\ell_2 \in L_2} x_{mn\ell_1\ell_2} \quad \leq \quad \sum_{g_1 \in G_1} \Gamma^1_{mg_1} y_{fg_1\ell_1}, \;\; n \in N, m \in \mathcal{M}_f, \ell_1 \in L_1 \qquad (4)$$

$$x_{mn\ell_1\ell_2} \quad \geq 0, \quad y_{fg_1\ell_1} \in \{0,1\}, \quad y_{fg_2\ell_2} \in \{0,1\} \quad z_{mn} \in \{0,1\}. \qquad (5)$$

The objective function (1) is the firm's total profits. It sums the variable profits for every selected path $x_{mn\ell} = 1$ and subtracts the fixed cost of all activated facilities $y_{fg_k\ell_k} = 1$ and markets $z_{mn} = 1$. The $M_f \times N$ inequalities defined in (2), are the *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 $x_{mn\ell_1\ell_2}$ path is set to one at the optimum), or will be equal to zero otherwise (all the $x_{mn\ell_1\ell_2}$ 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 Head et al. (2026).

The $M_f \times N \times L_2$ inequalities contained in (3) and the $M_f \times N \times L_1$ contained in(4) are *activity constraints* that govern whether a given facility is open for a model: the left-hand side sum equals one if a path through a facility in ℓ_k is used (only a single $x_{mn\ell_1\ell_2}$ path is set to 1 at the optimum), or equals zero otherwise (all the $x_{mn\ell_1\ell_2}$ paths are set to 0). These constraints guarantee that a facility must be active to be used in supply chains specific to groups of cell ($k = 1$) and vehicle ($k = 2$) types.

Equation (5) restricts facility activation and market entry to be binary. Some statements of the uncapacitated FLP explicitly constrain the $x_{mn\ell_1\ell_2}$ 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 (the xs) to be positive. While fractional assignments are not explicitly excluded, the x are binary at the optimum.[13] The brute force alternative would involve $2^{G_1 \times L_1 + G_2 \times L_2}$ combinations of facility choices. At the median levels of G_k and L_k across the firms and locations used in our estimation, this represents 9.2×10^{25} possible combinations. Our MILP approach solves this problem in about a second. Head et al. (2026) explain why this approach is so efficient. We detail computation times by number of locations and stages and also compare performance with the "squeezing" method of Arkolakis et al. (2023).

5.3 Roadmap to estimation of the model

The MUFLP setup is very general, but we need to make more specific modeling choices before we can estimate the parameters and conduct realistic policy simulations. To estimate the parameters of the model, we divide the problem into three steps. In section 6, we use the assignment (or sourcing) decisions in the data (which are conditional on open markets and facilities) to estimate the bilateral variable costs $\tau^k_{\ell_k \ell_{k+1}}$ for all locations at each level of production. We then, in section 7, show how to use those parameters to recover variable profits in levels. In section 8, we then estimate all the remaining parameters using simulated method of moments matching those generated from the MUFLP solution to their counterparts in our data. Those parameters include those governing the distribution of fixed costs, which we describe later in that section.

6 Estimation of path costs via sourcing regressions

Since our model satisfies Assumption 1, path costs and the market level aggregator (A_n) are sufficient to determine variable profit maximizing model by model. Given the facility and entry vectors, y and z, the maximization of total profits subsumes cost minimization by choice of x, which we refer to as the sourcing decision. In this section, we use the data on sourcing decisions to estimate costs on each "edge" (origin-destination) of the path from cell manufacture to EV consumer. In particular we estimate the impacts of distance, borders, trade agreements and tariffs on variable costs.

6.1 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

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[13]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*.

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. 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).[14]

The variable costs for a particular chain depend on three key aspects: (i) a location-stage production cost shifter, $w_{\ell_k}^k$, 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 $\varepsilon_{m\ell_k \ell_{k+1}}^k$.[15]

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

$$\text{Cells:} \quad c_{m\ell_1\ell_2}^1 = w_{\ell_1}^1 \tau_{\ell_1\ell_2}^1 \varepsilon_{m\ell_1\ell_2}^1, \tag{6}$$

$$\text{Vehicles:} \quad c(\boldsymbol{\ell}_{mn}) = \left(w_{\ell_2}^2\right)^{\alpha_{22}} \left(c_{m\ell_1\ell_2}^1\right)^{\alpha_{12}} \tau_{\ell_2 n}^2 \varepsilon_{m\ell_2 n}^2, \tag{7}$$

where $\alpha_{k2} \in (0,1)$ denotes the cost share of stage $k = 1, 2$ factors in final assembly ($k = 2$). 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 $\tau_{\ell_2 n}^2$.

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.

Substituting upstream cost (6) into the next stage's cost equation (7), the logged cost of the complete production path is

$$\ln c(\boldsymbol{\ell}_{mn}) = \alpha_{22} \ln w_{\ell_2}^2 + \ln \tau_{\ell_2 n}^2 + \alpha_{12}(\ln w_{\ell_1}^1 + \ln \tau_{\ell_1\ell_2}^1) + u(\boldsymbol{\ell}_{mn}), \tag{8}$$

where $u(\boldsymbol{\ell}_{mn}) = \alpha_{12} \ln \varepsilon_{m\ell_1\ell_2}^1 + \ln \varepsilon_{m\ell_2 n}^2$ is the structural interpretation of the error term. The optimal sourcing decisions, x, minimize log costs conditional on the open facilities at both production stages ($y_{f\ell_1 g_1}^1$ and $y_{f\ell_2 g_2}^2$) and served markets (z_{mn}).

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[14]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.

[15]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.

6.2 Conditional choice estimation of variable costs

The probability of choosing path ℓ_{mn} is given by the product of the conditional probabilities at each stage:

$$\mathbb{P}(\ell_{mn}) = \mathbb{P}^1_{\ell_1|\ell_2}(m) \times \mathbb{P}^2_{\ell_2|n}(m). \tag{9}$$

Breaking down the probability into these logarithmically separable probabilities greatly facilitates estimation. There are several ways to obtain a tractable formulation of the choice probabilities at each stage. The best known method is the Nested Logit approach by McFadden (1978), modeling $u(\ell_{mn})$ as single shock with a generalized extreme value distribution that allows for correlated errors. Here we follow the presentation by Anderson et al. (1992, chapter 2), where the correlation is driven by two parameters, θ_1 and θ_2, one for each production stage. Intuitively, larger values of θ_k implies that alternatives within a stage k are closer substitutes. If $\theta_1 = \theta_2$, the error term $-u(\ell_{mn})$ is a Gumbel shock (log of a Fréchet), as in Antràs and De Gortari (2020) and Allen and Arkolakis (2022).

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 combine equation (6) with our GEV assumption to derive the conditional probability of ℓ_1 being the cost-minimizing location of supplying to ℓ_2 as

$$\mathbb{P}^1_{\ell_1|\ell_2}(m) = \frac{\left(w^1_{\ell_1} \tau^1_{\ell_1\ell_2}\right)^{-\theta_1}}{\Phi^1_{\ell_2}(m)}, \text{ with } \Phi^1_{\ell_2}(m) = \sum_{g_1 \in G_1} \Gamma^1_{mg_1} \sum_{\ell_1 \in L_1} y_{fg_1\ell_1} \left(w^1_{\ell_1} \tau^1_{\ell_1\ell_2}\right)^{-\theta_1}, \tag{10}$$

where (as in the MUFLP) $\Gamma^1_{mg_1} = 1$ if model m uses group g_1 for cells, and $y_{fg_1\ell_1} = 1$ if location ℓ_1 has activated this group g_1. Our estimating equation is

$$\mathbb{P}^1_{\ell_1|\ell_2}(m) = \exp\left[\text{FE}^1_{\ell_1} + \text{FE}^1_{\ell_2}(m) + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right], \tag{11}$$

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. The second fixed effect is specific to the *chooser* and is given by

$$\text{FE}^1_{\ell_2}(m) = -\ln\left\{\sum_{g_1 \in G_1} \Gamma^1_{mg_1} \sum_{\ell_1 \in L_1} y_{fg_1\ell_1} \exp\left[\text{FE}^1_{\ell_1} + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right]\right\}.$$

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

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sourced.[16]. The correspondence between estimated coefficients and structural variables is

$$w^1_{\ell_1} = \exp\left[-\text{FE}^1_{\ell_1}/\theta_1\right]$$

$$\tau^1_{\ell_1\ell_2} = \exp\left\{-\left[\beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right]/\theta_1\right\}$$

$$\Phi^1_{\ell_2}(m) = \exp\left[-\text{FE}^1_{\ell_2}(m)\right]$$

Since tariffs are direct cost shifters, and they have a unit passthrough elasticity, the coefficient β^t_1 estimates θ_1 (as in Head and Mayer, 2019).

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 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

$$\mathbb{E}c^1_{\cdot,\ell_2}(m) = \left(\Phi^1_{\ell_2}(m)\right)^{-1/\theta_1}. \tag{12}$$

We refer to this term as the *inclusive cost* which depends on the sourcing potential of ℓ_2 and differs across car models due to various choice sets of the firm $\mathcal{L}_1(f)$ and the cell group g_1 used by m.

The second decision to consider is the one made by a model-market combination when sourcing the EV from an assembly plant. Using (7), the probability that ℓ_2 is selected as the location of assembly is

$$\mathbb{P}^2_{\ell_2|n}(m) = \frac{\left[\left(w^2_{\ell_2}\right)^{\alpha_{22}}\left(\mathbb{E}c^1_{\cdot,\ell_2}\right)^{\alpha_{12}}\tau^2_{\ell_2 n}\right]^{-\theta_2}}{\Phi^2_n(m)}, \quad \text{with}$$

$$\Phi^2_n(m) = \sum_{g_2 \in G_2} \Gamma^2_{mg_2} \sum_{\ell_2 \in L_2} y_{fg_2\ell_2}\left[\left(w^2_{\ell_2}\right)^{\alpha_{22}}\left(\mathbb{E}c^1_{\cdot,\ell_2}(m)\right)^{\alpha_{12}}\tau^2_{\ell_2 n}\right]^{-\theta_2}. \tag{13}$$

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

$$\mathbb{P}^2_{\ell_2|n}(m) = \exp\left[\text{FE}^2_{\ell_2} + \text{FE}^2_n(m) + \beta^2_D \ln D_{\ell_2 n} + \beta^2_t \ln\left(1 + t^2_{\ell_2 n}\right) + \beta^2_\Phi \text{FE}^1_{\ell_2}(m)\right], \tag{14}$$

where $\text{FE}^1_{\ell_2}(m)$ was estimated in equation (11), and accounts for determinants of the upstream (cells) costs. The correspondence between the estimated coefficients and structural parameters is

$$\left(w^2_{\ell_2}\right)^{\alpha_{22}} = \exp\left(-\text{FE}^2_{\ell_2}/\theta_2\right)$$

$$\tau^2_{\ell_2 n} = \exp\left\{-\left[\beta^2_D \ln D_{\ell_2 n} + \beta^2_t \ln\left(1 + t^2_{\ell_2 n}\right)\right]/\theta_2\right\}$$

$$\alpha_{12} = -\theta_1 \beta^2_\Phi/\theta_2$$

$$\Phi^2_n(m) = \exp\left[-\text{FE}^2_n(m)\right]$$

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[16]These narrow definitions of choosers ensure single-sourcing in almost all cases as we see in figure 4

Again, as tariffs shift costs and final prices proportionately, the coefficient β_2^t provides a direct estimate of θ_2. The Antràs and De Gortari (2020) approach of a single independent path-shock would imply $\theta_1 = \theta_2$ in the two probability equations.[17] As we estimate the two equations separately, we do not impose this coefficient restriction. 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 (11) and (14) as high-dimensional fixed effects PPML regressions.

Combining the two production stages, we can express the log of the variable cost of the full path as a function of our current estimates and some additional parameters:

$$\ln c(\boldsymbol{\ell}_{mn}) = -\kappa \Big\{ \mathrm{FE}_{\ell_2}^2 + \beta_D^2 \ln D_{\ell_2 n} + \beta_t^2 \ln\left(1 + t_{\ell_2 n}^2\right) \tag{15}$$
$$- \beta_\Phi^2 \left[\mathrm{FE}_{\ell_1}^1 + \beta_D^1 \ln D_{\ell_1 \ell_2} + \beta_t^1 \ln\left(1 + t_{\ell_1 \ell_2}^1\right) \right] \Big\} + u(\boldsymbol{\ell}_{mn}).$$

The Gumbel shape parameter $\kappa = 1/\theta_2$ scales up and down the relative importance of observed determinants of marginal costs relative to fixed costs. Assuming that ad-valorem tariffs on vehicles $(1 + t_{\ell_2 n})$ proportionately shift path cost $c(\boldsymbol{\ell}_{mn})$, we obtain this parameter as a simple transformation of the impact of tariffs on vehicle sourcing decisions: $\kappa = -1/\beta_t^2$. The coefficient on the inclusive cost of cells provides the weights to use on the cell stage relative to vehicle assembly. Our model implies $-\beta_\Phi^2 = \alpha_{12}(\theta_2/\theta_1)$. For reasons outlined in Ben-Akiva and Lerman (1985), our prior is that $\theta_2 \leq \theta_1$. Consequently, $-\beta_\Phi^2$ is a lower bound of the α_{12} cost share. In practice, our tariff estimates at both stages imply that $\theta_2 \approx \theta_1$, which means that β_Φ^2 should be close to α_{12}.

6.3 Filters applied before estimation

The simulated method of moments we use in section 8 to estimate fixed costs parameters is computationally intensive. We therefore reduce the number of markets, firms, and models in our analysis. Because our counterfactuals only consider policy changes in North America and Europe, we drop 29 "China-only" firms that are dedicated to the Chinese market. This definition is based on a threshold of fewer than 2000 cars sold outside China. The precise selection criteria for the filtered sample are:

1. Restrict world sales to the 24 countries that dominate either EV production (cell or assembly) or EV sales. These countries account for 99.9% of cells produced, 98.6% of EVs produced, and 97.1% of EV sales.[18]

2. Keep 15 largest firms, ranked by world sales after excluding China-only firms (who account

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[17]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).

[18]This definition of world comprises Austria, Belgium, Canada, China, Czechia, Denmark, Finland, France, Germany, Hungary, Italy, Japan, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, South Korea, Spain, Sweden, Switzerland, United Kingdom, United States .

Table 3: Top 15 firms in 2022

No.	Firm	# Markets	# Models	Sales	Cum. shr.
1	Tesla	23	4	1,296,470	22.8
2	BYD	10	14	903,239	38.7
3	SAIC	17	21	807,223	52.9
4	Volkswagen	24	23	600,159	63.4
5	Geely	24	15	394,257	70.3
6	Hyundai	23	15	351,553	76.5
7	Stellantis	18	19	297,034	81.7
8	BMW	24	8	237,472	85.9
9	Renault	19	6	168,535	88.9
10	Mercedes-Benz	24	9	164,960	91.8
11	Nissan-Mitsubishi	23	8	158,739	94.6
12	Ford	22	4	124,818	96.8
13	General Motors	7	7	83,013	98.2
14	Toyota	23	8	49,374	99.1
15	Rivian	3	3	24,334	99.5

Number of markets and sales are restricted to the 24 countries used in SMM estimation.
Sample excludes firms that sell fewer than 2,000 cars outside China.

for 23.4% of world sales, but just 0.3% of sales outside China). Those top 15 firms, shown in Table 3, account for 99.5% of world production excluding China-only firms.

3. Restrict to the 137 models offered by the 15 large firms that have price data available in 2022. Prices are needed in the SMM because i) we need market shares in value to compute variable profits, ii) we allow fixed costs to vary with the implied quality of the model.[19]

None of the above filters is needed for the sourcing estimation because prices of cars are not relevant for sourcing decisions and the PPML estimator used for sourcing is very quick. However, we impose the filters to ensure the parameters correspond to the sample used later in the SMM. When estimating fixed costs we found it helpful to also aggregate potential plants from their specific latitude and longitudes to 15 locations of each stage with 5 per continent (Americas, Europe, Asia).[20] We do not impose this aggregation in the sourcing regressions because the point locations give more precise distance and country information for estimating the distance and border effects.

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[19]Appendix C details how we retrieve quality for each car model.

[20]In the SMM stage, Americas has Canada, Mexico, and 3 regions in the United States; Europe has a German-speaking region (Germany + Netherlands + Austria), a French-speaking region (France + Belgium + Luxembourg), Eastern Europe, Southern Europe (Italy + Spain + Portugal + Greece), and UK. Asia consists has Japan, South Korea, and 3 regions in China. When measuring distances, location latitude and longitude are averages of plants' coordinates for each stage within each location.

6.4 Sourcing estimation results

Table 4 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 4: Combined sourcing regression results

Stage:	(1) Cells	(2) Vehicle
Border	-0.953^a	-1.04^a
	(0.319)	(0.254)
log distance	-0.382^a	-0.112^c
	(0.021)	(0.062)
RTA	0.458	0.869^a
	(0.320)	(0.214)
Inc. cost of cells		-0.234^a
		(0.084)
log GDP per capita	0.213^c	0.206^b
	(0.118)	(0.087)
log(1+tariff)	-8.49^a	-8.56^a
	(2.34)	(1.74)
Observations	7,945	15,793
Squared Correlation	0.322	0.265

Note: The inclusive cost of cells are the expected costs of cells for assemblers, $\mathbb{E}c^1_{.,\ell_2}$, defined in equation (12). 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. Distance (measured using the great circle formula) influences cell sourcing but has a less significant effect on vehicle sourcing. This last result contrasts with the ones obtained (with a similar estimation method) for vehicles of all fuel types between 2000 and 2016 (and therefore mostly ICEs) from Head and Mayer (2019), where distance effects were stronger (the comparable coefficient being -0.323). BEVs therefore seem to be less sensitive to physical distance once assembled.[22]

Tariffs strongly influence sourcing decisions at both stages. The tariff elasticities are 8.49 and 8.56 for cells and vehicles, respectively. The coefficient on vehicle sourcing is remarkably similar to the one obtained by Head and Mayer (2019). Another influential policy variable is RTAs, which

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[21]Additional specifications that vary the control variables for each stage are shown in the online appendix tables O.A1 and O.A2. Those estimations also consider the whole sample available without the restriction imposed here on major countries and firms.

[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.

have a strong effect for EVs. This variable captures the removal of non-tariff barriers to trade which occurs inside those agreements, and seem more influential for cars than for batteries.

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 to use on the cell stage in equation (15). We can use the coefficient to determine the implied cost share of cells: $\alpha_{12} = -\theta_1 \beta_\Phi^2 / \theta_2$ As $\beta_\Phi^2 = -0.234$, if $\theta_1 = \theta_2$, the implied cost share of cells is around 23%. 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 figure 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 online appendix).

The regressions include source country fixed effects that we display and discuss in the online appendix O.A.2. We capture intra-national variation in productivity using log GDP per capita measured at the GAUL1 administrative level. This variable is more significant for cells than for vehicles. However, we do not use those country-level marginal cost and productivity estimates. There is selection bias in the choice sets of open facilities for each firm: our framework predicts that facilities are opened for a combination of low variable and fixed costs. We therefore use the SMM estimation developed in the next sections to recover both cost terms jointly.[23]

7 From Path Costs to Variable Profits

The nested logit parameters we have just estimated allow us to compute (log) path cost *differences* between any two paths based on their observable characteristics. We obtain the location-specific marginal cost differences $\text{FE}_{\ell_k}^k$ in the SMM estimation described in the following section. In that estimation, we need to compute—as a function of the remaining SMM parameters—the variable profit for any potential path in *levels*. This is because the firms' optimization problem shown in equation (1) subtracts fixed costs from the levels of variable profits. We now explain how we can recover variable profits in levels as a function of the path cost differences, using Exact Hat Algebra (EHA), pioneered by Dekle et al. (2007).

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[23] A second concern of the fixed effects for some countries is that they are identified by the choices of one or two models, leading to over-fitting. Despite these two concerns, the fixed effects retain a useful purpose in the sourcing regressions. Conditioning on them allows us to recover consistent estimates of the dyadic frictions.

7.1 Demand and Market Structure

Use of EHA is facilitated by the constant elasticity of substitution (CES) form for demand.[24] One convenient feature of CES is that the average own-price elasticity is widely reported in the literature. Table B1 in the appendix provides 18 different estimates, taken mainly from the Industrial Organization literature. We calibrate $\eta = 4.0$, the median of the negative of those estimates. Each country n spends an amount $R_n = \sum_m p_{mn} q_{mn}$ on light vehicles of all fuel types, where p_{mn} are delivered prices and q_{mn} are quantities. The price of model m in country n incorporates tariffs and consumer subsidies.

The EV share R_n^{EV}/R_n under CES is given by $(P_n^{\text{EV}}/P_n)^{1-\eta}$, where the P_n^{EV} and P_n are the price index for EVs and all light vehicles. The market share of model m (in values, as a fraction of *total* expenditures) depends on the ratio of the model's appeal-adjusted price p_{mn}/ξ_{mn} to P_n:

$$s_{mn} \equiv \frac{p_{mn} q_{mn}}{R_n} = \left(\frac{p_{mn}}{\xi_{mn}} \right)^{1-\eta} (P_n)^{\eta - 1}. \tag{16}$$

The all-vehicles price index, P_n, is decomposable as

$$(P_n)^{1-\eta} = \left(P_n^{ICE} \right)^{1-\eta} + \left(P_n^{EV} \right)^{1-\eta}, \qquad \text{with} \qquad P_n^{EV} = \left[\sum_m z_{mn} \left(\frac{p_{mn}}{\xi_{mn}} \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{17}$$

where z_{mn} is set to 1 for all models m sold in n (and 0 otherwise). The price index for internal combustion engine vehicles, P_n^{ICE}, is exogenous. For computational reasons, we approximate price/cost markups as $\eta/(\eta - 1)$.[25]

Let us now turn to specifying *path-specific* profits, as needed for the evaluation of equation (1). Prices are given by $p_{mn\ell} = [\eta/(\eta - 1)]c_{mn\ell}$, where delivered marginal costs, $c_{mn\ell}$, has two pieces. The first is the path cost $c(\ell_{mn})$, to which we return below. The second piece is a model-level cost shifter v_m. This would incorporate all causes of cross-model cost differences that do not depend on the path, such as the cost of producing a higher quality vehicle (more steel, more electronic sensors, etc.). For any path ℓ_{mn}, variable profits are

$$\pi_{mn\ell} = \frac{R_n s_{mn\ell}}{\eta}, \qquad \text{with} \qquad s_{mn\ell} = \left(\frac{\eta}{\eta - 1} \frac{c(\ell_{mn}) v_m}{\xi_{mn}} \frac{1}{P_n} \right)^{1-\eta}, \tag{18}$$

Any *change* in path ℓ shifts variable profits through *changes* in $(c(\ell_{mn})/P_n)^{1-\eta}$. The non-path

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[24]This assumption differs from most of the literature on the car industry which uses nested logit or mixed logit demands (Van Biesebroeck and Verboven, 2025). 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 a 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.

[25]Endogenizing markups would not matter much with this demand structure because individual EV firm market shares are small relative to all vehicles. We leave a thorough consideration of oligopoly pricing to future research.

specific-factors—$R_n, v_m, \xi_{mn}, \eta/(\eta-1)$—all cancel. This completes the specification of $\pi(c(\boldsymbol{\ell}_{mn}), A_n)$ used in the formulation of the firm's total profit shown in equation (1) (the MUFLP objective function). Variable profits depend on the path and the aggregator ($A_n = P_n^{\eta-1}$), thus complying with Assumption 1. We now show how $\pi_{mn\ell}$ for any potential path can be recovered from observed market shares, along with its cost change relative to the observed path.

7.2 Hat Algebra for Variable Profits

Following the notational standard established by Dekle et al. (2007), a variable with a "hat" on it, refers to the ratio of a model-predicted variable relative to its observed value. We use superscript $^\circ$ to denote the car industry configuration (comprising expenditure, paths, market shares, and the price index in each market) that we observe in the 2022 data. For each market n, let R_n° denote total expenditures on cars. This is associated with a reference (unobserved) price index P_n°. For each market n in our data, we can also measure $s_n^{\circ,\text{ICE}}$ as the aggregate market share of ICEs and s_{mn}° as the market share for EV model m in market n. These $^\circ$ values allow us to compute equilibrium outcomes for all the potential configurations relative to the observed configuration.

For any potential path $\boldsymbol{\ell}_{mn}$, the *changes* in path costs relative to the path *observed* in the data, denoted $\boldsymbol{\ell}_{mn}^\circ$, is given by

$$\hat{c}_{mn\ell} \equiv \frac{c_{mn\ell}}{c_{mn\ell^\circ}} = \frac{c(\boldsymbol{\ell}_{mn})}{c(\boldsymbol{\ell}_{mn}^\circ)}. \tag{19}$$

Using (16), we can express proportional changes in markets shares as function of changes induced by new paths as well as price index changes that aggregate the $\hat{c}_{mn\ell}$ across all models (model-market appeal ξ_{mn} is assumed invariant):

$$\hat{s}_{mn\ell} \equiv \frac{s_{mn\ell}}{s_{mn}^\circ} = \left(\frac{\hat{c}_{mn\ell}}{\hat{P}_n} \right)^{1-\eta}, \tag{20}$$

where $\hat{P}_n \equiv P_n/P_n^\circ$ is the (unobserved) change in the price index for market n. We describe later how we recover a measure of the related endogenous change in market demand. Therefore, with our assumption that overall expenditure of cars for each market (R_n) is constant, we can rewrite profit $\pi_{mn\ell}$ from (18) for any path as a function of cost *changes*:

$$\pi_{mn\ell} = \frac{1}{\eta} s_{mn}^\circ R_n^\circ \left(\frac{\hat{c}_{mn\ell}}{\hat{P}_n} \right)^{1-\eta}. \tag{21}$$

Hat algebra is helpful in obtaining variable profits by path *in levels* because it allows the market shares in the data to absorb many parameters that would otherwise need to be calibrated. Specifically, the observed market shares s_{mn}° absorb the demand shifters ξ_{mn}, the cost shifters v_m, the markup $\eta/(1-\eta)$, and the *level* of the price index, P_n°, that prevails in the observed equilibrium. The limitation of this approach is that we cannot obtain variable profits for a model in markets where it is not offered among the models used to obtain the observed market shares. Because of this, we take z_{mn} as given in estimation and policy simulations. The product entry decisions z_{mn}

are held fixed at their observed $\{0, 1\}$ status with the important proviso that the model permits the firm to exit markets if doing so raises profits. That is, the MUFLP decision does not force the firm to retain a model in a market if this entails fixed costs that exceed the variable profits. The fixed costs ϕ_{mn} of market entry are considered sunk and hence irrelevant.

The last computation needed in order to obtain variable profits in levels in (21) is $\hat{P}_n$. Hat algebra for $P_n^{1-\eta}$ yields:

$$\hat{P}_n^{1-\eta} = s_n^{\circ,\text{ICE}} + \sum_{m \in \mathcal{M}_n^{\circ}} s_{mn}^{\circ} \hat{c}_{mn}^{1-\eta}, \tag{22}$$

where $\mathcal{M}_n^{\circ}$ denotes the set of all EV models sold in market n in our data, and the observed market share of ICE models in n is

$$s_n^{\circ,\text{ICE}} = 1 - \sum_{m \in \mathcal{M}_n^{\circ}} s_{mn}^{\circ}. \tag{23}$$

In (22), $\hat{c}_{mn} = c(\boldsymbol{\ell}_{mn}^{*})/c(\boldsymbol{\ell}_{mn}^{\circ})$ (with the path $\boldsymbol{\ell}$ dropped) is defined in terms of the *optimal* chosen path denoted $\boldsymbol{\ell}_{mn}^{*}$ in the MUFLP optimization. Some models $m \in \mathcal{M}_n^{\circ}$ may be dropped for market n in that optimization choice, in which case $\hat{c}_{mn}^{1-\eta} = 0$.[26]

8   Simulated Method of Moments Estimation

In the previous section, we relied on hat algebra to reduce the number of parameters in the estimation (there are implicitly 3288 different ξ_{mn}). This method relies on observing initial market shares (s_{mn}°). We cannot use this parameterization approach to recover variable profits for markets that were not entered in the data.[27] Therefore, we treat the ϕ_{mn} as sunk costs: specifically, they are zero for markets entered in the data and infinite for those markets not entered. We therefore set the z_{mn} to zero for any market the model has not entered in the data. The firm chooses the optimal binary z_{mn} for all the remaining markets. The firm may choose to set $z_{mn} = 0$ when the production of model m is unprofitable. In that case, the facility fixed cost exceeds variable profits for that model, and the firm sets $z_{mn} = 0$ for all markets n (even those with positive sales in the data). This "soft" z constraint will help us recover the fixed cost parameters by targeting the number of models sold in each market.

8.1   Remaining Parameters: Fixed Effects and Fixed Costs

A choice of $\{\text{FE}_{\ell_k}^k, \phi_{fg_k\ell_k}\}$, along with our previously estimated parameters from section 6 (and calibrated ones from appendix C) fully determines the firms' objective function in (1). We group the locations into three continents $\mathcal{N} \in \{\text{Am}, \text{As}, \text{Eu}\}$ and estimate those remaining parameters

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[26]Alternatively, we could write the sum in (22) over the restricted set $\mathcal{M}_n$ of models chosen to be sold in m. However, note that (23) no longer holds when summing over $\mathcal{M}_n$.

[27]The alternative approach taken by Castro-Vincenzi et al. (2025) is to separately estimate the demand system in product characteristic space. This allows them to incorporate model entry into new markets and recover bounds for the associated fixed costs.

using SMM. We parameterize the fixed cost $\phi_{fg_k\ell_k}$ as a draw from a lognormal distribution

$$\ln \phi_{fg_k\ell_k} \sim \text{Normal}\left(\ln\left[\mu_{fg_k\ell_k} \times R_W^{\text{EV}}\right], \sigma_k\right),$$
$$\text{with } \mu_{fg_k\ell_k} = \exp\left[\ln \rho_{\mathcal{N}(\ell_k)}^k + \rho^{\text{HQ},k} \ln D_{h(f)\ell_k} + \rho^{\xi,k} \ln \tilde{\xi}_{fg_k}\right], \quad (24)$$

where $\rho_{\mathcal{N}}^k$ denotes the expected fixed cost of a single production line in continent $\mathcal{N}$ for stage k as a share of *observed* world EV revenue, R_W^{EV}. The $\rho^{\text{HQ},k}$ denotes the elasticities of fixed costs with respect to distance from firm headquarters, denoted $h(f)$, for each stage of production. $\rho^{\xi,k}$ is the elasticity of expected fixed costs with respect to quality, which corresponds to the geometric mean of ξ_{mn} across the destinations for the relevant fg_k. Note that changes in σ_k affect the *mean* of the log fixed cost for the *chosen* facilities. For the rest of the paper, we define $\boldsymbol{\rho} \equiv \{\rho_{\mathcal{N}}^k, \rho^{\text{HQ},k}, \rho^{\xi,k} \mid \mathcal{N} \in \{\text{Am}, \text{As}, \text{Eu}\}, k \in \{1, 2\}\}$ as the vector of 10 parameters that determine expected log fixed costs. We use the same continental grouping by $\mathcal{N} \in \{\text{Am}, \text{As}, \text{Eu}\}$ for the location-specific marginal cost differences, reducing those fixed effects to a vector $\textbf{FE} \equiv \{\text{FE}_{\mathcal{N}}^k \mid \mathcal{N} \in \{\text{As}, \text{Eu}\}, k \in \{1, 2\}\}$ of 4 parameters, normalizing the parameters for $\mathcal{N} = \text{Am}$ to zero. Overall, there are thus 16 parameters $\{\textbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}\}$ to estimate through SMM.

Fixed costs are likely to be higher for vehicle and cell manufacturing plants that produce more complex and powerful varieties. Equation (24) lets fixed costs vary with firm-level quality for the grouping of cells and car models that we use, computed by aggregating to the fg_k level the inferred levels of ξ_{mn}. Appendix C shows how we calibrate each ξ_{mn} and aggregate.

8.2 Selection Correction for Observed Paths

We need to compute the cost difference $\hat{c}_{mn\ell} = c(\boldsymbol{\ell}_{mn})/c(\boldsymbol{\ell}_{mn}^\circ)$ for every potential path $\boldsymbol{\ell}_{mn}$ relative to the path $\boldsymbol{\ell}_{mn}^\circ$ observed in the data. This requires draws of the shocks $u(\boldsymbol{\ell}_{mn})$ from our sourcing regression in section 6. Those shocks are distributed $u(\boldsymbol{\ell}_{mn}) \sim -\text{Gumbel}(0, \kappa)$, where $\kappa = 8.56$ is estimated as the tariff coefficient in Column 2 of Table 4. However, the shock for the observed path $u(\boldsymbol{\ell}_{mn}^\circ)$ is not a random draw from this distribution. It was the draw that led the firm to choose that path $\boldsymbol{\ell}_{mn}^\circ$. For example, if the path observables for $\boldsymbol{\ell}_{mn}^\circ$ imply a high cost (low estimated probability $\mathbb{P}(\boldsymbol{\ell}_{mn}^\circ)$ in equation 9), then the actual $u(\boldsymbol{\ell}_{mn}^\circ)$ draw must have been very low in order to induce the firm to choose that path $\boldsymbol{\ell}_{mn}^\circ$.

Following Hanemann (1984), we can adjust for this selection bias using the fact that the distribution of $u(\boldsymbol{\ell}_{mn})$—*conditional* on path $\boldsymbol{\ell}_{mn}^\circ$ being chosen—is also Gumbel, but with a location parameter shifted down by $-\kappa \ln \mathbb{P}(\boldsymbol{\ell}_{mn}^\circ)$. Therefore, we calculate $c(\boldsymbol{\ell}_{mn}^\circ)$ using a draw from the following distribution:[28]

$$u(\boldsymbol{\ell}_{mn}) \mid_{\boldsymbol{\ell}_{mn}=\boldsymbol{\ell}_{mn}^\circ} \sim -\text{Gumbel}\left(-\kappa \ln \mathbb{P}(\boldsymbol{\ell}_{mn}^\circ), \kappa\right). \quad (25)$$

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[28]For potential paths equal to the observed path $\boldsymbol{\ell}_{mn}^\circ$, the numerator of $\hat{c}$ uses the actual u from the denominator. That is, the draw from the conditional distribution. Hence, $\hat{c}_{mn\ell^\circ} = 1$ for the observed paths of all mn combinations.

8.3 Industry Equilibrium Constraints

A simulation j is characterized by a set of Lognormal draws for the fixed costs $\phi_{f g_k \ell_k, j}$ and Gumbel draws for the cost differences $\hat{c}_{mn\ell, j}$. In this simulation, the firm's realized variable profit for any potential path is given by (21), where variable profit $\pi_{mn\ell, j}$ now depends on the simulation-specific $\hat{c}_{mn\ell, j} / \hat{P}_{n, j}$. We assume that firms do not observe the cost draws of their competitors, and therefore face some uncertainty regarding the realized price index $\hat{P}_{n, j}$ in any given simulation j. In their optimization problem, firms therefore choose the optimal paths based on their anticipated profits:

$$\mathbb{E}\left[\pi_{mn\ell, j}\right] = \frac{1}{\eta} s_{mn}^{\circ} R_n^{\circ} \left(\hat{c}_{mn\ell, j}\right)^{1-\eta} \hat{\mathbb{A}}_n, \tag{26}$$

where $\hat{\mathbb{A}}_n \equiv \mathbb{E}\left[\left(\hat{P}_{n, j}\right)^{\eta-1}\right]$ denotes this anticipated level of market demand resulting from the uncertainty over the realized price index $\hat{P}_{n, j}$. The $\hat{\mathbb{A}}_n$ are endogenous variables that tie the individual firm optimizations together. The estimation sets the $\hat{\mathbb{A}}_n$ equal to their sample moments across simulations j:

$$\hat{\mathbb{A}}_n = \frac{1}{J} \sum_{j=1}^{J} \left(\hat{P}_{n, j}\right)^{\eta-1} = \frac{1}{J} \sum_{j=1}^{J} \left(s_n^{\circ, \text{ICE}} + \sum_{m \in \mathcal{M}_n^{\circ}} s_{mn}^{\circ} \hat{c}_{mn, j}^{1-\eta}\right)^{-1}, \tag{27}$$

where we have used the expression for $\hat{P}_{n, j}$ from (22).

Similar incomplete information approaches to market equilibrium have been used by Seim (2006), Sabal (2025), and Dingel and Tintelnot (2026). Whereas the first two papers model the industry as an oligopoly, we retain the monopolistic competition in the construction of a single anticipated demand adjustment $\hat{\mathbb{A}}_n$. In this respect, our approach resembles the "continuum-case rational expectations" beliefs in Dingel and Tintelnot (2026). Since equation (27) imposes an equilibrium constraint across simulations, the incomplete information approach offers the additional benefit of allowing us to use the tools of mathematical program with equilibrium constraints (MPEC) developed by Su and Judd (2012).[29]

8.4 Moments and Estimation

We draw path-level marginal cost shocks $u(\cdot)$ and fixed costs across locations for groups of models $J = 100$ times. For one set of draws and given a guess of parameters $\{\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}\}$, and market demand adjustments, $\hat{\mathbb{A}}_n$, we solve each firm's MMM-UFLP optimal location problem. We use 47 targeted moments, matching the simulated averages to their observed values in the data. The moments are organized into five blocks, grouping locations into the same three continents $\mathcal{N} \in \{\text{Am}, \text{As}, \text{Eu}\}$ corresponding to the cost parameters. The first block matches dyadic flows

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[29]The complete information counterpart would require each firm to observe the cost draws of all of its rivals and simultaneously solve all the location decisions and corresponding market demand vector. Our approach avoids cycling in the interconnected location decisions and dramatically reduces the computational burden.

across continents by targeting expenditure shares between and within continents at each stage.[30] The second block targets the number of car models sold in each continent expressed as a ratio relative to the data. The third block targets the number of production lines by continent $\mathcal{N}$ and stage k, as a ratio relative to the number of production lines in the data. A production line is an activated facility $y_{fg_k\ell_k} = 1$ for group g_k (a platform for assembly, and battery category for cells). The simulated number of production lines sums the $y_{fg_k\ell_k}$ for each stage and continent $\mathcal{N}$. The fourth block captures how those production lines vary with respect to the location of the firm's headquarters. It targets the share of production lines in a continent based on the continental headquarters of its owner (for both cells and assembly). Lastly, we target the standard deviations of realized log fixed costs from news articles, namely 1.50 for cell plants and 1.62 for assembly plants.

Moments in the first two blocks use bilateral flows and model entry contribute to the identification of the relative variable cost differences across continents and the level of variable costs relative to fixed costs. The remaining blocks help to identify the mean fixed costs by continent, how they vary with distance to firm headquarters and with quality, and their variance.

Formally, the vector of moment function, $v(\cdot)$, specifies the differences between the observed outcomes and those predicted by the model. At the true parameter value, $\mathbb{E}\big[v\big(\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}; \hat{\mathbb{A}}\big)\big] = 0$ and equation (27) holds. We estimate both market demand adjustments $\hat{\mathbb{A}}$ and structural parameters $\{\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}\}$ such that the SMM objective function is minimized subject to the market demand equations as constraints (MPEC):

$$\min_{\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}, \hat{\mathbb{A}}} \check{v}\big(\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}; \hat{\mathbb{A}}\big)' W \check{v}\big(\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}; \hat{\mathbb{A}}\big), \quad \text{subject to} \quad \hat{\mathbb{A}} = f(\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}; \hat{\mathbb{A}}), \tag{28}$$

where $\check{v}(\cdot)$ is the simulated estimate of the moment function, $f(\cdot)$ is the right-hand side of equation (27), and W is the SMM weighting matrix. We first use an identity matrix W, and then multiply the weights for the monadic moments by three (the number of continents). This equalizes the weights assigned to monadic and dyadic moment blocks.

One difficulty in estimating this type of problem is that there are frequently multiple local optima. To search for a global optimum, we implement 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.[31]

Table 5 shows the results of the estimation. The $\mathrm{FE}_{\mathcal{N}}^k$ estimates determine differences in log wages (variable costs) between $\mathcal{N}$ and North America. The $\boldsymbol{\rho}$ parameters determine the mean of the log fixed cost draws. Continental fixed cost differences are moderated by the distance to the firms' headquarters. Both sets of fixed costs rise as firms build plants further from their head-

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[30]For cells, the flows from continent o to d are evaluated using the vehicle values assembled in d with cells sourced from o.

[31]We implement TikTak with 1000 random starts. The algorithm retains the 25 starts with the best objective function values and augments this set with a "prepend" parameter vector (based on priors or a vector of previous estimates). We then use a local optimizer that imposes the endogenous market demand constraint, along with a tightened convergence criteria.

Table 5: SMM parameter estimates

Param.	$\mathcal{N}$	Description	Estimate	90% C.I.
FE^1	As	Variable cost advantage of cell plant	4.91	[2.14, 5.78]
FE^1	Eu	(by region, Am = 0)	5.94	[4.08, 7.97]
FE^2	As	Variable cost advantage of assembly plant	-0.21	[-1.36, 0.82]
FE^2	Eu	(by region, Am = 0)	-0.25	[-0.89, 0.97]
ρ^1	Am	Fixed cost of cell plant (by region)	0.30	[0.22, 0.90]
ρ^1	As		0.12	[0.04, 0.21]
ρ^1	Eu		0.54	[0.25, 1.07]
ρ^2	Am	Fixed cost of assembly plant (by region)	0.16	[0.11, 0.64]
ρ^2	As		0.03	[0.03, 0.25]
ρ^2	Eu		0.18	[0.16, 1.38]
$\rho^{HQ, dist,1}$		Fixed cost HQ distance elas. (cells)	0.47	[0.40, 0.83]
$\rho^{HQ, dist,2}$		Fixed cost HQ distance elas. (assembly)	0.78	[0.64, 1.75]
$\rho^{\xi_{fg1}}$		Fixed cost quality elas. (battery type)	3.40	[2.47, 3.96]
$\rho^{\xi_{fg2}}$		Fixed cost quality elas. (platform)	2.76	[2.31, 4.06]
σ_1		Fixed cost dispersion (cells)	2.12	[1.54, 2.74]
σ_2		Fixed cost dispersion (assembly)	1.99	[1.29, 2.33]

quarters, but the effect on assembly is an order of magnitude larger than on cells. The estimated $\sigma_1 = 2.12$ and $\sigma_2 = 1.99$ of the fixed cost distribution imply that standard deviations for realized log fixed costs to be 1.95 for cell plants, and 2.03 for assembly plants, which are slightly larger than the targeted 1.50 and 1.62 respectively.

Variable costs relative to America are given $\exp(-\kappa FE_{\mathcal{N}}^k)$. Relative mean fixed costs in stage k between two continents are given by the ratio of their respective $\rho_{\mathcal{N}}^k$ estimates. [32] Since the variable and fixed cost estimates can point in different directions, a calculation of relative average costs provides a useful composite measure of production-cost competitiveness. The ratio of average costs is a weighted average of the ratios of fixed and variable costs with the weights given by the respective shares of total costs. This implies we can back out relative average costs with the formula

$$\frac{AC_{\mathcal{N}}^k}{AC_{Am}^k} = \frac{FC}{TC} \times \frac{\rho_{\mathcal{N}}^k}{\rho_{Am}^k} + \left(1 - \frac{FC}{TC}\right) \times \exp(-\kappa FE_{\mathcal{N}}^k).$$

Our estimates imply the total fixed costs paid to world sales ratio is 7% in the BEV sector.[33] The constant markup assumption implies the ratio of variable costs to revenues is $(\eta - 1)/\eta = 0.75$, which in turn implies FC/TC = 0.085.

Table 6 makes use of these relationships to re-express the variable and fixed cost coefficients in a way that is much easier to interpret than the raw SMM parameter estimates shown in the first 10 rows of Table 5. Columns (3) and (6) computes average production costs for cells and assembly in

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[32]See equations (15) and (24) respectively.

[33]Predicted total realized fixed cost equals to 18.85 billion and world (anticipated) EV sales is 267.36 billion, and therefore $18.85/267.36 \approx 0.07$.

Europe and Asia, both compared to the Americas.

Table 6: Relative variable, fixed and average production costs (compared to North America)

Region	Cells			Vehicles		
Ratio:	var.	fixed	avg.	var.	fixed	avg.
Europe	-50.06	83.30	-38.67	2.93	12.54	3.75
Asia	-43.64	-57.80	-44.85	2.47	-78.79	-4.47

% difference with respect to costs in the Americas.

We estimate the fixed costs to be highest in Europe and lowest in Asia. This is true for both cells and vehicles, but Europe's disadvantage in cells is much larger. North America has a substantial cost disadvantage in average costs of cells relative to the other two continents. The gaps are much smaller for vehicles, and North America has a slight average cost advantage over Europe.

The confidence intervals shown in Table 5 are obtained via bootstrap sampling of firms, as in Antràs et al. (2017) and Bernard et al. (2022). We hold fixed the number of firms drawn by headquarters continent at six for Asia, four for North America, and five for Europe.[34] For each bootstrap sample, we construct the empirical moments used in the structural estimation, simulate 100 sets of cost shocks, and globally estimate parameters of the model for that sample.[35]

Sampling firms ensure that our key interdependencies, including dependencies across locations, models, and paths, are preserved within a firm. Although across firms, they are still correlated via endogenous price index, we estimate $\hat{\mathbb{A}}$ close to one across all countries in the baseline, implying that price indices are nearly fixed and dependencies across firms are weak. We further verify that the market demand adjustments remain close to one in bootstrap estimates.

The confidence intervals reported in Table 5 are based on the lower 5% and upper 5% quantiles of the bootstrap parameters. The wide range we see for some parameters arises in part because the procedure samples over a small number (15) of highly asymmetric firms. Thus, a particular bootstrap sample might replace a giant firm like Tesla with several instances of the much smaller Rivian. Since the variation in the bootstrap moments is so large, we see the confidence intervals as being conservative. What matters in the end is whether the imprecision in the estimates generates volatile counterfactual policy predictions. In the next section we show prediction ranges for counterfactuals. The reassuring finding is that policy effects are very stable across bootstrap parameter sets.

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[34]The results shown are based on 40 bootstrap samples drawn with replacement. Sampling within headquarter continents ensures that the bootstrap sample moments include activity on each continent.

[35]Depending on firms drawn in the bootstrap sample, EV revenue in each market, R_n^{EV}, is computed accordingly. Keeping ICE vehicle revenue in each market the same as in the full sample and summing it with bootstrapped EV revenue, we obtain the total vehicle revenue, R_n° equivalent, in each bootstrap sample. Market share in the bootstrap sample, s_{mn}° equivalent, is calculated by dividing the EV revenue of the drawn firms to the bootstrapped total vehicle revenue.

8.5 Targeted fit

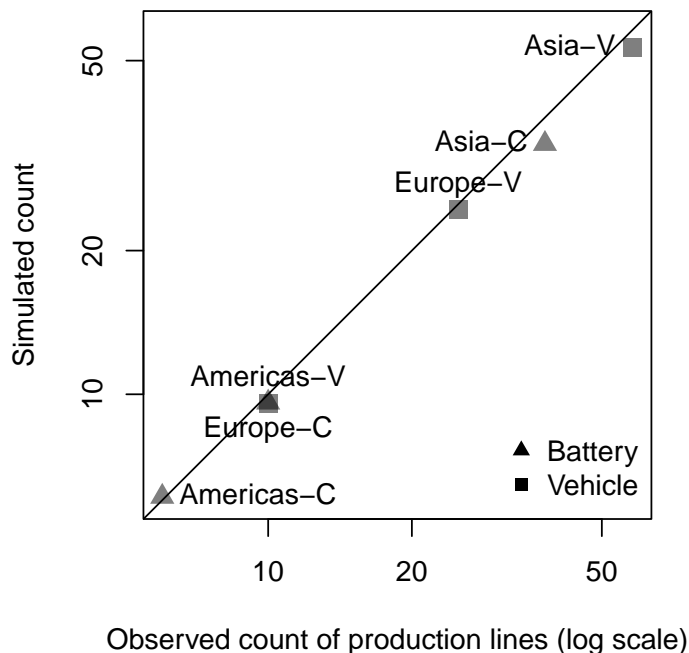Figure 8: Production lines by continent

Observed count of production lines (log scale)

Table 7: Model market entry

	# car models		Rev.
	data	baseline	(%)
Americas	49	43.0	92.1
Asia	111	99.9	92.5
Europe	83	77.2	94.2

Note: Model prediction at baseline is averaged across all simulations. Column (1) is the targeted data moment. Column (3) is the % of observed sales by car models we keep in the prediction, averaged across simulations.

The plausibility of our policy counterfactuals depends to a large extent on whether the estimated model can replicate the key features of intercontinental battery and EV production and trade. We therefore want to look closely at the fit of the targeted moments. Figure 8 shows the count of production lines on each continent in the data (horizontal axis) and in our estimated model (vertical axis). Thus, it captures whether the model accurately predicts the $y_{fg_k\ell_k}$ in the firm's problem, which in turn depends on correctly estimating fixed costs of activating plants. All six points fit the 45-degree line closely, with Asia's dominance of both stages clearly replicated by the model. Table 7 shows the fit of model entry, z_{mn} in the optimization. Because of the "soft z" procedure, the baseline has to lie below the data. However, predicted entry in all three continents is close to actual entry. Furthermore, the EV models that the simulation predicts to be profitable account for over 92% of actual revenues.

Figure 9 displays the continent-to-continent fits for two more important moments. Panels (a) and (b) show the number of production lines by headquarter-production dyads. For example, in panel (a), Europe-origin vehicle makers account for about 20% of the cell production lines in North America. This is only slightly more than what we see in the data. The fit for vehicles is also strong, with the simulation replicating strong intra-continental bias. The model predicts higher shares for Asian makers in North America than we see in the data. Panels (c) and (d) show the share each production origin accounts for in *expenditure*. For example, the simulations predict that vehicles with Asia-made cells make up about half of all vehicles assembled in Europe. In reality,
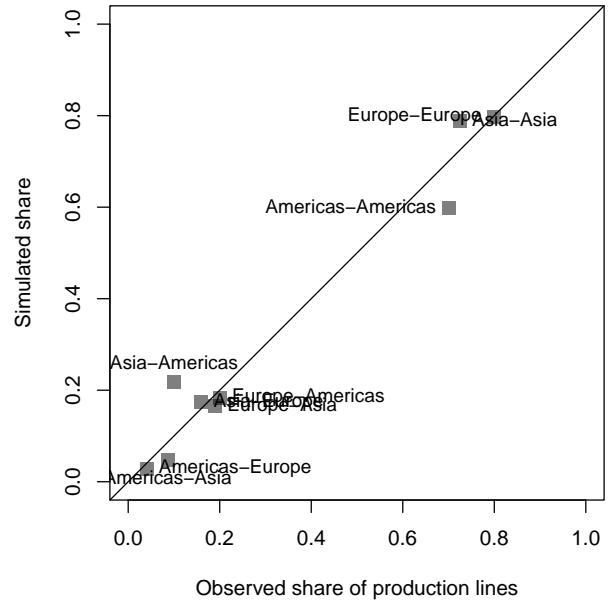
35

Figure 9: Fit of the targeted dyadic moments

Production lines by firm origin–production location
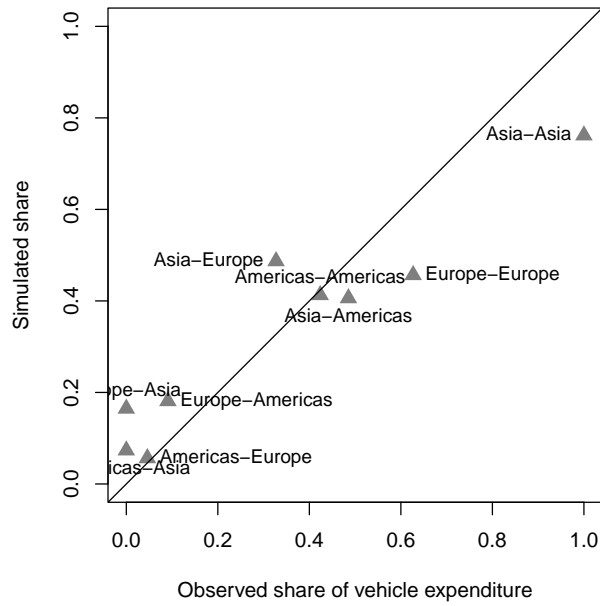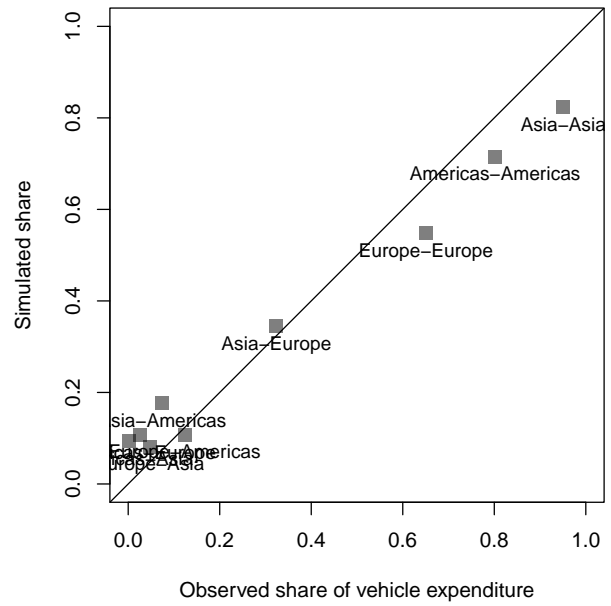
(a) battery cells
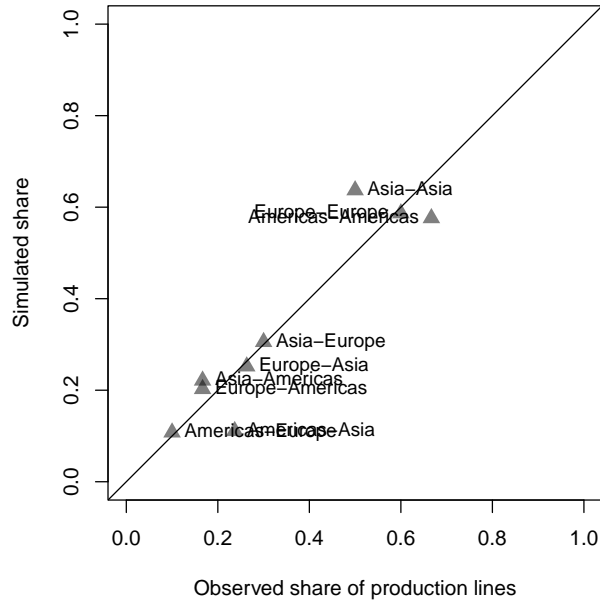
(b) vehicle assembly

Expenditure shares by production location–destination

(c) battery cells

(d) vehicle assembly

Note: The SMM targets these moments.

it is about 35%. Panel (d) again shows home bias in all three continents, but in this case it is based on location of assembly, rather than location of headquarters.[36]

9   Counterfactual Policy Simulations

In recent years governments in North America, Europe and Asia have put in place (and sometimes removed) policies to stimulate purchases of EVs such as consumer subsidies. Over time, contingencies have been added to those subsidies. We will focus on widely used requirements on the location of production along the supply chain. In our case, the location of assembly and cell production.

More specifically we model the following scenarios:

1. **Subsidy to EV buyers:** The government subsidizes EV purchases 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 and vehicle must be produced in the same continent as the buyer.

Policy 1 resembles the common practice in Europe and Canada (and the US before the 2022 Inflation Reduction Act) where subsidies were not contingent on production locations. Policy 2 adds the "buy domestic" requirement at the assembly level. We impose this at the continental level, which is similar to the IRA requirement that included Canada and Mexico. Policy 3 mirrors the IRA policies regulating the input sources of EVs to be eligible for the subsidy. The IRA phased in mineral and components requirements for obtaining a full $7500 subsidy. Had the policy not been eliminated in 2025, 100% of components would be required from the US or Free Trade Agreement (FTA) by 2029. Allcott et al. (2024) evaluate the effects of the IRA, taking into accounts its detailed requirements as well as the exemption for leased cars. Their framework takes production locations as given, whereas the simulations here focus on how policies induce changes in facility locations.

Upstream requirements for subsidies are not unique to the IRA. For example, France introduced in 2024 an "Eco score" cutoff for the CO2 emissions of the overall production process in order for an EV to be eligible to the demand subsidy. Without specifically naming China, the policy *de facto* excludes cars made with Chinese batteries.[37] In 2025 the French government added a 1000 Euro supplement for EVs with European batteries. In our simulation, the rule is that only cells produced inside the continent are eligible for the consumer subsidy.

Production subsidies and tariffs are additional policies that feature prominently in the auto industry. Our framework easily accommodates those policies, but we relegate their analysis to

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[36]Appendix E shows the fit of the estimated model with respect to several untargeted moments.

[37]Malgouyres et al. (2025) show that failure to attain the Eco-score minimum entails a 60% reduction in sales.

Appendix F due to space considerations (including combinations with consumer subsidies as in the original IRA). Another salient policy we do not explicitly model is an emission tax on ICEs. This is because our unconditional 20% subsidy for EVs (policy 1) is equivalent to a uniform 25% tax on ICEs in terms of all the market outcomes we describe.[38]

9.1 Policy Simulation Results

Up to now, we have used $\hat{c}_{mn,j}$ to denote the entire change in model m's delivered marginal cost to n. This cost also includes existing tariffs and subsidies that our counterfactual simulations hold constant across scenarios. We use $\hat{t}_{mn,j}$ to denote the *additional* subsidy enacted in our counterfactual scenarios, which we compare to a *baseline* case where $\hat{t}_{mn,j} = 1, \ \forall m, n, j$. Thus, while $\hat{c}_{mn,j}$ denotes the cost change in this baseline (relative to data), the cost change in a counterfactual scenario (relative to data) is given by $\hat{c}_{mn,j}\hat{t}_{mn,j}$.

In order to make the scenarios comparable, we set a common counterfactual subsidy rate of 20% at the continental level: $\hat{t}_{mn,j} = .8, \ \forall n \in \mathcal{N}$—whenever model m is eligible under the counterfactual scenario. Since eligibility may also depend on the location of production (cell or vehicle assembly), $\hat{t}_{mn,j}$ will vary across simulations j for a given model m and destination n based on the chosen path ℓ_{mn} (except in policy 1).

For each counterfactual, we report three sets of outcomes, aggregating from individual countries n to their respective continents $\mathcal{N}$, and averaging across simulations $j \in J$:

1. Changes in production lines (change in the sum of activated locations $y_{fg_k\ell_k}$ in continent $\ell_k \in \mathcal{N}$ for both cells and vehicles),

2. Changes in EV expenditure

3. Decomposition of expenditure changes into:

   (a) the direct effects of policy,

   (b) the changes in variable costs due to path changes,

   (c) the associated change in market demand ($\hat{\mathbb{A}}$),

   (d) changes in model entry (z, the number of varieties offered in each market).

We will report all of those outcomes for each scenario relative to the baseline case ($\hat{t}_{mn,j} = 1, \ \forall m, n, j$). Production lines are our proxy for production and employment, whereas EV expenditure is a proxy for emissions reductions. We do not model directly how CO2 emissions from internal combustion engines change in response to our policies. Since we hold total expenditure on vehicles fixed, the change in EV expenditure corresponds to the reduction in ICE expenditure. 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. Throughout the counterfactual exercises, we re-solve for the

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[38]See Section A.1 in the appendix for a derivation of this equivalence. The equivalence does not extend to the fiscal consequences for the government's budget balance.

new equilibrium price index via fixed point iteration such that the market equilibrium condition specified in (27) holds after the policy change.

The change in EV expenditure is computed as follows: In the data, the total EV expenditures in market n is $R_n^{\circ,\text{EV}} \equiv R_n \sum_{m \in \mathcal{M}_n^\circ} s_{mn}^\circ$. Let $R_{\mathcal{N}}^{\circ,\text{EV}} \equiv \sum_{n \in \mathcal{N}} R_n^{\circ,\text{EV}}$ denote the EV expenditures at the continent level. In each simulation j, an EV model's expenditure change (relative to the expenditure in the data) is $\hat{c}_{mn,j}^{1-\eta} \hat{t}_{mn,j}^{1-\eta} \hat{P}_{n,j}^{\eta-1}$. The continental change in EV expenditure is an average of those changes over continents (with weight $R_n^{\circ,\text{EV}}/R_{\mathcal{N}}^{\circ,\text{EV}}$), over simulations (with weight $1/J$), and over models (with weight s_{mn}°):

$$\bar{\hat{R}}_{\mathcal{N}}^{\text{EV}} = \sum_{n \in \mathcal{N}} \frac{R_n^{\circ,\text{EV}}}{R_{\mathcal{N}}^{\circ,\text{EV}}} \sum_j \frac{1}{J} \sum_{m \in \mathcal{M}_{n,j}} s_{mn}^\circ (\hat{c}_{mn,j}^{1-\eta} \hat{t}_{mn,j}^{1-\eta} \hat{P}_{n,j}^{\eta-1}) \tag{29}$$

9.1.1 North America

Figure 10: Counterfactual results with 20% subsidy in the Americas

(a) Continental production lines

(b) Expenditures on EVs

% change number production lines wrt baseline

% change total expenditure on EVs wrt baseline
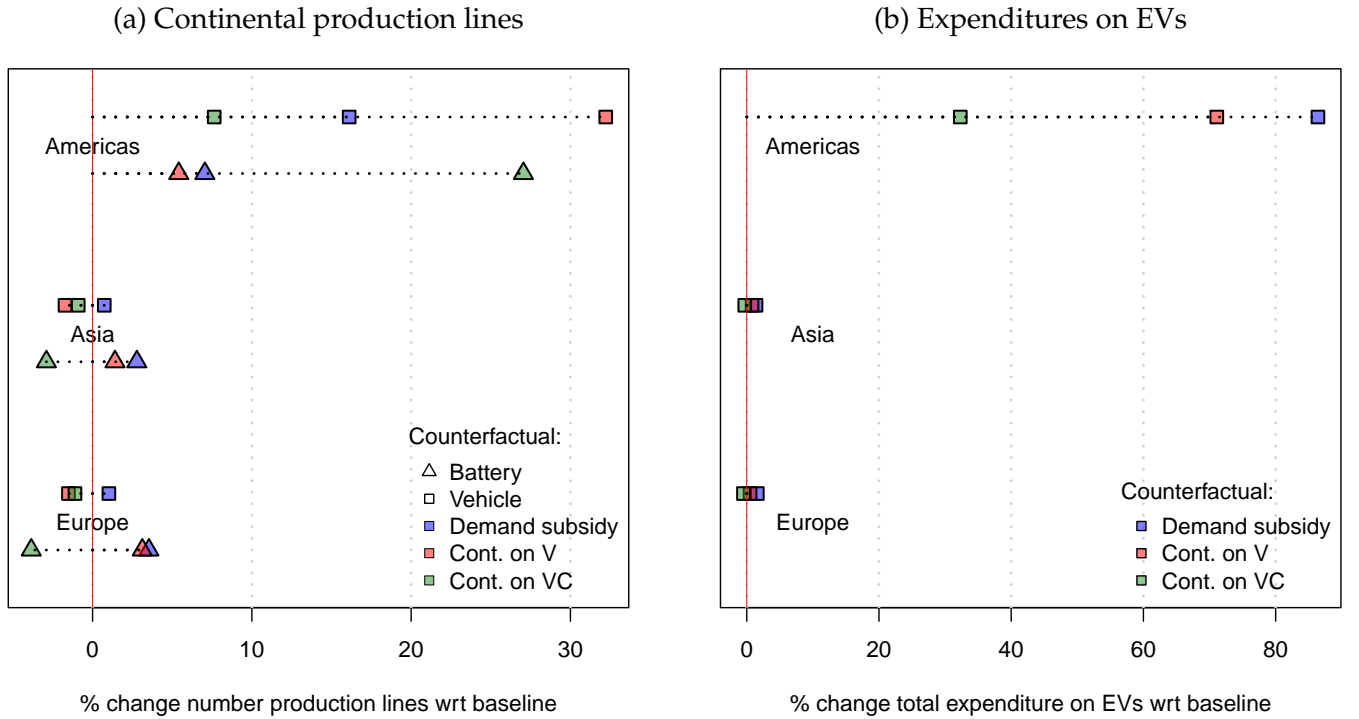
Figure 10(a) provides the continental summary of our y plant activation indicators in response to a 20% subsidy for EV purchases in North America (policies 1-3). Squares correspond to the change in assembly production lines and triangles in cell production lines for each continent. Those changes are taken with respect to the baseline prediction of the model, which as shown in Figure 8(a) is very close to the data. The unconditional subsidy (Policy 1 in blue) raises the number of production lines in the Americas by 16% for assembly and 7% for cells. This indicates a significant impact of the subsidy on production capacity, highlighting the effectiveness of financial

incentives in stimulating EV manufacturing. The complementarity between assembly and cell production in the subsidizing region also appears clearly in these results.

Figure 10(b) provides the percent change in expenditures on EVs implied by the policy changes (recalling that the total expenditure on cars is constant, this implies that the policies displace ICE sales). The unconditional subsidy increases expenditure on EVs by 86%. This increase is so large that the rise in the number of vehicles assembled in the Americas does not come at the expense of Europe or Asia. The number of assembly lines on those continents rise by 1% and 0.7%, respectively (the collateral benefit for cells is even a little higher for both regions). While the subsidy is ostensibly neutral in its application, because it is not contingent on production locations, it still reallocates production shares in favor of the subsidizing region. In a constant returns model without fixed costs, production in the three continents would be increased by the same proportion.

Imposing domestic final assembly as a condition for the subsidy (Policy 2 in red: "Buy American" generalized to include Canada and Mexico) raises production lines by nearly a third compared to the baseline. This hurts Asia by about 2% of their assembly lines relative to the baseline. European assembly is similarly adversely affected by the buy-American subsidy. Online appendix O.B displays dyadic results in Figure O.B3 and Table O.B4, in terms of the count of car models sourced from each continent. They show that the assembly-contingent subsidy promotes cell exports from Asia to the Americas (for 5 extra models), while lowering vehicle exports (4 less model).

While successful in terms of domestic protection, figure 10(b) shows that Policy 2 lowers expenditures on EVs and thus is not appealing as an environmental policy relative to the unconditional subsidy in Policy 1.[39] The policy is also unsuccessful at promoting cell-production in America. Hence, we turn to the natural alternative where the subsidy is contingent on *both* local assembly and cell production.

Policy 3 does indeed increase cells' production lines by 27% (4 times more than policy 1 and 5 times more than policy 2). However, the increase in costs implied by the relocation (recall that our estimates imply that America is the most costly place to produce cells) hurts vehicle assembly, which falls to less than a quarter of the increase in policy 2. Importantly, the weaker outcome on production is accompanied by a sharp reduction in the EV expenditure relative to the two other policies. Unless the objective is strongly biased in favor of the local production of batteries, policy 3 is dominated by the alternative subsidy schemes.[40] Policy 3 has the added drawback of alienating trade partners: Production of vehicles and cells in the two other continents unambiguously suffers from this extreme version of the local content restriction of the American demand subsidy.

All results in our main counterfactual figure 10 depend on the set of SMM estimates. Those coefficients are estimated with some error, so we would like to know how different the policy outcomes would be with a different set of estimates drawn from the parameter confidence interval.

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[39]Tables F6 and F7 in Appendix F presents the numbers underlying the visualizations in Figures 10 and 11.

[40]In appendix table F6 we see that augmenting policy 3 with a cell production subsidy would add vehicle production lines relative to policy 3 alone. 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.

Table 8: Variation in counterfactual production lines (North American policy)

| Policy | EV prod. lines (#) | | | | Cell prod. lines (#) | | | | EV expenditure (%) | | | |
| | Sim | | Boot | | Sim | | Boot | | Sim | | Boot | |
	Q1	Q3	Q1	Q3	Q1	Q3	Q1	Q3	Q1	Q3	Q1	Q3
Americas												
1: Unconditional	1	2	1.2	1.6	0	1	0.3	0.4	71.4	98.3	85.9	91.8
2: Continental V	2	4	2.3	3.3	0	1	0.3	0.5	56.5	83.3	69.8	75.7
3: Continental V+C	0	1	0.6	0.9	1	2	1.2	1.7	19.8	46.0	34.8	40.8
Asia												
1: Unconditional	0	1	0.4	0.5	0	2	0.9	1.1	0.0	1.9	1.2	1.7
2: Continental V	-1	0	-0.8	-0.5	0	1	0.4	0.6	-0.1	1.2	0.6	1.3
3: Continental V+C	-1	0	-0.4	-0.2	-2	0	-1.0	-0.8	-0.5	0.1	-1.1	-0.4
Europe												
1: Unconditional	0	1	0.4	0.5	0	1	0.4	0.5	0.3	2.7	1.6	2.0
2: Continental V	-1	0	-0.4	-0.2	0	1	0.2	0.3	-0.5	1.4	0.2	0.6
3: Continental V+C	0	0	-0.2	-0.1	-1	0	-0.4	-0.3	-1.2	0.1	-0.7	-0.3

Sim: Figures obtained from the variation over simulation draws of counterfactual outcomes with Table 5 parameter estimates. This is always an integer for production lines.
Boot: Figures obtained from the variation over bootstrapped estimates for *mean* outcomes over simulations.

On top of that, counterfactual changes shown in this figure are constructed from a set of 100 simulations. A different set of draws would lead to different policy outcomes. Table 8 investigates those two sources of variation in the three sets of predicted outcomes (EV and cell production lines and EV expenditures). For each of those outcomes, we provide the first and third quartiles over the simulations and bootstrap replications. The most salient feature of Table 8 is that the Boot interquartile ranges are almost always substantially more narrow than the Sim ranges. Thus, parameter variation matters less than variation in the draws of fixed and variable costs. The narrow bootstrap variation means that policies can still be ranked in terms of their outcomes. Policy 1 is best for expanding EV purchases, Policy 2 expands EV production lines the most and policy 3 is best at expanding cell production lines. Cross-continent effects are smaller than within-continent, but always positive for the unconditional subsidy. The V+C contingency in North America is systematically bad for production and EV adoption in Europe and Asia.

The three rows of Table 9 unpack the components of the North American EV expenditure shares of the North American subsidies.[41] The last column reproduces the expenditure change graphically shown in the top line of Figure 10(b).[42] The first column reports the share of paths (mn, j combinations) that are eligible for the subsidy. The second column reports the corresponding share of revenue. The revenue shares are larger, indicating that the paths for higher market

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[41]Section A.3 of the appendix derives a full decomposition of the average EV expenditure change $\bar{\hat{R}}_{\mathcal{N}}^{\mathrm{EV}}$ into the components $\tilde{\hat{t}}_{\mathcal{N}}, \tilde{\hat{c}}_{\mathcal{N}}, \bar{s}_{\mathcal{N}}^{\mathrm{EV}}, \hat{\mathbb{A}}_{\mathcal{N}}$. That decomposition also includes covariance terms between those components.
[42]Table O.B5 in the online appendix reports impacts of the North American policy for the other two continents.

shares models are more likely to be adjusted to attain eligibility. The next two columns report an average of the policy ($\hat{t}_{mn,j}$) and delivered ($\hat{c}_{mn,j}$) cost changes across continents, simulations, and models using the CES cost index (denoted with a˜). For the cost changes $\hat{c}_{mn,j}$, that CES cost index is:

$$\tilde{\hat{c}}_{\mathcal{N}}^{1-\eta} = \sum_{n \in \mathcal{N}} \frac{R_n^{\circ,\text{EV}}}{R_{\mathcal{N}}^{\circ,\text{EV}}} \sum_j \frac{1}{J} \sum_{m \in \mathcal{M}_{n,j}} \frac{s_{mn}^{\circ}}{\bar{s}_n^{\text{EV}}} \hat{c}_{mn,j}^{1-\eta}, \tag{30}$$

where $\bar{s}_n^{\text{EV}} \equiv (1/J) \sum_j \sum_{m \in \mathcal{M}_{n,j}} s_{mn}^{\circ}$ is the average share of EVs across simulations for market n accounting for dropped models from $\mathcal{M}_n^{\circ}$ that are not in $\mathcal{M}_{n,j}$ (the soft z for that model in simulation j is set to zero). Thus, all the weights in the CES index (across countries n, simulations j, and models m) sum to 1.

Table 9: Cost and expenditure changes in Americas

| Policy | Eligible share | | Cost index change | | Shifters | | EV Exp. change |
| | path | revenue | subsidy | costs | variety | demand | |
			$\tilde{\hat{t}}_{\mathcal{N}}$	$\tilde{\hat{c}}_{\mathcal{N}}$	$\bar{s}_{\mathcal{N}}^{\text{EV}}$	$\hat{\mathbb{A}}_{\mathcal{N}}$	$\tilde{\hat{R}}_{\mathcal{N}}^{\text{EV}}$
1: Unconditional	100.0	100.0	-20.0	-4.5	2.5	-16.5	86.4
2: Continental V	43.4	90.5	-17.4	-3.4	1.9	-13.6	71.1
3: Continental V+C	21.5	68.3	-14.7	2.2	0.8	-6.2	32.3

Policies defined at the beginning of section 9. Policies are applied in the Americas, and outcomes are for the Americas. For each column $X_{\mathcal{N}}$, defined in text, the number reported is the percentage difference in that variable between the policy scenario and baseline.

The CES cost index has the usual interpretation that it induces the same change in aggregate expenditures as the underlying set of individual cost changes averaged in the index (given our monopolistic assumption with a constant markup). $\tilde{\hat{t}}_{\mathcal{N}}^{1-\eta}$ is defined analogously as the CES cost index of the policy cost changes $\hat{t}_{mn,j}^{1-\eta}$ (with the same weights). Thus, for the unconditional subsidies (policy 1), $\tilde{\hat{t}}_{\mathcal{N}}$ is exactly 20% lower than in the baseline, while the reduced take-up seen in the two first columns reduces that number in the following rows. In the first row, we see that the path changes induced by the subsidies lower delivered marginal cost $\tilde{\hat{c}}_{\mathcal{N}}$ by 4.5% on average.

The next two columns aggregate the demand shifters for EV variety changes and market demand—$\bar{s}_{\mathcal{N}}^{\text{EV}} \equiv \sum_{n \in \mathcal{N}} (R_n^{\circ,\text{EV}}/R_{\mathcal{N}}^{\circ,\text{EV}}) \bar{s}_n^{\text{EV}}$ and $\hat{\mathbb{A}}_{\mathcal{N}} \equiv \sum_{n \in \mathcal{N}} (R_n^{\circ}/R_{\mathcal{N}}^{\circ}) \hat{\mathbb{A}}_n$—from markets n to continent $\mathcal{N}$. These are weighted averages of the market-level changes. For the EV varieties, the weights are the share of EV expenditures, whereas the weights are the total share of auto expenditures (including ICEs) for the overall market demand changes.

The EV variety shifter $\bar{s}_{\mathcal{N}}^{\text{EV}}$ captures the change in model entry between the baseline and a counterfactual scenario. It is positive for the subsidy scenarios, indicating that additional models are offered in those scenarios (relative to baseline). For the case of the unconditional subsidies (policy 1), those additional models represented 2.5% of EV expenditures in our 2022 data.

The market demand shifter $\hat{\mathbb{A}}_{\mathcal{N}}$ captures the endogenous change in market demand induced

by a policy. It averages the CES price index changes $\hat{P}_{n,j}$ across markets and simulations (see equation 27). This shifter represents the average expenditure change for a model at a constant price. Given constant markups, this applies to any model whose cost does not change ($\hat{c}_{mn,j} = 1$) including all ICE models. A negative market demand shifter thus captures an increase in competition. For the case of the unconditional subsidies, we estimate an increase equal to a 16.5% expenditure loss (relative to baseline) at constant prices.

Policy 1 allows all path leading to sales in America to obtain the 20% subsidy, which results in a 2.5% increase in $\bar{s}_{\mathcal{N}}^{\text{EV}}$ compared to baseline, an increased variety effect. With the subsidies, firms manage to rearrange their value chains such that the cost index falls by 4.5% (on top of the 20% subsidy). Partly compensating those cost reductions is the induced fall in the price index (an increase in competition in the Americas for all models), which shifts demand down by 16.5%. Overall, the net effect on EV expenditure is still largely positive at nearly 90%. Policy 2 imposes an additional constraint such that the share of paths receiving the subsidy falls drastically. The paths remaining eligible however remains very high, emphasizing that the models associated with larger sales tend to self-select into eligible paths. All effects are logically dampened by the local assembly constraint and the objective of favoring local assembly harms the objective of EV adoption by around 15 percentage points.

Policy 3 is even worse from an environmental perspective. This is because few EVs sold in the Americas end up qualifying for the subsidy when it is contingent on American cell sourcing. The third row of Table 9 shows that only 21.5% of the realized paths are eligible for the contingent consumer subsidies. The small number who do draw low enough fixed costs in the Americas to source cells within the region are still the largest selling vehicles since they represent 68% of sales. Policy 3 manages to be worse than non-intervention from the point of EV production in both Asia and Europe (as shown in figure 10(a)), while increasing EV production in the Americas *less* than the other two policies. This is an example where the policy is successful at attracting production of the major input (cells), but with a detrimental effect on the production of vehicles that use those local cells. The EV adoption objective is also reduced substantially, leaving few arguments in favor of this policy.
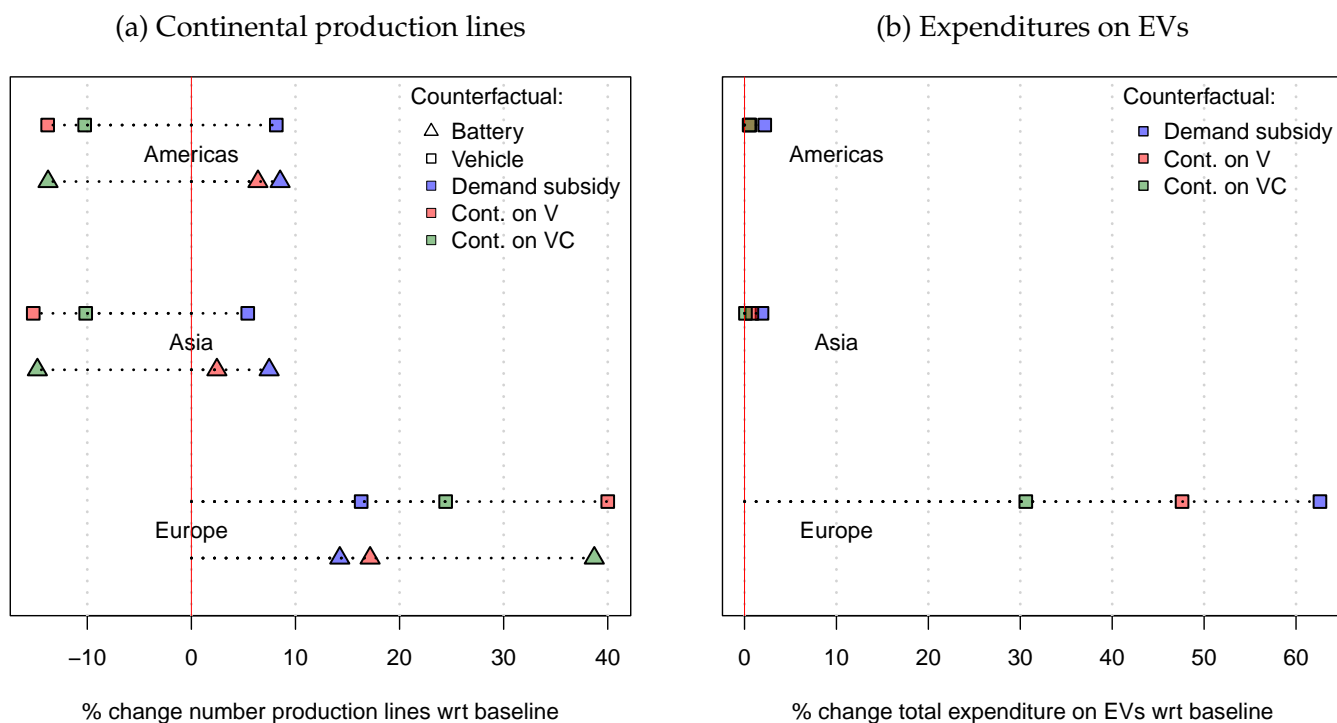
9.1.2 Europe

Figure 11 provides our main policy simulation results for Europe. While there are many shared aspects with North America, the predicted results for Europe differ in important dimensions. Panel (a) shows larger changes in production lines. The biggest impact is 10 extra vehicle production lines in Europe brought about by policy 2, 40% above the baseline level. The majority of the added lines comes at the expense of EV facilities in the other two regions (around -14% in each). In contrast to the North American version of this policy, there is little stimulus to cell production lines in Asia. On the expenditure side, the North American version of policy 1 is more successful, with EV expenditures rising by 86% as compared to 63% in Europe. In online appendix Table O.B3 we show these EU findings are approximately as robust across different sets

of parameter estimates as the results for North America shown in Table 8.

As was the case in North America, the policy 3 requirement of domestic cells lowers the number of assembly plants: the green square is to the left of the red square. The trade-off is less pronounced in Europe, where the V+C contingency yields more assembly lines than the unconditional subsidy (the blue square is to the left of the green square). We can see the explanation for this difference in the cost comparisons shown in Table 6. Europe is much more competitive in cell manufacturing than the US: Europe's average costs are 39% lower than in North America and only about 6% higher than Asia.

Figure 11: Counterfactual results with 20% subsidy in Europe

(a) Continental production lines

(b) Expenditures on EVs

% change number production lines wrt baseline

% change total expenditure on EVs wrt baseline

As noted earlier, the expenditure boost from unconditional subsidies in Europe is 24 ppt lower than the increase in North America. Table 10 helps us understand why. First, the reduction in variable costs is lower (3.0% vs 4.5%) and this difference is magnified by the demand elasticity of 4. Second, the variety effect is smaller (1.9% vs 2.5%). Third the demand contraction is larger (-20.1% vs -16.5%) because EV shares (in the 2022 data) were larger in Europe. Combining these effects, we predict expenditure increases in North America would be 18 ppt higher than Europe. The remaining gap comes from a mixture of covariance and aggregation effects explained in the complete decomposition shown in Appendix A.3.

The other decomposition results shown in Table 10 are broadly similar to those we saw for North America. Policy 3 reduces subsidy take-up to 47.3% of the potential paths (much higher than the 21.5% take-up of Policy 3 in North America). This to leads a lower effective subsidy of just 12.1%, resulting in substantial reductions in EV adoption compared to the other two policies.

The cost competitiveness of cell manufacturing in Europe mitigates the adverse cost effects of Policy 3 (column 4) which now rise by 0.2% instead of 2.2% in North America.

Table 10: Cost and expenditure changes in Europe

| Policy | Eligible share | | Cost index change | | Shifters | | EV Exp. |
| | path | revenue | subsidy | costs | variety | demand | change |
			$\tilde{\tilde{t}}_{\mathcal{N}}$	$\tilde{\tilde{c}}_{\mathcal{N}}$	$\bar{s}_{\mathcal{N}}^{\mathrm{EV}}$	$\hat{\mathbb{A}}_{\mathcal{N}}$	$\tilde{\tilde{R}}_{\mathcal{N}}^{\mathrm{EV}}$
1: Unconditional	100.0	100.0	-20.0	-3.0	1.9	-20.1	62.6
2: Continental V	68.4	85.3	-15.8	-1.6	1.3	-15.3	47.6
3: Continental V+C	47.3	66.8	-12.1	0.2	0.6	-9.9	30.6

Policies defined at the beginning of section 9. Policies are applied in Europe, and outcomes are for Europe. For each column $X_{\mathcal{N}}$, defined in text, the number reported is the percentage difference in that variable between the policy scenario and baseline.

9.1.3 Production Subsidies and Tariffs

In the main text we have focused on just three versions of the demand subsidy that allow us to consider the core trade-offs. Our framework can easily handle a range of other policies, and we now briefly summarize the simulated impacts of production subsidies and tariffs.[43] As seen in Table F7, cell production subsidies and tariffs are much less effective at increasing EV purchases than the consumer subsidies. The former increase EV expenditures by 5.1% and 6.3% in North America and Europe respectively. Tariffs on vehicles *lower* expenditure by about 10% on both continents, and this is worsened when those tariffs apply to cells as well. The Biden IRA policy of combining contingent consumer subsidies with cell production subsidies ("3+4") does indeed do more for EV adoption than Policy 3 in isolation, but it still performs worse in this dimension than Policies 1 and 2 on both continents, albeit with a smaller gap in Europe. From the point of view of opening new battery factories, Table F6 shows that cell production subsidies (policy 4) are more effective than clean EV consumer subsidies (policy 1). The combined policy (3+4) maximizes the number of cell factories in whichever continent it is applied.

Tables O.B5 and O.B6 in the online appendix dig into the details of the consequences of EV and battery tariffs. In both cases, we see rises in marginal costs and shrinking numbers of car models offered in the countries imposing the tariffs. Another notable feature is that despite the fact that majority of paths will be subject to tariffs, revenue shares of those paths are much lower (column 2). The effective tariff in column 3 resulting from a statutory 20% tariff is under 5% in North America (reflecting widespread tariff jumping by models with high market shares) and under 10% in Europe.

We have not computed welfare effects of the tariffs and subsidies. With large social costs of carbon, welfare will tend to rise or fall depending on changes in demand for the emission-reducing

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[43]The complete set of policy counterfactuals are reported in Appendix F.

product. In the Gerarden et al. (2025) analysis of tariffs on solar panels, the environmental component of welfare moves in the same direction as consumer surplus (down for tariffs, up for production subsidies) but is about twenty times larger.

9.2 Quantifying the role of fixed costs

We conclude with a different type of computational scenario that highlights the relevance of our framework—capturing the tradeoffs between fixed and variable production costs with endogenous facility choice—for the modeling of policy counterfactuals. To highlight those tradeoffs, we set the facility fixed costs to zero and then rerun the subsidy policy counterfactuals (Policy 1-3).[44]

We focus on the consequences for the induced change in the delivered marginal cost $\tilde{\hat{c}}_{\mathcal{N}}$ and associated EV expenditure share $\tilde{\hat{R}}_{\mathcal{N}}^{\mathrm{EV}}$ in the continent that implements the policy (for both Americas and Europe). Those outcomes are shown in panels (a) and (b) of Figure 12 respectively. For comparison, we replicate the results from Tables 9 and 10 that we previously reported with our estimated facility fixed costs. Recall that the cost change $\tilde{\hat{c}}_{\mathcal{N}}$ captures the average change in cost $\hat{c}_{mn,j}$ due to changes in the optimal chosen paths, which *do not include the subsidy*.

Figure 12: Comparison with zero fixed costs

(a) Path cost index   (b) EV expenditure

EV path cost index (% change, excl. subsidy)   EV expenditure (% change)
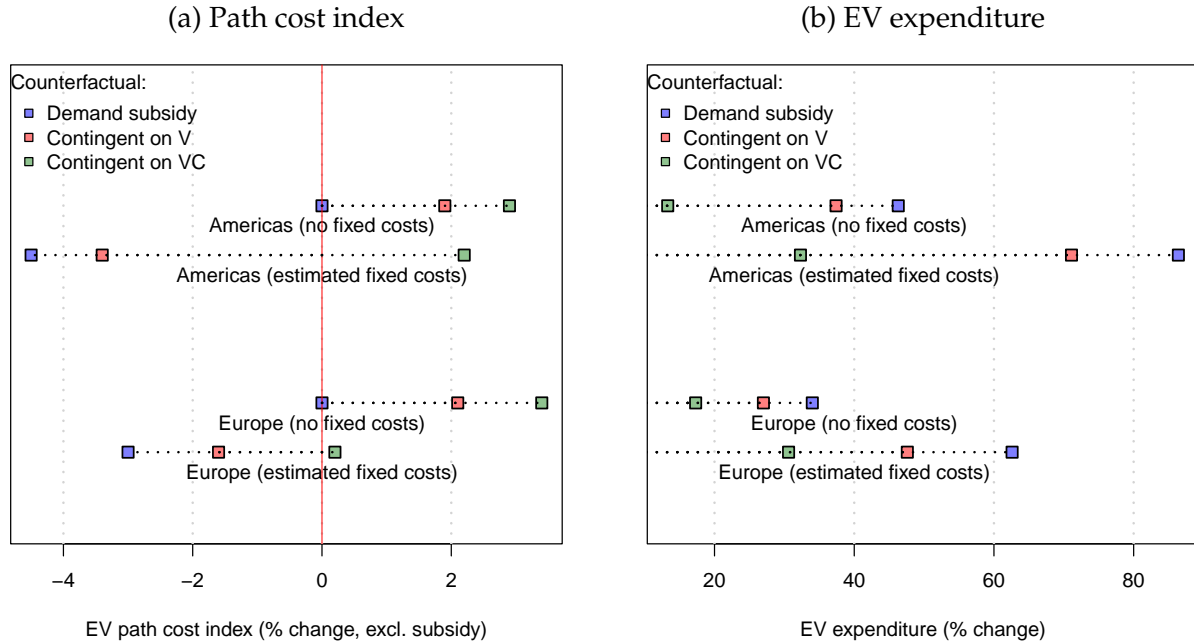
With no facility fixed costs, the MUFLP optimization is trivial: The lowest delivered path cost $\hat{c}_{mn,j}$ is always chosen among the set of paths through all the potential facilities in both stages. There are no inter-connections between chosen paths based on the set of open facilities (any facility can be opened at zero cost). Thus, the unconditional subsidy (Policy 1) will have no effect on the chosen paths and the resulting delivered marginal cost: the blue squares for this case are

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[44]For this exercise, we keep the variable cost parameters at their estimated values.

at zero for Policy 1. The EV prices will all be reduced by the constant subsidy $\tilde{t}_{\mathcal{N}} = .8$. The expenditure shares in panel (b) reflect that constant price change along with the endogenous change in market demand $\hat{\mathbb{A}}_{\mathcal{N}}$ such that expenditures on all cars (including ICEs whose prices do not change) remains constant. This is why the expenditure share increases are more muted for Europe: the share of EVs (ICEs) is higher (lower) than in the Americas, and therefore the decrease in market demand $\hat{\mathbb{A}}_{\mathcal{N}}$ is steeper.

In this case with no fixed costs, the contingent subsidies (policies 2 and 3) must weakly increase the delivered marginal cost for all models. Those policies may be successful in their protectionist goal of inducing a path change from a "Foreign" one in the baseline to a domestic one that is eligible for the subsidy. But such a change will result in increasing the delivered marginal cost above its minimum chosen under policy 1.[45]

As the restrictions on the subsidy eligibility increase, the average delivered marginal cost will initially increase, but then decrease beyond a threshold. In the limit when the restrictions are so onerous that they do not induce any path changes, then the resulting policy will not affect the average delivered marginal cost.[46] Thus, the cost increases associated with the more restrictive policy 3 could be *lower* than for policy 2 if it is close enough to that limit – although we do not find that to be the case empirically: the tougher restrictions on the subsidy in policy 3 induce higher costs than for policy 2.

As we have previously reported for our current framework with fixed costs, all three subsidy policies induce changes in the delivered costs $\tilde{\tilde{c}}_{\mathcal{N}}$. Under both the baseline and unconditional subsidy, the lowest delivered cost path is often not chosen due to constraints on open facilities induced by the fixed costs. The unconditional subsidy may induce a path change to one with a lower cost $\hat{c}_{mn,j}$: At the higher scale driven by the subsidy, this would involve a tradeoff with higher fixed facility costs (including a new facility on the new path). However, a subsidy cannot increase the delivered cost to the region being subsidized.[47] Thus, in our framework with fixed cost, the unconditional subsidy must decrease—at least weakly—the average delivered marginal cost $\tilde{\tilde{c}}_{\mathcal{N}}$.

This is not the case for the contingent subsidies: In those scenarios, a firm may be induced to choose a higher path cost $\hat{c}_{mn,j}$ that is eligible for the subsidy, so long as the higher cost is outweighed by the subsidy. Thus, our structure does not restrict the sign of the cost change $\tilde{\tilde{c}}_{\mathcal{N}}$ under policies 2 and 3. Furthermore, the cost saving under those contingent policies could be even greater than under the unrestricted subsidy. In appendix A.2, we construct a simple example highlighting this case and show that there is always a range of fixed costs such that a contingent subsidy induces a lower $\hat{c}_{mn,j}$ than the unconditional subsidy. Thus, the existence of substantial fixed costs introduces the possibility of a "win-win" outcome for industrial policy: adding trade

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[45]If the restricted policy does not induce a change in path, either because the original path is eligible or because the higher cost of the eligible paths outweigh the benefit of the subsidy—then the delivered marginal cost does not change.

[46]This initial increase and subsequent decrease in delivered cost is closely related to the "Laffer Curve" effect for rules of origins studied by Head et al. (2024).

[47]If the new path with the higher cost is optimal with the subsidy, it must be optimal without the subsidy.

restrictions (contingencies) can amplify price reductions as well as deliver a protectionist outcome (facility relocation).[48] However, we find that this does not hold empirically for the EV industry. There are substantial cost savings associated with the higher scale of production induced by an unconditional subsidy. But adding contingencies is not win-win. The assembly contingency achieves the protectionist goal but shrinks the cost savings. And the full local content requirement is lose-lose: it fails to deliver assembly relocation and wipes out the cost savings.

10   Conclusion

Combining subsidies for consumers to buy EVs with incentives for EV makers to source their batteries locally has been a persistent theme of industrial policy in this sector. As described in Barwick et al. (2025), the Chinese government restricted subsidy eligibility to EVs whose batteries came from a "White List" of (Chinese) suppliers. The Biden administration's IRA continued in this vein with a set of escalating upstream requirements to receive the full $7500 consumer credit for EV purchases. While both of those policies have been phased out, the *Financial Times* reported[49] that the European Commission plans to introduce "Made in Europe" requirements of up to 70 per cent for cars and other products. The report generated complaints by auto makers and praise by battery makers.

Analyzing the effects of subsidies with and without local content restrictions is not straightforward because the success of such policies depends in large part on the willingness of industries to relocate production. 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.

We find that these increasing returns are empirically important: A 20% unconditional consumer subsidy to EVs decreases consumer prices by 25% (for North America) and 23% (for Europe). Those additional price decreases stem from the changes in production paths that would be irrelevant under constant returns to scale. Theoretically, those price decreases could be magnified by introducing local content requirements, which would also satisfy protectionist objectives (the win-win outcome we previously described). Empirically, we find that those production contingencies *shrink* the price savings relative to the unconditional subsidy, leading to substantially lower EV adoption. The combined cell and assembly contingency halves the EV adoption increase relative to the unconditional subsidy.

The unconditional subsidy works both as an environmental and industrial policy, delivering higher EV adoption and additional production lines—both in the subsidizing region and in the

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[48]In addition, for a green industry, lower prices both increase consumer surplus and reduce emission externalities.
[49]December 2nd, 2025

other regions. Adding contingencies can deliver some protectionist outcomes, but with different magnitudes and signs. Relative to the unconditional subsidy, the assembly contingency relocates vehicle plants to the subsidizing region, increasing the number of plants by 14% (North America) and 20% (Europe). But they fail to induce the relocation of cell plants.

Imposing the combined cell and assembly contingency induces mixed protectionist outcomes relative to the unconditional subsidy: For North America, there is a relocation of cell production, with a 20% increase in facilities. But this is offset by a 7% decrease in assembly facilities. On the other hand, the same policy for Europe achieves an unambiguous protectionist goal of raising both cell and vehicle production (21% for cells and 7% for vehicles).

As we have just described, the relative appeal of different industrial policies involves a complex set of tradeoffs that arise from the endogenous plant relocations across multiple stages of production in an industry equilibrium. Policymakers face similarly difficult evaluations of alternatives for other industries that involve high fixed costs spread across multiple stages of production. For example, the US IRA also specifically targeted the renewable power and semiconductor industries. Those sectors, among others, are common targets for industrial policy—including trade restrictions—by governments around the world. Our framework provides a way of computationally evaluating the effectiveness of a broad range of policy scenarios intended to promote those sectors.

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Appendix

A Additional Theoretical Results

A.1 Equivalence between ICE Taxes and Unconditional Subsidies

In this section, we show that a common subsidy $\hat{t}_{mn,j} = \hat{t}_n < 1$ for all EV models m sold in market n is equivalent to an ICE tax $\hat{t}'_n = (\hat{t}_n)^{-1} > 1$ on vehicles sold in n. Under the EV subsidy, the CES price index in n is given by:

$$\hat{P}_{n,j}^{1-\eta} = s_n^{\circ,\text{ICE}} + \hat{\mathbb{C}}_{n,j}^{1-\eta} = s_n^{\circ,\text{ICE}} + \hat{t}_n \hat{C}_{n,j}^{1-\eta}.$$

Under an ICE tax, the CES price index P'_n in n is given by:

$$\hat{P}'^{1-\eta}_{n,j} = \hat{t}'^{1-\eta}_n s_n^{\circ,\text{ICE}} + \hat{C}'^{1-\eta}_{n,j},$$

where $\hat{C}'_{n,j}$ is the new cost index in simulation j under that tax.

Let $\mathbb{A}'_n$ denote the associated anticipated market demand under the tax. If $\hat{\mathbb{A}}'_n = \hat{t}_n^{1-\eta} \hat{\mathbb{A}}_n$, then the anticipated profits for all models m in any simulation j will be identical in both the subsidy and tax scenarios. In that case, all firms will make the same location choices leading to the same cost index in the two scenarios in all simulations j: $\hat{C}'_{n,j} = \hat{C}_{n,j}, \forall j$.

This will hold whenever $\left(\hat{t}_n^{1-\eta} \right)^{-1} \hat{P}_{n,j}^{1-\eta} = \hat{P}'^{1-\eta}_{n,j}, \forall j$, or equivalently whenever:

$$s_n^{\circ,\text{ICE}} \left(\hat{t}_n^{1-\eta} \right)^{-1} + \hat{C}_{n,j}^{1-\eta} = \hat{t}'^{1-\eta}_n s_n^{\circ,\text{ICE}} + \hat{C}'^{1-\eta}_{n,j}, \quad \forall j.$$

Lastly, note that this will be satisfied for all j so long as $\hat{t}'_n = (\hat{t}_n)^{-1}$.

A.2 Delivered Marginal Cost Reductions from Subsidies

With increasing returns to scale (fixed costs and constant marginal costs), it is straightforward to show that a subsidy can reduce the delivered marginal cost. Less intuitively, we also show that adding an upstream restriction on a subsidy can achieve a further reduction in delivered marginal costs relative to an unconditional one. We demonstrate these propositions with a simple two-country example. Recall that $\hat{c}_{mn,j}$ is the change (relative to the data) in delivered marginal cost—exclusive of the subsidy itself—for a given m, sold in market n in simulation j. Let $\hat{c}'_{mn,j}$ denote the cost change under the unconditional subsidy (Policy 1) and $\hat{c}''_{mn,j}$ the cost change under the conditional subsidy (it may require assembly as in Policy 2 or cells and assembly as in Policy 3). Variables without primes correspond to the baseline. We show that there will always be a combination of fixed costs and variable cost differences such that $\hat{c}''_{mn,j} < \hat{c}'_{mn,j} < \hat{c}_{mn,j}$.

Let there be two countries East (E) and West (W). The maintained assumption is that the consumer in E will be served by a plant in E, no matter what decision is made for the W consumer. Hence, we can focus on $n = W$ and take a representative m and j. There are two paths $\ell = E$ and $\ell = W$, which correspond to the production location being in the East or West for customers served in West. Under the unconditional policy, both paths are eligible. Let $\hat{c}_W < \hat{c}_E$, which means that the path $\ell = W$ featuring local production has lower delivered marginal cost. The policies are defined such that $\hat{t}'_E = \hat{t}'_W = 1 - s$ and $\hat{t}''_E = 1$ and $\hat{t}''_W = 1 - s$, where the subscript indicates the path to $n = W$ and s is the *ad valorem* subsidy for eligible paths. We assume that model m has a small enough market share that we can ignore changes in the price index in response to the chosen path. We can therefore set $\hat{P}_W = \hat{P}'_W = \hat{P}''_W = 1$. Letting k denote the determinants of variable profit that do not depend on the path, we can then specify variable profits from sales in W under both policies and paths:

$$\pi_W = k\hat{c}_W^{1-\eta}, \qquad\qquad \pi_E = k\hat{c}_E^{1-\eta},$$
$$\pi'_W = \pi_W(1-s)^{1-\eta}, \qquad\qquad \pi'_E = \pi_E(1-s)^{1-\eta},$$
$$\pi''_W = \pi'_W, \qquad\qquad \pi''_E = \pi_E.$$

For any $s > 0$, $\pi''_E < \pi'_E$, since the contingency reduces the variable profit of serving W remotely.

Given $\hat{c}_W < \hat{c}_E$, the difference in variable profit between the choice of W versus E is lowest under the baseline, higher under Policy 1, and highest under Policy 2:

$$\pi_W - \pi_E < \pi'_W - \pi'_E < \pi''_W - \pi''_E.$$

Let ϕ_W denote the fixed cost of activating W ($y_W = 1$), thereby permitting path $\ell = W$. Those profit differences above define four possible ranges for this fixed cost. When $\phi_W < \pi_W - \pi_E$, the firm always chooses W over E. When $\pi_W - \pi_E < \phi_W < \pi'_W - \pi'_E$, the firm no longer chooses W under the baseline. In this case, both subsidies (Policies 1 and 2) decrease the delivered marginal cost to W. When $\pi'_W - \pi'_E < \phi_W < \pi''_W - \pi''_E$, the firm no longer chooses W under the unconditional subsidy. This is the less intuitive case where the local content requirements decrease the delivered marginal cost. And lastly for completeness, the firm will never invest in W when ϕ_W exceeds $\pi''_W - \pi''_E$.

We show those four ranges for the fixed cost ϕ_W in Figure A1 with $k = 1$ (choice of numeraire for profits), $\hat{c}_W = 1$ (horizontal shifter for the whole plot), and $s = .2$. The variable profit differences between W and E are increasing for all scenarios, reflecting the well-known "proximity versus concentration" tradeoff.

A.3 Decomposition of Continental EV Expenditure Change

In Tables 9 and 10 of the main text, we provided a breakdown of the continental EV expenditure changes $\hat{\bar{R}}_{\mathcal{N}}^{\mathrm{EV}}$ into CES cost index changes $\hat{\bar{c}}_{\mathcal{N}}$ and $\tilde{\bar{t}}_{\mathcal{N}}$ that average the cost and policy changes

Figure A1: Delivered marginal cost reductions
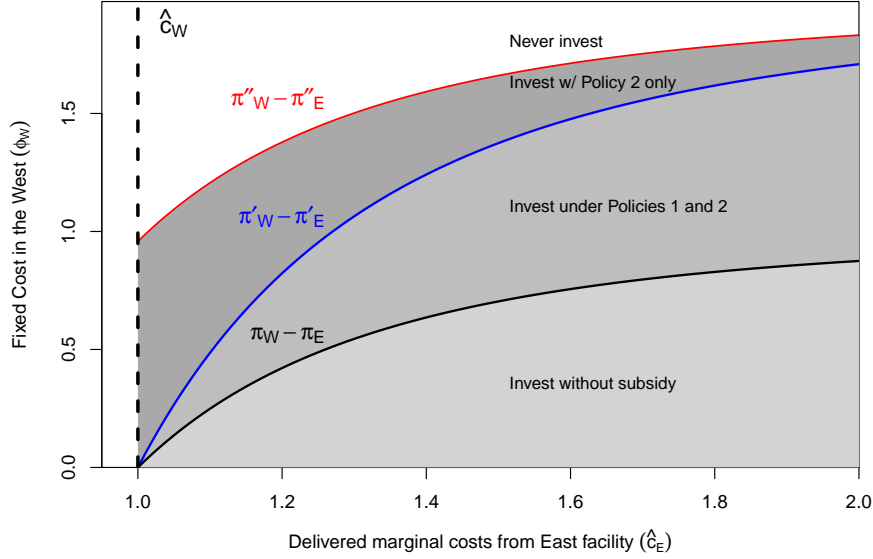
at the model-market-simulation level ($\hat{c}_{mn,j}$ and $\hat{t}_{mn,j}$) and the aggregate shifters for EV variety changes $\bar{s}_{\mathcal{N}}^{\text{EV}}$ and market demand $\hat{\mathbb{A}}_{\mathcal{N}}$. In this appendix, we derive a full decomposition of that EV expenditure changes $\hat{\bar{R}}_{\mathcal{N}}^{\text{EV}}$ into those components, along with their covariances.

As shown in (29), $\hat{\bar{R}}_{\mathcal{N}}^{\text{EV}}$ aggregates the market-level average EV expenditures $\hat{\bar{R}}_{n}^{\text{EV}}$:

$$\hat{\bar{R}}_{\mathcal{N}}^{\text{EV}} = \sum_{n \in \mathcal{N}} \frac{R_n^{\circ,\text{EV}}}{R_{\mathcal{N}}^{\circ,\text{EV}}} \hat{\bar{R}}_n^{\text{EV}}, \qquad \hat{\bar{R}}_n^{\text{EV}} = \sum_j \frac{1}{J} \sum_{m \in \mathcal{M}_{n,j}} s_{mn}^{\circ} (\hat{c}_{mn,j}^{1-\eta} \hat{t}_{mn,j}^{1-\eta} \hat{P}_{n,j}^{\eta-1}).$$

This market-level expenditure can then be decomposed as follows:

$$\hat{\bar{R}}_n^{\text{EV}} = \hat{A}_n \frac{\bar{s}_n^{\text{EV}}}{s_n^{\circ,\text{EV}}} \left[\tilde{\hat{c}}_n^{1-\eta} \tilde{\hat{t}}_n^{1-\eta} + \text{Cov}(\hat{c}_{mn,j}^{1-\eta}, \hat{t}_{mn,j}^{1-\eta}) \right] + \text{Cov}\left[\left(\hat{P}_{n,j}^{\text{EV}} \right)^{1-\eta}, \hat{P}_{n,j}^{\eta-1} \right], \qquad (\text{A.1})$$

where the market-level CES cost index change for $\tilde{\hat{c}}_n$ is defined analogously to $\tilde{\hat{c}}_{\mathcal{N}}$ for a continent $\mathcal{N}$ with a single market n; the market-level CES cost index change for $\tilde{\hat{t}}_n$ is defined in the same way based on $\tilde{\hat{t}}_{\mathcal{N}}$; and $\hat{P}_{n,j}^{\text{EV}}$ is the price index change for EVs only.[50] The covariance terms are

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[50]Using (17) and (22), this price index change is given by:

$$\left(\hat{P}_{n,j}^{\text{EV}} \right)^{1-\eta} = \frac{1}{s_n^{\circ,\text{EV}}} \sum_{m \in \mathcal{M}_n^{\circ}} s_{mn}^{\circ} (\hat{c}_{mn,j} \hat{t}_{mn,j})^{1-\eta} = \frac{1}{s_n^{\circ,\text{EV}}} (\hat{P}_{n,j}^{1-\eta} - s_n^{\circ,\text{ICE}})$$

given by:

$$\text{Cov}(\hat{c}_{mn,j}^{1-\eta}, \hat{t}_{mn,j}^{1-\eta}) \equiv \frac{1}{J\bar{s}_n^{\text{EV}}} \sum_j \sum_{m\in\mathcal{M}_{n,j}} s_{mn}^{\circ} \left(\hat{c}_{mn,j}^{1-\eta} - \tilde{c}_n^{1-\eta}\right) \left(\hat{t}_{mn,j}^{1-\eta} - \tilde{t}_n^{1-\eta}\right),$$

$$\text{Cov}\left[\left(\hat{P}_{n,j}^{\text{EV}}\right)^{1-\eta}, \hat{P}_{n,j}^{\eta-1}\right] \equiv \frac{1}{J} \sum_j \left[\left(\hat{P}_{n,j}^{\text{EV}}\right)^{1-\eta} - \left(\bar{\hat{P}}_n^{\text{EV}}\right)^{1-\eta}\right] \left(\hat{P}_{n,j}^{\eta-1} - \hat{\mathbb{A}}_n\right),$$

where $\bar{\hat{P}}_n^{\text{EV}}$ is the CES price index that averages the $\hat{P}_{n,j}^{\text{EV}}$ across simulations such that $\left(\bar{\hat{P}}_n^{\text{EV}}\right)^{1-\eta} = \sum_j \left[\left(\hat{P}_{n,j}^{\text{EV}}\right)^{1-\eta}\right]/J$. The second covariance derivation also uses the definition of $\hat{\mathbb{A}}_n$ in (27) as the average across simulations of $\hat{P}_{n,j}^{\eta-1}$.

Tables 9 and 10 decompose the average EV sales into the continental average of the four components $\hat{A}_n$, $\frac{\bar{s}_n^{\text{EV}}}{s_n^{\circ,\text{EV}}}$, $\tilde{c}_n^{1-\eta}$, $\tilde{t}_n^{1-\eta}$ in (A.1). This decomposition is exact at the country level when the two covariance terms are zero. The covariance $\text{Cov}(\hat{c}_{mn,j}^{1-\eta}, \hat{t}_{mn,j}^{1-\eta})$ reflects the fact that the CES index of a product is not exactly equal to the product of the CES indexes – except when one of the product components is constant, as in the unconditional subsidy. In the other cases, it is second order (it would not show up in a log-linearization of the CES index); and empirically those covariances are small. The second covariance $\text{Cov}\left[\left(\hat{P}_{n,j}^{\text{EV}}\right)^{1-\eta}, \hat{P}_{n,j}^{\eta-1}\right]$ reflects the capacity for market-level EV sales to increase by displacing ICE sales as P_n^{EV} decreases and P_n^{ICE} remains constant (recall that total vehicle sales R_n are held constant). When the EV share is low, this covariance is negligible. As the EV share rises, the covariance term becomes increasingly negative, offsetting the cost reduction terms.

B 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.

B.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 2023. However, the last year is currently a projection.

B.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 2023. 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.

B.3 IHS New Registrations (NRQ,NRP)

The data we refer to as "newreg" comes to us in two pieces: The NRQ files has quantities and no prices. The NRP file has prices and quantities, but not for all models. NRP is also not available for 5 of our markets of interest: Czechia, Slovakia, Mexico, Hungary and Korea. NRQ does not have quantities for Japan. We explain how we deal with those different missing data in section C.

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.

B.4 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.

B.5 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.

B.6 Sub-national per capita GDP

We construct measures of sub-national level of per capita Gross Domestic Product (GDP) using data from Kummu et al. (2018).[51] They provide a global harmonized and gap-filled per capita GDP dataset at national and sub-national (provincial, municipality) administrative units from 1990 to 2015. We then map EV battery cell and assembly plants' coordinates to their sub-national boundaries by the shortest distance. Once the link between plant and administrative unit is established, we use the per capita GDP measure in 2015 given in constant 2011 international US dollars.

B.7 Demand elasticity estimates

Table B1 provides the preferred (absolute) value of the average own price elasticities estimated in 18 studies that estimate demand for cars (ICE and EVs). 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 B1, the median over all 18 studies is 4. A recent paper by Van Biesebroeck and Verboven (2025) also provides average own-price elasticities for 14 recent papers (mostly for ICEs), with a median value of 5, very close to our right column. We set η to the overall median value: 4.

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[51]The dataset can be downloaded from `https://datadryad.org/dataset/doi:10.5061/dryad.dk1j0`.

Table B1: 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		

C Calibration of demand parameters

As shown in section 8.1, expected fixed cost draws rise with the quality of the cars associated with each factory, which we denote as $\tilde{\xi}_{fg_k}$. The implicit assumption is that manufacturing cells or vehicle assembly for higher-quality cars requires more complex and expensive equipment. The primitive underlying the firm-group quality index is ξ_{mn}, the model-market demand shifters we refer to as "appeal" following Hottman et al. (2016). The distinction we draw between appeal and quality is that the former varies across countries, depending on consumer perceptions, whereas the latter consists of the universally valued elements of the vehicle. We obtain our quality index as a geometric mean across markets where the model is sold and the models in a given group:[52]

$$\tilde{\xi}_{fg_k} = \exp\left(\sum_n \sum_{m \in \mathcal{M}_f} z_{mn} \Gamma^k_{mg_k} \ln \xi_{mn}\right)$$

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. Demand is given by

$$q_{mn} = R_n P_n^{\eta-1} \xi_{mn}^{\eta-1} p_{mn}^{-\eta}, \tag{C.2}$$

Inverting (C.2), we recover ξ_{mn} as a ratio of appeal relative to the geometric mean of EV models in market n.[53] Letting $\tilde{p}_n$ and $\tilde{q}_n$ denote the geometric means of EV prices and quantities in market

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[52]Recall from equation (4) that $\Gamma^k_{mg_k} = 1$ for m in group g_k and zero otherwise.

[53]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.

n, the inversion yields

$$\xi_{mn} = \left(\frac{p_{mn}}{\tilde{p}_n}\right)^{\frac{\eta}{\eta-1}} \left(\frac{q_{mn}}{\tilde{q}_n}\right)^{\frac{1}{\eta-1}}, \tag{C.3}$$

where we have adopted the Hottman et al. (2016) normalization that the geometric mean of ξ_{mn} is one in every market n (only relative appeal matters). Using our estimate of $\eta = 4$, we compute the relative appeal, ξ_{mn} of each EV model in each market.

The next step is to attribute groups for each model m (that is to fill in the $\Gamma^k_{mg_k}$ matrix). The **newreg** data does not provide information on characteristics of the cell or the platform on which the vehicle was built. However, it provides "trims", which are destination specific names ("Long-range" or "Standard" for instance), associated with the weight of the vehicle and its price, and also the power of the electric motor. For vehicle platforms, things are straightforward since all our models of interest are built on a single platform in 2022, independently of their trim, plant of assembly and destination. For cell groups, a little more work is needed. As shown in Table D3, most brand-model combinations come with only one cell group (NC-Pouch for instance), independently of the trim. However, 11 car models have two cell groups in substantial proportions (those are high sales vehicles such as the Tesla 3 and Y, the VW ID.3 and ID.4, the Kia Niro and the MG 4 for instance). For those, we have to map trims to cell groups. Manual online search shows that more powerful battery packs are associated with heavier and pricier vehicles and more powerful electric motors. We therefore compute median price, weight, and horsepower, and classify each trim as above or below those medians. Taking the average of those classifications for a given trim-destination, we then attribute the most powerful cell group if the mean classification is ≤ 1.5.

Then we need to attribute a ξ_{mn} to model-destination combinations without price data in NRP. This is done with a regression-based approach on the sample with price data in NRP:

$$\log \xi_{mn} = -0.35 \times \text{Border}_{h(m)n} + 0.049 \times \text{RTA}_{h(m)n} + \text{FE}_m + \text{FE}_n + \epsilon_{mn},$$

where $h(m)$ is the headquarter country of brand-model m, adding distaste for non-domestic and non-RTA models to model and destination fixed effects (FE_m explains nearly three quarters of the quality variance in our sample). We then reconstruct missing ξ_{mn} as $\exp(\text{FE}_m - 0.35 \times \text{Border}_{h(m)n} + 0.049 \times \text{RTA}_{h(m)n})$.

Table C2 shows the top 10 and bottom 10 models in terms of appeal (for the models serving at least 10 markets, and not accounting for observations reconstructed with the method above). Topping the list of appeal are models by Porsche, BMW, Audi and all four Tesla models. The four top models are between 2.5 and 3 times more attractive than the average offer over the set of countries where they are sold. It is revealing that the destination in which those are particularly appealing is China, a market in which many inexpensive models are available. Our computations reveal that, given its high price, the Mercedes-Benz EQS must be 6 times more attractive than the average model in China to achieve its actual level of sales there, against less than 2 times the average model sold in Canada. The bottom appeal list features smaller cars made by a groups of firms that has almost no intersection with the set of firms making the top 10 models. The models in

Table C2: Quality and market-level appeal of the top 10 and bottom 10 models

brand model	N mkts	Quality ($\tilde{\xi}_m$)	best ξ_{mn} country	value	worst ξ_{mn} country	value
Highest quality models							
Porsche Taycan	19	3.02	CHN	5.82	CAN	1.91
Tesla Model Y (N)	18	2.86	CHN	4.24	JPN	1.96
Mercedes-Benz EQS	19	2.76	CHN	6.09	CAN	1.76
BMW iX	18	2.55	CHN	4.12	FRA	1.55
Audi e-tron GT	18	2.06	AUT	3.38	PRT	1.41
Tesla Model 3 (N)	19	1.87	CAN	3.26	NOR	1.23
Audi e-tron	18	1.85	NOR	2.84	POL	1.10
Tesla Model S	15	1.85	USA	4.07	PRT	0.87
Tesla Model X	14	1.74	USA	4.59	PRT	1.08
BMW i4	19	1.68	PRT	2.31	CAN	0.92
Lowest quality models							
Citroen C4	14	0.70	ESP	1.14	POL	0.34
Toyota bZ4X	15	0.68	CHN	1.03	USA	0.41
Renault Zoe	15	0.65	FRA	1.24	NOR	0.37
Skoda Enyaq Coupe	11	0.64	CHE	1.07	BEL	0.44
Kia Niro (N)	10	0.55	GBR	1.06	USA	0.25
Opel Corsa	15	0.55	DEU	0.98	FIN	0.32
MG ZS (N)	13	0.54	GBR	0.92	CHN	0.17
BMW iX1	10	0.53	NOR	0.80	GBR	0.20
Kia Soul	12	0.51	PRT	0.76	ITA	0.21
Dacia Spring	11	0.38	ITA	0.68	DNK	0.22
MG 4 (N)	11	0.36	GBR	0.57	AUT	0.19

Note: Models ranked by their quality, $\tilde{\xi}_m$, measured as the model m geometric mean of ξ_{mn} over all markets n in 2022. Only models with data in 10 or more market included.

that bottom group are revealed to have an appeal between 35 and 70% of the average car. Another notable pattern is that there seem to be some home brand advantage: The Renault Zoe has most appeal in France, and the two MG models have most appeal in the UK, where the brand was born (even though it is now owned and operated by SAIC).

D Additional empirical results

D.1 Evidence on multi-sourcing and capacity increases

Figures D2 and D3 are examples of multi-sourcing for vehicles found in our data. In figure D2, we focus on sales of Tesla models in Germany. The Model S and Model X are always sourced in Fremont, those are single sourcing cases all along. The Model 3 (in blue) comes from both Fremont and Shanghai in 2020. But this year is also the opening of the Chinese factory. Sales from Shanghai continue to increase thereafter, while the Californian-made Model 3 are not exported to Germany as soon as 2021. The story is very similar with the Model Y (in red). It comes in 2021 from Shanghai, and there is multi-sourcing in 2022, with the Berlin factory opening and gradually ramping up production. The made-in-China Model Y volumes fall in 2023 and go to zero in 2024. Both cases of multi-sourcing appear to be transitions. The story is the same for the Volkswagen ID.4 sold in North America as shown in figure D3(a). The model is launched in 2021 in the USA and Canada, and sourced in the German plant of Mosel. The US-based Chattanooga plant starts producing this car in 2022, with the flows from Germany going to zero in 2023. Mexican imports are negligible, but come from the US factory.

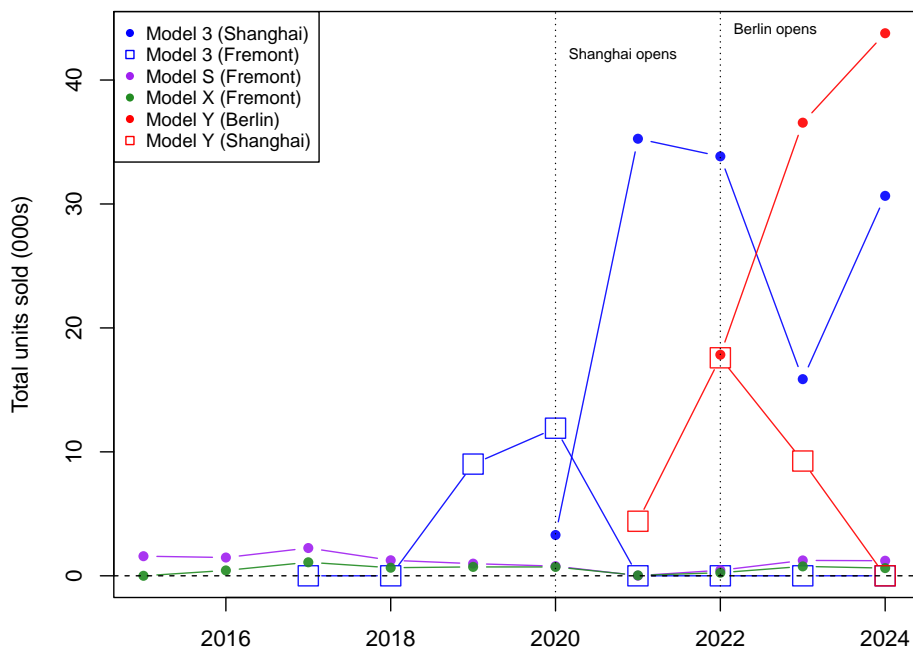Figure D2: Transitory multi-sourcing by Tesla in Germany

Figure D3(b) shows a different case where the same VW ID.4 is imported by Sweden from two German plants starting in 2022, and continues that way onward. It turns out that those two factories are producing different shapes of the NCM battery which powers this car. Although we do not observe it directly in our sales data, those ID.4s coming from Mosel and Emden are likely to be different trims with different battery specifications. We will treat those as such in our regressions.

Figure D3: Transitory vs trim-based multi-sourcing

(a) VW ID.4 sold in Sweden
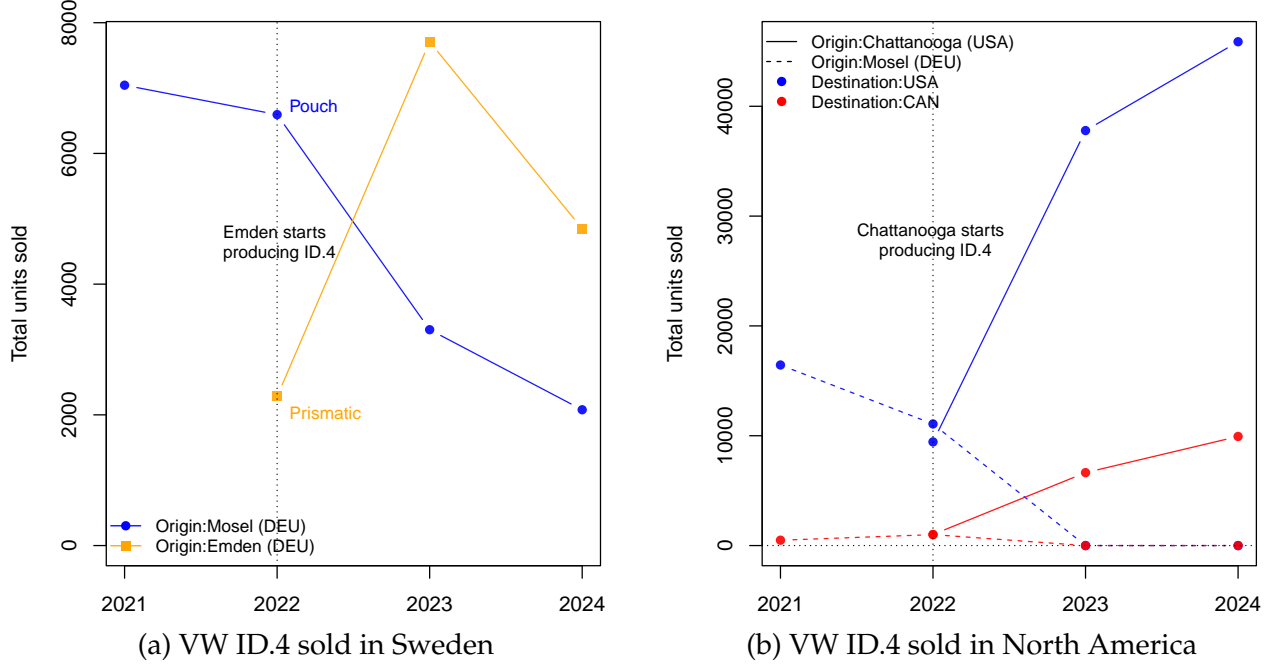
(b) VW ID.4 sold in North America

Figure D4 shows capacity increases in two factories owned by Tesla: the first one in Fremont, California, and the Shanghai factory opened in 2020. Total output in 000s of cars produced is depicted in black, and specific models are in other colors. In both cases, we see that the production goes from relatively small amounts (around 50 thousands in 2015 for Fremont, and less than 200 thousands for Shanghai in 2020) to several multiples of the initial number very fast. The Fremont factory output is multiplied by around 10 in 8 years, and the factor is more than 4 in 3 years for Shanghai. Capacity constraints do not seem a dominant feature in this industry.

D.2 Cell and vehicle groupings

Our model assumes that a distinct fixed cost is paid for each group g_k installed in cell and assembly plants. The matrix Γ^1 with rows m and column g_1 is composed of indicators equal to 1 if model m uses group g_1 for cells and zero otherwise. The groups for cells distinguish combinations of material category (NCM or LFP) and shape (cylinder, pouch or prismatic) of the cell. For vehicles, the indicators in the Γ^2 matrix specify the *platform* g_2 for each model m, e.g. "GEN III" for Tesla Model 3 and Model Y, "MEB" for VWs such as ID.4, ID.3, Audi Q4, and Skoda Enyaq. Platforms

Figure D4: Tesla's production increases in Fremont and Shanghai
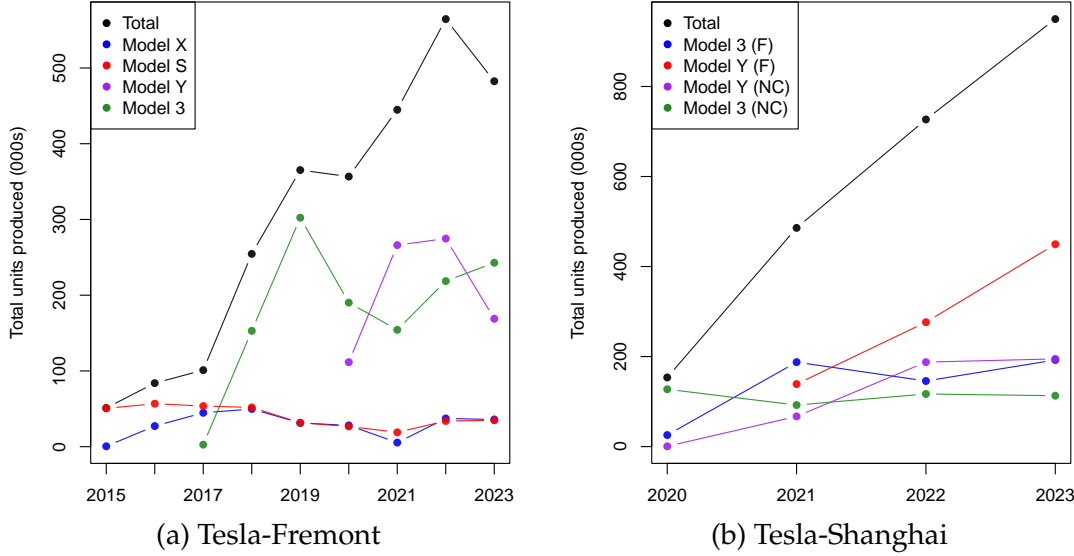
(a) Tesla-Fremont

(b) Tesla-Shanghai

establish the architecture of core vehicle systems (e.g. steering, chassis) and dictate the placement of their components. They require a specific organization of the assembly line and its machine tools.

Table D3: Cell variants per model

# of matcat-shapes per model	count
Single group	102
Two groups	24
— one dominant by 75%	13
— none dominant	11

Note: The table counts material-shape groups cells used in a model in 2022 and separates models into Single to Two groups categories (material consists of two categories, NMC or LFP).

Table D3 computes the number of cell groups (material category and shape) that can be found for each of the car models we consider in the counterfactual analysis. Out of the 128 models, there are 24 which are built with two different cell groups. In more than half of the cases (13 out of 24), one group is largely dominant (more than three quarters of the output), such that we attribute the dominant group to this car model. For the remaining 11 car models with no dominant group, we consider both versions as separate car models, which brings the overall number to 139.

Table D4 describes how many variants of the cells are produced in a typical cell factory. It turns out that the vast majority of plants (85%) produce only one shape or one material category (70%) of cells. Even for both characteristics constituting g_1, the most frequent case (63%) is that a plant produces only one combination. Even expressed in shares of total output (measured in GWh), a

little more than a quarter of world cell production takes places in plants producing more than two groups.

Table D4: Cell plants are specialized in shape and material produced

# variants:	Shape			Mat. Cat.			Shape & Mat. Cat.		
	count	%	% GWh	count	%	% GWh	count	%	% GWh
1	73	84.9	66.0	60	69.8	45.5	54	62.8	37.8
2	12	14.0	32.0	24	27.9	33.9	26	30.2	35.7
3	1	1.2	2.1	2	2.3	20.6	4	4.7	4.1
4	0	0.0	0.0	0	0.0	0.0	2	2.3	22.4

Note: The table gives counts and shares of shapes and material category produced in cell plants. Material category consists of two categories (NMC or LFP). Counts are number of cell plants in 2022.

E Untargeted fit

This section provides evidence of the model's fit to untargeted moments. Figure E5 compares the continent-to-continent shares of cell and vehicle sourcing, with the observed shares in 2022 on the x-axis, and the predictions on the y-axis. Figure E6 draws similar bilateral shares, but in terms of counts of sourcing assignments $m\ell_k\ell_{k+1}$ rather than volumes of BEV and cell sourcing. For the two figures, the fit is overall good with the most salient deviation being the lower realized shares of Asia to Europe and America shares in both stages of production.

Figure E5: Untargeted fit of the estimated model: origin-destination model sourcing

(a) battery cells

(b) vehicle assembly
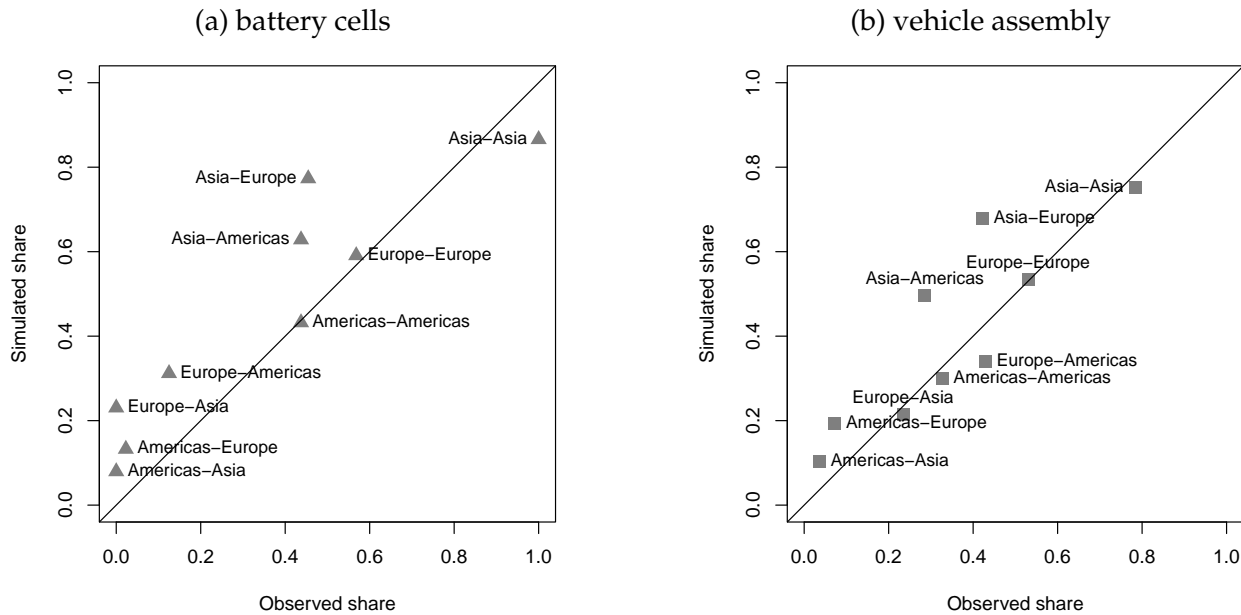
Notes: These are the share of BEV models each continent sources from the others, for both cells and vehicles.

Table E5 lists a number of monadic untargeted moments for both stages and the 3 continents. The numbner of locations entered, the count of plants, the number of car models per plant, and the number of model-plant combinations active. Our model does reasonably well in terms of location entered and plants opened, but overestimates the counts of models per plant.

Figure E6: Untargeted fit of the estimated model: origin-destination sourcing arcs

(a) battery cells (b) vehicle assembly
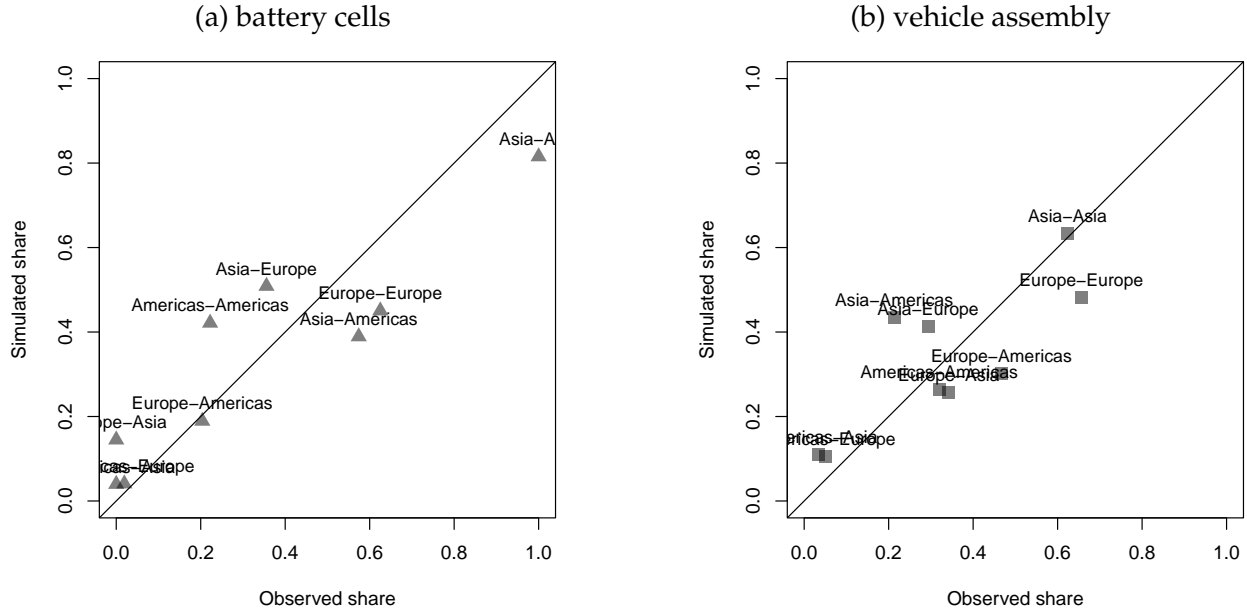
Notes: These are the share of assignments $m\ell_k\ell_{k+1}$ over all assignments received at destination aggregated to continental level, for both cells and vehicles.

Table E5: Untargeted fit in other extensive margins

Continent	Stage	Potential locations	Data				Model Prediction			
			# loc. entered	# plants	# models per plant	# model-plant combination	# loc. entered	# plants	# models per plant	# model-plant combination
Americas	C	4	4	6	1.3	8	3.2	5.4	3.5	18.8
Asia	C	5	4	29	4.1	118	5	28.4	5.2	148.3
Europe	C	3	2	9	3	27	3.0	8.9	5.3	47.7
Americas	V	5	5	9	2	18	4.3	8.4	2.8	23.2
Asia	V	5	5	24	4	96	5	31.9	3.7	118.7
Europe	V	5	5	15	2.9	44	5.0	18.9	3.7	70.4

Predicted values are averages across simulations.

F   Additional Counterfactual Results

F.1   Policy Results

Here, we provide results for the full set of counterfactual scenarios. We analyzed five different policy changes (with only the first three are reported in the main text):

1. **Subsidy to EV buyers:** The government subsidizes EV purchases 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 and vehicle must be produced in the same continent as the buyer.

4. **Production subsidy for domestically produced cells:** We denote the combination of production subsidies with the contingent consumer subsidy policy 3 as "3+4".

5. **Tariffs on imported cells and vehicles:** Tariff on both imported cells and vehicles are policy 5. A variant ("5V") restricts the tariff to vehicles.

In order to make the scenarios comparable, we set a common counterfactual tariff or subsidy rate of 20% at the continental level: $\hat{t}_{mn,j} = .8$, $\forall n \in \mathcal{N}$ for the subsidies and $\hat{t}_{mn,j} = 1.2$, $\forall n \in \mathcal{N}$ for the tariff—whenever model m is eligible under the counterfactual scenario. Also discuss what eligibility means for the tariff.

Section 9 in the main text presents the results graphically for a subset of the policies we investigated. Here we present the complete set of results in tabular form, for production lines in Table F6 and for EV expenditures in Table F7. Those are provided for all our counterfactual policies.

Table F6: Production lines[†] by policy

Receiving				Policy[*]				
Production	0	1	2	3	4	3+4	5V	5
North American policies								
				Vehicles				
Americas	9.6	11.1	12.6	10.3	9.9	10.9	10.6	9.1
Asia	53.2	53.6	52.3	52.7	53.2	52.7	52.2	52.5
Europe	24.4	24.6	24.0	24.1	24.3	24.0	23.9	24.2
				Cells				
Americas	6.1	6.5	6.4	7.8	8.1	9.7	6.0	6.3
Asia	33.5	34.4	33.9	32.5	32.8	31.8	33.1	32.7
Europe	9.6	9.9	9.9	9.2	9.4	9.0	9.4	9.3
European policies								
				Vehicles				
Americas	9.6	10.3	8.2	8.6	9.7	8.5	8.2	8.3
Asia	53.2	56.1	45.1	47.8	53.0	46.7	45.6	46.5
Europe	24.4	28.4	34.2	30.4	25.4	31.9	28.5	27.1
				Cells				
Americas	6.1	6.6	6.5	5.3	5.7	4.8	5.9	5.7
Asia	33.5	36.0	34.3	28.5	31.6	26.3	32.1	31.0
Europe	9.6	11.0	11.3	13.3	11.7	14.9	9.8	10.3

[†] Production lines are defined as model-plant combinations.
[*] Policies defined at the beginning Appendix F. Policy 0 is the baseline with all existing 2022 policies absorbed in the estimated path costs.

Table F7: Expenditures on EVs by policy[*]

Receiving			Policy				
Production	1	2	3	4	3+4	5V	5
North-American policies							
Americas	86.4	71.1	32.3	5.1	46.2	-9.8	-16.1
Asia	1.4	0.8	-0.3	1.9	1.1	-0.3	-1.1
Europe	1.6	0.5	-0.5	1.2	0.7	-0.8	-1.7
European policies							
Americas	2.2	0.6	0.5	6.2	5.9	-1.2	-1.8
Asia	1.9	0.8	0.1	4.3	4.7	-0.8	-1.3
Europe	62.6	47.6	30.6	6.3	43.2	-10.6	-14.7

[*] Policies defined at the beginning Appendix F.

F.2 Zero vs Baseline Fixed Costs

Table F8: Comparison with zero fixed costs

Policy	Path cost index change		EV expenditure change	
	No FC	Baseline FC	No FC	Baseline FC
Americas				
1: Unconditional	0.00	-4.50	46.30	86.40
2: Continental V	1.90	-3.40	37.40	71.10
3: Continental V+C	2.90	2.20	13.30	32.30
4: Subsidy C	0.10	0.50	2.20	5.10
3+4	4.70	3.20	19.70	46.20
5V: Tariff V	1.40	1.10	-7.20	-9.80
5: Tariff V+C	1.10	1.70	-12.50	-16.10
Europe				
1: Unconditional	0.00	-3.00	34.00	62.60
2: Continental V	2.10	-1.60	27.00	47.60
3: Continental V+C	3.40	0.20	17.30	30.60
4: Subsidy C	0.20	-0.40	3.80	6.30
3+4	4.70	0.30	23.90	43.20
5V: Tariff V	1.60	0.90	-6.30	-10.60
5: Tariff V+C	1.40	1.00	-9.10	-14.70