Industrial Policies for Multi-stage Production: The Battle for Battery-powered Vehicles

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Motivation for multi-stage industrial policy

Industrial policies with endogenous facility location choices

How do subsidies and tariffs shape global supply chains?

- Industries targeted by industrial policies often share key features
  - High fixed costs $\rightarrow$ Most locations won't receive plants
  - There is a core input that drives costs of the downstream product
- Design of policies to capture these value chains is challenging
- We develop a framework to quantify the effects of the new industrial policy regime and apply it the battery electric vehicle (BEV) industry.

Main Takeaway:

- Endogenizing facility location choices matters for policy evaluation
- Local production requirements and environmentalism are not complements

Policies promoting EV production in the US (2022–2024)

- Consumer subsidy for passenger vehicles up to \$7,500 ($\approx$ 15%–20%)
  1. no production contingencies (before IRA, most of EU, Canada)
  2. require vehicle **assembly** in North America (after IRA)
  3. require battery **cells** manufactured in North America (by full IRA)
- Tax credit for US battery production: 20–30% of battery cost
- Tariffs on China-made EVs (25% $\rightarrow$ 100%)
- Dept. of Energy loans (e.g. \$6.6bn for Rivian in Georgia)
- 13 states have zero-emission vehicle (ZEV) mandates

Today's policy counterfactuals are for the consumer subsidies.

Why approach a global problem with locational restrictions?

1. National security takes precedence
2. Political feasibility constraints
3. "Subsidy leakage effect" (Bown, Snyder, & Staiger vaccine paper)
4. By promoting local production, lower delivered marginal cost, and hence increase EV adoption.

Explanations 1–3 grant that "clean" subsidies are preferable from a pure emissions-reduction perspective.

The last motivation is possible, but far from certain. Depends on parameters.

A new framework for evaluating industrial policy

What are the technical challenges in modelling the impact of industrial policies on global supply chains?

- Multi-stage production with trade costs $\implies$ vertical interdependencies
- Increasing returns to scale (high fixed investment costs) $\implies$ interdependent *paths* of supply
- Higher dimension with endogenous multi-product and multi-market entry $\implies$ interdependent product-market offering
- This paper applies a new method (adapted from an operations research approach) for solving this "MMM" uncapacitated facility location problem (MMM-UFLP).

The 2024 literature on industrial policy and clean energy

Industrial policies (IP) and clean technology:

- IP along chain/across sectors: Aghion et al. (2024), Bartelme et al. (2024)
- IP in semiconductors, solar panels: Bown and Wang (2024), Goldberg et al. (2024), Barwick et al. (2024a), Bollinger et al. (2024)
- IP in general: Juhász et al. (2024a, 2024b)

Electric vehicles and IRA:

- Distribution effect for leasing/buying, new/used, other attributes (range, capacity): Allcott et al. (2024a, 2024b), Barwick et al. (2024b)
- Learning-by-doing: Barwick et al. (2024c)

This paper: Effect of IP along chain on location decisions and trade

Positioning this paper in the GVC/Plant location literature

		Number of production stages	
		Single ($K = 1$)	Multiple ($K > 1$)
Constant returns?	yes	ARRY 2018 Head & Mayer 2019	Antràs & de Gortari 2020 Tyazhelnikov 2022 Johnson & Moxnes 2023
	no	Tintelnot 2017 AFT 2017, AES 2024 Oberfield et al 2024 Castro-Vincenzi 2024[†]	de Gortari 2020 note AFFT (2024a, 2024b) This paper *

[†] features capacity constraints, other non-CRS have fixed costs

* also incorporate multi-product and multi-market entry (stage $K + 1$)

Substitutes or Complements?

Combinatorial discrete choice solutions in literature

- Jia (2008) reduces configurations needed for evaluation if the problem is supermodular
- Arkolakis, Eckert and Shi (2024) extend Jia to allow either super- or sub-modular

The MMM-UFLP problem is neither super- or sub-modular

- Within production stages, plants substitute for each other
- Across stages,
  1. production plants across different stages complement each other
  2. distribution facilities at consumer markets complement production plants

Our approach specifies firms' problem as a mixed integer linear programming problem (MILP), and solves using tools from the OR literature.

Things we leave out

Our model omits features of the industry, which are potentially important but incorporating them here would be distracting/infeasible.

- Dynamics: Dynamic models with foresight need to consider the solution to the static problem—which is already at the frontier of difficulty.
- Rich substitution: IO models seek to have realistic patterns of cross-price elasticities. Key feature in our model is the own-price elasticity: paths with lower marginal costs $\rightarrow$ higher final demand. Combining GVCs with BLP adds a major layer of complexity.
- Bargaining between vertically related firms: Some firms are vertically integrated, others conduct joint ventures. We assume that the firms solve the profit maximization problem for the vertical chain efficiently and then make any necessary transfers.

Outline of Talk

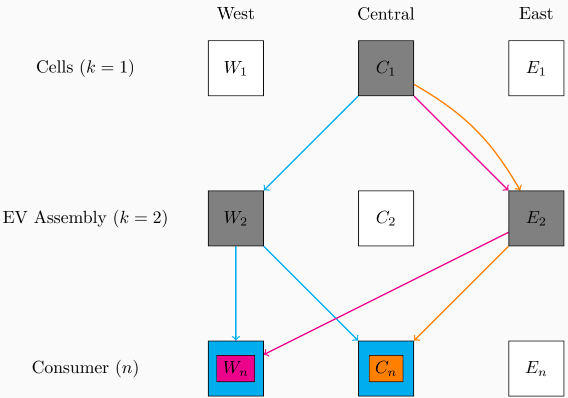
1. Setting up and solving the MMM-UFLP
2. Features of the BEV industry that make it fit into the MMM-UFLP framework
3. Estimate variable cost parameters: Worldwide sourcing and production of batteries and vehicles
4. Estimate fixed costs: Simulated method of (intercontinental) moments
5. Policy counterfactuals inspired by IRA
6. (if time) A look at post-IRA investments
7. (if time) Computational findings

Multi-product Multi-market Multi-Stage Uncapacitated Facility Location Problem

Motivating the MILP approach to solve FLPs

- Facility location choices are hard combinatorial problems because of interdependencies.
- As choice sets grow to realistic numbers, the number of alternatives to evaluate explodes.
- The economics literature going back to Jia (2008) reduces the alternatives by exploiting either super- or sub-modularity (Arkolakis, Eckert and Shi)
- Multi-stage problems feature substitution (within stages) and complementarity (across stages): calls for a different approach.
- Mixed integer linear programming (MILP) solves the problem via constraints on paths and exploiting fast commercial LP software.

Optimization over Paths with Constraints



Firm chooses

- models m to sell in n s.t. market entry cost $\phi_{nm} \to z_{nm} = \{0, 1\}$,
- plants to open at each k s.t. plant fixed cost $\phi_{\ell k} \longrightarrow y_{\ell k} = \{0, 1\}$,
- the **optimal path** ℓ_{nm} $\forall n, m$ through open facilities

The cyan, magenta, orange lines: paths chosen by 3 car models

Gray squares are **activated** facilities.

What does activate mean (in the EV industry)?

- A plant is active if it has paid the indivisible fixed cost required to produce positive amounts
- Fixed costs are paid for serving specific client firm f (car makers)
- The fixed cost covers a limited range of potential outputs
  - For cells, $g_1(m)$ maps models to a combination of cell material categories and shapes, e.g. Tesla Model S uses "Nickel-Cobalt-Manganese-Cylinder"
  - For vehicles, $g_2(m)$ gives the platform, 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.
- Our method allows for these additional constraints (applicable in other industries). We will show relevance to EVs later.

From Paths to Profits

- Key requirement for MILP to work: variable profit can be written as a function of paths and a single market aggregator
- Delivered MC $c(\ell_{nm})$ depends on the path chosen ℓ_{nm} and variable cost parameters (to be estimated)
- Quantity demanded, q, is determined by firm's $c(\ell_{mn})$ (quality-adjusted by ξ_{mn}) and aggregate index of those costs P_n across all models
- Variable profits for tuple (m, n) if path ℓ_{mn} is chosen: $\pi(c(\ell_{mn}))$
- P_n is a function of path costs of all models in market n, including gas vehicles. It is taken as given in the individual firm's optimization.

MMM UFLP: objective, variables (x, y, z), & constraints

$$
\begin{aligned}
\max_{\mathbf{x},\mathbf{y},\mathbf{z}} \quad & \sum_{m\in M_f}\sum_{n\in N}\sum_{\ell_1\in L_1}\sum_{\ell_2\in L_2} \pi(c(\boldsymbol{\ell}_{mn}))x_{mn\ell_1\ell_2} \\
& - \sum_{g_1\in G_1}\sum_{\ell_1\in L_1} \phi_{fg_1\ell_1} y_{fg_1\ell_1} - \sum_{g_2\in G_2}\sum_{\ell_2\in L_2} \phi_{fg_2\ell_2} y_{fg_2\ell_2} - \sum_{m\in M_f}\sum_{n} \phi_{mn} z_{mn}
\end{aligned}
$$

subject to

$$
\begin{aligned}
\sum_{\ell_1\in L_1}\sum_{\ell_2\in L_2} x_{mn\ell_1\ell_2} &\leq z_{mn}, \quad n\in N, m\in M_f && (1)\\
\sum_{\ell_1\in L_1} x_{mn\ell_1\ell_2} &\leq y_{fg_2(m)\ell_2}, \quad n\in N, m\in \mathcal{M}_f, \ell_2\in L_2 && (2)\\
\sum_{\ell_2\in L_2} x_{mn\ell_1\ell_2} &\leq y_{fg_1(m)\ell_1}, \quad n\in N, m\in \mathcal{M}_f, \ell_1\in L_1 && (3)\\
x_{mn\ell_1\ell_2} &\geq 0, \quad y_{fg_1\ell_1}\in\{0,1\}, \quad y_{fg_2\ell_2}\in\{0,1\} \quad z_{mn}\in\{0,1\}. && (4)
\end{aligned}
$$

What range of problems does our method handle?

1. No restrictions on complementarity or substitution between facilities (super vs sub modularity)
2. Firms with multiple products, potentially grouped by characteristics
3. Endogenous market entry to multiple markets up to $K = 3$ production stages are feasible in relatively quick times,
4. Because our focus is the GVC supply side, we simplify other aspects via CES demand, monopolistic comp., Cobb-Douglas across stages.
5. *Many Extensions Possible:* Logit demand, Leontief production, production "trees", oligopoly.

Necessary industry characteristics for this framework

1. Inputs from different plants are perfect substitutes if all dimensions of the product are specified $\Longrightarrow$ highly disaggregated sourcing data needed (ours comes from IHS Markit)
2. Constant marginal costs; plants are "uncapacitated": no long run capacity constraints
3. Together 1+2 $\Longrightarrow$ single sourcing from the least-delivered-cost plant
4. Fixed costs should be high enough that CRS models are not adequate, but low enough that extensive margin is active

Application to the BEV Industry

Six EV features that fit with the MUFLP framework

1. Cells account for over 1/4 of final cost (3/4 of battery cost, which are 1/3 of vehicle)
2. Cells production is usually close (median distance of about 500km) to vehicle assembly
3. Cell factory investment costs are huge: avg. $2.5bn (based on 83 articles), assembly plants average $0.8bn (198 articles).
4. Cell plants serve few clients (often VI or JV); large fixed costs to add clients
5. Despite high fixed costs, active 2015–2022 extensive margin: number of cell plants has doubled; assembly plants tripled on all 3 continents.
6. Multi-sourcing declines with product detail to a few percent for both cells and assembly.

Batteries (upstream) are expensive

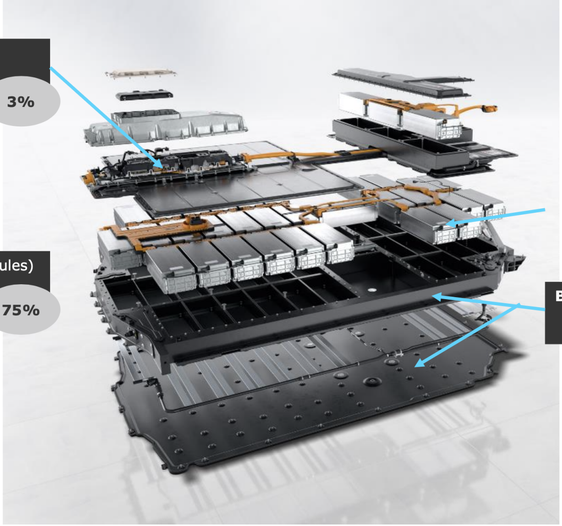
Batteries (€ 8k) cost twice as much as gas engine + transm. (€ 4k)

Fact 1b: Cells are the most expensive part of the battery

BMS Battery Management System

3%

Electronique de pilotage de la batterie



Module et Pack Batterie

34% du contenu d'un VE ~8000€

Module Batterie (cellules)

75%

Module regroupant les cellules composant le cœur de la batterie avec leur chimie spécifique des anodes / cathodes / électrolyte

Batterie Pack

23%

Boîtiers / carters du pack batterie avec fonctionnalités thermiques et de structure

Battery cells represent > 1/4 of EV cost

High up-front investment costs, especially for batteries

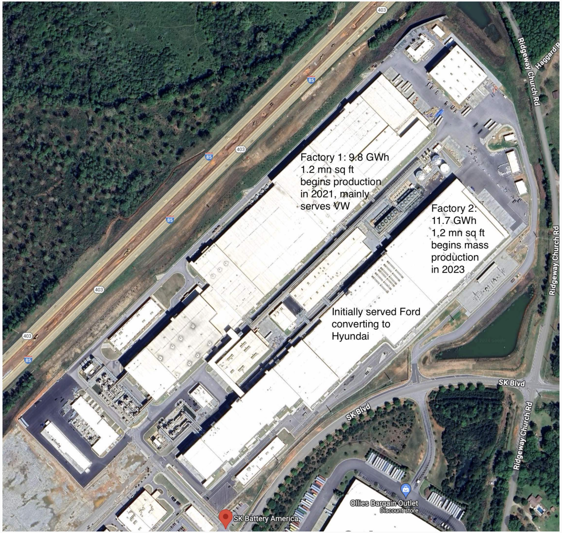
	Cost ($US bn)		Article
Stage	Mean	Std. Dev.	Count
Cells	2.53	2.60	83
Packs	0.67	0.71	20
Vehicle Assembly	0.79	0.94	198
Battery and Vehicle	4.09	3.54	13

Source: news articles (2007–2023)

Despite the high investment costs, the new plant margin for vehicles and cells has been active on the 3 continents.

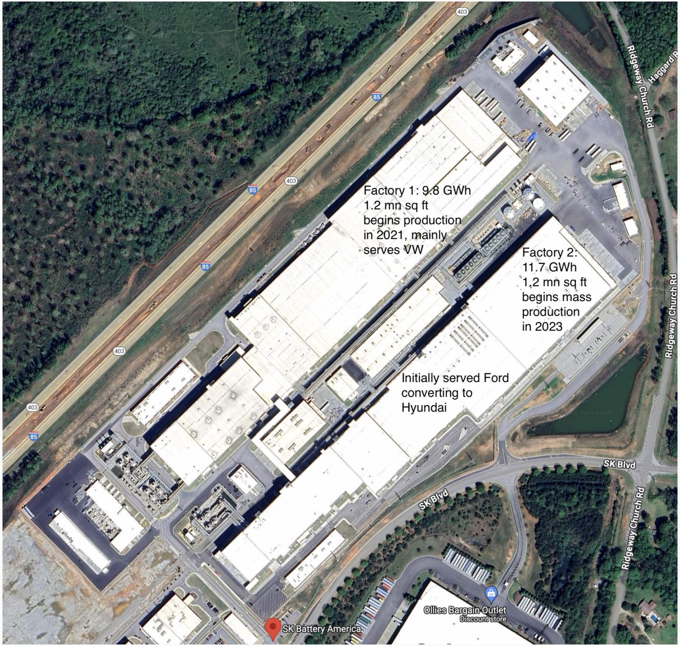
SK On’s pair of Commerce, GA cell plants

serves VW-Chattanooga



2nd plant to serve Hyundai

SK On's pair of Commerce, GA cell plants

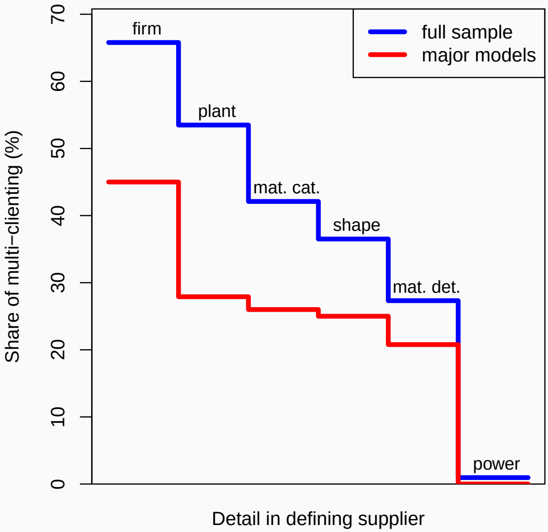


SK On prepares the 2nd factory in Commerce, GA

LG Energy's new Michigan cell factory extension

ACC (Stellantis+Mercedes-Benz+Saft JV) battery plant

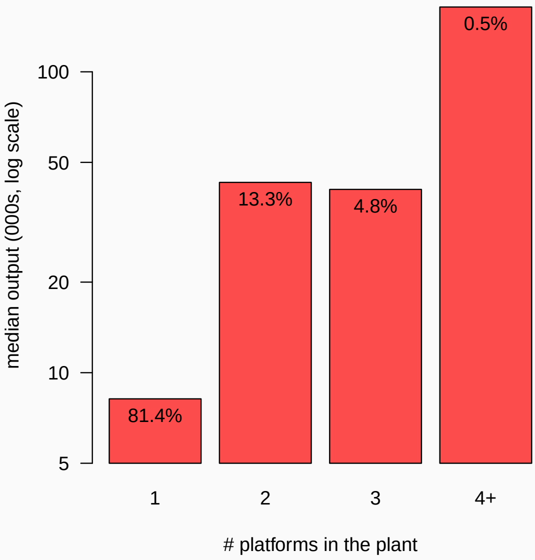
Cell plants single clients for specific battery types



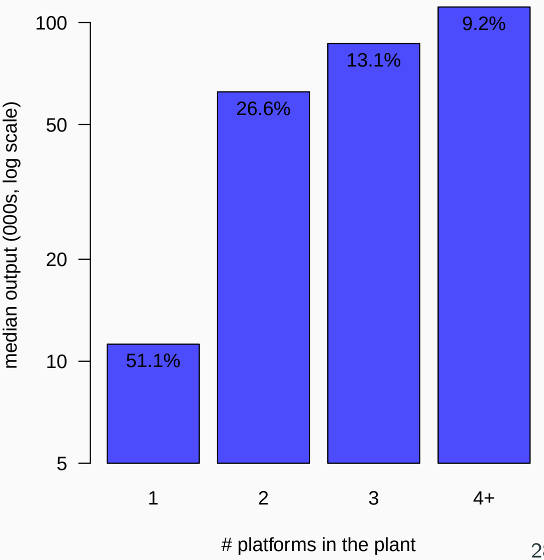
- All battery cell plants supply a type of battery (material (detailed)-shape-power) to a single major car maker.
- We model cell fixed costs at the carmaker-stage-material (category)-shape-location level.
- For major models, 75% single-clienting at this level

Size of plant and count of platforms

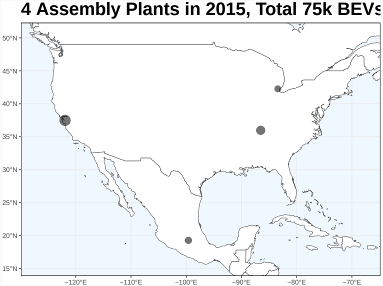
(a) EV models

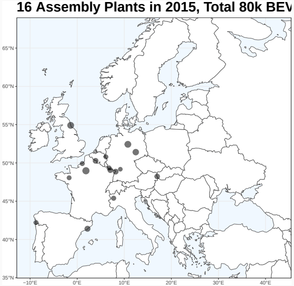


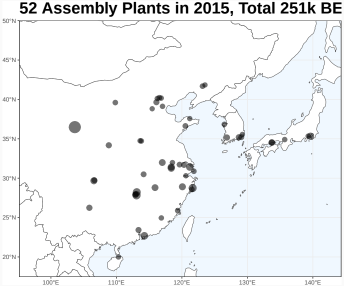
(b) All models

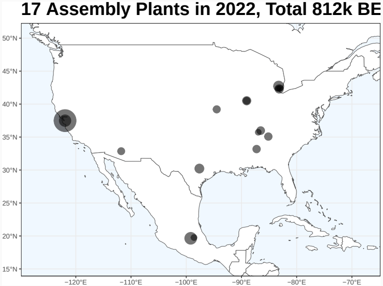


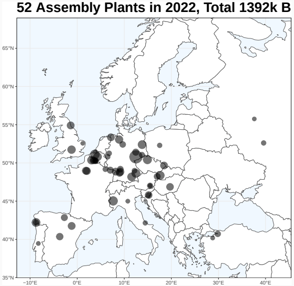
Active extensive margin for EV Assembly

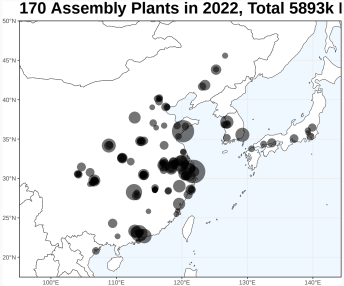






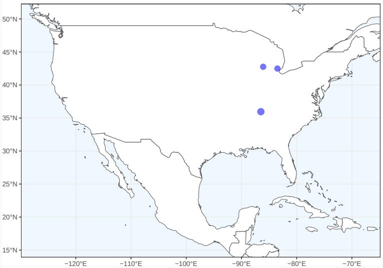




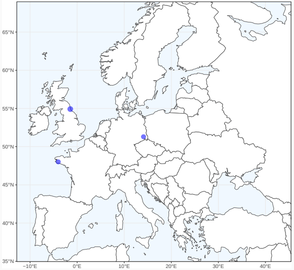


Active extensive margin for Cells

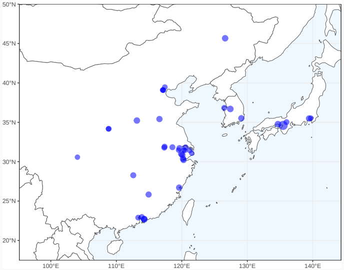
3 Cell Plants in 2015, Total 0.6GWh



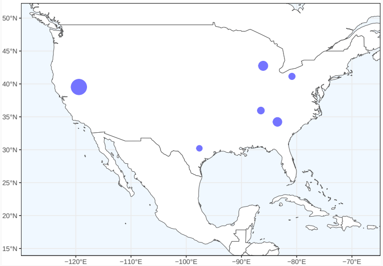
3 Cell Plants in 2015, Total 0.6GWh



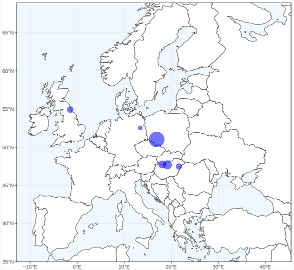
39 Cell Plants in 2015, Total 10.9GWh



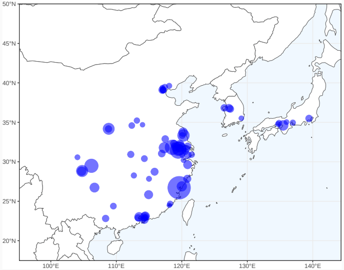
6 Cell Plants in 2022, Total 34.1GWh



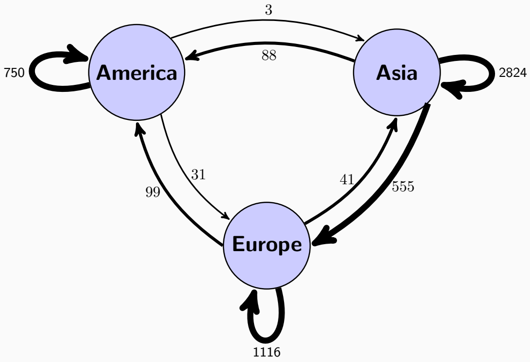
6 Cell Plants in 2022, Total 64.8GWh



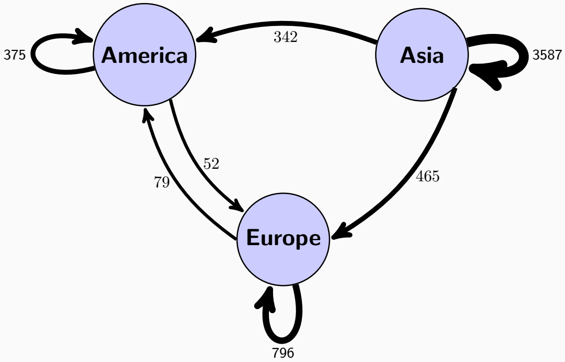
74 Cell Plants in 2022, Total 374.2GWh



Vehicle and cell trade is mostly intra-continental, but Asia exports

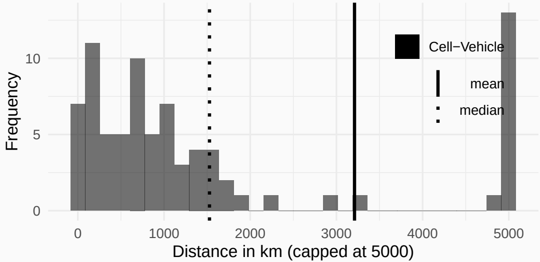


Vehicles (000s)

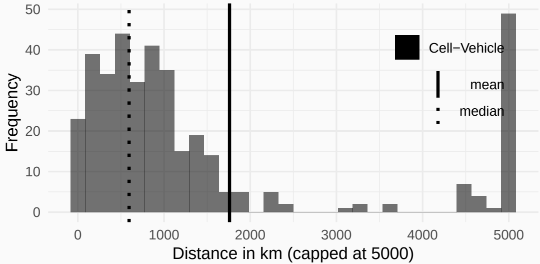


Cells (000s of vehicles)

Mainly short distances between stages—with exceptions

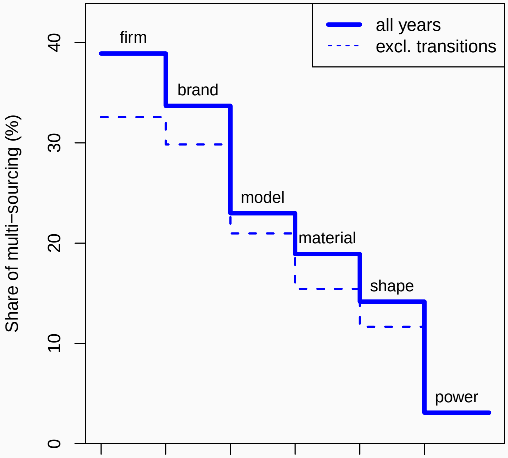


2015

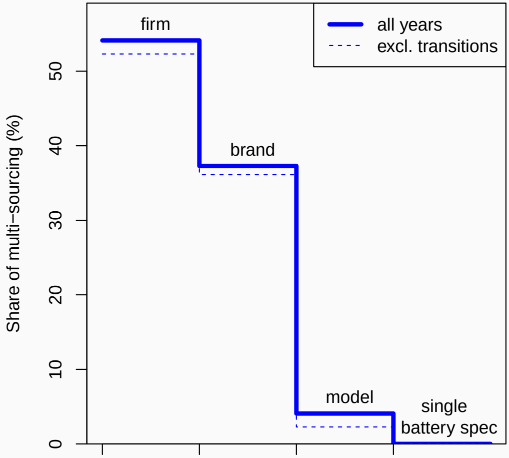


2022

Multi-sourcing is rare for narrowly defined inputs



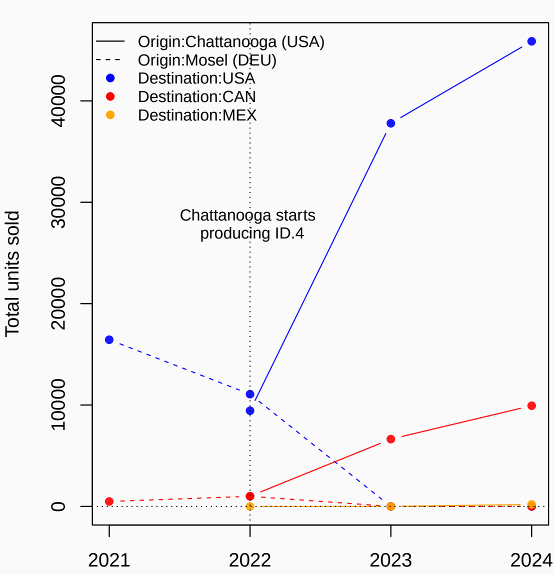
Cells



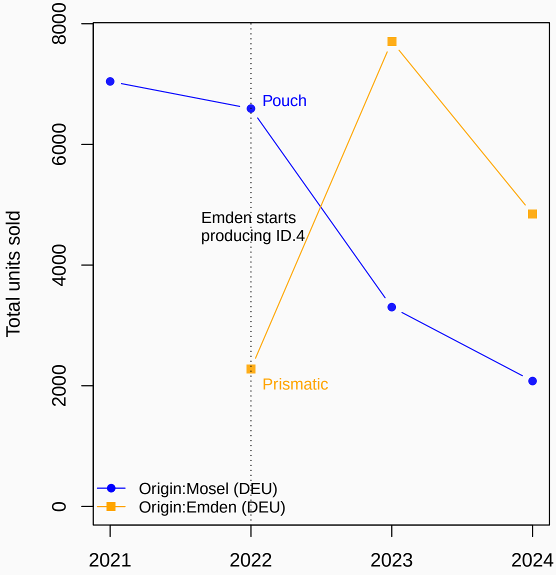
Electric Vehicles

Rarity of multi-sourcing $\Longrightarrow$ rarity of capacity constraints, LoV

Multi-sourcing can be transitory or trim-based



(a) VW ID.4 sold in North America



(b) VW ID.4 sold in Sweden

Estimation of the model applied to BEV value chain

Estimation Roadmap

Step 1: Conditional on active facilities ($\mathbf{y}$,$\mathbf{z}$) for each firm, estimate discrete choice assignment ($\mathbf{x}$) problem via sequential (cells, assembly) nested logit

- Equivalent to minimizing log path costs, C-D $\implies$ linear in parameters
- Sourcing decisions reveal edge costs as function of observables (geography, tariffs, productivity)
- The supplier country fixed effects reveal marginal *cost differences*

Step 2: Calibrate demand elasticity η to the literature median (4), and car relative appeal ξ_{mn} using model-market level prices and sales

Step 3: Estimate fixed cost parameters by matching moments of the data to the simulated model (SMM)

Step 1: Variable costs of paths and quality

- Variable costs

$$
\begin{aligned}
\text{Cells costs:} \quad c^1_{m\ell_1\ell_2} &= w^1_{\ell_1}\tau^1_{\ell_1\ell_2}\varepsilon^1_{m\ell_1\ell_2}, \\
\text{Vehicle path costs:} \quad c(\boldsymbol{\ell}_{mn}) &= \left(w^2_{\ell_2}\right)^{\alpha_{22}} \left(c^1_{m\ell_1\ell_2}\right)^{\alpha_{12}} \tau^2_{\ell_2 n}\varepsilon^2_{m\ell_2 n}, \\
\text{Vehicle variable costs:} \quad c_{mn} &= \tilde{\xi}_m^{\alpha_c} c(\boldsymbol{\ell}_{mn}),
\end{aligned}
$$

- α_c is the elasticity of varible costs with respect to quality, $\tilde{\xi}_m$.
- Variable profits: $\pi_{mn} = (\mu - 1)\, c_{mn} q_{mn}$, where μ is the markup.
- Variable profits maximized by minimizing log path costs (model-level quality drops out here, but affect facility activation decisions in step 3)
- Log path costs:

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

Step 2: CES Demand Car Relative Appeal (Quality)

- CES demand for all cars (EV and ICE) with calibrate demand elasticity to the literature median $\eta = 4$

$$q_{mn} = R_n \left(P_n\right)^{\eta-1} \xi_{mn}^{\eta-1} p_{mn}^{-\eta}$$

where Price index $n \in N$ consumer countries/markets
$P_n = \left[\sum_m z_{mn} \left(p_{mn}/\xi_{mn}\right)^{1-\eta}\right]^{1/(1-\eta)}$

- Model-market appeal (ξ_{mn}) relative to market mean appeal ($\tilde{\xi}_n$), with observed p_{mn} and q_{mn}

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

- "Quality": $\tilde{\xi}_m$ the geometric mean across all markets of a model's appeal.
- Idiosyncratic appeal ($\xi_{mn}/\tilde{\xi}_m$) is "free"; quality ($\tilde{\xi}_m$) requires more expensive inputs (longer range batteries, larger body, faster motor).

Appeal of top 10 and bottom 10 models

brand model	N mkts	geom. mean	best ξ_{mn} country	best ξ_{mn} value	worst ξ_{mn} country	worst ξ_{mn} value
Most appealing 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
Least appealing models						
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 geometric mean ξ_{mn}, 10 or more markets.

Discrete choice approach to variable profits

Stage 1 (cells) estimating equation is

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

Stage 2 (vehicle assembly) estimating equation is

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

"Inclusive cost": $\mathrm{FE}^1_{\ell_2}(m) = -\ln \sum_{\ell \in L_1(m)} \exp[\mathrm{FE}^1_\ell + \boldsymbol{X}'_{\ell_1\ell_2}\boldsymbol{\beta}^1_\tau]$

Log path costs as a function of discrete choice estimates ($\boldsymbol{\beta}$), shocks, and SMM parameters ($\boldsymbol{\kappa}$):

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

κ scales the variable cost relative to the fixed cost and the variance of the unobserved u shocks. β^2_Φ is coefficient on inclusive cost of cells.

Sequential Nested Choice estimation of variable costs

- **Stage** $k = 1$**:** Battery cell sourcing
  - **Chooser:** Assembly plant in ℓ_2 for model m
  - **Choice:** Battery cell plant in ℓ_1
  - **Choice set:** Plants that make the model's cell type for that maker
  - **Determinants:** trade costs (β_τ^1), fixed effects of supplier countries ($\mathrm{FE}_{\ell_1}^1$)
- **Stage** $k = 2$**:** Vehicle sourcing
  - **Chooser:** dealership network in country n sourcing model m
  - **Choice:** EV assembly plant in country ℓ_2
  - **Choice set:** Plant that assembles the model's platform
  - **Determinants:** trade costs (β_τ^2), fixed effects of supplier countries ($\mathrm{FE}_{\ell_1}^1$), plus inclusive cost from cell stage $\rightarrow -\beta_\Phi^2$

Variable Costs to Variable Profits

Log path costs:

$$\ln c(\boldsymbol{\ell}_{mn}) = -\kappa\left\{\mathrm{FE}^2_{\ell_2} + \boldsymbol{X}'_{\boldsymbol{\ell_2 n}}\beta^2_\tau + \beta^2_\Phi\left[\mathrm{FE}^1_{\ell_1} + \boldsymbol{X}'_{\boldsymbol{\ell_1\ell_2}}\beta^1_\tau\right]\right\} + \underbrace{u(\boldsymbol{\ell}_{mn})}_{\text{Gumbel}(0,\kappa)}$$

- κ converts the sourcing probability coefficients into cost shifters.

Variable profits:

$$\pi(c(\boldsymbol{\ell}_{mn}), P_n) = \left(\frac{c_{mn}}{P_n/\mu}\right)^{1-\eta}\frac{R_n}{\eta} = \left(\frac{c(\boldsymbol{\ell}_{mn};\kappa,\boldsymbol{\beta},\mathrm{FE})\left(\tilde{\xi}_m^{\alpha_c}/\xi_{mn}\right)}{C_n^{\mathrm{EV}}}\right)^{1-\eta}\frac{R_n^{\mathrm{EV}}}{\eta}$$

- cost increases w/ a model's mean appeal $\tilde{\xi}_m$ (quality) with elas. α_c
- For now, we take price index P_n as exogenous and calculate $C_n^{\mathrm{EV}} \equiv \left[\sum_m z_{mn}\left(c(\boldsymbol{\ell}_{mn})\left(\tilde{\xi}_m^{\alpha_c}/\xi_{mn}\right)\right)^{1-\eta}\right]^{1/(1-\eta)}$ using observed paths.

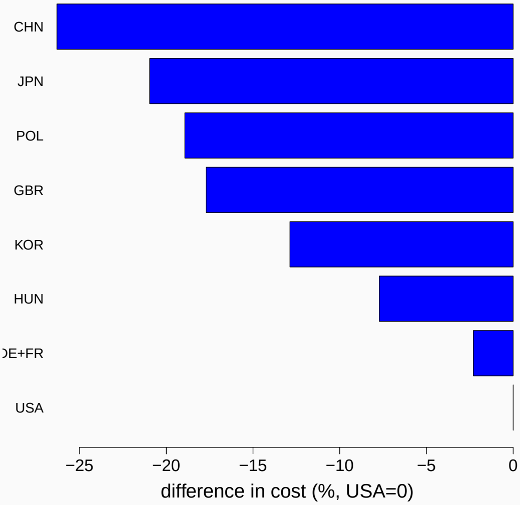
legend: sourcing estimation, calibrated parameters, SMM estimates

Nested Logit Sourcing Results

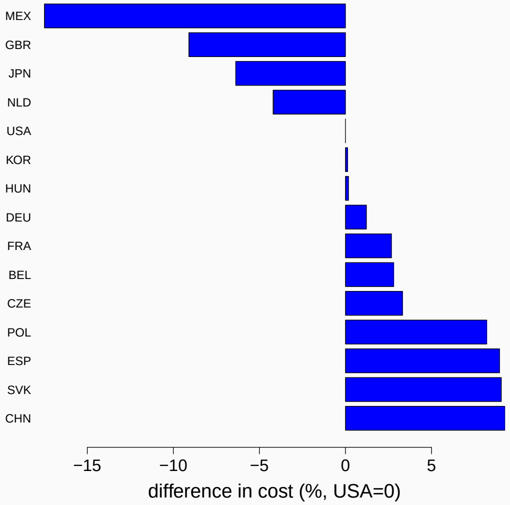
	Cells	Vehicles
border	-0.953^{a}	-1.04^{a}
	(0.319)	(0.254)
log distance	-0.382^{a}	-0.112^{c}
	(0.021)	(0.062)
RTA	0.458	0.869^{a}
	(0.320)	(0.214)
Inclusive cost of cells		-0.234^{a}
		(0.084)
log GDP per capita	0.213^{c}	0.206^{b}
	(0.118)	(0.087)
log(1+tariff)	-8.49^{a}	-8.56^{a}
	(2.34)	(1.74)
Observations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

- Home plants (border $=0$) are $\approx \exp(1) = 2.7$ times more likely to be chosen
- Trade agreements also important
- Tariff elasticities are large
- Coef on inclusive cost $\Longrightarrow$ cell cost share 23.4%.
- Productivity effects based on within-country variation

Cost differences: Batteries and Cars



Cells



BEV Assembly

Step 3: Simulated Method of Moments

- Sourcing estimates cannot reveal fixed costs, as these choices condition on open facilities
- Fixed costs assumed log-normal with mean shifted by continent (Asia, Europe, Americas) and distance to firms' headquarter.

$$\ln \phi_{\ell_k} \sim \mathcal{N}(\rho^k_{\text{As/Eu/Am}} + \rho^k_{\text{HQ}} \ln \text{dist}_{\ell_k}, \sigma_k)$$

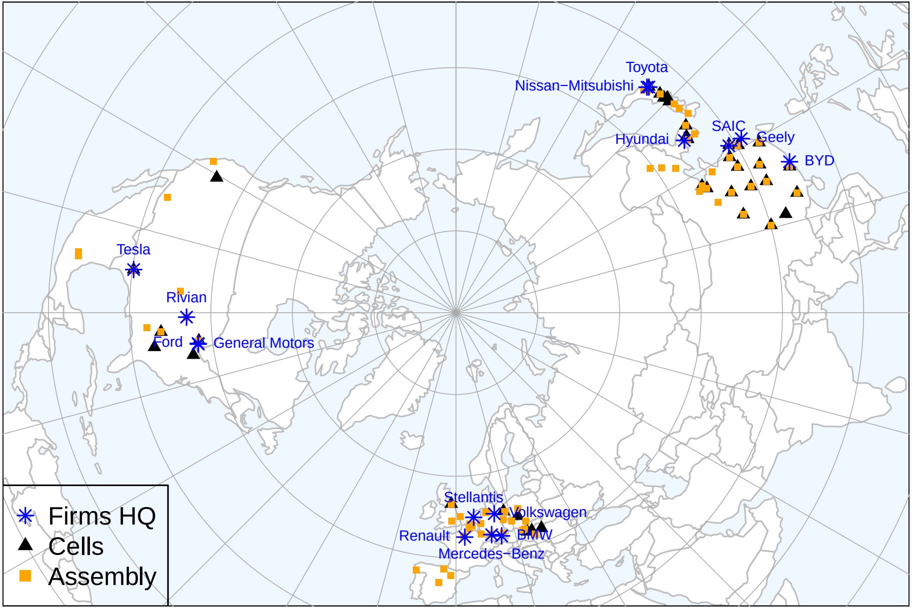
- Two other parameters to estimate: α_c and κ
- **Simulated Moments to Fit** (target)
  - Number of production lines by stage and continent ($\rho^k_{\text{As/Eu/Am}}$)
  - Fraction of production lines by HQ-continent and destination-continent pairs for each stage (ρ^k_{HQ})
  - Fraction of models sourced by (origin-continent, destination-continent) pairs for each stage (κ)
  - Market share of high quality models (α_c)

Filters to speed up SMM computation

- Despite speed of solving MUFLP, SMM estimation is time-consuming and memory hungry: many sets of draws, many starting parameters, so we need shortcuts
- 15 large MNCs (136 models + 11 trim-groups) that account for 90% of world sales (99% outside China)
- GAUL1 ($\approx$ province) plant locations in 24 countries

Stage	Americas	Asia	Europe	Total	Configurations
1: Cells	6	24	6	36	69bn
2: Assembly	10	33	25	68	3e+20

The top 15 EV makers and their location alternatives



15 top firms in 2022

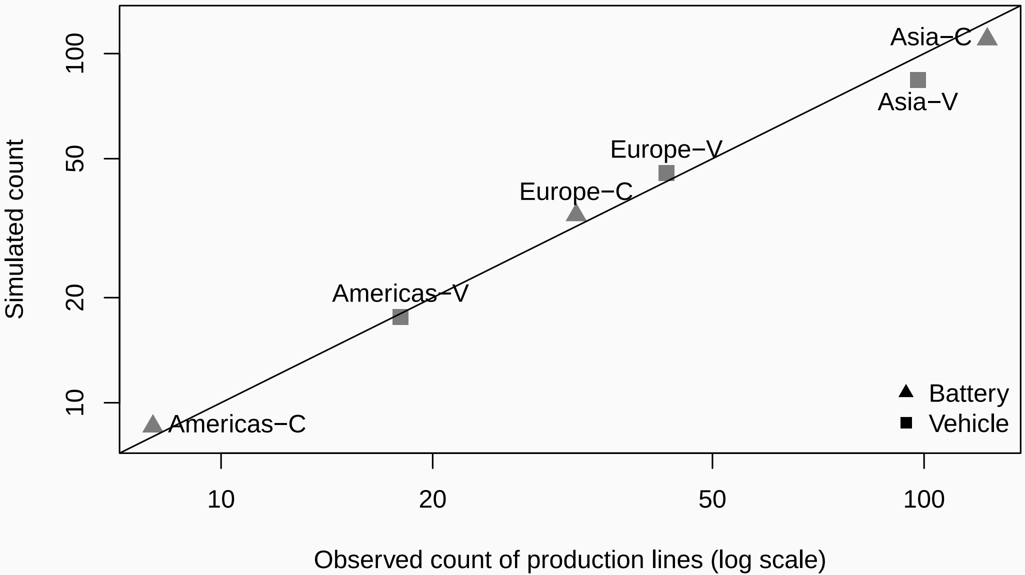
No.	Manufacturer	# Markets	# Models	Production Cum. Share (%)	Sales-exCHN Cum. Shr (%)
1	Tesla	23	4	20.5	28.0
2	Volkswagen	24	23	30.0	42.4
3	Hyundai	23	15	35.6	54.1
4	Stellantis	18	19	40.3	63.7
5	BMW	24	7	44.0	69.7
6	Renault	19	6	46.7	75.3
7	Mercedes-Benz	24	9	49.3	80.0
8	Geely	24	15	55.6	84.4
9	Ford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

SMM Parameter Estimates

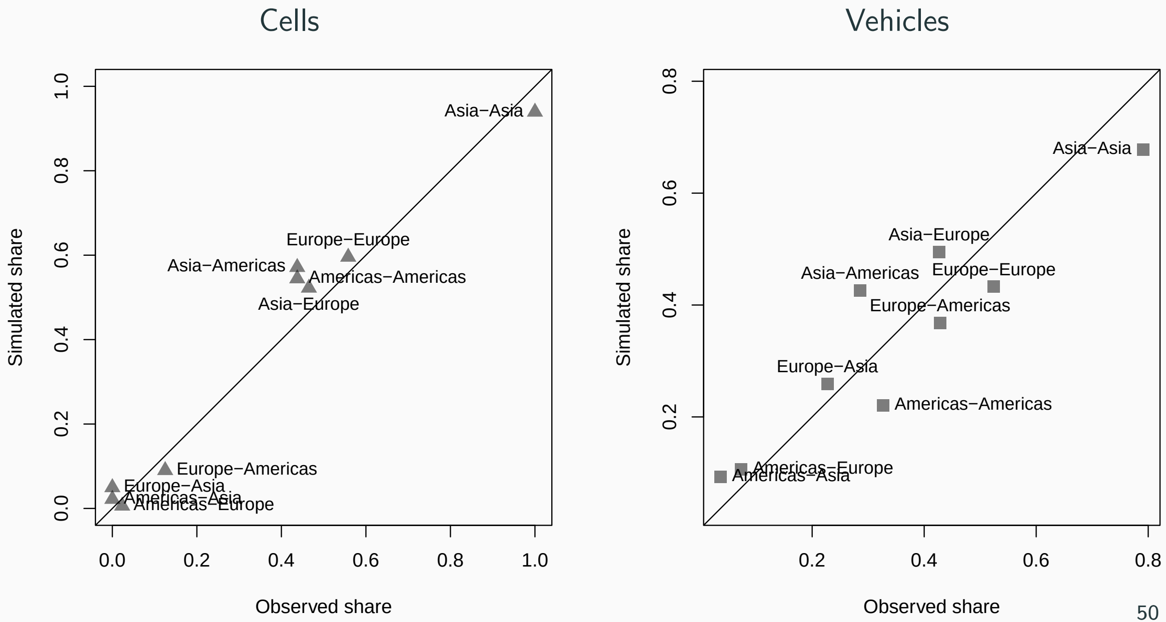
Parameter	Description	Estimate
κ_2	Variable cost (VC) weight	0.12
α_c	Cost elasticity of quality	0.10
ρ_1 (Asia)	Fixed cost of cell plant	0.07
ρ_1 (Europe)	(by continent)	0.10
ρ_1 (Americas)		0.46
ρ_2 (Asia)	Fixed cost of assembly plant	0.06
ρ_2 (Europe)	(by continent)	0.20
ρ_2 (Americas)		0.17
ρ_1 (HQ dist)	FC HQ-dist. elas. (cells)	0.61
ρ_2 (HQ dist)	FC HQ-dist. elas. (assembly)	0.73

No SEs yet, estimation takes $\approx$ 17 hours with 50 draws (parallelized)

Calibrated Fit to Data: Production Lines by Continent

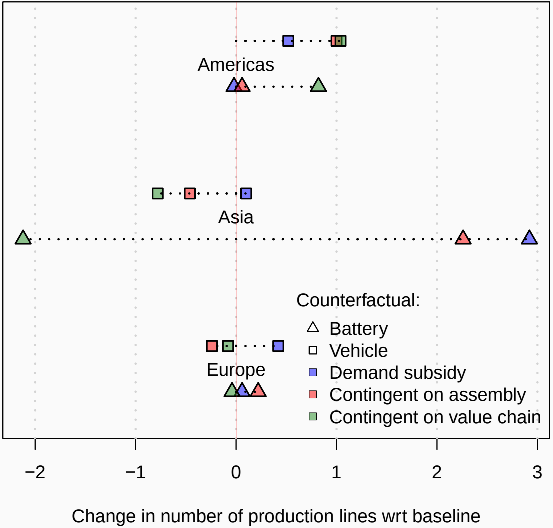


Calibrated Fit to Data: Inter-Continental Model Sourcing

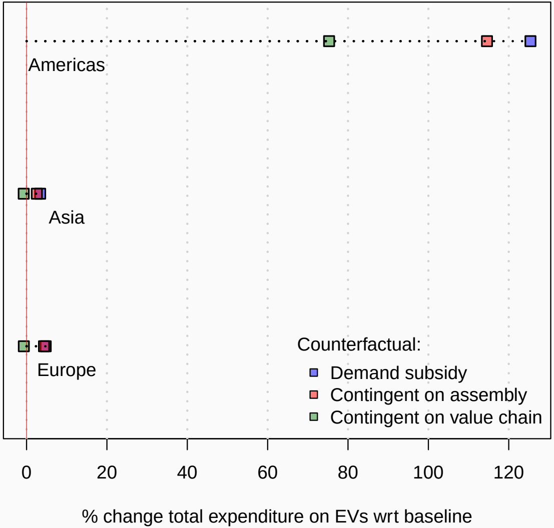


Counterfactual: BEV Policies

Predicted Impact of North American BEV Subsidies

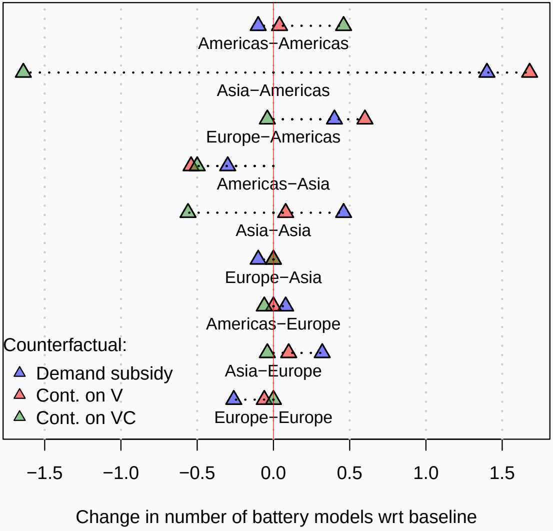


Production Locations

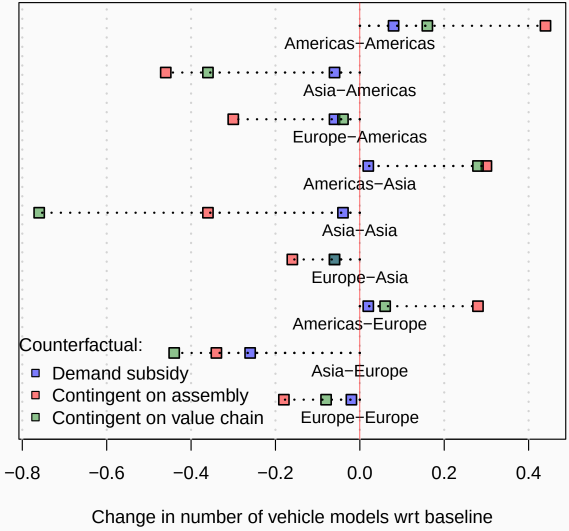


BEV Expenditure Shares

Predicted Effects for Cross-Continental Flows



Battery Cells



Vehicle Assembly

Contributions of subsidies and cost reductions to EV sales

Policy	Share	Cost index redn.			Tot. Exp.
	Elig.	subsidy	costs	total	increase
1: Unconditional	100	20	4.2	23.3	125.4
2: Continental V	22.7	18.4	4.2	22.0	114.6
3: Continental V+C	14.5	17.8	-1.5	16.5	75.3

Cost reductions driven by consumer subsidies account for 1/5 of total expenditure increase.

Contributions to cost changes (in %) in other continents

Policy	Share Elig.	Cost index redn. subsidy	Cost index redn. costs	Cost index redn. total	Tot. Exp. increase
		Europe			
1: Unconditional	0	0	1.4	1.4	4.8
2: Continental V	0	0	1.3	1.3	4.3
3: Continental V+C	0	0	-0.3	-0.3	-0.7
		Asia			
1: Unconditional	0	0	1.0	1.0	3.4
2: Continental V	0	0	0.8	0.8	2.6
3: Continental V+C	0	0	-0.3	-0.3	-0.7

EV subsidies in America decrease costs in the other continents as well—but not if they require local cells.

What we've learned so far

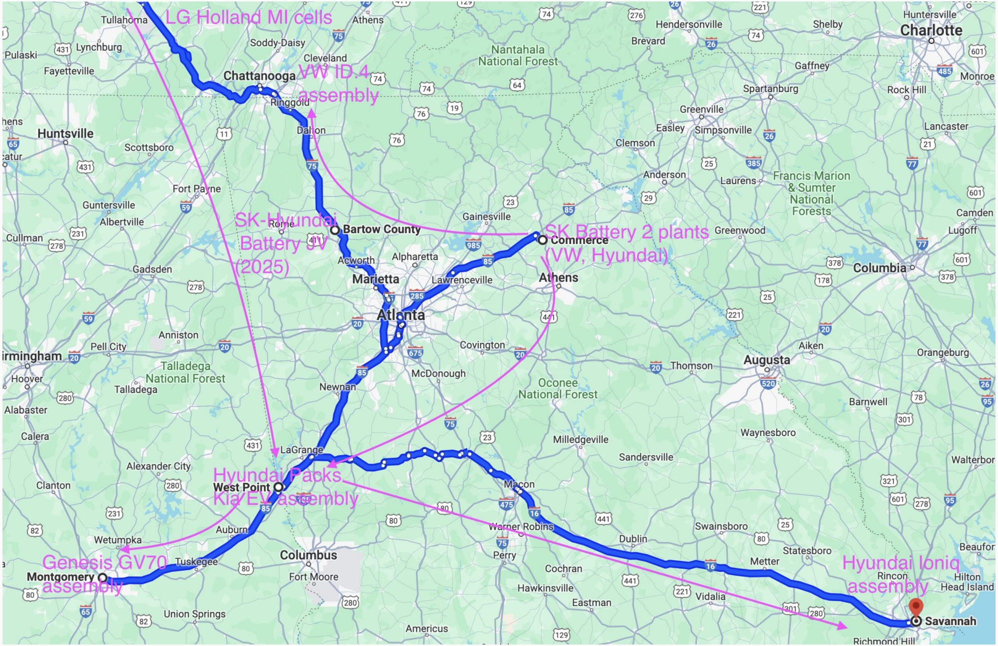
- Algorithm for solving the optimization problems that combine substitution and complement patterns across locations
- Relevance for evaluating the impact of large industrial policies that induce discrete change in locations
- Increasing returns (fixed costs) and multiple production stages are empirically relevant for many sectors
- Preliminary counterfactual results show that IRA subsidies increase EV expenditure, but restrictions on location of cell production are counter-productive
- With IRS, protectionist policies potentially align with emissions goals. Based on our estimates, a clean consumer credit would have done more to promote EV adoption

Epilogue: Post IRA investments

Top 10 models excluded by Rule 1 from the IRA buyer credit

Rank	Brand	Model	2022 Sales (US)	Assembly location announcements
1	Hyundai	Ioniq 5	23741	Adds from Korea to Savannah, GA
2	Kia	EV6	21978	Adds EV9 from Korea to West Point, GA
3	BMW	i4	11462	Stays in Germany
4	Polestar	2	8758	Polestar 3 to Ridgeville, SC
5	Porsche	Taycan	8425	Stays in Germany
6	BMW	iX	7394	Stays in Germany
7	Kia	Niro	7262	Stays in Korea
8	Audi	e-tron	7233	Stays in Belgium
9	Hyundai	Kona	4719	Stays in Korea
10	Volvo	C40	4693	Stays in Belgium

Korean BEV cluster: new paths for some IRA-affected models



Hyundai Ioniq Savannah, GA plant (December 2022)

Hyundai Ioniq near Savannah, GA plant (October 2024)

Appendix

UFLP is a limit case of AES, allows comparison to MILP

- AES cost function for variety ω (general case)

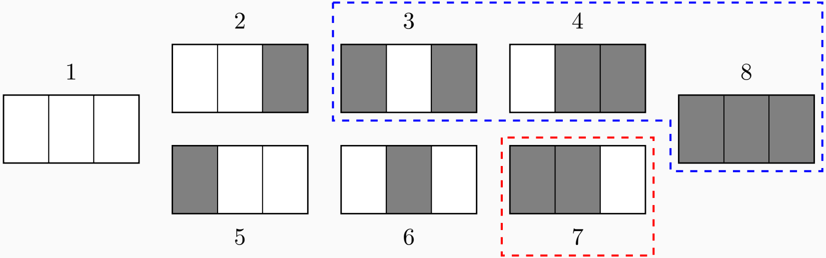
$$c_n(\mathcal{L}, \omega) = \left[\sum_{\ell \in \mathcal{L}} c_{\ell n}(\omega)^{-\theta} \right]^{-1/\theta}, \quad \text{where} \quad c_{\ell n} = w_\ell \tau_{\ell n}(\omega)/z_\ell(\omega).$$

- Limit case as $\theta \to \infty$: $\quad c_n(\mathcal{L}, \omega) = \min_{\mathcal{L}} c_{\ell n}(\omega).$
- Perfect substitution implies single-sourcing (least cost plant)
- Plug minimized cost into the profit function (taking P_n as given).

$$\pi(c_{\ell n}) \propto c_\ell^{1-\sigma}$$

- Firm chooses $\mathcal{L}$ to maximize the sum of all destination-specific profit
- Randomness: cost shocks (w_ℓ) and locations on grid ($\tau_{\ell n}$)
- Simulate L potential locations, N consumer markets

How submodularity can reduce evaluations



1. Configurations $i = 1...8$ of $[y_i^W, y_i^C, y_i^E]$
2. Evaluate 1 and 2: If $\pi_2 < \pi_1$ then position $y_i^E = 0$ for all i.
3. No need to evaluate $i = 3, 4, 8$
4. Evaluate 5 and 6: Whichever is higher will dominate 7.
5. Select larger of π_1 and winner of 5 vs 6.

$\Longrightarrow$ only need to evaluate 4 options (50% of all possibilities)

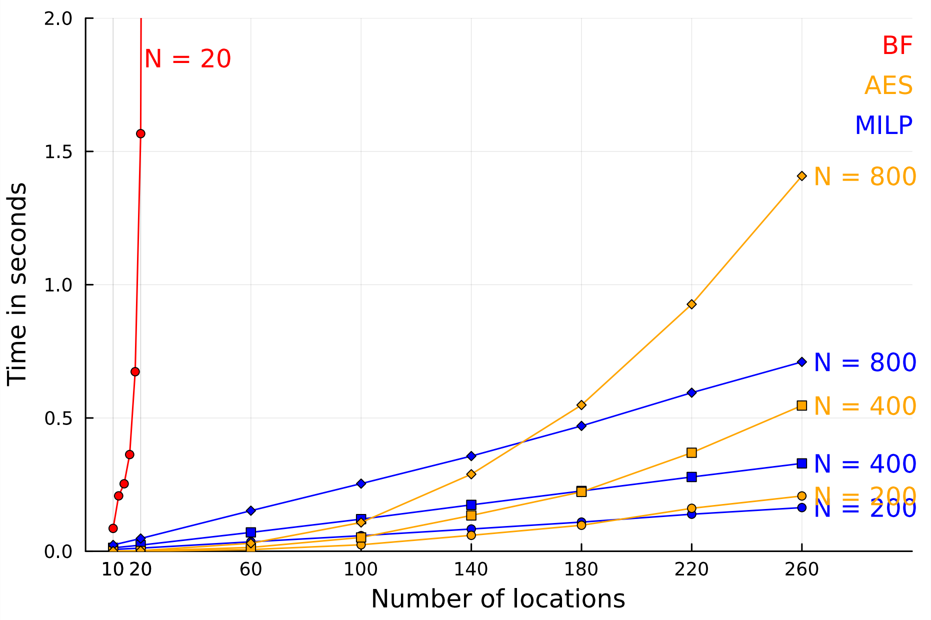
MILP formulation of the UFLP

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

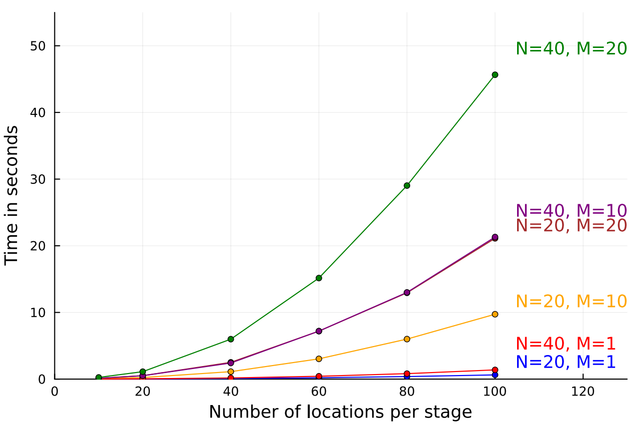
subject to

$$\begin{aligned}
\sum_{\ell \in L} x_{\ell n} &= 1, \quad n \in N \\
x_{\ell n} &\leq y_\ell, \quad n \in N, \ell \in L \\
x_{\ell n} &\geq 0, \quad n \in N, \ell \in L \\
y_\ell &\in \{0, 1\}, \quad \ell \in L
\end{aligned}$$

Comparing AES, MILP, and brute force

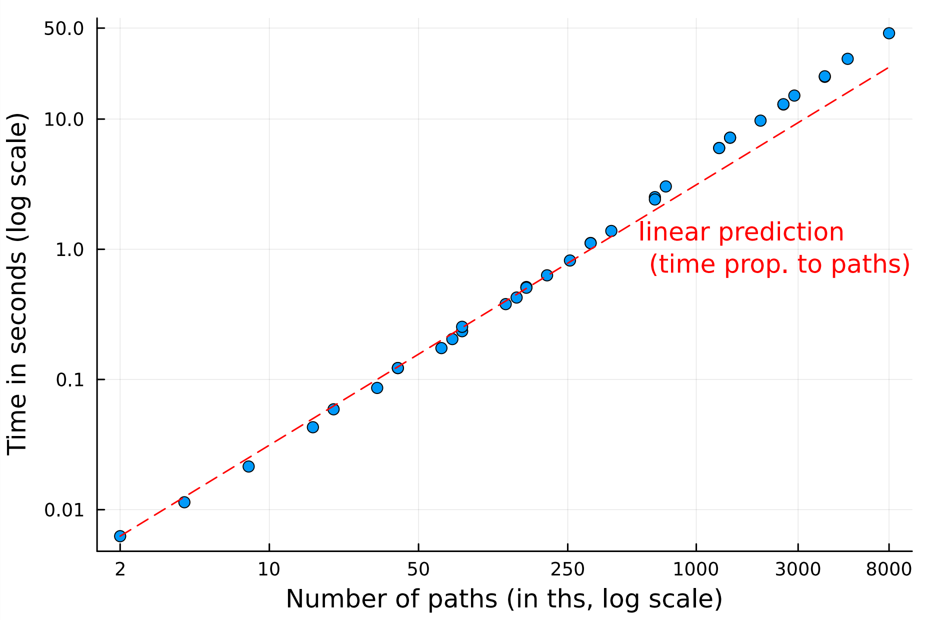


Computational performance for $K = 2$, MILP



- Multi-product firms with two production stages and endogenous market entry
- When $K = 2$, possible path for each model-market mn is L^2. Time increases exponentially with the potential number of locations per stage.
- N and M are equivalent in characterizing the problem dimension.

Computation time is approximately linear in number of paths



How Gurobi does it

- The solver is commercial and the code is not public. Best open source alternative (HIGHS) is 5–10 times slower.
- The key component one can track is the "linear relaxation." LP is really fast even for large problems.
- Gurobi tells us when the LP gives binary y results.
- When the linear relaxation is integral, we don't need the time-consuming methods: cutting planes, heuristics, branch & bound (smart, exhaustive search).
- Our experience, confirming past OR lit, is that the LP relaxation worked in the vast majority of cases. But no guarantees outside special cases.