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

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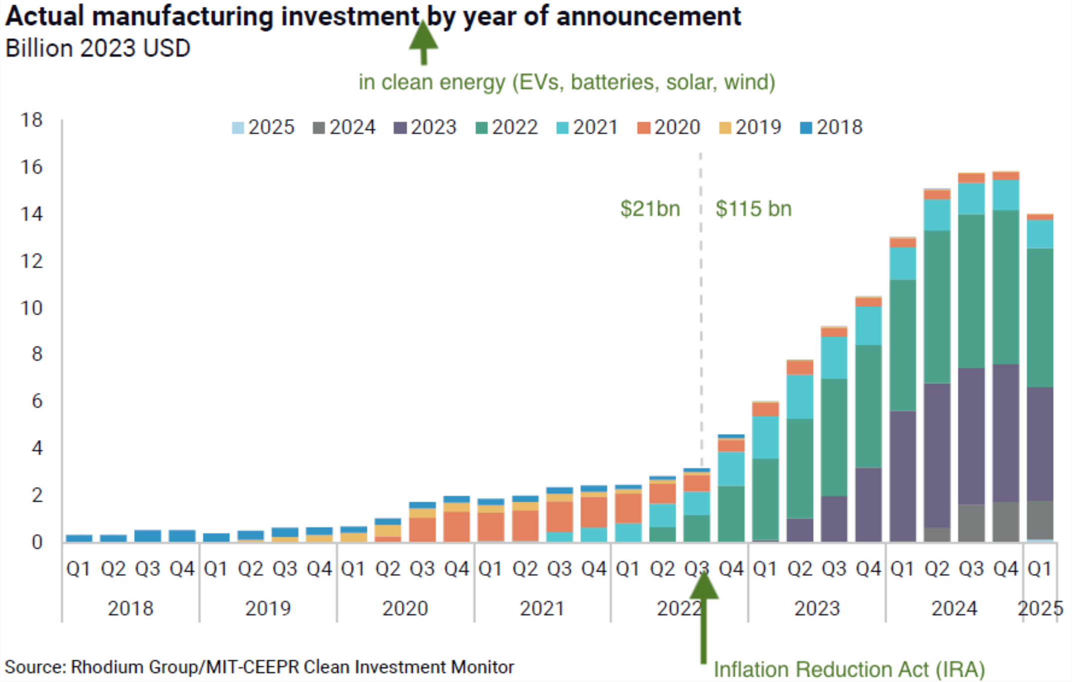
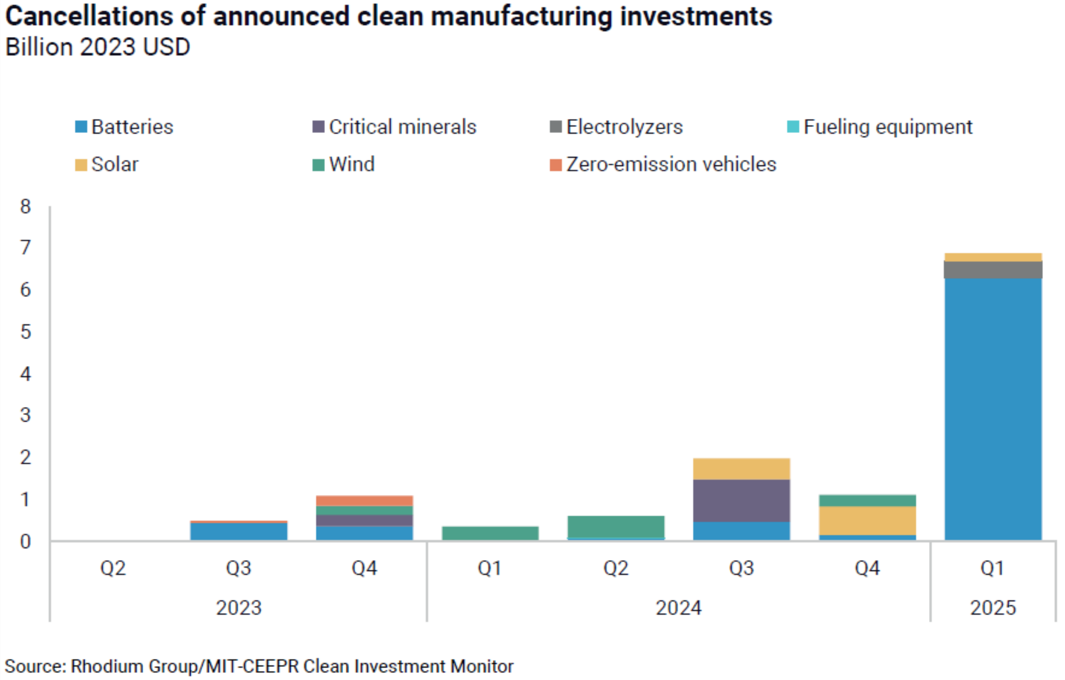

Actual manufacturing investment by year of announcement
Billion 2023 USD
in clean energy (EVs, batteries, solar, wind)
2025
2024
2023
2022
2021
2020
2019
2018
$21bn
$115 bn
0
2
4
6
8
10
12
14
16
18
Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1 Q2 Q3 Q4 Q1
2018
2019
2020
2021
2022
2023
2024
2025
Source: Rhodium Group/MIT-CEEPR Clean Investment Monitor
Inflation Reduction Act (IRA)


Cancellations of announced clean manufacturing investments
Billion 2023 USD
Batteries
Critical minerals
Electrolyzers
Fueling equipment
Solar
Wind
Zero-emission vehicles
8
7
6
5
4
3
2
1
0
Q2
Q3
Q4
Q1
Q2
Q3
Q4
Q1
2023
2024
2025
Source: Rhodium Group/MIT-CEEPR Clean Investment Monitor

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 (substitutes)
  - There is a core input that drives costs of the downstream product (complements)
- Policy design in this context 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 Takeaways:

- Endogenizing facility location choices matters for policy evaluation
- Upstream 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 3 types of 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)

Our main difference from this lit: focus on endogenous location decisions.

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 $K+1$)

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.
- Uncertainty: Our framework is static with known policies.
- 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.
- Inefficient Bargaining between cell makers and vehicle assemblers. We assume that "lead firms" solve the profit maximization problem for the vertical chain efficiently and then make transfers in response to bargaining power

Outline of Talk

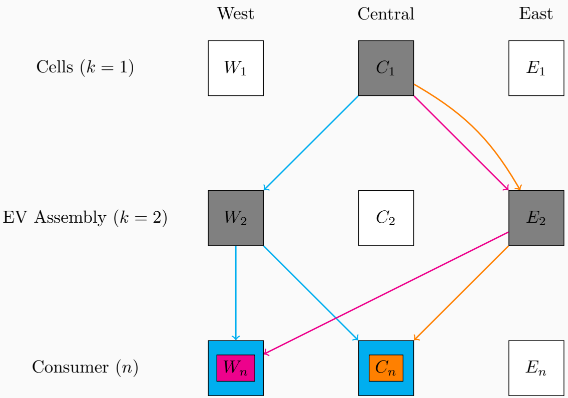
1. Setting up and solving the MMM-UFLP
2. Features of the BEV industry that make it fit into the MMM-UFLP framework
3. Estimate dyadic trade cost (gravity) parameters: Worldwide sourcing and production of batteries and vehicles
4. Estimate production and fixed costs: Simulated method of (intercontinental)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

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

Solving Facility Location Choice: New Computational Method

- 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.
- Integer programming 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. Colour squares are entered markets.

From Paths to Profits

- Key requirement for integer programming 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: $\pi(c(\ell_{mn}), A_n)$
- A_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.

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 for a client f (car maker)
- Paid for each group g_k 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.

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

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

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

subject to

$$\sum_{\ell_1\in L_1}\sum_{\ell_2\in L_2} x_{mn\ell_1\ell_2} \leq z_{mn}, \quad n \in N, m \in M_f \tag{1}$$

$$\sum_{\ell_1\in L_1} x_{mn\ell_1\ell_2} \leq y_{fg_2(m)\ell_2}, \quad n \in N, m \in \mathcal{M}_f, \ell_2 \in L_2 \tag{2}$$

$$\sum_{\ell_2\in L_2} x_{mn\ell_1\ell_2} \leq y_{fg_1(m)\ell_1}, \quad n \in N, m \in \mathcal{M}_f, \ell_1 \in L_1 \tag{3}$$

$$x_{mn\ell_1\ell_2} \geq 0, \quad y_{fg_1\ell_1} \in \{0,1\}, \quad y_{fg_2\ell_2} \in \{0,1\} \quad z_{mn} \in \{0,1\}. \tag{4}$$

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, grouped by characteristics
3. Endogenous market entry to multiple markets
4. Because our focus is the GVC supply side, we simplify other aspects via CES demand, constant markups, fixed cost shares across 2 stages.
5. The method permits many generalizations (e.g. more stages, multiples inputs at a given stage)

Necessary industry characteristics for this framework

1. Inputs from different plants are perfect substitutes (no love of variety) if all dimensions of the product are specified $\Longrightarrow$ 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

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 cost are huge: avg. $2.5bn (based on 83 news 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

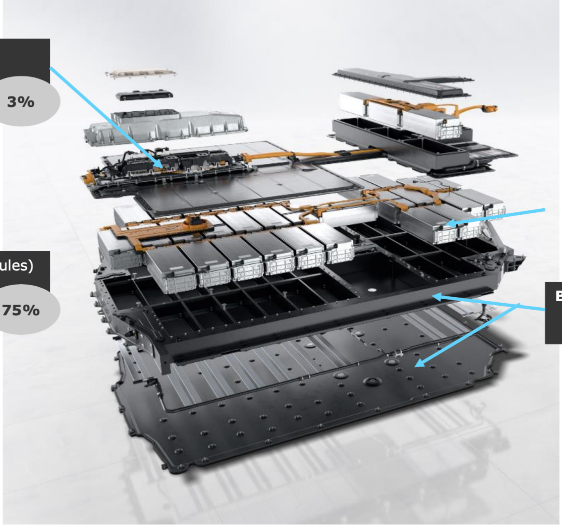
Batteries (€ 8k) cost twice as much as gas engine + transm. (€ 4k)

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

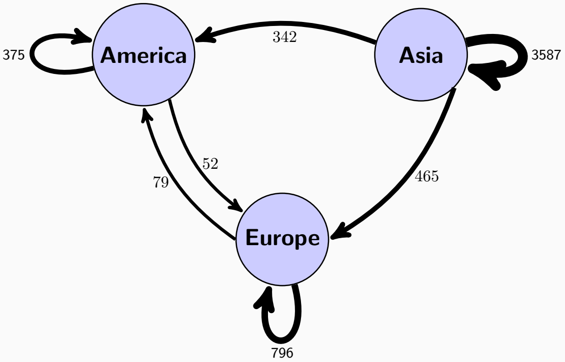
Batterie Pack

23%

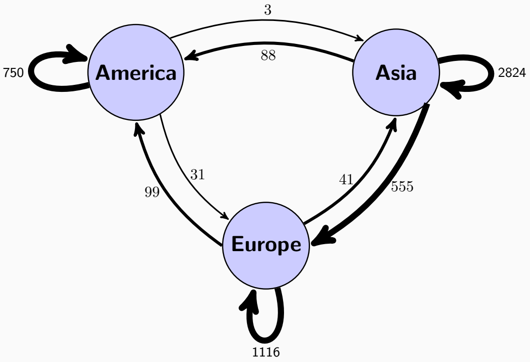
Boîtiers / carters du pack batterie avec fonctionnalités thermiques et de structure

Battery cells represent > 1/4 of EV cost

Cell and vehicle trade is mostly intra-continental, but Asia exports

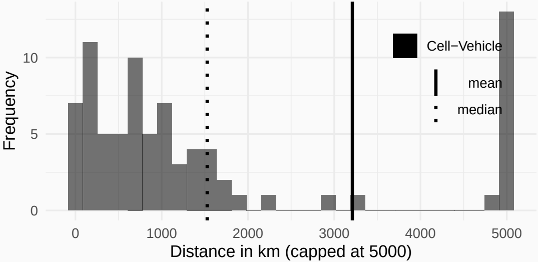


Cells (000s of vehicles)

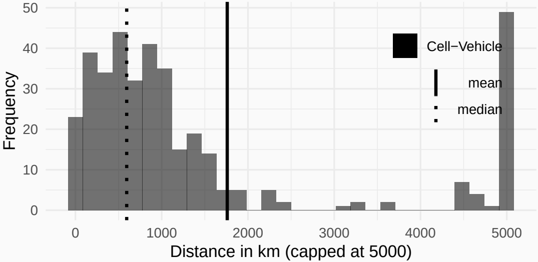


Vehicles (000s)

Mainly short distances between stages—with exceptions

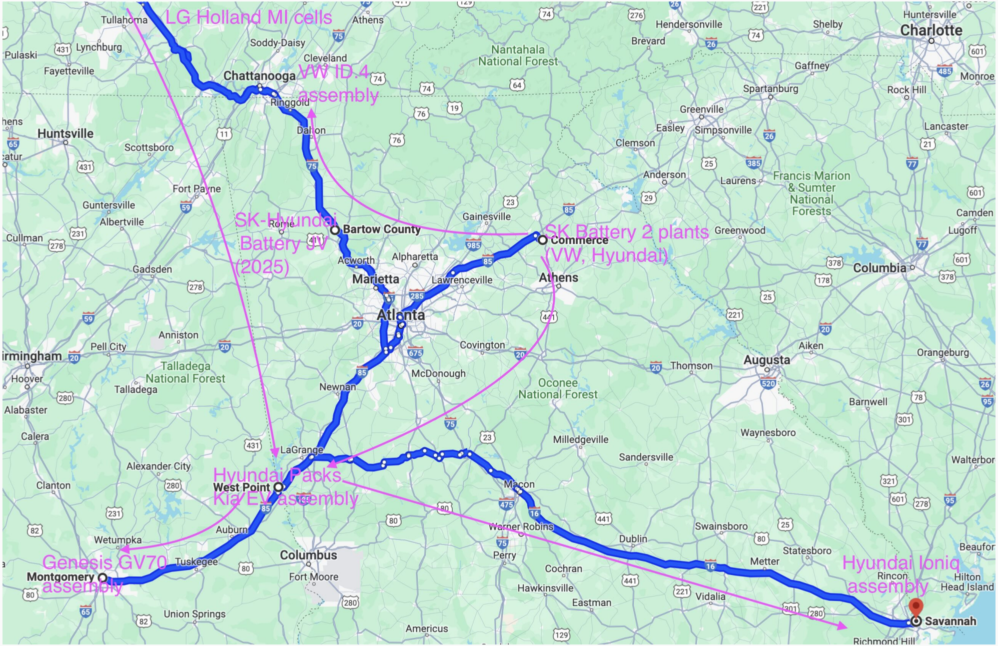


2015



2022

Korean BEV cluster forming in Southeast US



High up-front investment costs, especially for batteries

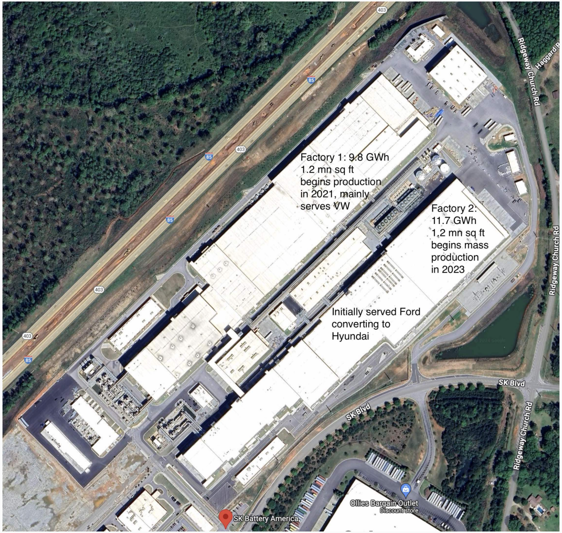
	Cost ($US bn)		Article
Stage	Mean	Std. Dev.	Count
Cells	2.53	2.60	83
Vehicle Assembly	0.79	0.94	198
Battery and Vehicle	4.09	3.54	13

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

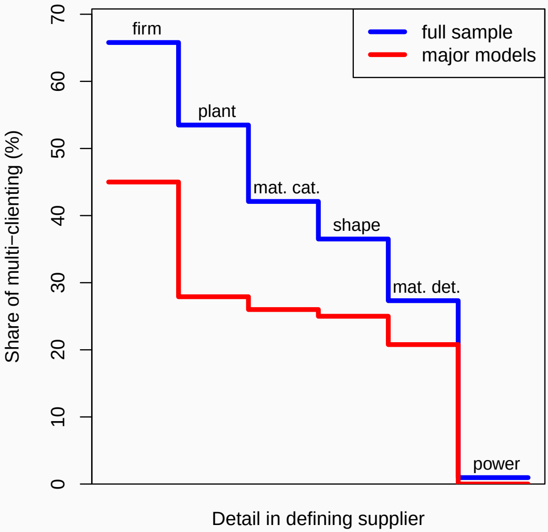


2nd "block" to serve Hyundai

LG Energy's new Michigan cell factory extension

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

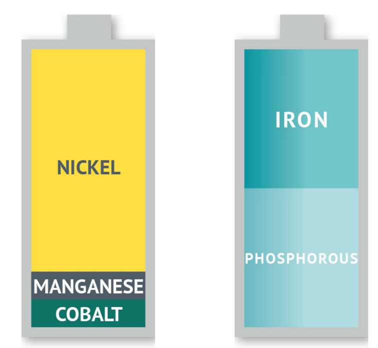
Cell plants single clients for specific battery types

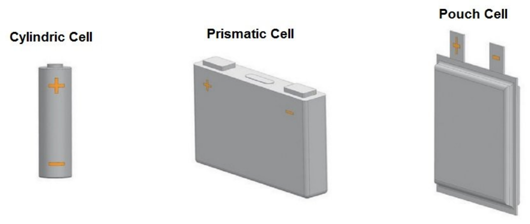


- All battery cell plants supply a type of battery (material (detailed)-shape-power) to a single major car maker.
- We model cell fixed costs at the carmaker-stage-material (category)-shape-location level.
- For major models, 75% single-clienting at this level

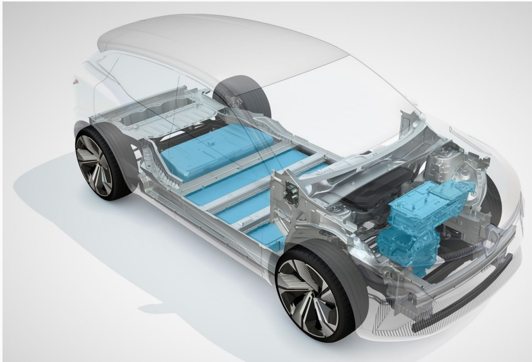
Fixed costs pertain to location-firm-groups

Battery cells grouped by
material category $\downarrow$ & shape $\rightarrow$





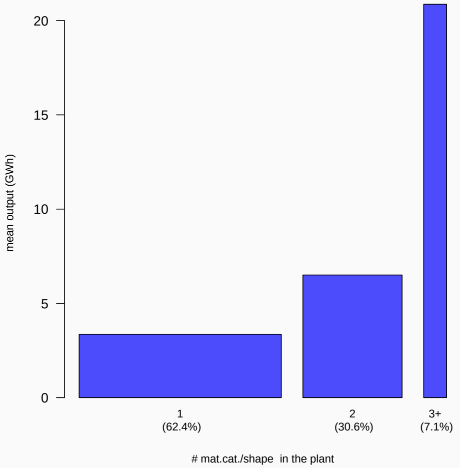
Vehicle assembly grouped by platform $\downarrow$



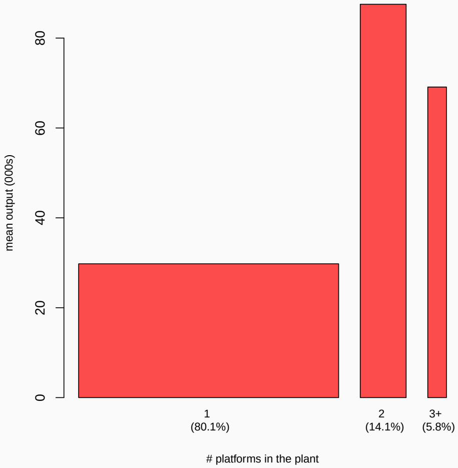
$g_1(m)$ assigns models to cell groups, $g_2(m)$ assigns models to assembly groups

Size of plant and count of platforms

(a) Cell plants

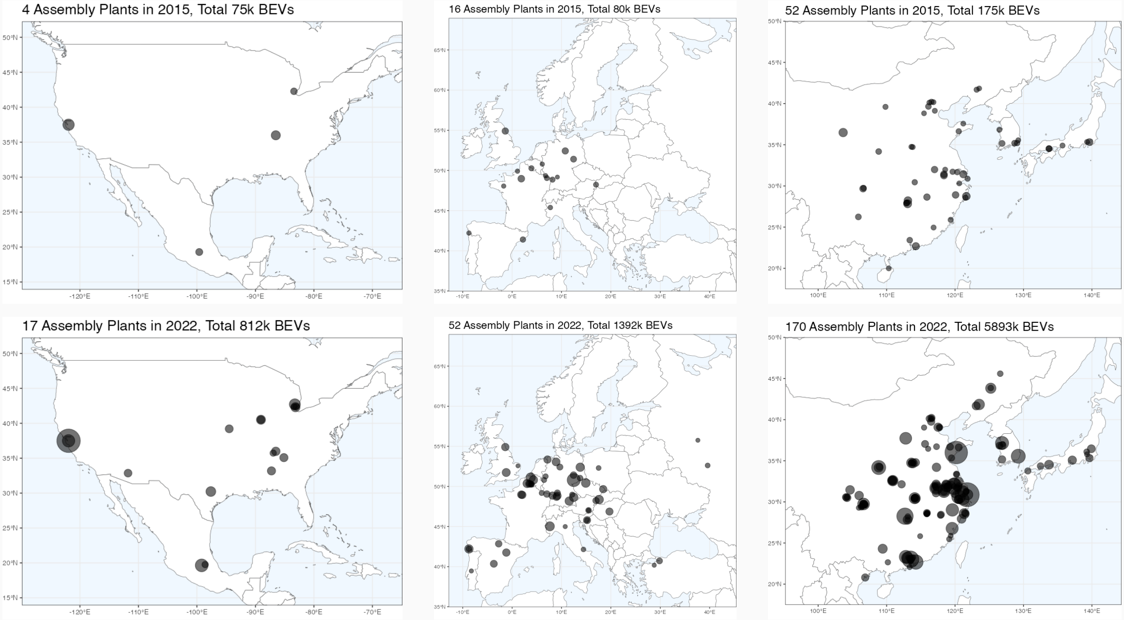


(b) Vehicle plants



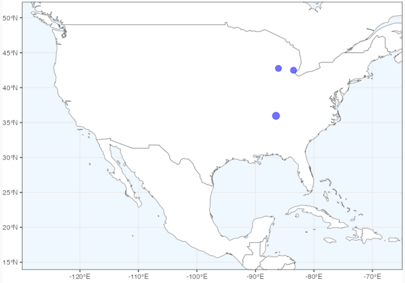
Majority of plants produce a single group; Multi-group plants are, on average, much larger

Active extensive margin for EV Assembly

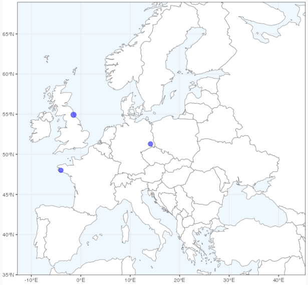


Active extensive margin for Cells

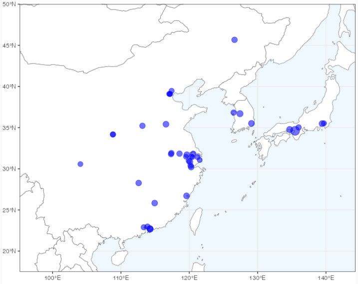
3 Cell Plants in 2015, Total 0.6GWh



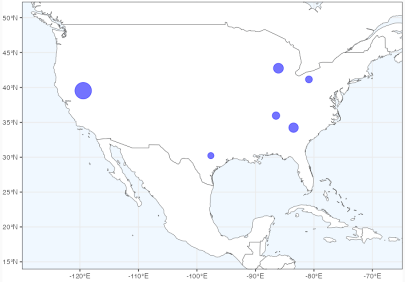
3 Cell Plants in 2015, Total 0.6GWh



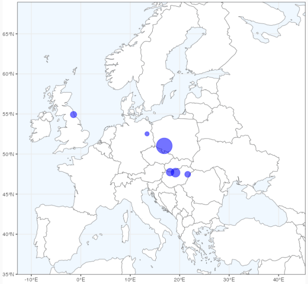
39 Cell Plants in 2015, Total 9.8GWh



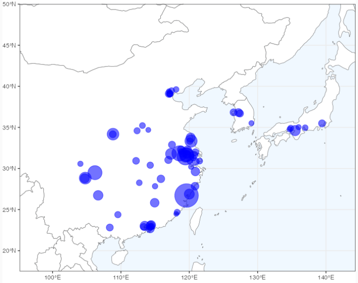
6 Cell Plants in 2022, Total 34.1GWh



6 Cell Plants in 2022, Total 64.8GWh



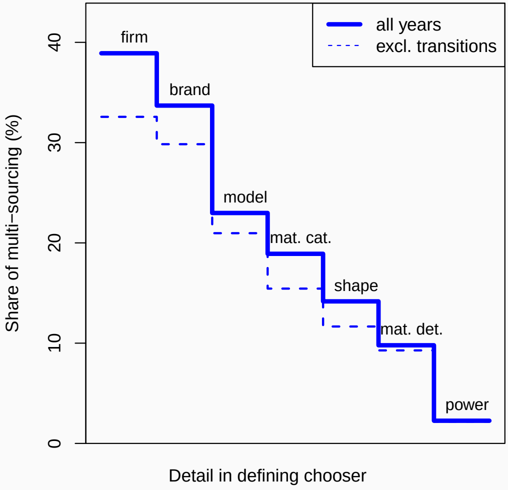
74 Cell Plants in 2022, Total 374.2GWh



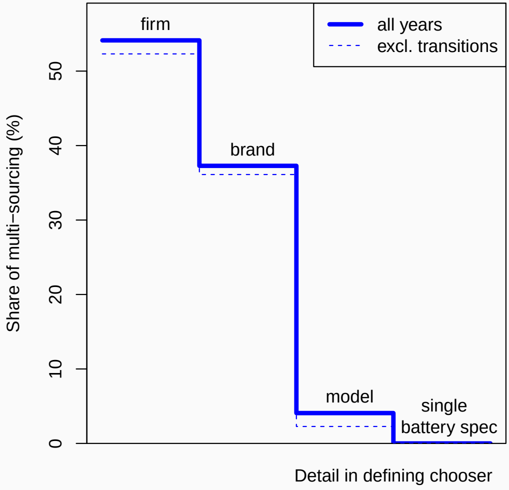
Top 10 models excluded by Rule 1 from the IRA buyer credit

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

Multi-sourcing is rare for narrowly defined inputs



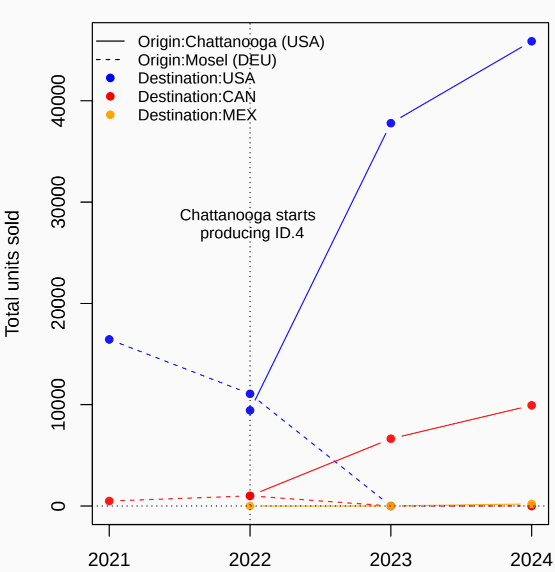
Cells



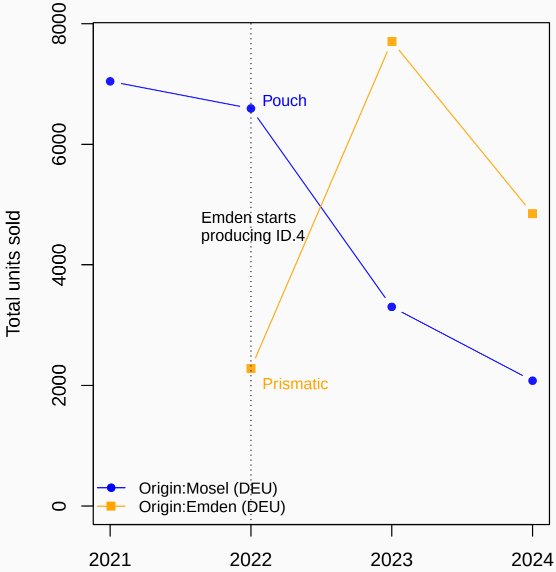
Electric Vehicles

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 (distance, borders, trade agreements, tariffs) and cell cost share.

Step 2: Estimate fixed and variable cost parameters at continental level by matching moments of the data to the simulated model (SMM)

Step 1: Variable costs of paths

- Variable costs

$$\text{Cells costs:} \quad c^1_{m\ell_1\ell_2} = w^1_{\ell_1} \tau^1_{\ell_1\ell_2} \varepsilon^1_{m\ell_1\ell_2},$$
$$\text{Vehicle path costs:} \quad c(\boldsymbol{\ell}_{mn}) = \left(w^2_{\ell_2}\right)^{\alpha_{22}} \left(c^1_{m\ell_1\ell_2}\right)^{\alpha_{12}} \tau^2_{\ell_2 n} \varepsilon^2_{m\ell_2 n}.$$

- Conditional on active facilities ($\mathbf{y}$,$\mathbf{z}$), each firm sources cells and vehicles to minimize:

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

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 $L_1(m)$ making the model's cell type for that maker
  - **Determinants:** trade costs (β_τ^1), fixed effects of supplier countries
- **Stage** $k = 2$: Vehicle sourcing
  - **Chooser:** dealership network in country n sourcing model m
  - **Choice:** EV assembly plant in country ℓ_2
  - **Choice set:** Plants that assembles the model's platform
  - **Determinants:** trade costs (β_τ^2), fixed effects of supplier countries, inclusive cost from cell stage $\rightarrow -\beta_\Phi^2$

Sequential Nested Logit Estimation of Variable Costs (Cont.)

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: $\mathrm{FE}^1_{\ell_2}(m) = -\ln \sum_{\ell \in L_1(m)} \exp[\mathrm{FE}^1_\ell + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)]$

Nested Logit Sourcing Results

	Cells	Vehicles
log distance	-0.363[a]	-0.137[b]
	(0.014)	(0.067)
RTA	0.075	0.479[a]
	(0.362)	(0.171)
Inc. cost of cells		-0.278[a]
		(0.088)
log GDP per capita	0.234[c]	0.195[b]
	(0.121)	(0.088)
log(1+tariff)	-10.0[a]	-6.95[a]
	(2.46)	(2.19)
Border_As	-0.421	-2.00[a]
	(0.344)	(0.646)
Border_Am	-1.62[c]	-1.58[b]
	(0.871)	(0.754)
Border_Eu	-1.59[a]	-0.017
	(0.555)	(0.169)
Observations	7,945	15,793

- Home plants (border $=0$) are $\approx \exp(1.6) \approx 5$ times more likely to be chosen in the US
- Trade agreements also important
- Tariff elasticities are large ($\theta_1 = 10$ for cells, $\theta_2 = 7$ for vehicles)
- Coef on inclusive cost $\rightarrow$ cell cost share $-\theta_1\beta_\Phi/\theta_2 = 40\%$.
- GDP/cap effects based on within-country variation since regression includes country fixed effects

Remaining Variable Cost Parameters (SMM)

Log path costs (Logit, SMM):

$$\ln c(\boldsymbol{\ell}_{mn}) = -\kappa\Big\{\mathrm{FE}^2_{\ell_2} + \beta^2_D \ln D_{\ell_2 n} + \beta^2_t \ln\left(1 + t^2_{\ell_2 n}\right) - \beta^2_\Phi\left[\mathrm{FE}^1_{\ell_1} + \beta^1_D \ln D_{\ell_1\ell_2} + \beta^1_t \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right]\Big\} + \underbrace{u(\boldsymbol{\ell}_{mn})}_{-\mathrm{Gumbel}(0,\kappa)} .$$

- β^2_Φ is coefficient on inclusive cost of cells
- κ is Gumbel shape parameter for the unobserved $u(\cdot)$ shocks (dispersion)
  - Assume that ad-valorem tariffs on vehicles $t_{\ell_2 n}$ proportionately shift path cost $c(\boldsymbol{\ell}_{mn})$:

$$\kappa\beta^2_t = -1 \iff \kappa = \frac{-1}{\beta^2_t}$$

Simplified demand and market structure

- Sales of model m delivered to market n are $s_{mn}R_n$, where s_{mn} denotes market share (in values) and R_n is total expenditures on cars.
- CES demand for vehicle models (EV and ICE) with R_n fixed and demand elasticity calibrated to the literature (18 estimates) median $\eta = 4$
- Market shares (over all vehicles):

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

where P_n is associated price index, decomposable as

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

- As s_{mn} are small, approximate price/cost markups as constant $\eta/(\eta-1)$.

Costs + demand → variable profits

- Delivered marginal cost is multiplicative in path costs and an arbitrary model-specific shifter: $c_{mn\ell} = c(\ell_{mn})\upsilon_m$
- For any path ℓ_{mn} variable profits and market share are:

$$\pi_{mn\ell} = \frac{R_n s_{mn\ell}}{\eta}, \qquad s_{mn\ell} = \left(\frac{\eta}{\eta-1}\frac{c_{mn\ell}}{\xi_{mn}}\frac{1}{P_n}\right)^{1-\eta}$$

- Market share captures the unobserved cost and demand shifters
- Key: Any change in path ℓ, shifts variable profits by a factor $\left(\hat{c}_{mn\ell}/\hat{P}_n\right)^{1-\eta}$. The non-path specific-factors—R_n, υ_m, ξ_{mn}, $\eta/(\eta-1)$—all cancel.

Hat Algebra for Variable Profits

- For any potential path ℓ_{mn}, we can construct changes in path costs relative to the observed/chosen path ℓ°_{mn}:

$$\hat{c}_{mn\ell} = \frac{c_{mn\ell}}{c_{mn\ell^{\circ}}} = \frac{c(\ell_{mn})}{c(\ell^{\circ}_{mn})}$$

- We can then construct the variable profits in levels using information only on the observed market shares s°_{mn} (for the chosen paths ℓ°_{mn}):

$$\pi_{mn\ell} = \frac{1}{\eta} s^{\circ}_{mn} R^{\circ}_{n} \hat{s}^{1-\eta}_{mn\ell}, \qquad \hat{s}_{mn\ell} = \left(\frac{\hat{c}_{mn\ell}}{\hat{P}_n}\right)^{1-\eta}$$

The change in the endogenous price index satisfies:

$$\hat{P}^{1-\eta}_{n} = s^{\circ, ICE}_{n} + \sum_{m} s^{\circ}_{mn} \hat{c}^{1-\eta}_{mn} = 1 + \sum_{m} s^{\circ}_{mn} (\hat{c}^{1-\eta}_{mn} - 1),$$

where $\hat{c}_{mn} = c(\ell^{*}_{mn})/c(\ell^{\circ}_{mn})$ for the optimal chosen path ℓ^{*}_{mn}

Completing the parameter set

- Last parameters needed are the fixed costs $\phi_{fg_k\ell_k}$, of activation ($y_{fg_k\ell_k}$).
- Cannot estimate in sourcing regressions, as those take the $y_{fg_k\ell_k}$ as given.
  $\implies$ rely on simulated method of moments (SMM).
- Distribution of fixed costs draws by location-stage:

$$\ln \phi_{fg_k\ell_k} \sim \mathcal{N}\left(\ln\left[\rho^k_{\ell_k} \times R^{\text{EV}}_w\right], \sigma\right),$$

- Means expressed as a fraction of worldwide EV revenues, R^{EV}_w.
- The expectation of the fixed cost draws, $\rho^k_{\ell_k}$, depends on
  - distance to headquarter (HQ) w/ elasticity $\rho^{\text{HQ},k}$,
  - platform inferred quality w/ elasticity $\rho^{\xi,k}$.
  - continent-stage means, ρ^k_r, for $r \in \{\text{As}, \text{Eu}, \text{Am}\}$
- To avoid selection bias in the sourcing equations, the SMM also estimates continental variable cost differences: FE^k_r for $r \in \{\text{As}, \text{Eu}\}$

Simulated moments we target

1. Shares of models sourced by origin-destination continent pair (dyads) [18]
2. Shares of revenue (continent d's spending on EVs from continent o) [18]
3. Number of production lines ($\sum_{\ell_k \in r} y_{fg_k\ell_k}$) scaled by data [6]
4. Number of models offered by continent r scaled by data [3]
5. Shares of production lines (firm HQ continent by production continent) [18]

Moments formed by stage $k = 1, 2$ & continent $r = \text{Am}, \text{As}, \text{Eu}$

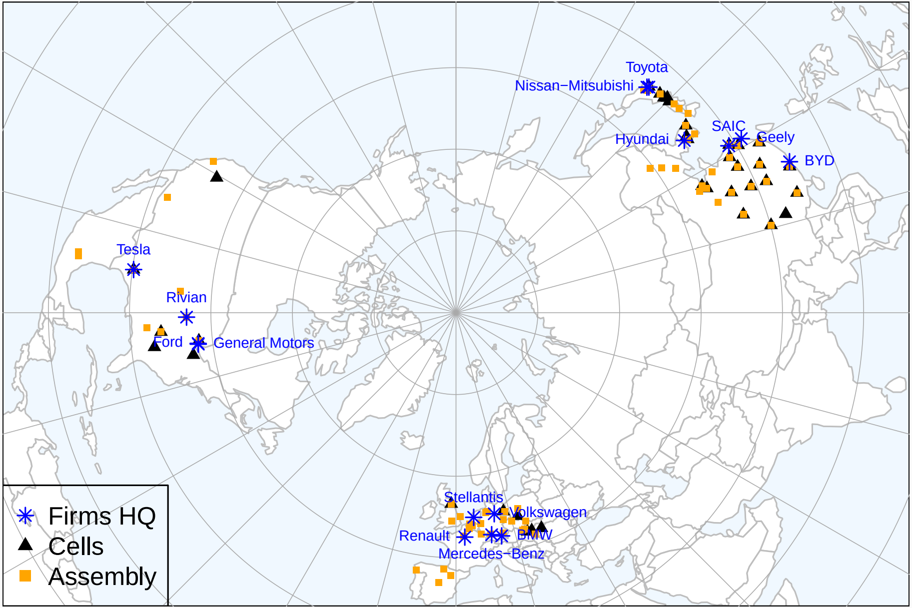
We overweight the moment match the number of origin-destination pair share moments ($6 \times 3 = 18$).

Filters to speed up SMM computation

- Despite speed of solving MUFLP, SMM estimation is time-consuming and memory hungry:
  - Many sets of draws of path and fixed cost shocks
  - Global optimization requires many starting parameters,

  so we need some dimension reduction
- 15 large MNCs that account for 77% of world sales (98% outside China)
- 137 models
- 24 countries (97% sales, 99.9% cells, 99% EV assembly)
- 27 geographic aggregates: 15 potential locations for assembly, 12 for cells

The top 15 EV makers and their location alternatives



15 top firms in 2022

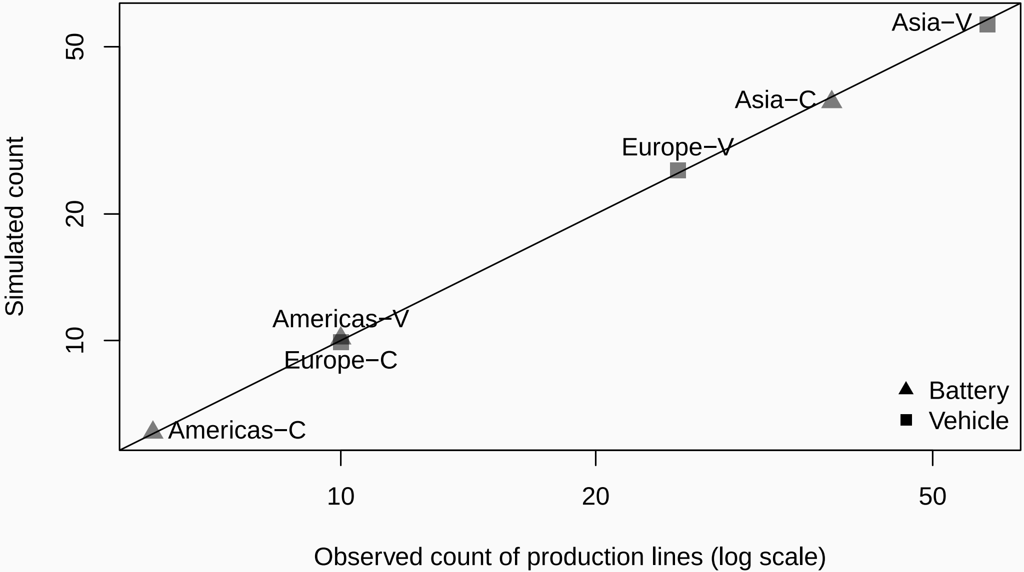
No.	Manufacturer	# Markets	# Models	Production Cum. Share (%)	Sales-exCHN Cum. Shr (%)
1	Tesla	56	4	17.9	28.3
2	Volkswagen	65	23	25.9	42.2
3	Hyundai	53	15	30.7	53.6
4	Stellantis	20	19	34.6	62.5
5	BMW	61	8	37.9	68.5
6	Renault	38	6	40.3	74.2
7	Mercedes-Benz	57	9	42.6	78.9
8	Geely	52	15	48.0	83.6
9	Ford	36	4	49.6	87.3
10	SAIC	33	22	60.4	90.8
11	Nissan-Mitsubishi	51	8	62.6	94.2
12	General Motors	10	7	63.7	95.7
13	Toyota	40	8	64.3	96.8
14	Rivian	4	3	64.6	97.6
15	BYD	24	14	76.6	98.3

Simulated Method of Moments Estimates

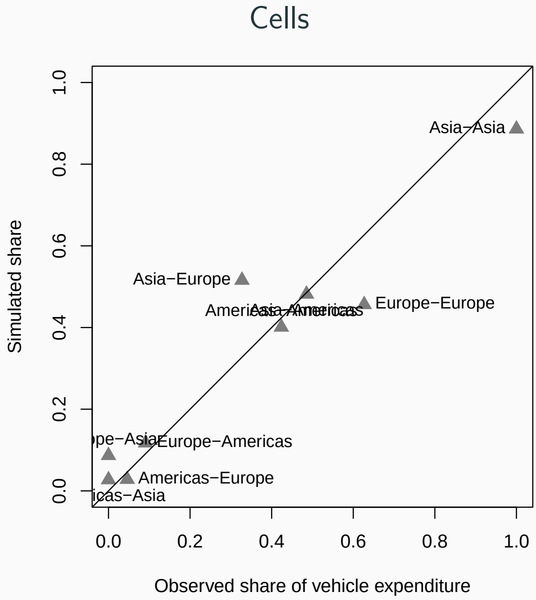
Par.	r	Description	Est.
σ		Fixed cost dispersion	2.73
FE^1	As	Var. cost adv. (C)	8.85
FE^1	Eu	(by region, $\mathrm{Am} = 0$)	6.17
FE^2	As	Var. cost adv. (V)	-0.37
FE^2	Eu	(by region, $\mathrm{Am} = 0$)	0.37
ρ^1	Am	Fixed cost	0.56
ρ^1	As	of cell plant	0.38
ρ^1	Eu	(by region)	1.26
ρ^2	Am	Fixed cost	0.43
ρ^2	As	of assembly	0.08
ρ^2	Eu	(by region)	1.21
$\rho^{\mathrm{HQ,\ dist},1}$		FC HQ dist. elas. (C)	1.02
$\rho^{\mathrm{HQ,\ dist},2}$		FC HQ dist. elas. (V)	1.58
$\rho^{\xi_{fg_1}}$		FC quality elas. (C)	3.91
$\rho^{\xi_{fg_2}}$		FC quality elas. (V)	2.63

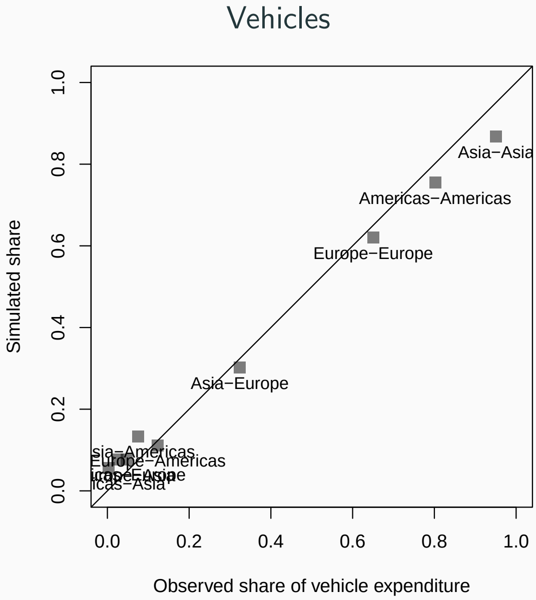
- Asia cell variable cost is 30% of that in Americas ($\exp(-1/6.95 \times 8.85) = 0.28$)
- Asia and America variable assembly costs are similar.
- US fixed costs of assembly are over 5 times those in Asia ($0.43/0.08 = 5.4$)
- Proximity to V maker lowers FC.
- Better battery type or platform quality increases FC.
- Fixed costs of open facilities $\approx$ 6% of world revenue.

Calibrated Fit to Data: Production Lines by Continent

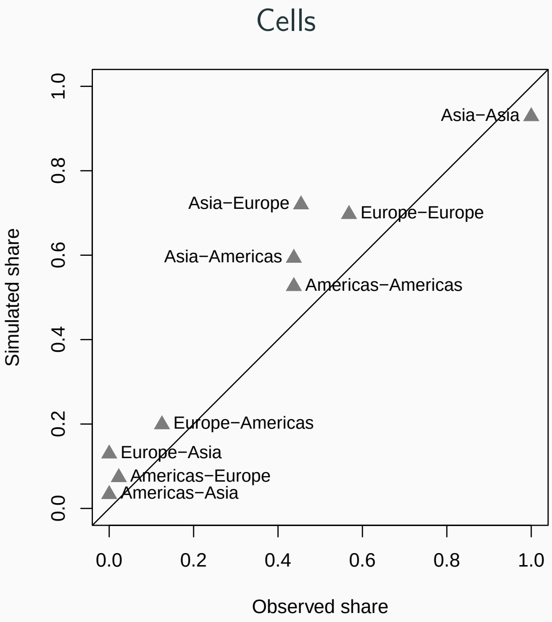


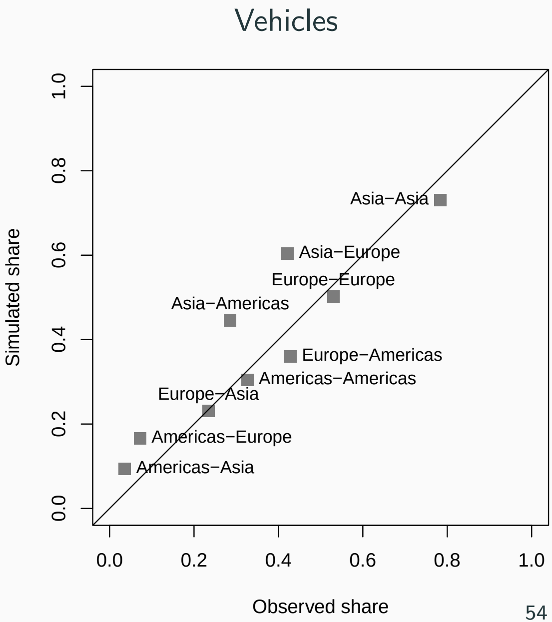
Calibrated Fit to Data: Inter-Continental Market share (revs)



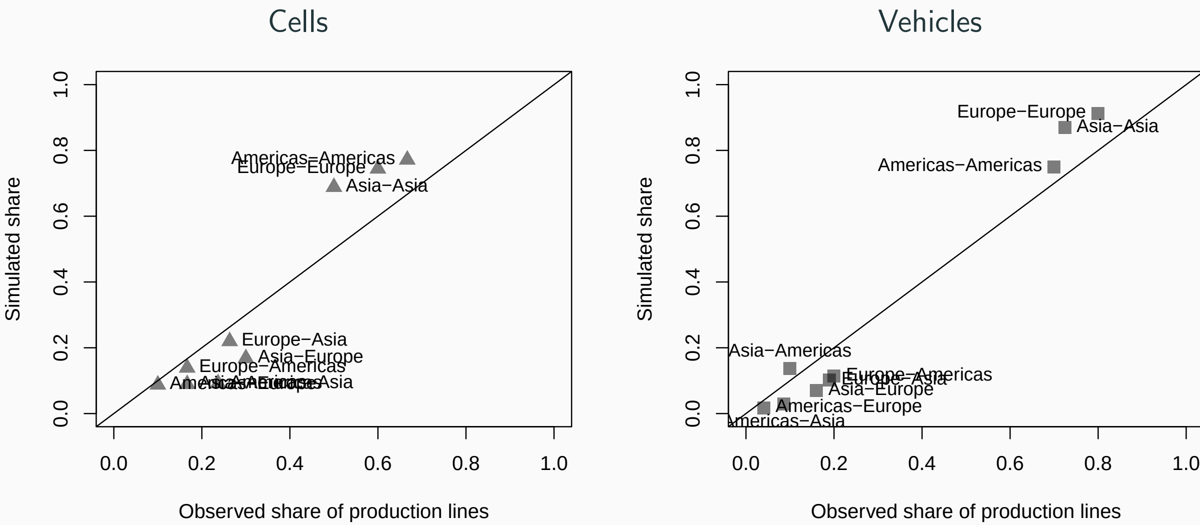


Calibrated Fit to Data: Inter-Continental Model Sourcing





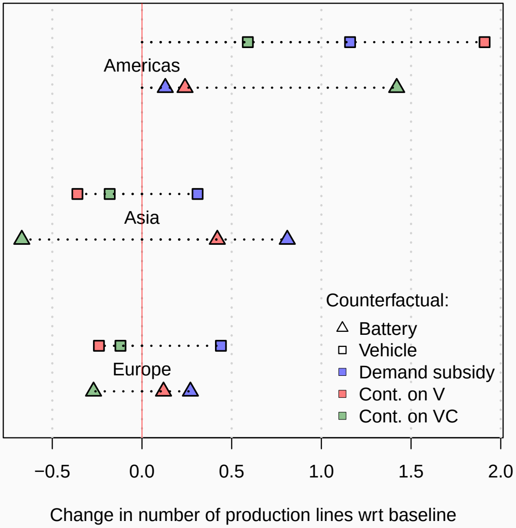
Calibrated Fit to Data: Production lines by headquarters



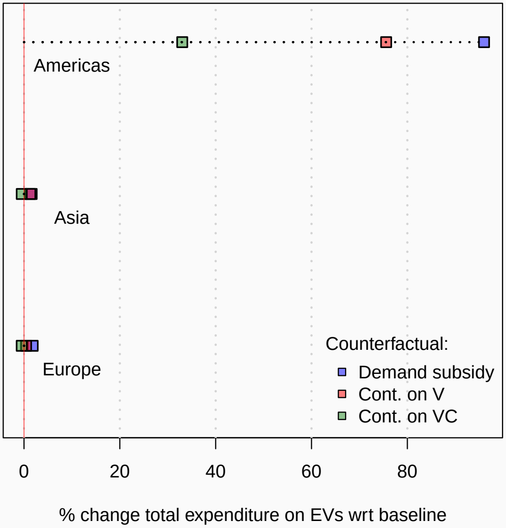
Counterfactual: BEV Policies

Predicted Impact of North American BEV Subsidies

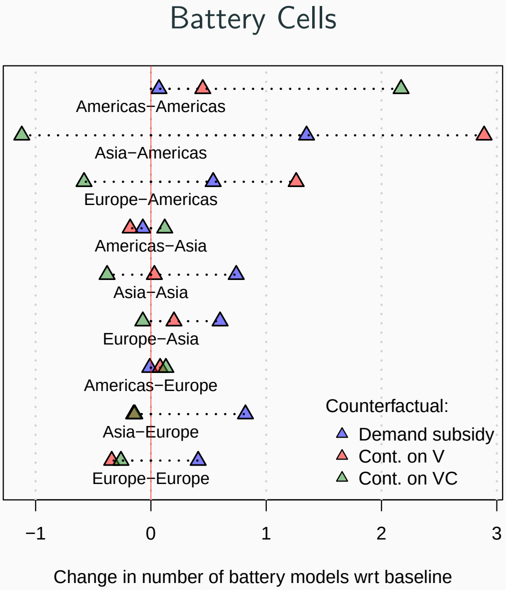
Production Lines ($\sum_f y_{g\ell}$)

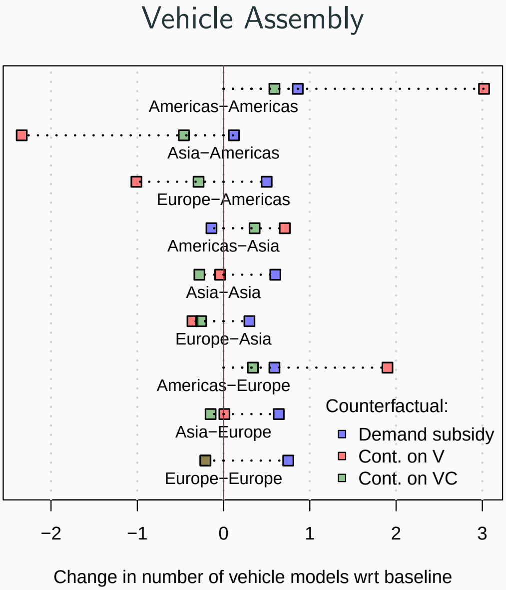


BEV Expenditures ($\sum_m p_{mn}q_{mn}$)



Predicted Effects for Cross-Continental Flows





What drives increased EV spending?

- The calibrated demand elasticity converts a uniform subsidy s into an expenditure increase of $(1-s)^{1-\eta}-1=(1-0.2)^{1-4}-1=$95%.
- New facilities permit new paths and closures cut off paths: c_{mn} changes
- Many models not eligible under policies 1 and 2.
- Decomposing the implied contributions of subsidy and path cost changes:

$$\text{subsidy}: \left(\sum_{m\in \text{EV}}\sum_{n\in \text{Am}} r_{mn}(1-\mathbb{I}_{mn}s)^{1-\eta}\right)^{1/(1-\eta)}$$

$$\text{path costs}: \left(\sum_{m\in \text{EV}}\sum_{n\in \text{Am}} r_{mn}(\hat{c}_{mn})^{1-\eta}\right)^{1/(1-\eta)}$$

$$\text{total}: \left(\sum_{m\in \text{EV}}\sum_{n\in \text{Am}} r_{mn}(1-\mathbb{I}_{mn}s)^{1-\eta}(\hat{c}_{mn})^{1-\eta}\right)^{1/(1-\eta)}$$

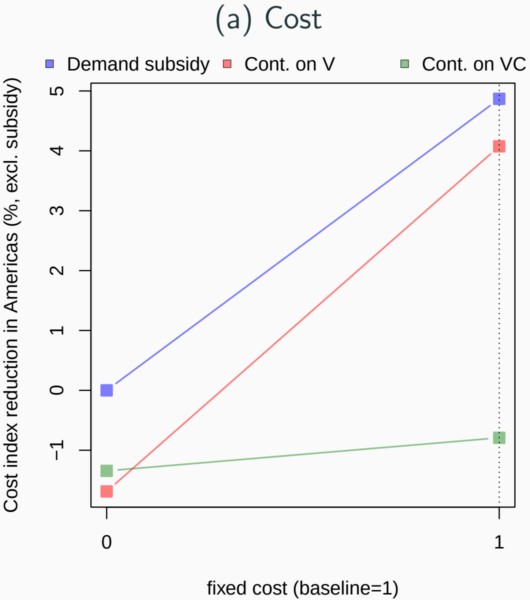
- $\mathbb{I}_{mn}=1 \implies m$ eligible for s in n; r_{mn} is initial (revenue) market share.

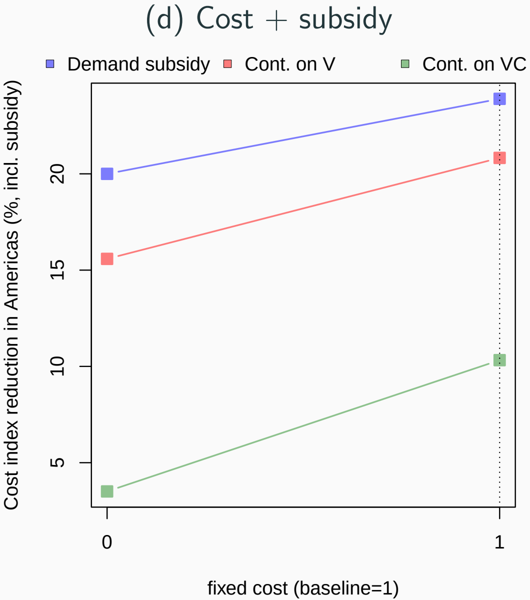
Contributions of subsidies and cost reductions to EV sales

Policy	Elig. share # path	Elig. share revenue	Cost index redn. subs.	Cost index redn. costs	Prices ($\hat{P}_n$)	Tot. costs	Tot. Exp.
1: Unconditional	100	100	20.0	4.9	-7.5	18.2	87.3
2: Continental V	35.0	89.7	17.1	4.1	-6.0	16.1	73.9
3: Continental V+C	19.6	60.1	11.2	-0.8	-2.3	8.3	32.1

- The unconditional subsidy yields the largest reduction in path costs (about 1/4 of the total)
- Production location restrictions do not make sense if sole goal is to promote EV adoption.

Impact of Plant Fixed Cost on Delivered Marginal Cost Reduction





Contributions to cost changes (in %) in other continents

Policy	Elig. share # path	Elig. share revenue	Cost index redn. subs.	Cost index redn. costs	Prices ($\hat{P}_n$)	Tot. costs	Tot. Exp.
			Europe				
1: Unconditional	0	0	-0.0	0.6	-0.2	0.4	1.3
2: Continental V	0	0	-0.0	0.2	-0.1	0.1	0.3
3: Continental V+C	0	0	-0.0	-0.3	0.1	-0.2	-0.5
			Asia				
1: Unconditional	0	0	-0.0	0.5	-0.1	0.4	1.4
2: Continental V	0	0	-0.0	0.4	-0.1	0.4	1.3
3: Continental V+C	0	0	-0.0	-0.2	0.0	-0.2	-0.5

EV subsidies that require local cells lower EV adoption in Europe and Asia.

What we've learned so far

- Increasing returns (fixed costs) and multiple production stages generate complex, jumpy policy responses
- MILP can be effective for solving optimization problems that combine substitution and complement patterns across locations
- With IRS, protectionist policies potentially align with emissions goals.
- Precise estimation of the core parameters presents challenges; results still tentative. But we have moderate confidence that
  - A clean consumer credit would have done more to promote EV adoption
  - Non-enviromental objectives needed to justify upstream restrictions.

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)

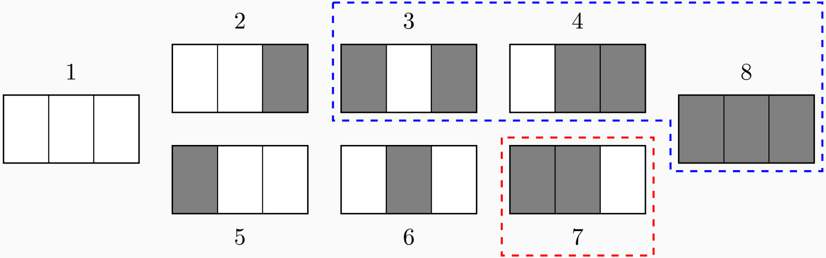
$$c_n(\mathcal{L},\omega) = \left[\sum_{\ell \in \mathcal{L}} c_{\ell n}(\omega)^{-\theta}\right]^{-1/\theta}, \quad \text{where} \quad c_{\ell n} = w_\ell \tau_{\ell n}(\omega)/z_\ell(\omega).$$

- 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)

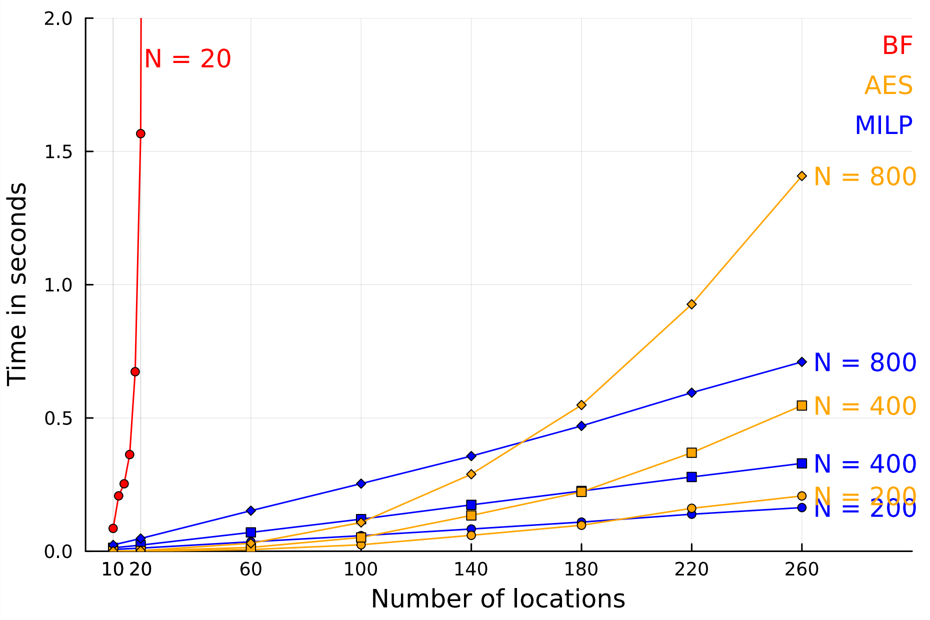
MILP formulation of the UFLP

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

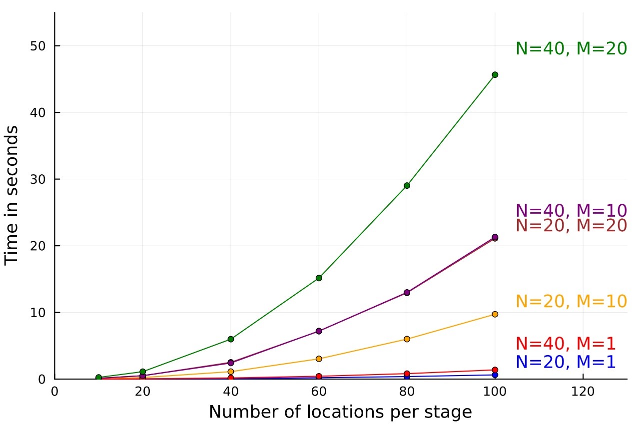
subject to

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

Comparing AES, MILP, and brute force

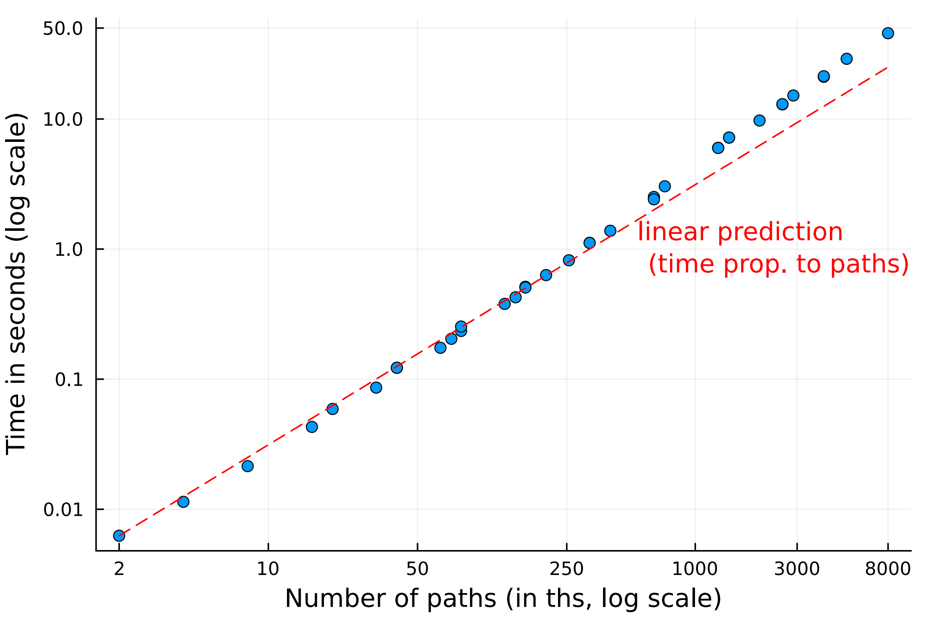


Computational performance for $K = 2$, MILP



- 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.