Estimating models of plant location choice

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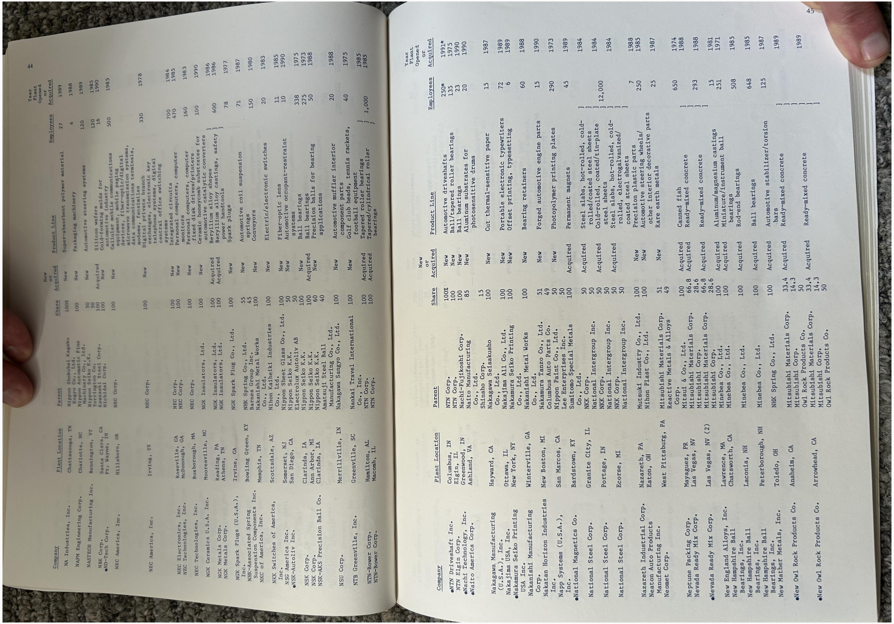
Data in 1992: Keith's starting point for location choice estimation



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Company	Plant Location	Parent	Share	New or Acquired	Product Line	Employees	Year Plant Opened or Acquired
NA Industries, Inc.	Chattanooga, TN	Nippon Shokubai Kagaku Kogyo Co., Ltd.	100%	New	Super-absorbent polymer material	27	1989
NAPM Engineering Corp.	Charlotte, NC	Nippon Automatic Fine Machinery Co., Ltd.	100	New	Packaging machinery	4	1988
NASTECH Manufacturing Inc.	Bennington, VT	Nippon Seiko K.K. Torrington Co.	50 50	New	Automotive steering systems	120	1989
NBK Corp.	Santa Clara, CA	Kawasaki Steel Corp.	100	Acquired	Silicon wafers	120	1985
●ND-Tech Corp.	Ft. Wayne, IN	Nichidai Corp.	100	New	Cold-forming molds for automotive industry	16	1990
NEC America, Inc.	Hillsboro, OR	NEC Corp.	100	New	Cellular mobile communications equipment, mobile paging devices, fiber-optic/digital microwave transmission systems, data communications terminals, modems, facsimiles	500	1985
NEC America, Inc.	Irving, TX	NEC Corp.	100	New	Digital private branch exchanges, electronic key telephone systems, digital central office switching systems	330	1978
NEC Electronics, Inc.	Roseville, CA	NEC Corp.	100	New	Integrated circuits	700	1984
NEC Technologies, Inc.	McDonough, GA	NEC Corp.	100	New	Personal computers, computer monitors	470	1985
NEC Technologies, Inc.	Boxborough, MA	NEC Corp.	100	New	Personal computers, computer fixed disk drives/printers	160	1983
NGK Ceramics U.S.A. Inc.	Mooresville, NC	NGK Insulators, Ltd.	100	New	Ceramic honeycomb substrates for automotive catalytic converters	100	1990
NGK Metals Corp.	Reading, PA	NGK Insulators, Ltd.	100	Acquired	Beryllium alloy shapes	] 400	1986
NGK Metals Corp.	Athens, TN	NGK Insulators, Ltd.	100	Acquired	Beryllium alloy castings, safety power handtools	]	1986
NGK Spark Plugs (U.S.A.), Inc.	Irvine, CA	NGK Spark Plug Co., Ltd.	100	New	Spark plugs	78	1977
NHK-Associated Spring Suspension Components Inc.	Bowling Green, KY	NHK Spring Co., Ltd. Barnes Group Inc.	55 45	New	Automotive coil suspension springs	71	1987
NKC of America, Inc.	Memphis, TN	Nakanishi Metal Works Co., Ltd.	100	New	Conveyors	150	1980
NKK Switches of America, Inc.	Scottsdale, AZ	Nihon Kaiheiki Industries Co., Ltd.	100	New	Electric/electronic switches	20	1983
NSG America Inc.	Somerset, NJ	Nippon Sheet Glass Co., Ltd.	100	New	Fiber-optic lens	11	1985
●NSK-Autoliv Inc.	San Diego, CA	Nippon Seiko K.K. Electrolux Autoliv AB	50 50	New	Automotive occupant-restraint systems	10	1990
NSK Corp.	Clarinda, IA	Nippon Seiko K.K.	100	New	Ball bearings	338	1975
NSK Corp.	Ann Arbor, MI	Nippon Seiko K.K.	100	Acquired	Ball bearings	275	1973
NSK-AKS Precision Ball Co.	Clarinda, IA	Nippon Seiko K.K. Amatsuji Steel Ball Manufacturing Co., Ltd.	60 40	New	Precision balls for bearing applications	50	1988
NSU Corp.	Merrillville, IN	Nakagawa Sangyo Co., Ltd.	100	New	Automotive muffler interior component parts	20	1988
NTB Greenville, Inc.	Greenville, SC	Nankai Travel International Co., Inc.	100	New	Golf club heads, tennis rackets, football equipment	40	1975
NTN-Bower Corp.	Hamilton, AL	NTN Corp.	100	Acquired	Tapered roller bearings	] 1,000	1985
NTN-Bower Corp.	Macomb, IL	NTN Corp.	100	Acquired	Tapered/cylindrical roller bearings	]	1985

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Company	Plant Location	Parent	Share	New or Acquired	Product Line	Employees	Year Plant Opened or Acquired
●NTN Driveshaft Inc.	Columbus, IN	NTN Corp.	100%	New	Automotive driveshafts	250*	1991*
NTN Elgin Corp.	Elgin, IL	NTN Corp.	100	New	Ball/tapered roller bearings	135	1975
●Nachi Technology, Inc.	Greenwood, IN	Nachi-Fujikoshi Corp.	100	New	Ball bearings	23	1990
●Naito America Corp.	Ashland, VA	Naito Manufacturing Co., Ltd. Shinsho Corp.	85 15	New	Aluminum substrates for photosensitive drums	20	1990
Nakagawa Manufacturing (U.S.A.), Inc.	Hayward, CA	Nakagawa Seisakusho Co., Ltd.	100	New	Cut thermal-sensitive paper	15	1987
Nakajima USA, Inc.	Ottawa, IL	Nakajima All Co., Ltd.	100	New	Portable electronic typewriters	72	1989
●Nakamura Seiko Printing USA Inc.	New York, NY	Nakamura Seiko Printing Co., Ltd.	100	New	Offset printing, typesetting	6	1989
Nakanishi Manufacturing Corp.	Winterville, GA	Nakanishi Metal Works Co., Ltd.	100	New	Bearing retainers	60	1988
Nakatan Horizon Industries Inc.	New Boston, MI	Nakamura Tanzo Co., Ltd. Columbus Auto Parts Co.	51 49	New	Forged automotive engine parts	15	1990
Napp Systems (U.S.A.), Inc.	San Marcos, CA	Nippon Paint Co., Ltd. Lee Enterprises Inc.	50 50	New	Photopolymer printing plates	290	1973
●National Magnetics Co.	Bardstown, KY	Sumitomo Special Metals Co., Ltd.	100	Acquired	Permanent magnets	45	1989
National Steel Corp.	Granite City, IL	NKK Corp. National Intergroup Inc.	50 50	Acquired	Steel slabs, hot-rolled, cold-rolled/coated steel sheets	]	1984
National Steel Corp.	Portage, IN	NKK Corp. National Intergroup Inc.	50 50	Acquired	Cold-rolled, coated/tin-plate steel sheets	] 12,000	1984
National Steel Corp.	Ecorse, MI	NKK Corp. National Intergroup Inc.	50 50	Acquired	Steel slabs, hot-rolled, cold-rolled, electrogalvanized/coated steel sheets	]	1984
Nazareth Industrial Corp.	Nazareth, PA	Mutsuki Industry Co., Ltd.	100	New	Precision plastic parts	7	1988
Neaton Auto Products Manufacturing Inc.	Eaton, OH	Nihon Plast Co., Ltd.	100	New	Automotive steering wheels/other interior decorative parts	250	1985
Neomet Corp.	West Pittsburg, PA	Mitsubishi Materials Corp. Reactive Metals & Alloys Corp.	51 49	New	Rare earth metals	25	1987
Neptune Packing Corp.	Mayaguez, PR	Mitsui & Co., Ltd.	100	Acquired	Canned fish	650	1974
Nevada Ready Mix Corp.	Las Vegas, NV	Mitsubishi Materials Corp. Mitsubishi Corp.	66.8 28.6	Acquired	Ready-mixed concrete	]	1988
●Nevada Ready Mix Corp.	Las Vegas, NV (2)	Mitsubishi Materials Corp. Mitsubishi Corp.	66.8 28.6	Acquired	Ready-mixed concrete	] 293	1988
New England Alloys, Inc.	Lawrence, MA	Minebea Co., Ltd.	100	Acquired	Aluminum/magnesium castings	15	1981
New Hampshire Ball Bearings, Inc.	Chatsworth, CA	Minebea Co., Ltd.	100	Acquired	Miniature/instrument ball bearings	251	1971
New Hampshire Ball Bearings, Inc.	Laconia, NH	Minebea Co., Ltd.	100	Acquired	Rod-end bearings	508	1985
New Hampshire Ball Bearings, Inc.	Peterborough, NH	Minebea Co., Ltd.	100	Acquired	Ball bearings	648	1985
New Mather Metals, Inc.	Toledo, OH	NHK Spring Co., Ltd.	100	Acquired	Automotive stabilizer/torsion bars	125	1987
●New Owl Rock Products Co.	Anaheim, CA	Mitsubishi Materials Corp. Mitsubishi Corp. Owl Rock Products Co.	33.4 14.3 50	Acquired	Ready-mixed concrete	]	1989
●New Owl Rock Products Co.	Arrowhead, CA	Mitsubishi Materials Corp. Mitsubishi Corp. Owl Rock Products Co.	33.4 14.3 50	Acquired	Ready-mixed concrete	]	1989

Zooming in on an example

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		100	Acquired	Silicon wafers	120 16	1985 1990

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Clarinda, IA	Nippon Seiko K.K.	100	New	Ball bearings	338	1975
Ann Arbor, MI	Nippon Seiko K.K.	100	Acquired	Ball bearings	275	1973
Clarinda, IA	Nippon Seiko K.K. Amatsuji Steel Ball Manufacturing Co., Ltd.	60 40	New	Precision balls for bearing applications	50	1988
					20	1988

Year	Product	Location
1973	Ball bearings	Ann Arbor, MI
1975	Ball bearings	Clarinda, IA
1988	Precision balls	Clarinda, IA
1989	Steering systems	Bennington, VT

Data in 1995: Thierry's JETRO data (more NSK in Europe)

- Germany:

Neuweg Fertigung GmbH	NSK Ltd. (NKS Europa Holding GmbH)	1954	Manufacture and sales of bearings

- Italy:

Industria Cuscinetti S.p.A.	NSK Ltd. (NSK- RHP Europe Ltd.)	1969	Manufacture and sales of bearings

- United Kingdom:

NSK BEARINGS EUROPE LTD.	NSK Ltd. (NSK- RHP Europe Ltd.)	1975	R&D and manufacture of ball bearings
NSK STEERING SYSTEMS EUROPE LTD.	NSK Ltd.	1999	Manufacture and sales of automobile parts
NSK- AKS Precision Ball Europe Ltd.	NSK Ltd., Amatsuji Steel Ball Mfg. Co., Ltd.	1989	Manufacture of steel balls for bearings

Questions asked (or left under the rug until recently)

Asked:

- Why not only one plant?
  $\Rightarrow$ returns to scale vs trade costs is a well developed setup to explain this even in the 1990s
- Why choose those locations inside each region?
  $\Rightarrow$ Tradeoffs between production costs, proximity to demand, agglomeration economies, and policies that might affect all of those.

Masked:

- Are those decisions to produce bearings spatially interdependent?
- Bearings are used in many things, including car parts. How is the location interdependence along the value chain working?

Motivation for estimating location choice models

Government policies aim to shape location decisions

Does it work? We need estimated models of facility location choices to conduct counterfactuals.

1. China's special economic zones, and many other similar policies
2. "Million dollar plants"
3. 2022 Inflation Reduction Act (industrial policy for green energy) ... now mimicked by the "Made in Europe" provision of the Industrial Accelerator Act in the EU.

China's FDI special economic zones

- Starting in 1980, China designated a series of incentive zones to attract foreign investment
- Reductions in income taxes, tariffs on imported inputs, land user fees.
- Other privileges include ease of establishment, autonomy of operations, preferential access to inputs, streamlined bureaucracy.
- Head and Ries (1996, JUE), estimated that these zones increased investments by 30%, comprising a static increase of 13%, and a 17% additional gain via agglomeration.
- Possibly an underestimate.

Shenzhen (the first SEZ), then and now

pop. 30,000

pop. 18mn (2024)

Other related policy initiatives, not always as successful

Table 18.2 Summary of evidence on enterprise zones

Study	Country	Program	Results
Neumark and Kolko (2010)	United States	California enterprise zones	No significant evidence of employment effects measured at establishments in zones: estimates range from −1.7% to +1.8% (levels), with large confidence intervals (≈−8% to +6%); no evidence of spillovers
Kolko and Neumark (2010)	United States	California enterprise zones	Zones more involved with marketing and outreach exhibited positive employment effects; zones focused on tax credits exhibited negative effects
Elvery (2009)	United States	California and Florida enterprise zones	No evidence of positive employment effects on zone residents: estimates for California range from −0.4% to −2.6% and for Florida from −1% to −4%
Freedman (2013)	United States	Texas enterprise zone program	Positive effect on employment growth among zone residents (1–2% per year, sometimes significant); employment effects concentrated in jobs paying less than $40,000 annually and in construction, manufacturing, retail, and wholesale; positive effects on job growth among zone employers (3–8% per year, rarely significant) Negative and insignificant effects on share black and with income below the poverty line Significant negative effect on vacancy rate (−4%) Significant positive effect on median home value (10.7%)
Ham et al. (2011)	United States	State enterprise zones, federal Empowerment Zones, federal Enterprise Communities	State programs: significant positive impacts on unemployment rate (−1.6 percentage points), poverty rate (−6.1 percentage points), average wage and salary income (≈1.6%), employment (≈3.7%)[a]

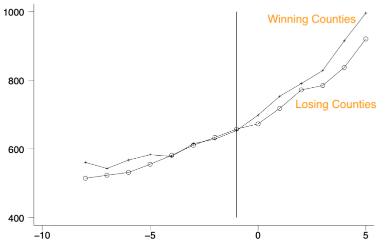
Bidding for Industrial Plants: Does Winning a 'Million Dollar Plant' Increase Welfare?

Michael Greenstone & Enrico Moretti

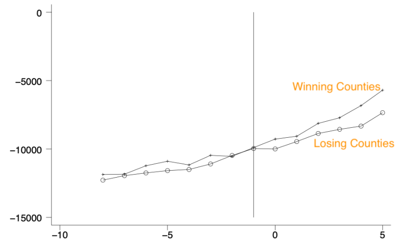
WORKING PAPER 9844 **DOI** 10.3386/w9844 **ISSUE DATE** July 2003

Increasingly, local governments compete by offering substantial subsidies to industrial plants to locate within their jurisdictions. This paper uses a novel research design to examine the consequences of successfully bidding for a plant on county-level labor earnings, property values, and public finances. Each issue of the corporate real estate journal Site Selection includes an article titled The Million Dollar Plant that describes how a large plant decided where to locate. These articles report the county where the plant chose to locate (i.e., the 'winner'), as well as the one or two runner-up counties (i.e., the 'losers'). The losers are counties that have survived a long selection process, but narrowly lost the competition. We use these revealed rankings of profit-maximizing firms to form a counterfactual for what would have happened in the winner counties in the absence of the plant opening. We find that a plant opening is associated with a 1.5% trend break in labor earnings in the new plant's industry in winning counties (relative to losing ones) after the opening of the plant (relative to the period before the opening). Property values may provide a summary measure of the net change in welfare, because the costs and benefits of attracting a plant should be capitalized into the price of land. We find a positive, relative trend break of 1.1% in property values. Further, we fail to find any deterioration in local governments' financial position. Overall, the results undermine the popular view that the provision of local subsidies to attract large industrial plants reduces local residents' welfare.

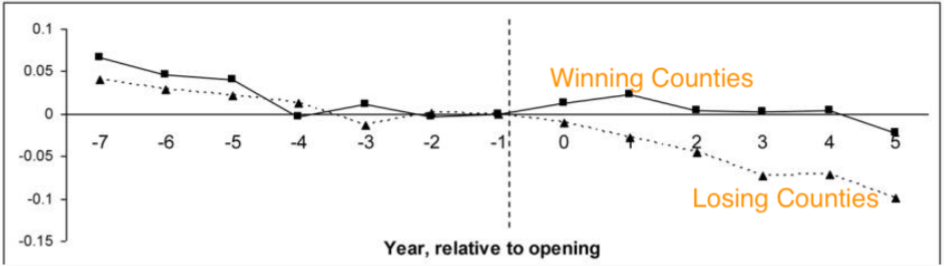
Winning counties trend better than losers



Wagebill



Property Values



Total factor productivity (2010, JPE)

Other related policy initiatives, not always as successful

Table 18.3 Summary of evidence on discretionary grants

Study	Country	Program	Results
Crozet et al. (2004)	France	Prime d'Aménagement du Territoire	Small, nonrobust effects of PAT subsidies on foreign multinational firm location decisions
Devereux et al. (2007)	United Kingdom	Regional Selective Assistance	Small effects on location decisions of foreign multinational firms and domestic multiplant firms Heterogeneity in the effectiveness of grants in influencing location choice; grants having a greater effect in areas with higher existing employment in the firm's industry
Criscuolo et al. (2012)	United Kingdom	Regional Selective Assistance	Positive effects on plant employment (43% increase in employment for participant plants) and firm investment, but restricted to plants that are part of smaller firms (<150 firm employees); no evidence of effects on firm TFP or wages Positive effects on employment and number of plants at the area level (a 10% subsidy rate increases area employment by 2.9%) and negative effects on unemployment (a 10% subsidy rate reduces unemployment by 6.9%) No evidence, on average, of employment or plant displacement from noneligible to eligible areas, but some evidence of displacement for plants that are part of larger firms
Bernini and Pellegrini (2011)	Italy	Law 488	Output growth in subsidized firms around 8–10% higher over on average 3.6 years, employment growth 16–17% higher, and growth in physical capital around 40% higher; labor productivity growth and TFP growth 7% and 8% lower, respectively Effects on output and employment appear to be greater for small firms
Bronzini and de Blasio (2006)	Italy	Law 488	Increase in investment over the initial 2 years following receipt of the subsidy, but at 5 years, recipient firms show a decrease in investment relative to controls; program may act to bring forward investment that might otherwise have occurred at a later date, rather than subsidizing additional investment
Greenstone et al. (2010)	United States	Location subsidies for large plant entry	Substantial effects on incumbent plant productivity in successful locations; incumbent plant TFP 12% higher after 5 years Heterogeneity in magnitude of TFP effects across industries and across locations Positive effect on county-level wages (2.7%)

Policies promoting EV production

US (2022–2025):

- 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

EU (2024-):

- France: Eco-bonus to **condition subsidies on clean value chains**.
- Tariffs on China-made EVs (up to 35%) since Oct 2024
- Industrial Acceleration Act: subsidies allowed if 70% content "Made in EU"

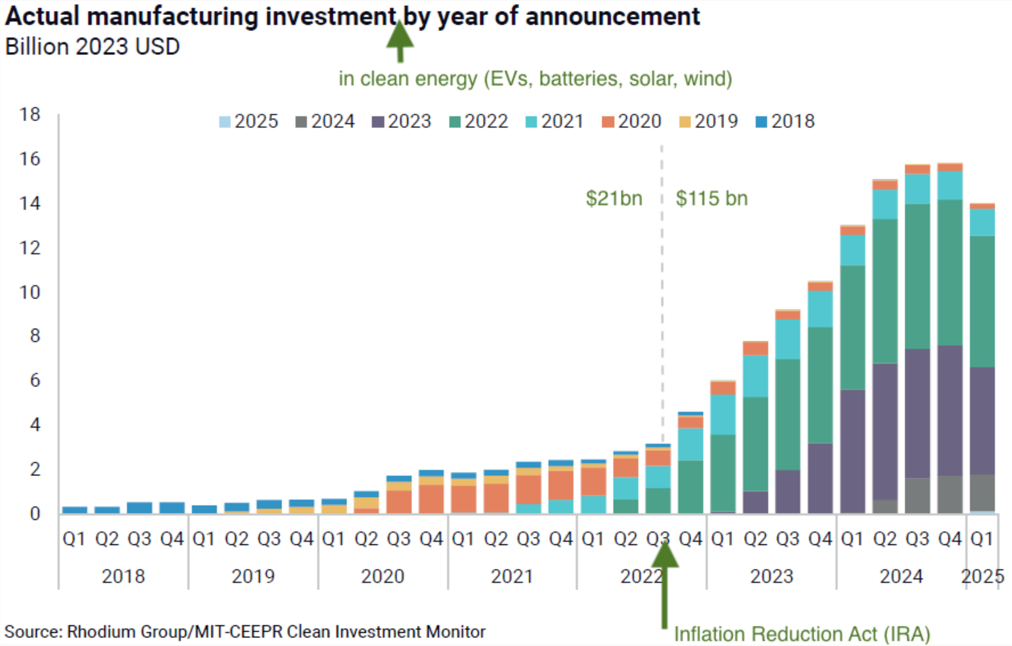
Top 10 models excluded by Rule 1 from the IRA buyer credit

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

Hyundai Ioniq Savannah, GA plant (December 2022)

Hyundai Ioniq near Savannah, GA plant (October 2024)

Investment seems to soar and fall with IRA



A brief history of location choice estimation

An abbreviated—and very selective—review of methods

Models of static, granular plant location choice:

1. Multinomial choice (conditional logit)
2. Binary choice (logit/probit)
3. Combinatorial discrete choice for interdependent decisions.
   (a) Jia–AFT-AES, solve pb via super/sub-modularity
   (b) Multi-stage and multi-product problems solved by MILP
   (c) SMM estimation

Conditional logit

- When ?
  (a) Each plant location i is an independent multinomial choice, $y_{i\ell}$, between L_i options. $y_{i\ell^*} = 1$ and $y_{i\ell} = 0$ for all $\ell \neq \ell^*$
  (b) With single sourcing, conditional on "activated" supplier facilities, input sourcing is also a conditional logit problem.
- How?
  (a) Estimated via "clogit" in Stata
  (b) Guimarães, Figueirdo, Woodward (2003, REStat), pointed out that likelihood of Poisson is the same as clogit, except for a constant.
  (c) With chooser FEs, estimate the multinomial choice model in R using fixest::fepois (very fast) ... or Stata ppmlhdfe (still fast).

Conditional logit with theory

We have LHS variable and an estimator

- How to structure the RHS variables ?
  1. "Fundamental NEG equation" (HM 2004): $\Pi_i = \frac{c_i^{-\epsilon}\mathrm{RMP}_i}{\epsilon+1} - F_i$,
  2. $\mathrm{RMP}_i = \sum_n \tau_{in}^{-\epsilon} E_n P_n^{\epsilon}$ (Real Market Potential estimated by gravity)
  3. c_i includes wages, taxes, agglomeration effects that increase productivity and Supply Potential (cost index of inputs) + an EV shock.
  4. Impose $F_i = F$, and determinants of $\log[(\Pi_i - F)(\epsilon + 1)]$ can be estimated with conditional logit
- Issues:
  1. The smaller problem: non-independence of choices (IIA) $\rightarrow$ Nested logit
  2. The bigger problem: interdependence (substitutes and complements)

Binary choice

- When?
  (a) Each investment i is an independent binary choice, $y_{i\ell}$ is evaluated for each of the L options, multiple 1s are allowed.
  (b) This approach makes sense for investments serving autarkic markets, non-traded services, such as retailers...
  (c) ...assuming no chain effects
- How?
  (a) Head and Mayer (2019) used probit for decision of each car brand to open dealership network in a country (No Renaults in Canada)
- Issues:
  1. The smaller problem: if many FEs, incidental parameter bias (BIFE)
  2. The bigger problem: interdependence (substitutes and complements)

Can we “fix” the bigger problem within clogit?

Ideas I played around with (maybe implemented in lit)

- Substitutable locations:
  - Introduce a dummy for previous locations chosen by same firm ?
  - Cut the set of alternatives to be ones not already chosen.
  - Market potential variable cutting the ones likely to be already covered?
- Complementary locations:
  - Market potential for parts constructed using firms as buyers
  - Supply potential for assemblers using part suppliers location

None of those is either easy or satisfactory

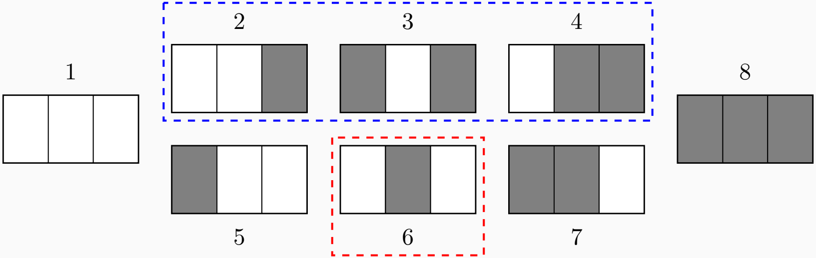
+ real world has both substitutes and complements

+ binary market entry decisions add to the problem

Combinatorial discrete choice: Supermodularity

- Multinomial / binomial choice: evaluate profits L times for each i.
- Combinatorial problem: evaluate 2^L possible configurations (a lot).
- Jia (2008) solves the interdependence problem by adapting Tarski's (1955) fixed point theorem and Topkis's (1978) monotonicity theorem
- Her method allows her to solve the problem of Wal-mart choosing store locations in the presence of "chain effects": Nearby stores split the costs of operation, delivery, and advertising to achieve scale economies.
- The complementarity between nearby stores leads to super-modular profits.
- AFT (2017 AER) have similar property with sourcing model.
- Supermodularity implies far fewer than 2^L evaluations.

Squeezing: How supermodularity can reduce evaluations



1. Configurations $i = 1...8$ of $[y_i^W, y_i^C, y_i^E]$
2. Evaluate 7 and 8: If $\pi_8 < \pi_7$ then position $y_i^E = 0$ for all i.
3. No need to evaluate $i = 2, 3, 4$ (blue dashed rectangle)
4. Evaluate 1 and 5: If $\pi_1 < \pi_5$ then position $y_i^W = 1$ for all i.
5. $i = 6$ is out; select larger of π_7 and π_5 (evals $= 4 \ll 8 =$ BF)

Combinatorial discrete choice: Submodularity

- The one-stage facility location problem is one in which a plant in one location substitutes for plants in nearby locations, because it offers an alternative way to serve the same markets.
- When both fixed costs and transport costs are important, we have the concentration vs proximity tradeoff.
- Arkolakis, Eckert, and Shi (forth. AER) develop an algorithm that serves submodular profit functions as well as supermodular ones.
- As with Jia's algo, the AES squeezing algo dramatically cuts the number of configurations to evaluate.

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

- AES cost function for variety ω (general case)

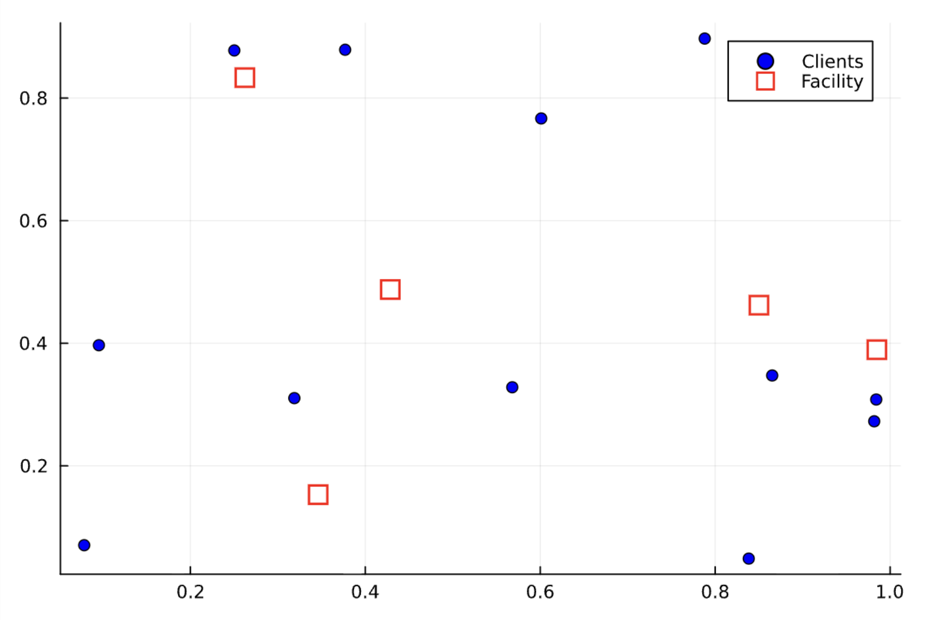
$$c_n(\mathcal{L},\omega) = \left[\sum_{\ell\in\mathcal{L}} c_{\ell n}(\omega)^{-\theta}\right]^{-1/\theta}, \quad \text{where} \quad c_{\ell n} = w_\ell \tau_{\ell n}(\omega)/z_\ell(\omega).$$

- 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

Facility location problem: setup



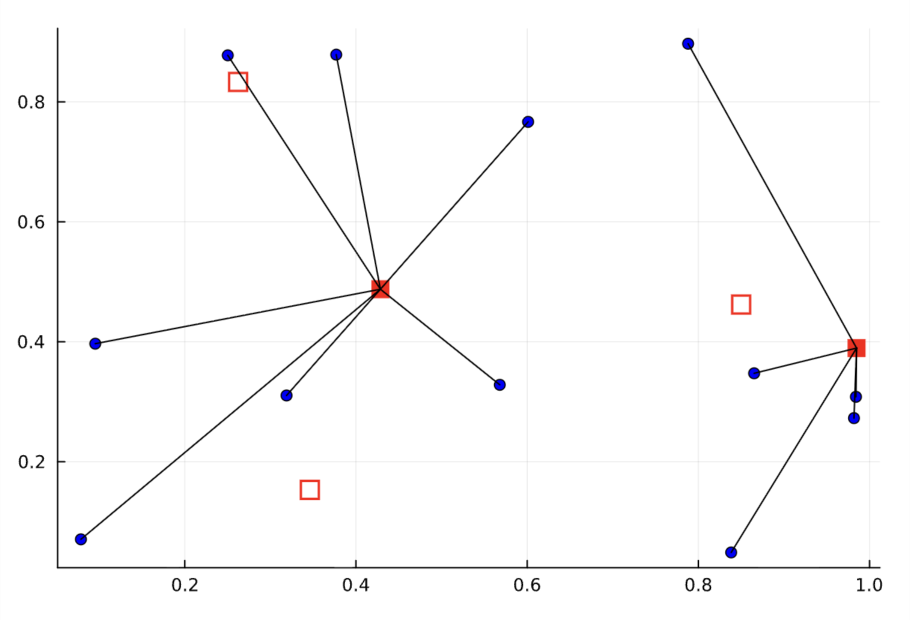
Single stage FLP can also be formulated as a MILP

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

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

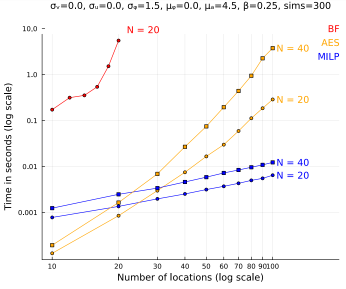
- Mixed integer linear programming (MILP) problem
- Consumers, production sites located randomly on the unit square
- Costs depend on distance from ℓ to n and a random ℓn shock

Example of solved facility location problem

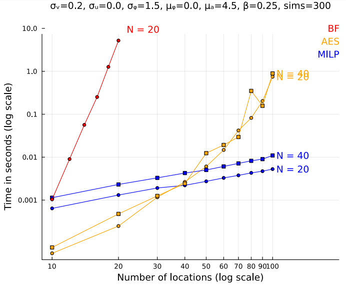


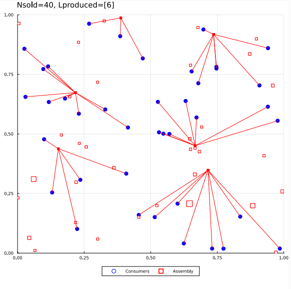
Comparing AES, MILP, and brute force

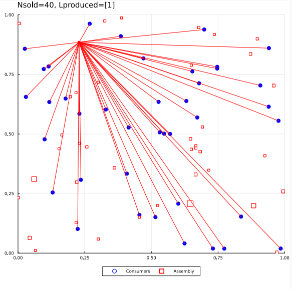
(a) Low site heterogeneity



(b) High site heterogeneity





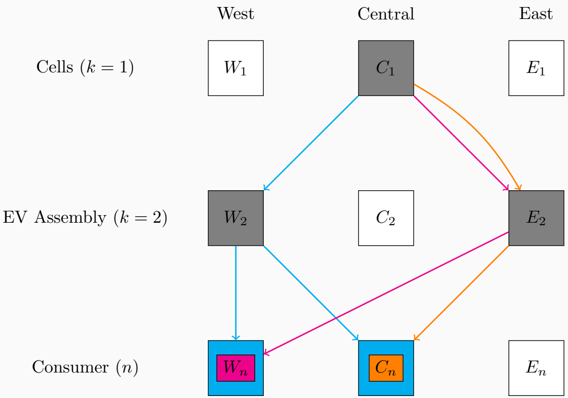


Multi-stage production calls for MILP

- One mechanism for submodularity: plants at same stage k are substitutes
- Two mechanisms for supermodularity:
    1. plants at different stages $k \leq K$ complement each other
    2. distribution $(K+1)$ facilities complement production plants

  $\Rightarrow$ Parametric restrictions to ensure global sub- or super- may not exist for our model and we prefer not to rely on them.
- Multi-stage profit maximization problems are easy to formulate as MILP.

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 market aggregator
- Delivered MC $c(\boldsymbol{\ell}_{nm})$ depends on the path chosen $\boldsymbol{\ell}_{nm}$ and variable cost parameters (to be estimated)
- Quantity demanded, q, is determined by firm's $c(\boldsymbol{\ell}_{mn})$, its appeal ξ_{mn}, market size, and an index of costs and appeal of competitors
- Variable profits for tuple (m, n) if path $\boldsymbol{\ell}_{mn}$ is chosen: $\pi(c(\boldsymbol{\ell}_{mn}), A_n)$
- A_n is a function of path costs of all models in market n, including gas vehicles.

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

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

subject to

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

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

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

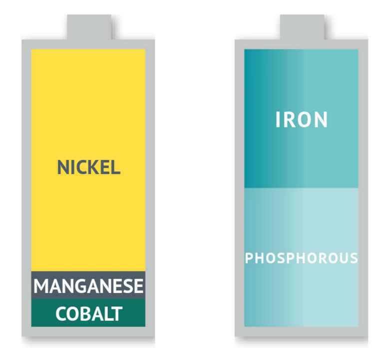
$$x_{mn\ell_1\ell_2} \geq 0, \quad y_{fg_1\ell_1}\in\{0,1\}, \quad y_{fg_2\ell_2}\in\{0,1\} \quad z_{mn}\in\{0,1\}. \tag{4}$$

What does activate ($y_{fg_k\ell_k} = 1$) mean in the BEV industry?

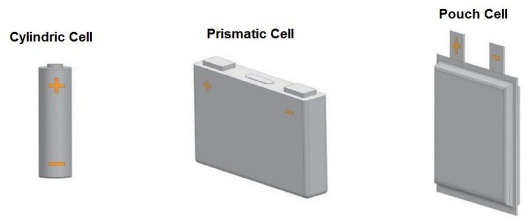
- A plant is active if it has paid the indivisible fixed cost required to produce positive amounts for a client f (car maker)
- Paid for each group g_k of potential outputs
  - For cells, $g_1(m)$ maps models to a combination of cell material categories and shapes, e.g. Tesla Model S uses "Nickel-Cobalt-Manganese/Cylinder"
  - 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.

Fixed costs pertain to location-firm-groups

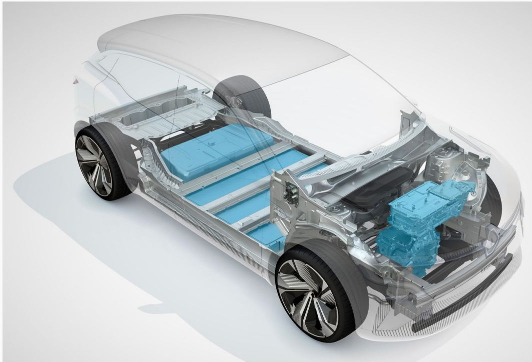
Battery cells grouped by material category $\downarrow$ & shape $\rightarrow$



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



Vehicle assembly grouped by platform $\downarrow$



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. Market interdependence between firms (via price index)
5. Because our focus is the GVC supply side, we simplify other aspects via CES demand, constant markups, efficient bargaining across firms.
6. The method permits many generalizations (e.g. more stages, multiple 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 $\implies$ 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 $\implies$ single sourcing from the least-delivered-cost plant

Estimation of the model applied to BEV value chain

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. Multi-sourcing declines with product detail to a few percent for both cells and assembly.

Challenges in estimating the model

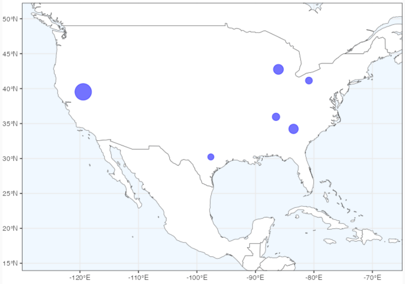
- Our estimation requires solving the MUFLP millions of times
  - Many sets of draws of path and fixed cost shocks (100)
  - Global optimization requires many starting parameter sets (1000),
  - Many iterations to fit the parameters (4700)

$\Rightarrow$ need some dimension reduction: lower number of locations and parameters

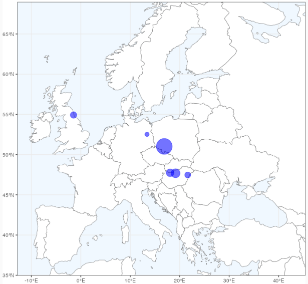
- We cannot estimate 1260 fixed costs fixed costs and 591 thousand path costs, so we parameterize them in terms of observables.

Mapping the cell and vehicle plants in 2022

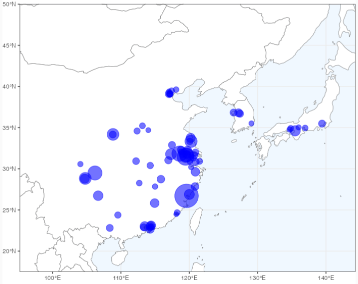
6 Cell Plants in 2022, Total 34.1GWh



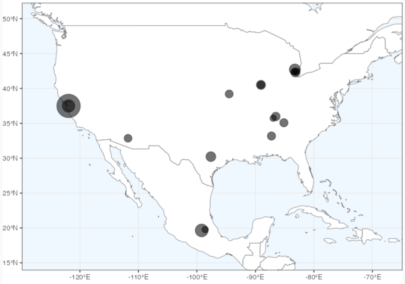
6 Cell Plants in 2022, Total 64.8GWh



74 Cell Plants in 2022, Total 374.2GWh

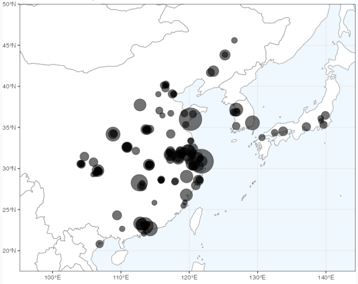


17 Assembly Plants in 2022, Total 812k BEVs



52 Assembly Plants in 2022, Total 1392k BEVs

170 Assembly Plants in 2022, Total 5893k BEVs



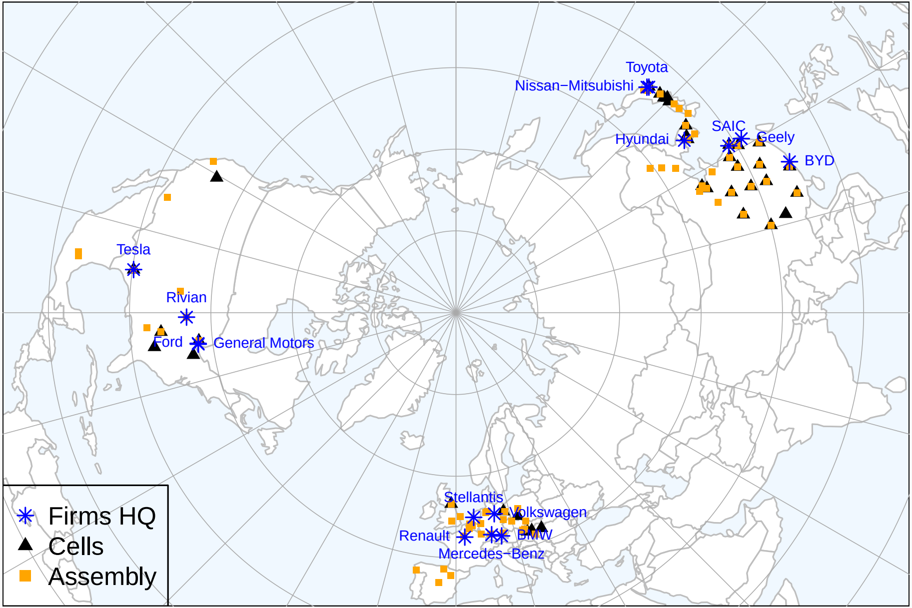
Data

Data (from S&P) contains universe of cell, assembly locations and flows for all EV models since 2015. We calibrate the model to 2022.

We reduce the estimation data to

- **Top 15 EV makers** and their **137 BEV models**, together 77% of world sales and 99% outside China
- Locations are across **24 countries**, together 97% world sales, 99.9% world battery production and 99% world EV production
- Entry is defined at geographic aggregates and product group level, **12 potential locations** for a median of **2 cell groups** per firm, and **15 potential locations** for a median of **4 assembly platforms** per firm $\longrightarrow 2^{24+60}$ total configurations

The top 15 EV makers and their location alternatives



Estimation roadmap

Step 1: Estimate bilateral trade costs for cells and vehicles
Conditional on active facilities ($\mathbf{y}$,$\mathbf{z}$) for each firm, estimate discrete choice sourcing ($\mathbf{x}$) via sequential (cells, assembly) nested logit for Cobb-Douglas production

Step 2: Use CES demand structure to map variable profits in levels to function of path observables and remaining parameters

Step 3: Estimate marginal cost of production, fixed costs, and endogenous market demand shifters by matching moments of the data to the simulated model (SMM) subject to market equilibrium as constraints (MPEC)

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^1_τ), 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^2_τ), fixed effects of supplier countries, inclusive cost from cell stage $\rightarrow -\beta^2_\Phi$

Nested Logit Choice probabilities

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
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

- Home plants (border $=0$) are $\approx$ 3 times more likely to be chosen
- Trade agreements also important
- Tariff elasticities are large ($\theta_1 \approx \theta_2 = 8.5$)
- Coef on inclusive cost $\rightarrow$ cell cost share of about 23%
- GDP/cap effects based on within-country variation since regression includes country fixed effects

Path cost changes $\implies$ level of variable profits

Log path costs (Logit, SMM):

$$\ln c(\boldsymbol{\ell}_{mn}) = \frac{1}{\beta_t^2}\Big\{\text{FE}^2_{\ell_2} + \beta_D^2 \ln D_{\ell_2 n} + \beta_t^2 \ln\left(1 + t^2_{\ell_2 n}\right) - \underbrace{\beta_\Phi^2}_{\text{IC coef.}} \left[\text{FE}^1_{\ell_1} + \beta_D^1 \ln D_{\ell_1\ell_2} + \beta_t^1 \ln\left(1 + t^1_{\ell_1\ell_2}\right)\right]\Big\} + \underbrace{u(\boldsymbol{\ell}_{mn})}_{-\text{Gumbel}(0, -1/\beta_t^2)}.$$

Expected variable profits levels using observed market shares s°_{mn} (for observed paths $\boldsymbol{\ell}^\circ_{mn}$) and cost change of potential path costs relative to the observed path, $\hat{c}_{mn\boldsymbol{\ell}} = c(\boldsymbol{\ell}_{mn})/c(\boldsymbol{\ell}^\circ_{mn})$:

$$E[\pi_{mn\boldsymbol{\ell}}] = \frac{1}{\eta} s^\circ_{mn} R_n (\hat{c}_{mn\boldsymbol{\ell}})^{1-\eta} A_n$$

where $A_n = E\left[(\hat{P}_n)^{\eta-1}\right]$ captures endogenous change in market demand

Endogenous market demand

- CES demand for all cars (EV and ICE) with demand elasticity $\eta = 4$
- Firms only know their own cost differentials $\hat{c}_{mn\ell*}$ but not other firms
- Assume
  - Constant total car expenditures R_n
  - Monopolistic competition and constant markup
  - Paths of EVs do not affect ICE prices: $\hat{P}_n^{ICE} = 1$
- Change in the price index satisfies:

$$\hat{P}_n^{1-\eta} = s_n^{\circ,ICE} + \sum_m s_{mn}^{\circ} \hat{c}_{mn\ell*}^{1-\eta}$$

- Minimize SMM objective subject to solving for the expected market demand $\hat{A}_n$ using sample mean across J simulations *as constraints*:

$$\hat{A}_n = \frac{1}{J}\sum_{j=1}^{J}(\hat{P}_{n,j})^{\eta-1} = \frac{1}{J}\sum_{j=1}^{J}\left(s_n^{\circ,ICE} + \sum_m s_{mn}^{\circ}\hat{c}_{mn\ell*,j}^{1-\eta}\right)^{-1}$$

Completing the parameter set

- Last parameters needed are the fixed costs $\phi_{fg_k\ell_k}$, of activation $(y_{fg_k\ell_k})$.
- Distribution of fixed costs draws by location-stage:

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

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

Simulated method of moments (SMM)

Target 47 moments formed by stage $k = 1, 2$ & continent $\mathcal{N} \in \mathrm{Am}, \mathrm{As}, \mathrm{Eu}$

1. Number of production lines $(\sum_{\ell_k \in \mathcal{N}} y_{fg_k \ell_k})$ [6]
2. Share of continent $\mathcal{N}$ spending on EVs from continent $\mathcal{N}'$ [18]
3. Number of models offered in continent $\mathcal{N}$ [3]
4. Shares of production lines (firm HQ continent by production continent) [18]
5. Standard deviation of realized fixed cost from news articles [2]

Let $v(\cdot)$ be the difference between simulated moments and data. SMM solves

$$\min_{\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}} v\left(\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}\right)' W v\left(\mathbf{FE}, \boldsymbol{\rho}, \boldsymbol{\sigma}\right),$$

where W is a weighting matrix. The simulated moments average over $J = 100$ sets of draws of path cost and fixed cost shocks.

Simulated Method of Moments Estimates

Par.	$\mathcal{N}$	Description	Est.	SE
FE^1	As	Var. cost adv. (C)	4.91	(1.16)
FE^1	Eu	(by region, Am = 0)	5.94	(0.94)
FE^2	As	Var. cost adv. (V)	-0.21	(0.4)
FE^2	Eu	(by region, Am = 0)	-0.25	(0.48)
ρ^1	Am	Fixed cost	0.30	(0.21)
ρ^1	As	of cell plant	0.12	(0.05)
ρ^1	Eu	(by region)	0.54	(0.2)
ρ^2	Am	Fixed cost	0.16	(0.12)
ρ^2	As	of assembly	0.03	(0.05)
ρ^2	Eu	(by region)	0.18	(0.09)
$\rho^{\text{HQ, dist},1}$		FC HQ dist. elas. (C)	0.47	(0.08)
$\rho^{\text{HQ, dist},2}$		FC HQ dist. elas. (V)	0.78	(0.07)
$\rho^{\xi_{fg_1}}$		FC quality elas. (C)	3.40	(0.39)
$\rho^{\xi_{fg_2}}$		FC quality elas. (V)	2.76	(0.44)
σ_1		FC dispersion (C)	2.12	(0.31)
σ_2		FC dispersion (V)	1.99	(0.27)

- Asia and EU have lower cell variable costs than US
- but their assembly costs are higher.
- US and EU fixed costs (FC) of assembly are 5–6 times those in Asia (0.16/0.03, 0.18/0.03)
- Proximity to V HQ lowers FC.
- Plants making higher quality have higher FC.
- Fixed costs of open facilities ≈ 7% of world revenue.

Estimated relative costs in Asia and Europe vs. North America

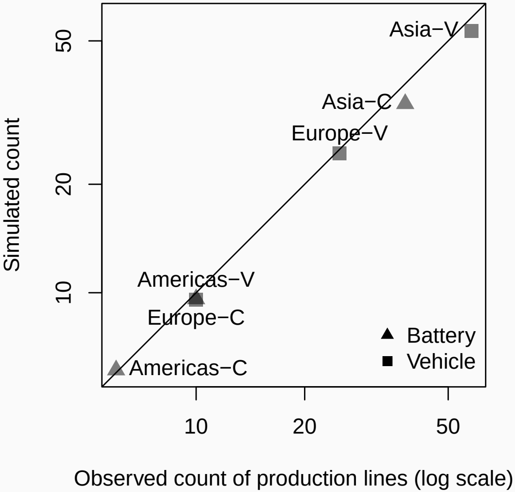
Region		Cells			Vehicles	
Ratio:	var.	fixed	avg.	var.	fixed	avg.
Europe	-50.06	83.30	-38.67	2.93	12.54	3.75
Asia	-43.64	-57.80	-44.85	2.47	-78.79	-4.47

% difference with respect to costs in the Americas.

The ratio of average costs is a weighted average of the ratios of fixed and variable costs with weights as respective shares of total costs, 8.5% and 91.5%.

Fit to data

Production lines by continent



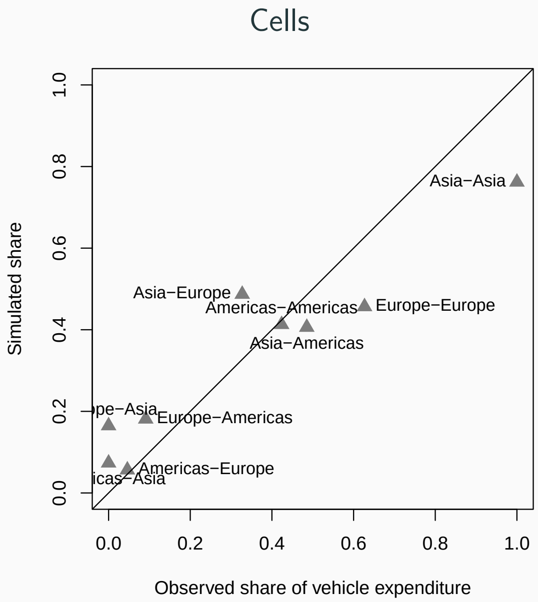
Model market entry

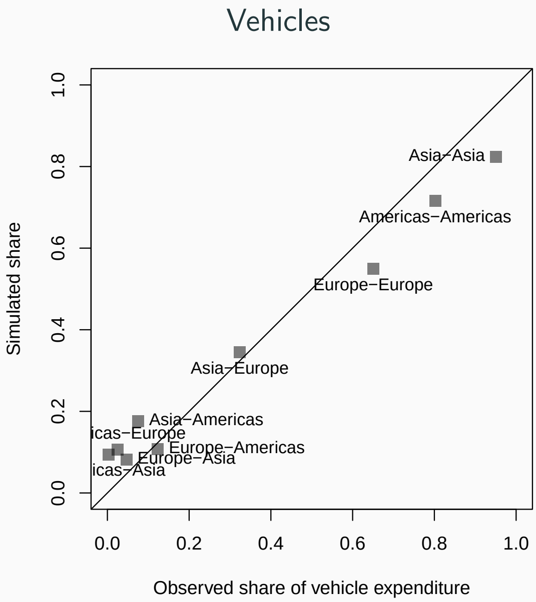
	# car models		Rev.
	data	baseline	(%)
Americas	49	43.0	92.1
Asia	111	99.9	92.5
Europe	83	77.2	94.2

Rev. is % of observed sales by car models we keep in the prediction.

▸ Other moments

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





Reflections of an SMM newbie

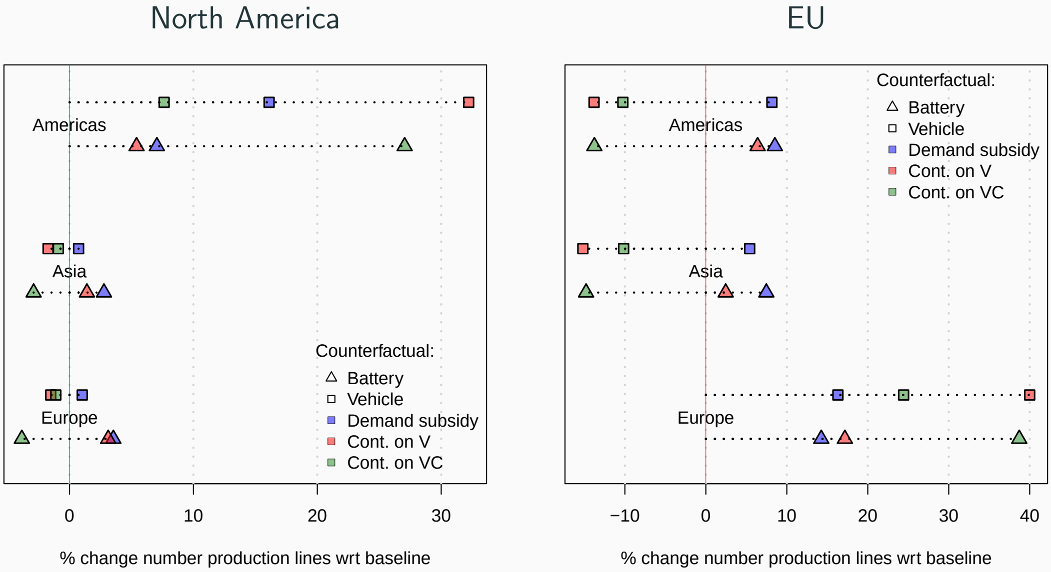
- Irony: the "hard" problem of combinatorial discrete choice was the easy part; SMM was brutal.
- The computer resources for SMM are massive due to high number of sims (J) and starts (TikTak)
- It only gets worse when you try to bootstrap ($B \times J = 400$ cores)
- Selection and weighting of moments allows uncomfortably high "researcher degrees of freedom"
- Things were so much simpler with conditional logits !

Counterfactual: BEV Policies

Policies we evaluate

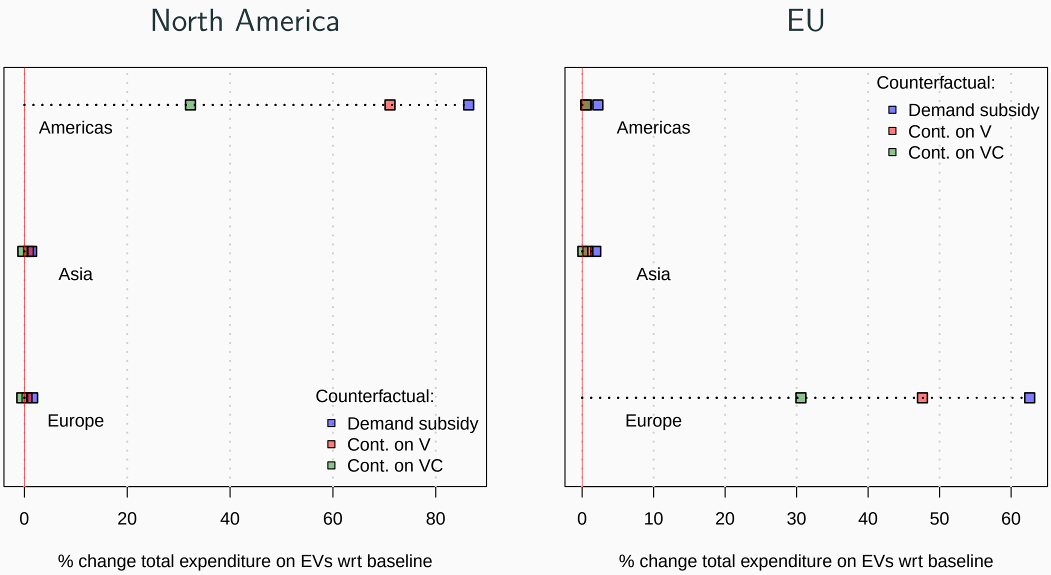
1. **Subsidy to EV buyers** 20% subsidy to all consumers from a given continent for all vehicles.
2. **Subsidy contingent on V** Only cars assembled in the same continent as the buyer are eligible for the 20% subsidy.
3. **Subsidy contingent on VC** Both cell production and vehicle assembly must be in the same continent as the buyer to be eligible for 20% subsidy.
4. Production subsidies of 20% for continental cells.
5. Tariffs of 20% on imported cells and vehicles.

North America vs. EU on production lines



- Upstream restriction works better in EU (more productive in battery cells).

North America vs. EU on EV expenditures



- Smaller gain in EV expenditure in EU due to tighter competition

Final thoughts

- Trade and industrial policies increasingly target many sectors
- In order to assess the ultimate impact of those policies on various objectives (domestic production/employment, consumer prices, environmental, geopolitical)
  - Must be able to evaluate how those policies will reshape global production networks
  - Need models & tools that can handle the massive complexity associated with those network choices and deliver realistic predictions
- In our application to BEV industry,
  - With IRS, production location restrictions can lower delivered cost s.t. protectionist policies align with emissions goals.
  - ... But our counterfactual results show empirically: A clean subsidy would have done more to promote EV adoption.