

Combinatorial Discrete Choice

Teaching slides

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Motivation

- ▶ Discrete choice problems with complementarities among options
 - ▶ Tesla choosing in which countries to operate production plants
 - ▶ Starbucks choosing blocks in Manhattan to operate shops
 - ▶ A government choosing locations for critical infrastructure
- ▶ Without more structure: an intractable NP hard problem
- ▶ [This paper](#). Solve such combinatorial discrete choice problems
- ▶ [Key](#). Economic complementarities provide exploitable structure

Part I

Theory

Notation

- ▶ Set of discrete options L

Index individual items in L by ℓ , so that $\ell \in L$

- ▶ Define collection of subsets (power set) of L as: $\mathcal{P}(L)$

Denote individual element in $\mathcal{P}(L)$ by \mathcal{L} , so that $\mathcal{L} \in \mathcal{P}(L)$

- ▶ Define the space of objective functions $\mathcal{F} = \{f : \mathcal{P}(L) \rightarrow \mathbb{R}\}$

Denote an individual objective by f , so that $f \in \mathcal{F}$

Outline

Squeezing and branching

- Single crossing in differences

- Squeezing

- Lattice foundation

- Branching

Generalized squeezing

- Single crossing differences in type

- Generalized squeezing

Characterization

- **Maximization over subsets.** Choose the subset of items $\mathcal{L} \subseteq L$
leading example: multinational location problem

$$\mathcal{L}^* = \arg \max_{\mathcal{L} \subseteq L} f(\mathcal{L})$$

- **Marginal value operator.** For an item ℓ , the value with it compared to without it,
contingent on \mathcal{L}
discrete analogue to derivative

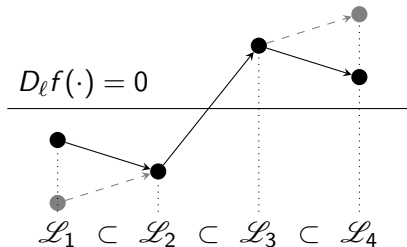
$$D_{\ell} f(\mathcal{L}) = f(\mathcal{L} \cup \{\ell\}) - f(\mathcal{L} \setminus \{\ell\})$$

- **Combinatorial discrete choice.** If the marginal value varies with \mathcal{L}

Single crossing differences in choices

From below. If ℓ is valuable given a small set, *remains* valuable given a large set:

$$D_{\ell}f(\mathcal{L}) \geq 0 \Rightarrow D_{\ell}f(\mathcal{L}') \geq 0$$

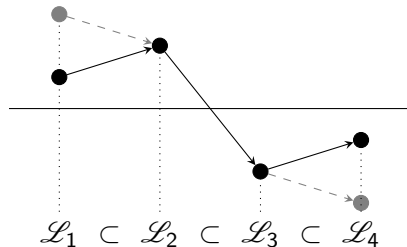


Supermodularity. More valuable given large set compared to small set

$$D_{\ell}f(\mathcal{L}) \leq D_{\ell}f(\mathcal{L}')$$

From above. If ℓ is valuable given a large set, *remains* valuable given a small set:

$$D_{\ell}f(\mathcal{L}) \geq 0 \Rightarrow D_{\ell}f(\mathcal{L}') \geq 0$$



Submodularity. More valuable given small set compared to large set

$$D_{\ell}f(\mathcal{L}) \geq D_{\ell}f(\mathcal{L}')$$

Single crossing differences in choices

Definition (Quasi-supermodularity and quasi-submodularity)

The function f is:

a) *quasi-supermodular* if, for all $\mathcal{L}, \mathcal{L}' \in \mathcal{P}(L)$,

$$f(\mathcal{L} \cup \mathcal{L}') \leq f(\mathcal{L}') \quad \Rightarrow \quad f(\mathcal{L}) \leq f(\mathcal{L} \cap \mathcal{L}')$$

b) *quasi-submodular* if, for all $\mathcal{L}, \mathcal{L}' \in \mathcal{P}(L)$,

$$f(\mathcal{L}) \geq f(\mathcal{L} \cap \mathcal{L}') \quad \Rightarrow \quad f(\mathcal{L} \cup \mathcal{L}') \geq f(\mathcal{L}')$$

Shannon and Milgrom 1994; Milgrom 2004

Corollary

Quasi-supermodularity is sufficient for SCD-C from below; quasi-submodularity is sufficient for SCD-C from above.

“Local optimality”

- ▶ Jia 2008. Central mapping:

$$\Phi(\mathcal{L}) = \{\ell \in L \mid D_{\ell}f(\mathcal{L}) \geq 0\}$$

“All items with non-negative marginal value to \mathcal{L} ”

- ▶ No deviation by one element. Necessary, not sufficient!

similar to a first order condition

$$\mathcal{L}^* = \Phi(\mathcal{L}^*)$$

- ▶ if ℓ is chosen ($\ell \in \mathcal{L}^*$), then it must contribute positive marginal value ($\ell \in \Phi(\mathcal{L}^*)$)
- ▶ if ℓ is *not* chosen ($\ell \notin \mathcal{L}^*$), then it cannot add value when included ($\ell \notin \Phi(\mathcal{L}^*)$)

Order-preserving (reversing)

Lemma

If f satisfies SCD-C from below (above), Φ is order-preserving (reversing).

Squeezing mapping

- ▶ Bounding pair $[\underline{\mathcal{L}}, \overline{\mathcal{L}}]$. Defines a restricted domain

$$\{\mathcal{L} \mid \underline{\mathcal{L}} \subseteq \mathcal{L} \subseteq \overline{\mathcal{L}}\} \subseteq \mathcal{P}(L)$$

- ▶ the full domain is represented $[\emptyset, L] = \mathcal{P}(L)$
- ▶ $[\underline{\mathcal{K}}, \overline{\mathcal{K}}]$ is “tighter” than $[\underline{\mathcal{L}}, \overline{\mathcal{L}}]$ if $[\underline{\mathcal{K}}, \overline{\mathcal{K}}] \subseteq [\underline{\mathcal{L}}, \overline{\mathcal{L}}]$, i.e. it defines a subdomain
- ▶ Squeezing mapping. Acts on bounding pairs

$$S([\underline{\mathcal{L}}, \overline{\mathcal{L}}]) = [\inf\{\Phi(\underline{\mathcal{L}}), \Phi(\overline{\mathcal{L}})\}, \sup\{\Phi(\underline{\mathcal{L}}), \Phi(\overline{\mathcal{L}})\}]$$

- ▶ Iterative application. Let $S^k([\underline{\mathcal{L}}, \overline{\mathcal{L}}])$ denote applying S iteratively k times

Main theorem: Single agent problem

Theorem 1 (Squeezing procedure)

If f satisfies SCD-C, then:

- a. let $[\underline{\mathcal{L}}^{(k)}, \overline{\mathcal{L}}^{(k)}] \equiv S^k([\emptyset, L]);$ then,

$$\emptyset \subseteq \dots \subseteq \underline{\mathcal{L}}^{(k)} \subseteq \underline{\mathcal{L}}^{(k+1)} \subseteq \overline{\mathcal{L}}^{(k+1)} \subseteq \overline{\mathcal{L}}^{(k)} \subseteq \dots \subseteq L$$

“iterative application weakly tightens the problem’s domain”

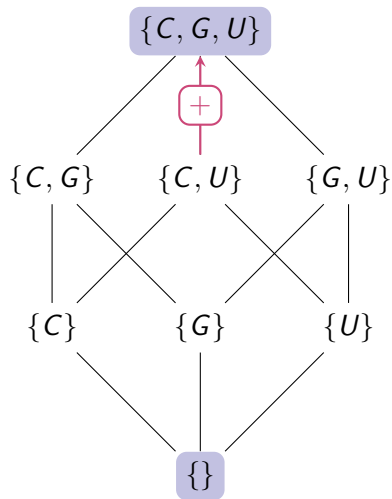
- b. if $\mathcal{L}^* \in [\underline{\mathcal{L}}, \overline{\mathcal{L}}]$, then $\mathcal{L}^* \in S([\underline{\mathcal{L}}, \overline{\mathcal{L}}])$

“if the optimum set is in the restricted domain, S will not discard it”

- c. $S^{|\mathcal{L}|}([\emptyset, L]) = S^{|\mathcal{L}|+1}([\emptyset, L])$

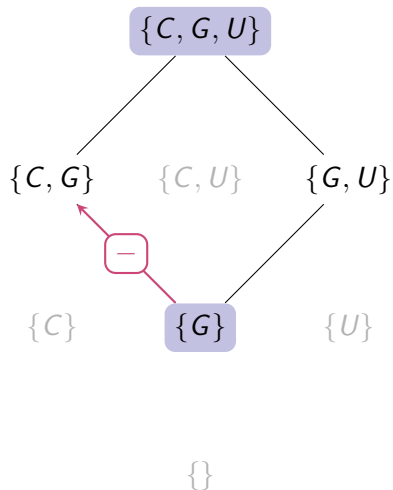
“iterating the squeezing step S converges to a fixed point in $|\mathcal{L}|$ steps or fewer”

Proof intuition: SCD-C from above



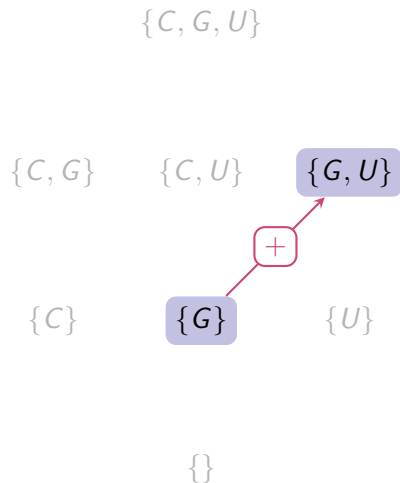
- ▶ Bounding pair. $\underline{\mathcal{L}} \subseteq \mathcal{L}^* \subseteq \overline{\mathcal{L}}$
 - $\underline{\mathcal{L}}$ tracks elements in \mathcal{L}^*
 - $\overline{\mathcal{L}}$ discards elements not in \mathcal{L}^*
 - $\overline{\mathcal{L}} \setminus \underline{\mathcal{L}}$ tracks elements maybe in \mathcal{L}^*
- ▶ Rule out suboptimal strategies.
 - ▶ check marginal value at points of extreme complementarity
 - ▶ iteratively squeeze: update the subset and superset
 - halve decision space each time

Proof intuition: SCD-C from above



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$$\{C, G, U\}$$

$$\{C, G\}$$

$$\{C, U\}$$

$$\{G, U\}$$

$$\{C\}$$

$$\{G\}$$

$$\{U\}$$

$$\{\}$$

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- ▶ Rule out suboptimal strategies.

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halve decision space each time

SCD-C from below

Lattice foundation

- ▶ Jia 2008. Solution method for supermodular f :

1. Central mapping. By construction, \mathcal{L}^* is a fixed point of:

$$\Phi(\mathcal{L}) \equiv \{\ell \in L \mid D_\ell f(\mathcal{L}) \geq 0\}$$

2. Order-preserving Φ . With supermodular f

3. Tarski 1955. Order-preserving Φ has a smallest and largest fixed point ...

4. Kleene 1936. ... identified by iterating $\Phi^\infty(\emptyset)$ and $\Phi^\infty(L)$

- ▶ SCD-C (from below). Necessary and sufficient condition for Φ to be order-preserving

SCD-C from above

Lattice foundation

- ▶ Order-reversing Φ . Tarski 1955; Kleene 1936 no longer apply
- ▶ Perfect substitutes intuition. Consider two elements, $\{a, b\}$
 - ▶ both items have positive marginal value in isolation, but neither have positive marginal value if the other is included

$$\Phi(\emptyset) = \{a, b\}$$

$$\Phi(\{a, b\}) = \emptyset$$

- ▶ the fixed points are uncomparable, i.e. there is neither a smallest nor largest fixed point — Tarski 1955 breaks down ...

$$\Phi(\{a\}) = \{a\}$$

$$\Phi(\{b\}) = \{b\}$$

- ▶ ... without the existence of smallest and largest fixed points, does iteration converge? To what?

SCD-C from above

Lattice foundation

A generalization of the notion of a fixed point:

Definition (Fixed edge)

Two sets, \mathcal{L} and \mathcal{L}' with

$$\Phi(\mathcal{L}) = \mathcal{L}' \quad , \quad \Phi(\mathcal{L}') = \mathcal{L}$$

- Klimeš 1981. Order-reversing Φ has an “extreme” fixed edge $\mathcal{L}^{\text{inf}}, \mathcal{L}^{\text{sup}}$!

$$\mathcal{L}^{\text{inf}} \subseteq \mathcal{L} \subseteq \mathcal{L}' \subseteq \mathcal{L}^{\text{sup}}$$

- Iteration. $\lim_{n \rightarrow \text{inf}} \Phi^{2n}(\emptyset) = \mathcal{L}^{\text{inf}}$ and $\lim_{n \rightarrow \text{inf}} \Phi^{2n+1}(\emptyset) = \mathcal{L}^{\text{sup}}$
vice versa from L

SCD-C from above

Lattice foundation

- ▶ Φ 's “Fixed edge convergence”. After enough applications, the mapping Φ alternates back and forth between the two points in the fixed edge
- ▶ Squeezing step. Converges to fixed point by construction:

$$S\left(\left[\mathcal{L}^{\text{inf}}, \mathcal{L}^{\text{sup}}\right]\right) = \left[\Phi\left(\mathcal{L}^{\text{sup}}\right), \Phi\left(\mathcal{L}^{\text{inf}}\right)\right] = \left[\mathcal{L}^{\text{inf}}, \mathcal{L}^{\text{sup}}\right]$$

by “flipping” the order of the two sets

Refinement: branching

- ▶ If $\mathcal{L}^{\text{inf}} = \mathcal{L}^{\text{sup}}$, then $\mathcal{L}^{\text{inf}} = \mathcal{L}^{\star}$
- ▶ Sometimes: converge, but $\mathcal{L}^{\text{inf}} \subset \mathcal{L}^{\star}$
e.g. when complementarities very strong

$\{C, G, U\}$

$\{C, G\}$

$\{C, U\}$

$\{G, U\}$

$\{C\}$

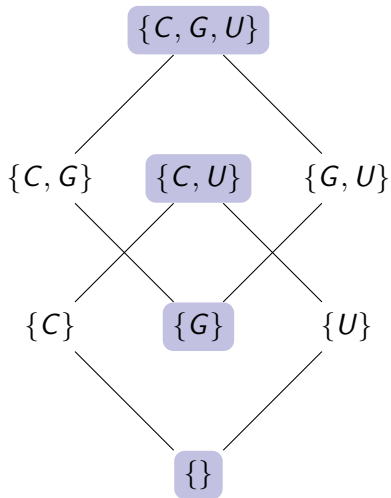
$\{G\}$

$\{U\}$

$\{\}$

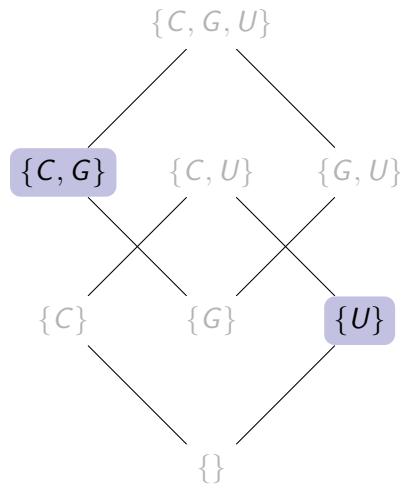
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e.g. when complementarities very strong
- ▶ Choose an item $\ell \in \overline{\mathcal{L}} \setminus \underline{\mathcal{L}}$, then
 - ▶ divide into two subproblems: with and without ℓ
 - ▶ squeeze on each problem, branching as needed



Refinement: branching

- ▶ If $\mathcal{L}^{\text{inf}} = \mathcal{L}^{\text{sup}}$, then $\mathcal{L}^{\text{inf}} = \mathcal{L}^{\star}$
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- ▶ Choose an item $\ell \in \overline{\mathcal{L}} \setminus \underline{\mathcal{L}}$, then
 - ▶ divide into two subproblems: with and without ℓ
 - ▶ squeeze on each problem, branching as needed tree
- ▶ End: “conditionally optimal” decision sets
 - ▶ among them, the global optimum
 - ▶ intuition: “brute force” one decision at a time, squeeze as much as possible



Outline

Squeezing and branching

- Single crossing in differences

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- Lattice foundation

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Generalized squeezing

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Heterogeneous agent problem

- ▶ **Augmented objective function.** $f : \mathcal{P}(L) \times \mathbb{R} \rightarrow \mathbb{R}$ maps the set \mathcal{L} and the agent type $z \in \mathbb{R}$ to a scalar payoff $f(\mathcal{L}, z)$
leading example: multinational location problem with heterogeneous productivity
- ▶ **Policy function.** Function $\mathcal{L}^* : \mathbb{R} \rightarrow \mathcal{P}(L)$ specifies the optimal decision set for each type z :

$$\mathcal{L}^*(z) = \arg \max_{\mathcal{L} \in \mathcal{P}(L)} f(\mathcal{L}, z)$$

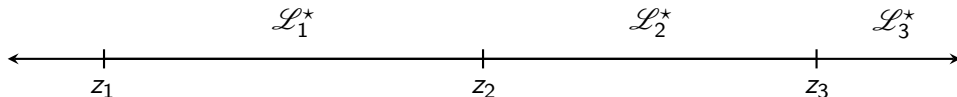
Single crossing differences in types

- **SCD in types (SCD-T).** For all elements $\ell \in L$, decision sets $\mathcal{L} \in \mathcal{P}(L)$, and types $z, z' \in \mathbb{R}$ such that $z < z'$,

$$D_{\ell}f(\mathcal{L}, z) \geq 0 \quad \Rightarrow \quad D_{\ell}f(\mathcal{L}, z') \geq 0$$

SCD-T is equivalent to the single-crossing differences condition of Milgrom 2004 (originally “single crossing” in Shannon and Milgrom 1994).

- **With SCD-C and SCD-T.** The policy function changes its value only at a finite number of cutoff productivities:



- **Approach.** Partition type space into intervals that share the same policy; and find policy associated with each interval

Type space partition

- **Bounding set functions.** Extend bounding pair to set-valued **functions** $\underline{\mathcal{L}}(\cdot)$ and $\overline{\mathcal{L}}(\cdot)$ with

$$\underline{\mathcal{L}}(z) \subseteq \mathcal{L}^*(z) \subseteq \overline{\mathcal{L}}(z)$$

for any productivity $z \in \mathbb{R}$

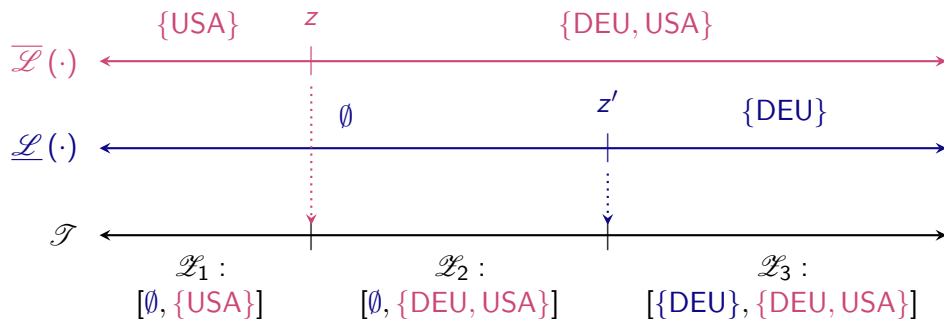
trivial bounding set functions: constant functions $[\emptyset, L]$

- **Induced partition.** From bounding set functions:

$$\mathcal{T}([\underline{\mathcal{L}}(\cdot), \overline{\mathcal{L}}(\cdot)]) = \{\mathcal{Z}_1, \dots, \mathcal{Z}_t, \dots, \mathcal{Z}_T\}$$

such that $\mathcal{Z}_t = \{z \in \mathbb{R} \mid \underline{\mathcal{L}}(z) = \underline{\mathcal{L}}_t, \overline{\mathcal{L}}(z) = \overline{\mathcal{L}}_t\},$

Type space partition



Together, the two set-valued functions imply the partitioning \mathcal{T} , which creates intervals of productivity.

Identifying cutoffs: intuition

- ▶ **SCD-C.** “Choice monotonicity” rules out decision sets without explicitly evaluating their payoff; together with ...
- ▶ **SCD-T.** “Type monotonicity” means choice monotonicity can discard decision sets for productivity **ranges** without evaluating the objective at any of the productivities

Generalized squeezing

- ▶ With SCD-C + SCD-T. For each ℓ and \mathcal{L} , there is a **unique type** indifferent between including ℓ in \mathcal{L}

$$0 = D_{\ell}(\mathcal{L}, z_{\ell}^g(\mathcal{L}))$$

- ▶ **Indifferent type.** Use to avoid evaluating $\Phi(\mathcal{L}, z)$ at each z for a given \mathcal{L} :

$$\Phi^g(\mathcal{L}, z) = \{\ell \mid z \geq z_{\ell}^g(\mathcal{L})\}$$

- ▶ Generalized squeezing mapping.

$$S^g([\mathcal{L}(\cdot), \mathcal{L}'(\cdot)]) = [\inf\{\Phi^g(\mathcal{L}(\cdot), \cdot), \Phi^g(\mathcal{L}'(\cdot), \cdot)\}, \sup\{\Phi^g(\mathcal{L}(\cdot), \cdot), \Phi^g(\mathcal{L}'(\cdot), \cdot)\}]$$

Main theorem: Policy function

Theorem 2 (Generalized squeezing procedure)

If f satisfies SCD-C and SCD-T,

- a. Theorem 1a. and 1b. hold at each z
- b. $(S^g)^{|\mathcal{L}|}([\emptyset, L]) = (S^g)^{|\mathcal{L}|+1}([\emptyset, L])$

Proof.

Let $\Phi(\mathcal{L}, z) \equiv \{\ell \mid D_\ell f(\mathcal{L}, z) \geq 0\}$ be the mapping Φ evaluated at the type z . Applying Theorem 1 element-wise, we have for all z that

$$\underline{\mathcal{L}}_t \subseteq \Phi(\overline{\mathcal{L}}_t, z) \subseteq \mathcal{L}^*(z) \subseteq \Phi(\underline{\mathcal{L}}_t, z) \subseteq \overline{\mathcal{L}}_t.$$

Then, it suffices to show that, for all z , $\Phi^g(\mathcal{L}, z)$ coincides with $\Phi(\mathcal{L}, z)$. The proof uses SCD-C and SCD-T to establish this equivalence. □

Proof intuition: SCD-C from above

For a given interval $\mathcal{Z}_t \in \mathcal{T}$:

1. select $\ell \in \overline{\mathcal{L}}_t \setminus \underline{\mathcal{L}}_t$, compute the two cutoffs

$$z_\ell^g(\underline{\mathcal{L}}_t) \leq z_\ell^g(\overline{\mathcal{L}}_t)$$

2. update bounding set functions:

- ▶ for all firms with productivity $z < z_\ell^g(\underline{\mathcal{L}}_t)$ in \mathcal{Z}_t , ℓ is not part of the optimal decision set: update upper bounding set function to $\overline{\mathcal{L}}_t \setminus \{\ell\}$ for these productivities
- ▶ for all firms with productivity $z > z_\ell^g(\overline{\mathcal{L}}_t)$ in \mathcal{Z}_t , ℓ is in the optimal decision set: update lower bounding set function to $\underline{\mathcal{L}}_t \cup \{\ell\}$ for these productivities

3. repeat for all $\ell \in \overline{\mathcal{L}}_t \setminus \underline{\mathcal{L}}_t$

4. use new bounding set functions to update partition

Part II

Application: MNEs

Outline

Quantitative framework

- Multinational firm CDCP

- SCD-C and SCD-T in firm problem

- Policy function and aggregation

Solution at work

- Solution method's performance

- Quantitative counterfactual

A model of multinational activity

- ▶ Setup.
 - ▶ Firms are born in origin country with productivity $z \sim g(z)$
 - ▶ Each firm produces a differentiated variety, compete monopolistically
 - ▶ There are L potential production locations
- ▶ Firm problem overview.
 - ▶ CDCP. Firms choose production locations subject to complementarities among locations and fixed costs
 - ▶ Heterogeneity. Productivity differences \rightarrow Firms choose different production location sets \rightarrow MNEs arise endogenously
- ▶ Full GE. Endogenous wages, firm entry, ...

The firm problem

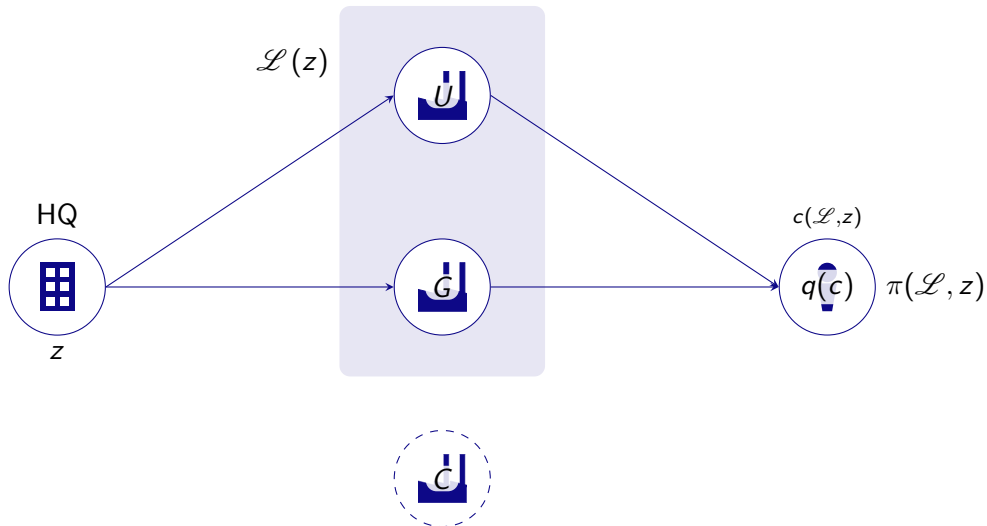
1. **Location choice (extensive margin).** Choose a set of production locations \mathcal{L} index origin country with i , production location with ℓ , destination market with n
2. **Price and quantity (intensive margin).** Choose price (quantity), contingent on CES marginal cost

a possible microfoundation: input sourcing (Tintelnot 2017; Antràs, Fort, and Tintelnot 2017; Arkolakis, Ramondo, et al. 2018) [details](#)

$$c_{in}(\mathcal{L}, z) = \frac{1}{z} \left[\sum_{\ell \in \mathcal{L}} \left(\frac{w_{\ell} \gamma_{i\ell} \tau_{\ell n}}{T_{\ell}} \right)^{-\theta} \right]^{-\frac{1}{\theta}} = \frac{1}{z} \left[\sum_{\ell \in \mathcal{L}} \xi_{i\ell n}^{-\theta} \right]^{-\frac{1}{\theta}}$$

- ▶ marginal cost declines in \mathcal{L}
- ▶ θ : substitutability (complementarity) among locations in cost

The firm problem



The firm problem

- ▶ **CES demand.** In each market n ,
 - ▶ the firm sets constant markup $\mu = \frac{\sigma}{\sigma-1}$ over marginal cost
 - ▶ let X_n be total expenditure and P_n be CES price index
- ▶ **Total profits.** Adding up over destination markets:

$$\pi_i(\mathcal{L}, z) \equiv \left[1 - \frac{1}{\mu}\right] \sum_n X_n \left(\frac{z P_n}{\mu}\right)^{\sigma-1} \left[\sum_{\ell \in \mathcal{L}} \xi_{i\ell n}^{-\theta}\right]^{\frac{\sigma-1}{\theta}} - \sum_{\ell \in \mathcal{L}} w_\ell f_{i\ell}$$

where $f_{i\ell}$ is the fixed labor cost of establishing production in location ℓ

- ▶ **Location choice policy function.** The firm chooses production locations to maximize total profits:

$$\mathcal{L}_i^*(z) = \arg \max_{\mathcal{L} \subseteq L} \pi_i(\mathcal{L}, z)$$

Firm location choice is a CDCP

- Marginal value of location k . Trades off the marginal cost savings with fixed cost:

$$\frac{1}{\sigma} \sum_n X_n \left(\frac{zP_n}{\mu} \right)^{\sigma-1} \left\{ \left[\xi_{ikn}^{-\theta} + \sum_{\mathcal{L}} \xi_{iln}^{-\theta} \right]^{\frac{\sigma-1}{\theta}} - \left[\sum_{\mathcal{L}} \xi_{iln}^{-\theta} \right]^{\frac{\sigma-1}{\theta}} \right\} - w_k f_{ik}$$

complementarities preclude deciding on each location independently from the other locations

- Applying our solution. Establish SCD first:
 - SCD-C. Sufficient condition: $\sigma - 1 \leq \theta$
 - θ cost-side cannibalization (or complementarity)
 - σ demand-side market-level scale effect
 - SCD-T. Sufficient condition: $\sigma > 1$

general demand

Policy function in practice

- ▶ Policy function $\mathcal{L}_i(z)$. Maps firm productivity z to production location set example
- ▶ Aggregation. Production in location ℓ of the average active firm from origin i requires integrating over optimal decision set for each active type z

$$\sum_n X_n \left(\frac{z P_n}{\mu} \right)^{\sigma-1} \int \frac{\mathbf{1}_{\ell}^*(z) \xi_{i\ell n}^{-\theta}}{\sum_{k \in \mathcal{L}^*(z)} \xi_{ikn}^{-\theta}} \left[\sum_{\mathcal{L}_i^*(z)} \xi_{i\ell n}^{-\theta} \right]^{\frac{\sigma-1}{\theta}} dG_i(z \mid \text{active})$$

- ▶ Gravity at the firm level (across locations), but not in the aggregate

Closing and quantifying the model

- ▶ Aggregate conditions. [details](#)
 - ▶ Free entry with entry labor cost f_i^e
 - ▶ Labor market clearing with H_ℓ units, inelastically supplied
 - ▶ Balance of payments
- ▶ Quantification. Calibrate with:
 - ▶ 32 countries using aggregate data [details](#)
Alviarez 2019; Feenstra, Inklaar, and Timmer 2015
 - ▶ two levels of complementarities to highlight how it shapes quantitative outcomes
 - ▶ Negative complementarities. $\frac{\sigma-1}{\theta} = \frac{2}{3}$
Arkolakis, Ramondo, et al. 2018
 - ▶ Positive complementarities. $\frac{\sigma-1}{\theta} = \frac{3}{2}$

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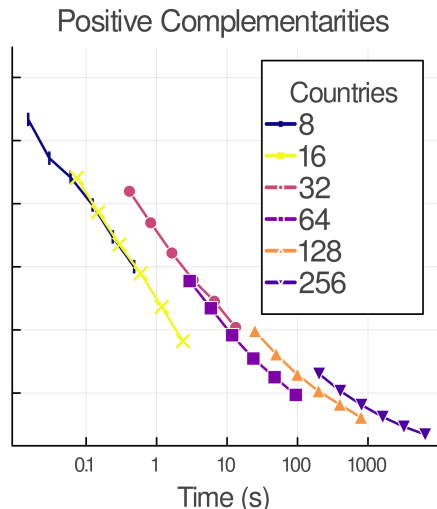
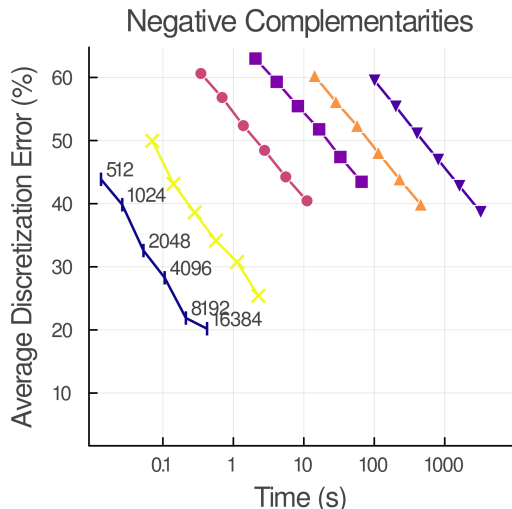
Speed

Solving for the policy function (s)

Countries	Negative Comp.			Positive Comp.		
	Naive (1)	Sqz. (2)	Policy (3)	Naive (1)	Sqz. (2)	Policy (3)
8	8	0.423	0.019	7	0.480	0.034
16	5454	2.26	0.039	4356	2.36	0.087
32	–	11.1	0.11	–	13.2	0.19
64	–	66.0	1.32	–	94.5	1.29
128	–	456	14.1	–	795	14.7
256	–	3239	331	–	6479	374
Grid points	2^{14}	2^{14}	–	2^{14}	2^{14}	–

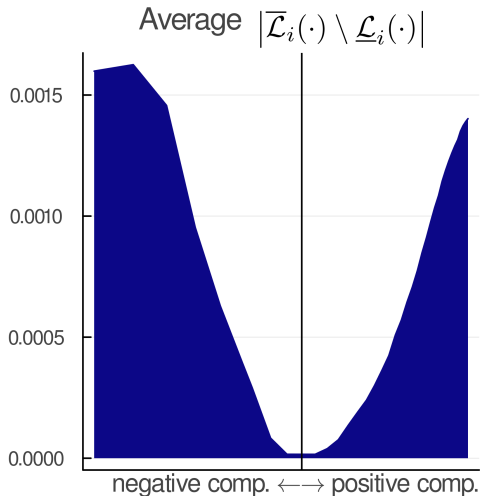
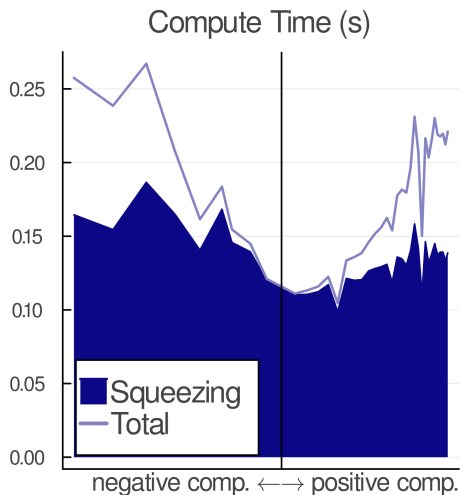
- ▶ Negative complementarities solve in comparable time
- ▶ Policy function is faster than incumbent (unhighlighted) approaches

Precision



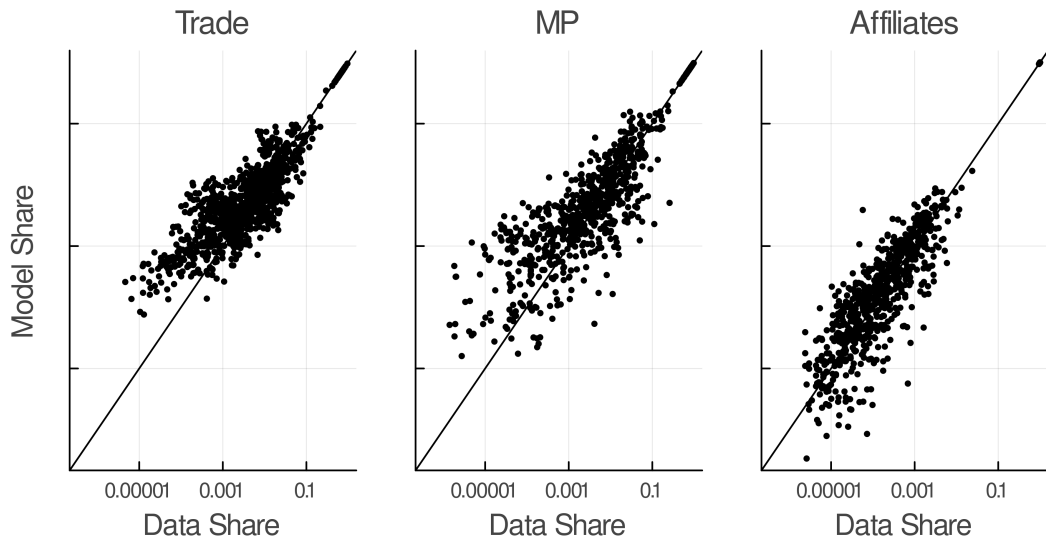
Average percentage error in $X_{i\ell n}$ from discretization: drops 5–10p.p. each grid point doubling while policy function introduces no error

Wide applicability



Fast computation across range of complementary (0.15–3.9); longer compute with strong complementarities

Micro-data not required



Calibration matches aggregates shares (with negative complementarities)

Revisiting the welfare equation

- ▶ Arkolakis, Costinot, and Rodríguez-Clare 2012. The welfare change from reverting to autarky:

$$\ln \frac{\hat{w}_i}{\hat{P}_i} = \underbrace{\ln \hat{\pi}_{iii}^{-\frac{1}{\sigma-1}}}_{\text{openness}}$$

Revisiting the welfare equation

- ▶ Arkolakis, Costinot, and Rodríguez-Clare 2012. The welfare change from reverting to autarky, revisited:

$$\ln \frac{\hat{w}_i}{\hat{P}_i} = \underbrace{\ln \hat{\pi}_{iii}^{-\frac{1}{\sigma-1}}}_{\text{openness}} + \underbrace{\ln \hat{M}_i^{\frac{1}{\sigma-1}} + \ln \hat{z}_i^{-\frac{\zeta}{\sigma-1}}}_{\text{varieties}} + \underbrace{\ln \hat{z}_i + \ln \left[\sum_{z_i^t \in \mathcal{T}_i} \lambda_{iii}^t (s_{iii}^t)^{\frac{\sigma-1}{\theta}-1} \right]^{\frac{1}{\sigma-1}}}_{\text{average productivity}}$$

- ▶ General “openness”. Applies for either trade and MP autarky

Welfare channels

Openness. Standard term captures reduction in real consumption, usually negative

$$\ln \hat{\pi}_{iii}^{-\frac{1}{\sigma-1}}$$

Varieties.

$$\ln \hat{M}_i^{\frac{1}{\sigma-1}} + \ln \hat{Z}_i^{-\frac{\zeta}{\sigma-1}}$$

- ▶ Trade and MP autarky shrink the profits of previously large firms engaged in these foreign activities → Selection cutoff falls
- ▶ More entry and easier survival
- ▶ Usually: more varieties, positive effect

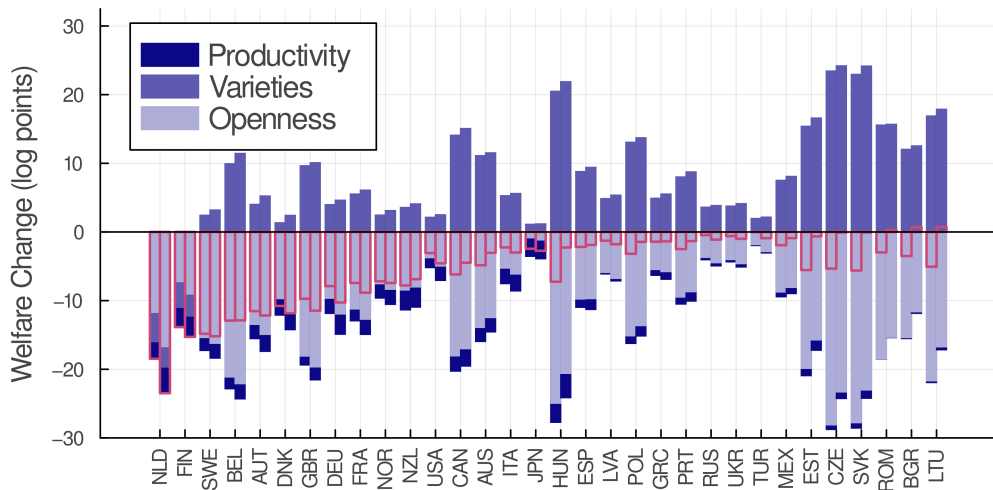
Welfare channels

Productivity.

$$\ln \hat{z}_i + \ln \left[\sum_{z_i^t \in \mathcal{T}_i} \lambda_{iii}^t (s_{iii}^t)^{\frac{\sigma-1}{\theta}-1} \right]^{\frac{1}{\sigma-1}}$$

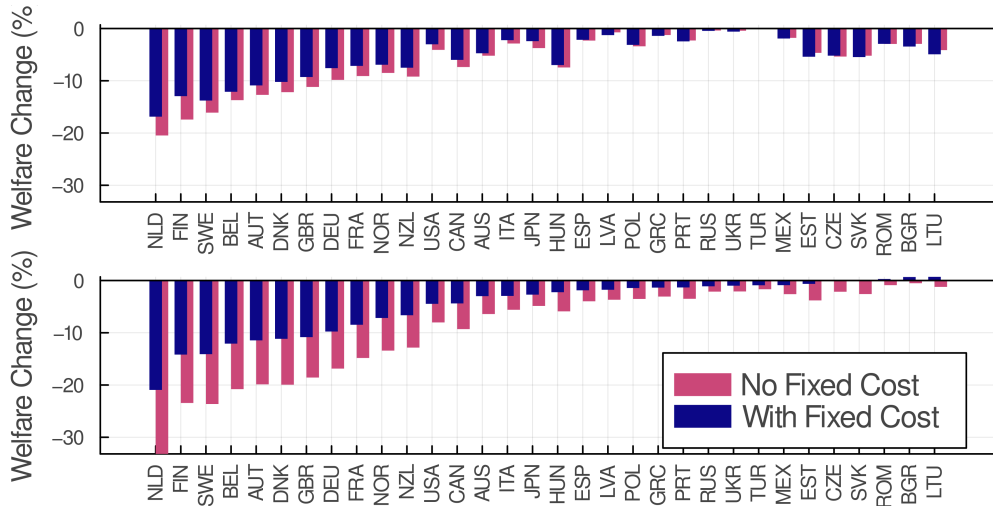
- ▶ Extensive margin: since selection cutoff falls, usually negative
- ▶ Intensive margin:
 - ▶ Trade and MP autarky shrink the profits of previously large firms engaged in these foreign activities → Relative firm sizes adjust
 - ▶ Sales-weighted in average productivity changes

MP autarky: Quantification



Left bars: results from the calibration with negative complementarities (right bars: positive complementarities)

MP autarky: Quantification



Top figure: results from calibrations with negative complementarities (bottom: positive complementarities)

To conclude

- ▶ Combinatorial discrete choice problems are common
 - ▶ Trade: multinational production, either export platforms or GVCs; firm sourcing partners; extended gravity export destinations
 - ▶ IO: input complementarity; product mix
 - ▶ (International) macro: tax avoidance and profit shifting, portfolio choice
 - ▶ Spatial economics: transport networks; real estate choices
 - ▶ ...
- ▶ We develop a new approach to CDCPs
 - ▶ With negative or positive complementarities
 - ▶ Policy function solution for aggregation
- ▶ Julia package: `CDCP.jl`

Part III

Appendix







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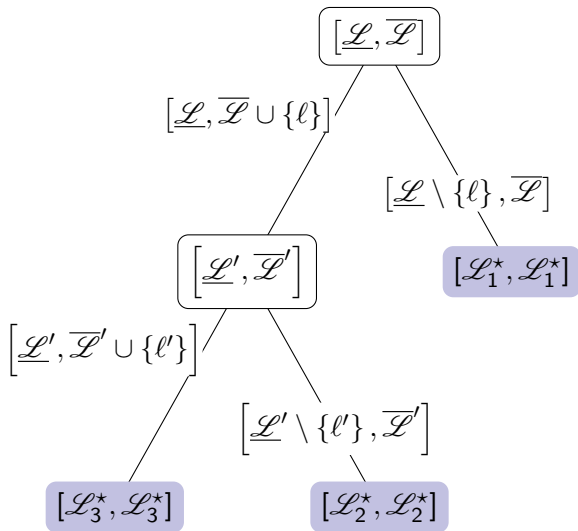
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Branching tree

- convergence when bounding pair coincides on each branch
- branching collects all fixed points of Φ
invariant to the items selected and order

back



Cost minimization for each destination n

- ▶ the unit cost of producing an input v at location $\ell \in \mathcal{L}$ then delivering it to market n is

$$\gamma_{i\ell} \frac{w_\ell}{z\varphi_\ell(v)} \tau_{\ell n}$$

$\gamma_{i\ell}$ arms-length iceberg cost of MP

w_ℓ labor cost in production location

z firm productivity

$\varphi_\ell(v)$ location-input shifter

$\tau_{\ell n}$ iceberg cost of trade

- ▶ tractable export platforms: for each destination n and input v , the firm chooses the least-cost production location

Cost minimization for each destination n

- ▶ negative complementarity: marginal cost declines in \mathcal{L} , but decreasingly so (cannibalization)

Antràs, Fort, and Tintelnot 2017; Tintelnot 2017

$$c_{in}(\mathcal{L}; z) = \left[\int_{\varphi} \left(\min_{\ell \in \mathcal{L}} \gamma_{i\ell} \frac{w_{\ell}}{z\varphi_{\ell}} \tau_{\ell n} \right)^{1-\eta} dF(\varphi; \mathcal{L}) \right]^{\frac{1}{1-\eta}}$$

- ▶ closed form with Fréchet location-input draws ($\eta < \theta + 1$)

Arkolakis, Ramondo, et al. 2018; Ramondo and Rodríguez-Clare 2013; Lind and Ramondo 2023

$$c_{in}(\mathcal{L}; z) = \frac{1}{z} \Gamma \left[\sum_{\ell \in \mathcal{L}} \left(\frac{\gamma_{i\ell} w_{\ell} \tau_{\ell n}}{T_{\ell}} \right)^{-\theta} \right]^{-\frac{1}{\theta}}$$

General demand function

- ▶ sufficient condition for supermodularity

$$\underbrace{\varepsilon_D}_{\text{demand elasticity}} \times \underbrace{\frac{d \ln p}{d \ln c}}_{\text{passthrough}} \geq \underbrace{\theta}_{\text{cannibalization}} + 1$$

- ▶ compares (positive) demand-side complementarity with (negative) supply-side complementarity
- ▶ sufficient condition for submodularity: flip the sign
- ▶ flexible framework for discrete decisions and complementarities

back

Policy function: Japan

- ▶ with negative complementarities

$[-\text{Inf}, 0.65]$	$+\text{String}[]$	
$[0.65, 3.14]$	$+["\text{JPN}"]$	
$[3.14, 3.302]$	$+["\text{ROM}"]$	
$[3.302, 3.351]$	$+["\text{ITA}"]$	
$[3.351, 3.403]$	$+["\text{GBR}"]$	$-["\text{ITA}", "\text{ROM}"]$
$[3.403, 3.574]$	$+["\text{ITA}"]$	
$[3.574, 3.631]$	$+["\text{ROM}"]$	
...		

- ▶ with positive complementarities

$[-\text{Inf}, 0.666]$	$+\text{String}[]$	
$[0.666, 4.253]$	$+["\text{JPN}"]$	
$[4.253, 4.354]$	$+["\text{DEU}", "\text{GBR}", "\text{FRA}", "\text{ITA}", "\text{POL}", "\text{ROM}"]$	
...		

Aggregate conditions

- Free entry. Require f_i^e to draw productivity

$$w_i f_i^e = \frac{1}{\sigma} \sum_n X_n \int \left(\frac{z P_n}{\mu} \right)^{\sigma-1} \Theta_{in}(\mathcal{L}_i^*(z))^{\frac{\sigma-1}{\theta}} dG_i(z) \\ - \int \sum_{\ell \in \mathcal{L}_i^*(z)} w_\ell f_{i\ell} dG_i(z)$$

- Price index. Aggregates over all firm origins i

$$P_n^{1-\sigma} = \sum_i M_i \int \left(\frac{z}{\mu} \right)^{\sigma-1} \Theta_{in}(\mathcal{L}_i^*(z))^{\frac{\sigma-1}{\theta}} dG_i(z)$$

Aggregate conditions

- Labor market clearing. Inelastically supplied H_ℓ units

$$\begin{aligned} w_\ell H_\ell = & \frac{\sigma - 1}{\sigma} \sum_{i,n} X_n M_i \int \frac{\mathbf{1}_{i\ell}^*(z) (w_\ell \gamma_{i\ell} \tau_{\ell n} / T_\ell)^{-\theta}}{\sum_{k \in \mathcal{L}_i^*(z)} (w_k \gamma_{ik} \tau_{kn} / T_k)^{-\theta}} \\ & \times \left(\frac{z P_n}{\mu} \right)^{\sigma-1} \Theta_{in}(\mathcal{L}_i^*(z))^{\frac{\sigma-1}{\theta}} dG_i(z) \\ & + \sum_i M_i \int \mathbf{1}_{i\ell}^*(z) w_\ell f_{i\ell} dG_i(z) + M_\ell w_\ell f_\ell^e \end{aligned}$$

- Balance of payments.

$$X_n = w_n H_n$$

Quantification

- ▶ Parameterization.
 - ▶ $g_i(\cdot) \sim$ Pareto with shape ζ and minimum \underline{z}_i
 - ▶ bilateral trade, MP, and fixed costs with gravity variables
- ▶ Calibration strategy.

Parameter	Target
σ	set to 4 Arkolakis, Ramondo, et al. 2018; Head and Mayer 2019
ζ	firm sales tail Arkolakis 2010
$T_{\ell}, \underline{z}_i$	GDP, total foreign MP outgoing
f_i, f_i^e	enterprise survival rate, count
$\tau_{\ell n}, \gamma_{il}, \nu_{il}$	trade, MP, and affiliate flow
details	

Bilateral costs

- **Parameterization.** Gravity variables $v \in \{\log \text{dist}, \text{COL}, \text{BOR}, \text{COM}\}$

Conte, Cotterlaz, Mayer, et al. 2023

$$\log \tau_{\ell n} = \sum_v \kappa_{\tau}^v v_{\ell n} + \mathbf{1}[\ell \neq n] \bar{\tau}_n + \log(1 + t_{\ell n})$$

$$\log \gamma_{il} = \sum_v \kappa_{\gamma}^v v_{il} + \mathbf{1}[i \neq \ell] \bar{\gamma}_n$$

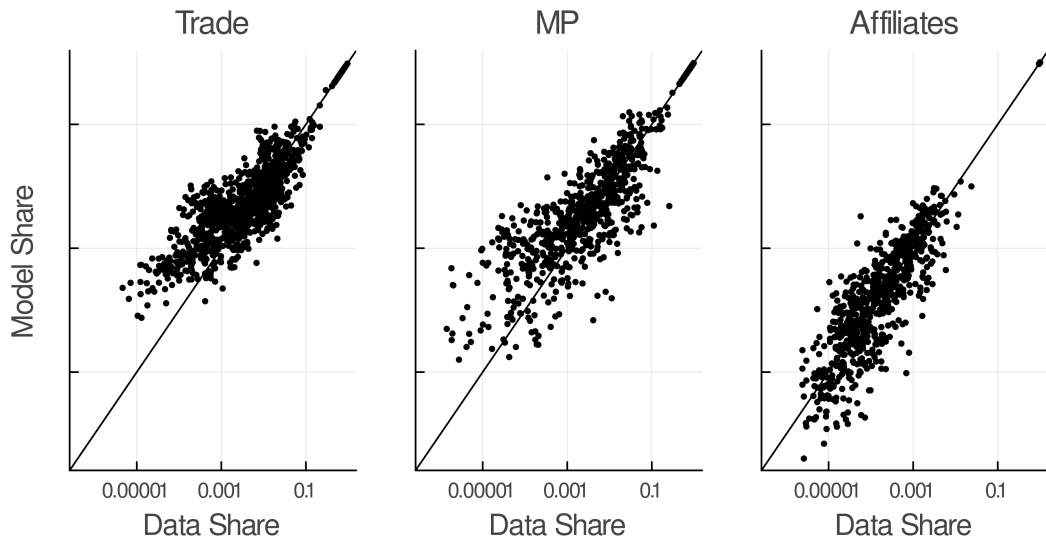
$$\log f_{il} = \sum_v \kappa_f^v v_{il} + \mathbf{1}[i \neq \ell] \bar{f}_n$$

- Match aggregate flows.

$\kappa_{\tau}^v, \kappa_{\gamma}^v, \kappa_f^v$ corresponding coefficient on gravity variables in trade, MP, and affiliate regressions

$\bar{\tau}_n, \bar{\gamma}_{\ell}, \bar{f}_{\ell}$ own shares of “trade” (absorption), “MP” (domestic production), and affiliates (domestic production locations)

Micro-data not required



Calibration matches aggregates shares (with positive complementarities)