Multimodal Transport Networks

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January 2026

Motivation

- Transportation links firms, workers, and locations via trade and production
  - Transportation networks shape gains from trade.
- Standard trade models often feature exogenous trade cost and a single-mode of transportation.
- They do not account for changes in congestion and endogenous re-routing & mode switching.

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ECONOMY | U.S. ECONOMY

Threat of Rail Strike Reveals Persistent Supply-Chain Risks to U.S. Economy

Businesses and policy makers plan for 'new normal' of potential disruption of supplies of everything from coal to components

By David Harrison Follow

Dec. 3, 2022 5:30 am ET

LOGISTICS REPORT

Dockworkers Extend Job Actions Delaying West Coast Port Cargoes

Retailers are seeking White House intervention as long-running labor contract talks falter over wages

By Paul Berger Follow

June 5, 2023 5:15 pm ET

BUSINESS | LOGISTICS

The Panama Canal Has Become a Traffic Jam of the Seas

More than 200 vessels are stuck on either side of the waterway as a serious drought cuts crossings

By Costas Paris Follow

Aug. 18, 2023 8:00 am ET

U.S.

I-95 Overpass Collapses in Philadelphia After Tanker Fire

Officials warn of challenging traffic conditions for months while the busy interstate is repaired

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- Multimodal transport networks shape how trade arises from agents' choices and infrastructure:
  - Routing: intermodal paths change when links/terminals are disrupted or improved.
  - Modal substitution: mode-specific cost advantages $\Rightarrow$ distance economies (containerization; Coşar & Demir, 2018).
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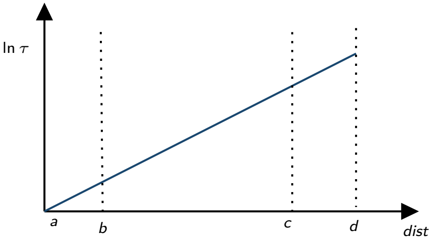
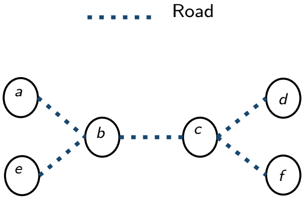
- Research question: How do network disruptions and investments affect welfare and emissions in a multimodal system?

Multimodal Routing: Modal Choice





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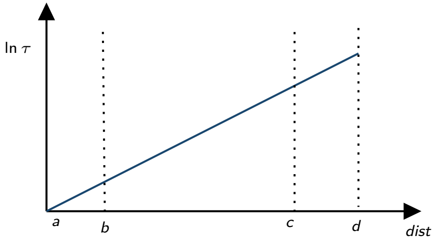

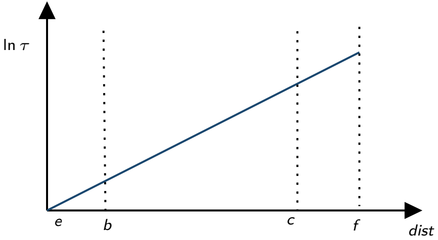

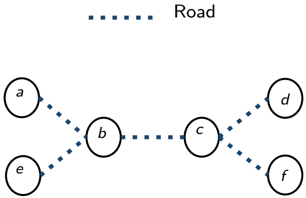

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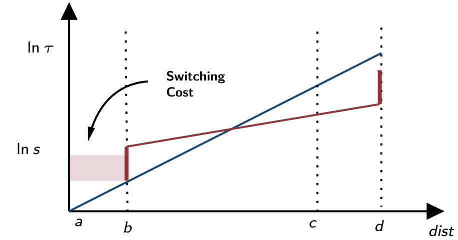

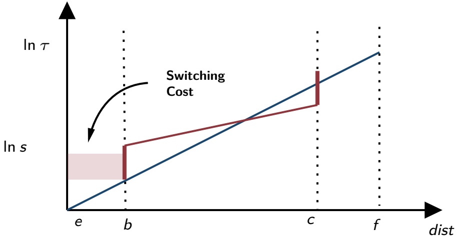

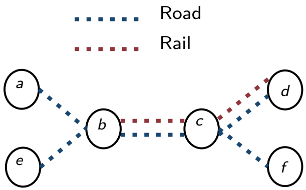

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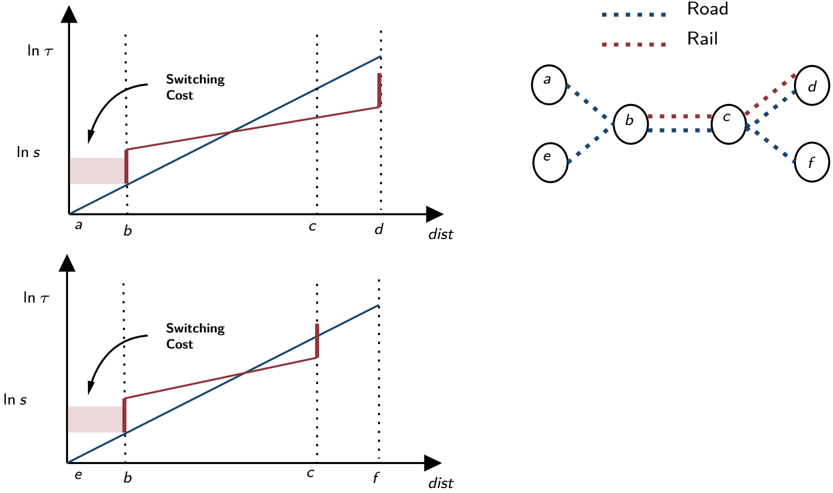

Distance Economies $\rightarrow$ Modal Substitution

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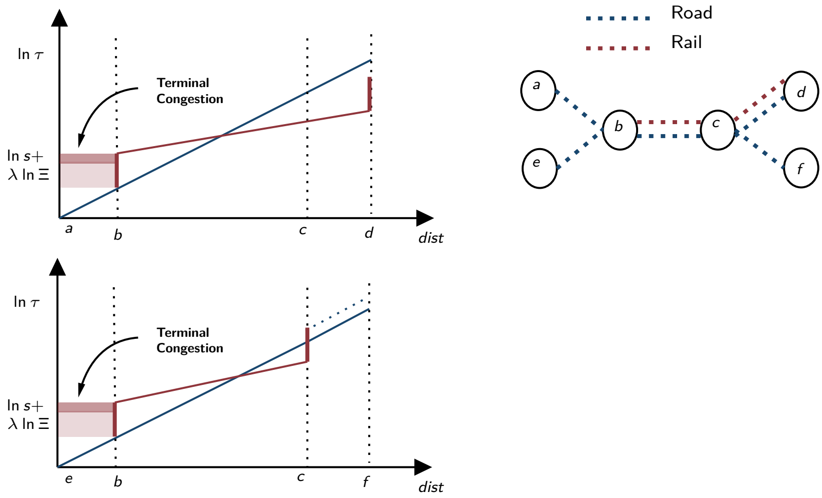

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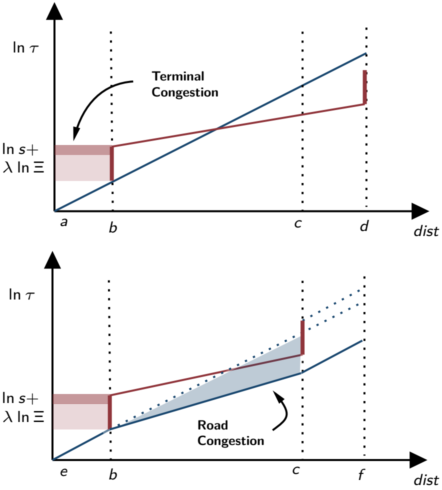

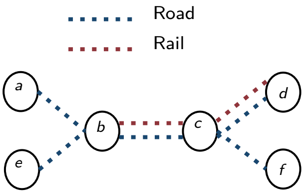

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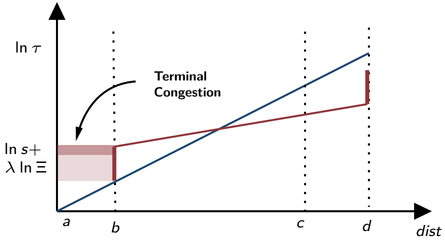

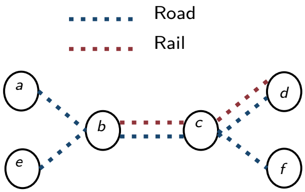

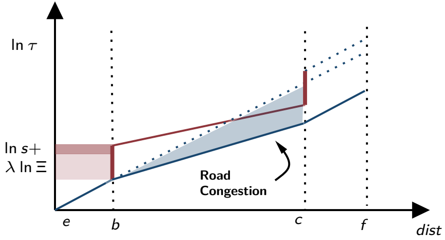

Δ Congestion $\rightarrow$ Modal Complementarity

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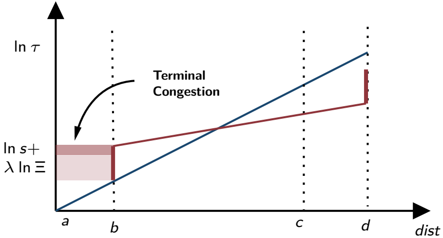

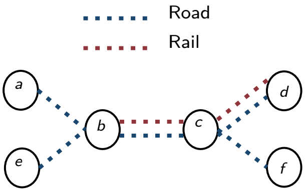

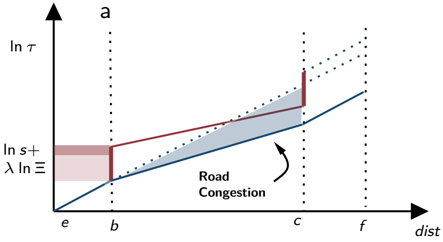

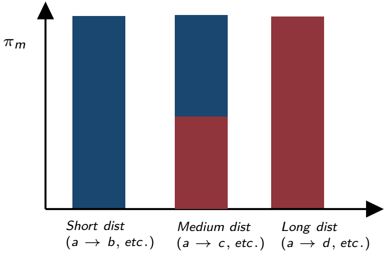

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- Develop quantitative spatial equilibrium model with endogenous transport cost:
  - Multiple modes, intermodal terminals, and congestion.
  - Recursive Generalized Extreme Value-based (GEV) route choice from Operations Research toolkit. (Daly & Bierlaire, 2006)

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- Counterfactuals:
  - First welfare estimates with multimodal transport network and QSM + environmental impact
  - Terminal improvements: \$300–700M GDP gains + \$23-45M env benefit, 2.5x higher without congestion
  - Disruptions: Losing rail access reduces GDP by \$230B.

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  - Disruptions: Losing rail access reduces GDP by $230B.
  - Rel to unimodal estimates: Our welfare estimates 1.25x higher from investments, highlighting complementarity across modes within multimodal networks

Related Literature and Contributions

- **Transport network in spatial eqm**: Add multi-modes & terminals, estimate modal sub elas

  Infrastructure investment on road networks and congestion (Redding & Turner 2015, Fajgelbaum & Schaal 2017, Allen & Arkolakis 2022, Fan & Luo 2020, Fan, Lu, and Luo 2021), Maritime shipping networks (Kalouptsidi, Brancaccio, & Papageorgiou 2020, Heiland, Moxnes, Ulltveit-Moe, & Zi 2022, Ganapati, Wong, & Ziv 2022, Wong 2022) and rail networks (Degiovanni and Yang 2023)

  Urban transportation (Severen 2022, Zarate 2021, Tsivanidis 2022, Almagro, Barbieri, Castillo, Hickock & Salz 2022, Kreindler & Miyauchi 2021, Miyauchi, Nakajima & Redding 2022)

- **Ports**: Study intermodal terminals (incl ports) within multimodal network & GE, estimate congestion elas

  Container technology and port development (Brooks, Gendron-Carrier & Rua 2018, Ducruet et al. 2020), Port investments and congestion (Kalouptsidi, Brancaccio, & Papageorgiou 2024)

- **Multimodal transport in transport lit**: Embed multimodal routing within GE framework

  Traffic assignment (Bell 1995, Kitthamkesorn, Chen & Xu 2015, Boyles, Lownes & Unnikrishnan 2021, Li, Xie & Bao 2022), Estimation of freight transport price elasticities (Winston 1981, McFadden, Winston & Boersch-Supan 1986, Rich, Kveiborg & Hansen 2011, Beuthe, Jourquin Urbain 2014)

- **Environmental impact of transport**: Substitution & complementarity within multimodal network

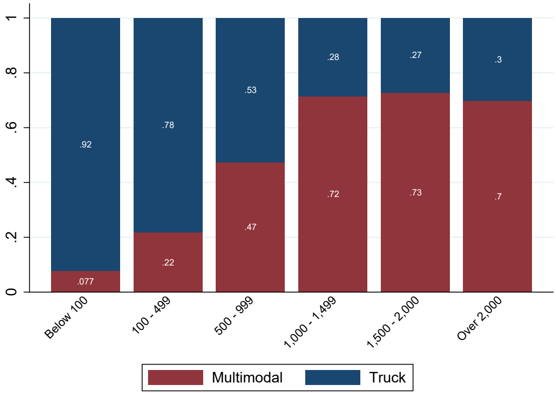
  Shipping (Cristea, Hummels, Puzzello, & Avetisyan 2013, Shapiro 2016, Lugovskyy, Skiba & Terner 2022) and maritime (Mundaca, Strand, & Young 2021) emissions in response to regulation/policy changes

Outline of Talk

1. **Data: US Multimodal Freight Transportation**
2. Theory: QSM with Multiple Modes and Congestion
3. Estimation: Terminal Congestion and Modal Substitution
4. Calibration and Validation
5. Counterfactual: Terminal Improvements & Network Disruptions

Transportation within the US by Mode and Distance

- Trucks used for short dist (first & last mile), multi-modal transport for long dist



by Value Including Air

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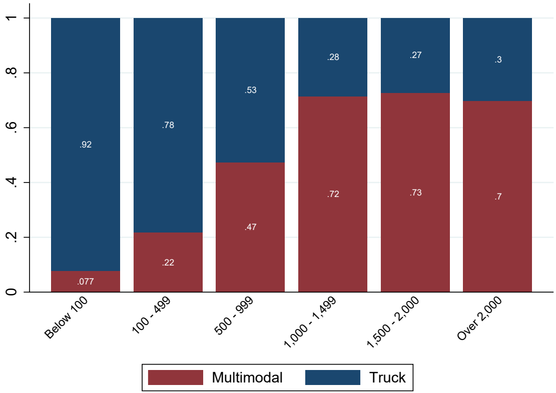

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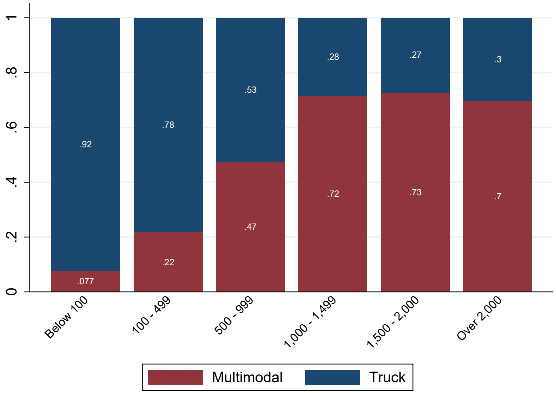

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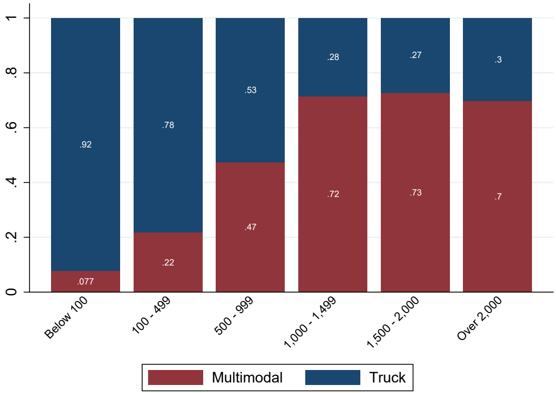


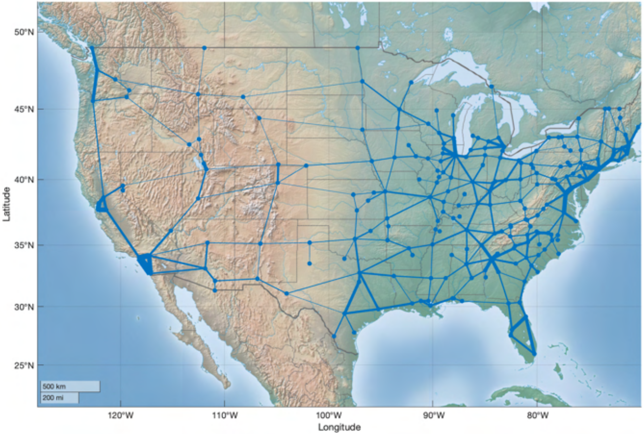
Multimodal share ↑ over time: container is fastest growing rail traffic segment: 5x in 1984-2019

by Value Including Air

Data

1. Traffic data for road transportation Road
2. Traffic data for rail transportation Rail
3. Traffic data for waterbourne transportation Barges
4. Geographic information on US multimodal freight network (road, rail, intermodal terminals, and ocean ports)

US Road Traffic

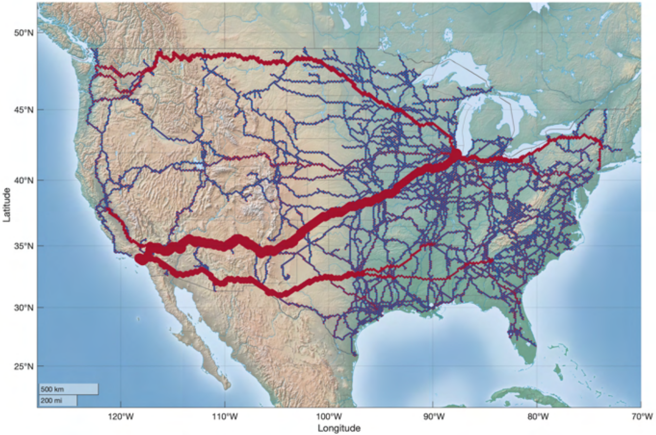


The traffic depicted is presents the traffic along the graph representation of the interstate highway system, depicting data from the 2012 Highway Performance Monitoring System (HPMS) dataset by the Federal Highway Administration.

US Rail Traffic

- Confidential waybill rail data, 1984-2019 (STB)
  - Stratified sample of waybills representing 1-3% of all US rail traffic
  - Key Variables:
    - Route information: Origin-Interchanges-Destination
    - Car Type: Intermodal vs not
    - Carloads and Tonnage

US Rail Traffic



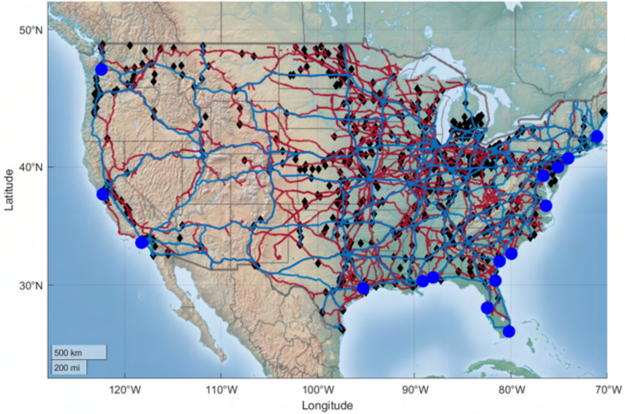
Domestic rail traffic data for Class I carriers (largest in US) conditional on intermodal capability. Shortest routes are imputed between origin, interchange stations, and destination to assign total tonnage to individual rail segments along the multimodal network.

US Waterbourne Traffic

Domestic waterborne traffic data for manufactured goods from the USACE Waterborne Commerce statistics. Shortest routes are imputed between origin and destination to assign total tonnage to individual segments of the domestic water network.

US Multimodal Freight Network

- Class I multimodal railroad (red lines), interstate highway (blue lines), intermodal terminals that allow road/rail switches (black diamonds), top ocean ports (blue circles), and waterways



GIS information from Topologically Integrated Geographic Encoding and Referencing (TIGER) Database, Census Bureau.

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- CES Consumption: Preferences over goods $\nu \in [0, 1]$ (EoS: σ) Details

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- CRS Production: Price of good ν in destination j from origin i is:

$$p_{ij} = \frac{w_i}{A_i} \tau_{ij}$$

  - with marginal cost $\frac{w_i}{A_i}$, origin-specific efficiency A_i, wages w_i, endog. transport cost τ_{ij}

Endogenous Transport Cost

- Transport cost (τ_{ij}): Good ν transported to destination via any feasible route Competition

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Route Choice (Gen 1)

Dijkstra or Fast Marching Method (Allen & Arkolakis 2014)

$$\tau_{ij} = \min_{r \in \mathcal{R}_{ij}} \{\tau_{ij,r}\}$$

Endogenous Transport Cost

- Transport cost (τ_{ij}): Good ν transported to destination via any feasible route Competition

Route Choice (Gen 2)

Explicit enumeration (Allen & Arkolakis 2022)

$$\tau_{ij} = \mathbb{E}\left[\min_{r \in \mathcal{R}_{ij}} \{\tau_{ij,r}\epsilon_r\}\right]$$

Endogenous Transport Cost

- Transport cost (τ_{ij}): Good ν transported to destination via any feasible route Competition

Route Choice (Gen 3)

Implicit enumeration (Daly & Bierlaire 2006) Illustration

$$\tau_{ij} = \mathbb{E}\left[\min_{k \in \mathcal{N}(i)} \{t_{ik}\tau_{kj}\varepsilon_{kj}\}\right]$$

- Avoids curse of dimensionality
- Allows to incorporate nested mode choice and flexible EoS

Endogenous Transport Cost

- Transport cost (τ_{ij}): Good ν transported to destination via any feasible route Competition

Route Choice (Gen 3)

Implicit enumeration (Daly & Bierlaire, 2006) Illustration

$$\tau_{ij} = \mathbb{E}\left[\min_{k\in\mathcal{N}(i)} \{t_{ik}\tau_{kj}\varepsilon_{kj}\}\right] = \left(\sum_{k\in\mathcal{N}(i)} (t_{ik}\tau_{kj})^{-\theta_i}\right)^{-\frac{1}{\theta_i}}$$

- Choices are made between nodes $k \in \mathcal{N}(i)$, with costs to j influenced by $\varepsilon_{kj}(\nu)$, an iid Fréchet variable with shape θ_i.
- This enables recursive characterization of market access terms.

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At each link, agents choose a transport mode Illustration

$$t_{ik} = \mathbb{E}\left[\min_{m \in \mathcal{M}(i,k)} \{t_{ik,m}\varepsilon_{ik,m}\}\right]$$

- The choice from i to k spans modes m with costs $t_{ik,m}$

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- The choice from i to k spans modes m with costs $t_{ik,m}$ and iid Fréchet shocks $\varepsilon_{ik,m}$ (dispersion η).

Congestion

1. Switching Costs:
   - Incorporate mode-specific costs with switching costs at intermodal terminals:

$$t_{ik,m} = s_{ii,m} \tau_{ik,m} s_{kk,m}$$

2. Intermodal Congestion:
   - Introduce congestion at terminals as an iso-elastic function of total terminal traffic $\Xi_{ii,m}$:

$$s_{ii,m} = \bar{s}_{ii,m} \left(\Xi_{ii,m}\right)^{\lambda_m}$$

   - where λ_m measures congestion, and $\bar{s}_{ii,m}$ is exogenous terminal infrastructure.

3. Road Congestion:
   - Account for road congestion as an iso-elastic function of road traffic, $\Xi_{kl,1}$ at the link level:

$$t_{kl,1} = \bar{t}_{kl,1} \left(\Xi_{kl,1}\right)^{\lambda_1}$$

Equilibrium, Comparative Statics and CfI

1. Equilibrium (at link-level)
   - Recursive Routing and Sourcing. Details
   - Market clearing with spillovers $A_i = \bar{A}_i L_i^{\alpha}$, $u_i = \bar{u}_i L_i^{\beta}$. Equilibrium determines $\{y_j, l_j\}$ under free labor mobility, given transport costs $\{t_{ik}\}$ and geography $\{\bar{a}_j, \bar{u}_j\}$. Details
2. Comparative Statics Details
   - The impact of a change in mode m' cost $t_{kl,m'}$ on traffic flows $\Xi_{kl,m}$ for mode m on the same segment can be decomposed into a direct substitution effect and indirect modal complementarity
3. Counterfactuals Details
   - Given data on traffic $\left(\Xi_{ik}, \Xi_{ik,m}\right)$, income (Y_i), and calibrated parameters $\{\alpha, \beta, \{\theta_i\}, \eta, \lambda_1, \lambda_2\}$, solve for counterfactual $\left(\hat{y}_i, \hat{l}_i, \hat{\chi}\right)$ as the solution of a nested fixed point problem.

Theory: QSM with Multiple Modes and Congestion

Theory overview:

- Generalizes QSM + (realistic) Endog Transport Cost
  - Incorporate multiple modes ($\eta \neq \theta$)
  - Allows for heterogeneous EoS ($\theta_i \neq \theta$)

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- Generalizes QSM + (realistic) Endog Transport Cost
  - Incorporate multiple modes ($\eta \neq \theta$)
  - Allows for heterogeneous EoS ($\theta_i \neq \theta$)
- Counterfactuals with low data requirement
  - Elasticities $\{\alpha, \beta, \theta, \eta, \lambda_1, \lambda_2\}$
  - Aggregate and modal traffic ($\Xi_{ij}, \Xi_{ij,m}$)
  - Economic activity (Y_i, E_j)

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3. **Estimation: Terminal Congestion and Modal Substitution**
4. Calibration and Validation
5. Counterfactual: Terminal Improvements & Network Disruptions

Estimation: Terminal Congestion and Modal Substitution

Empirics overview:

1. Estimate congestion at intermodal terminals (λ_m)
2. Estimate modal elasticity of substitution (η)

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   - Elasticity of dwell time at ports (i.e. AIS) and intermodal terminals on traffic

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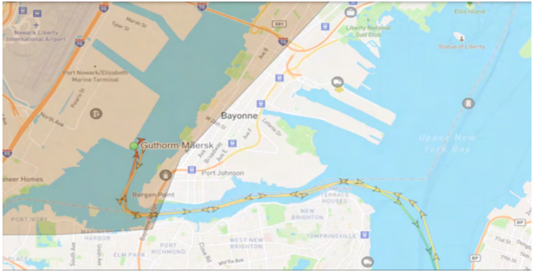
Data: Congestion at Intermodal Port Terminals

- AIS Vessel Traffic Data (June 2015–Dec 2021, Marine Cadastre):
  - 1-minute vessel locations in US waters (200 land stations), with vessel info (IMO, tonnage), position, speed, and status (moving, moored, anchored).
  - Ship dwell time: Time spent moored at zero speed.
- Port Matching: Top 30 US ports (95% container trade).
  - Port Traffic: Daily sum of moored ship capacity weighted by time spent at port.
  - Compute 28-day moving averages of port traffic (21-, 14-, 7-day for robustness).
- Congestion Elasticity:
  - High-detail data captures dwell times with fixed effects.
  - Positive relationship found between rail dwell times and port traffic Results.

Ship Dwell Time Calculation

- Ship path indicated by line, redder color = slower speed. Darker regions are port areas

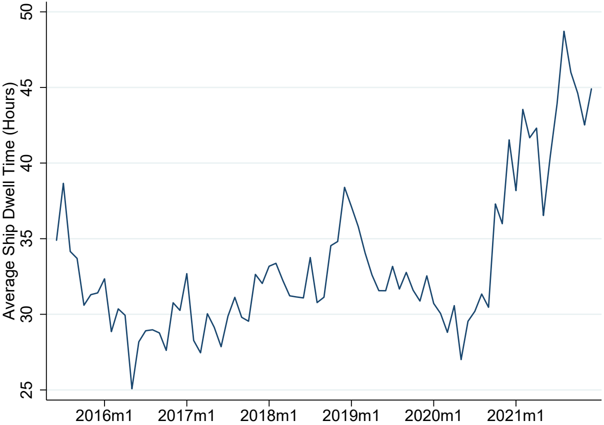


CMA CGM Christophe Colomb (13.8k TEUs) at Port of LA

Guthorm Maersk (11k TEUs) at Port of Newark

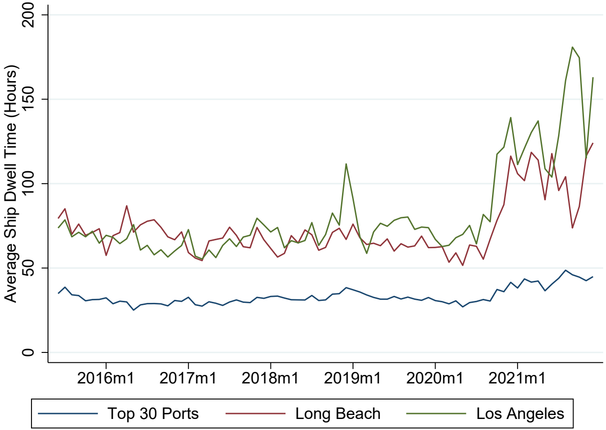
Containership Dwell Times at Port

- 1,444 containerships: Average 33.3 hours per ship (sd 5 hours). Post 2021 av 42.8 hours



Containership Dwell Times at Port

- 1,444 containerships: Average 33.3 hours per ship (sd 5 hours). Post 2021 av 42.8 hours
  - LB: 73.6 hours (post 2021, 104 hours); LA: 82.1 hours (post 2021, 136 hours)



Estimate intermodal congestion (λ_m)

$$\ln \text{Ship Dwell Time}_{spdmy} = \beta_1 \ln \text{Port Traffic}_{pdmy} + \varphi_{sp} + \rho_{py} + \psi_{dmy} + \varepsilon_{spdmy}$$

- β_1: elasticity of ship dwell times to port traffic OLS.[1]
- ψ_{dmy} captures aggregate events; φ_{sp} controls for ship-port characteristics; ρ_{py} for port-specific time trends.
- Shorter moving averages (21, 14, 7 days) yield smaller elasticity estimates Details.

[1] where $\text{Ship Dwell Time}_{spdmy}$ is the hours ship s spent at port p on day of the week d month m and year y, $\text{Port Traffic}_{pdmy}$ is 28-day moving average amount of port traffic at port p ending on day d month m and year y, φ_{sp} is ship-port fixed effects, ρ_{py} is port-year fixed effects, and ψ_{dmy} is day-month-year fixed effects.

Congestion Elasticity: IV

- Use a demand shifter for port traffic that is independent of confounding ship dwell time determinants ϵ_{spdmy}. Balance test

- Shift Share IV:

$$\text{Port Trade Exposure}_{pmy} = \sum_{O} \sum_{N} X_{on\setminus p,my} \times \omega_{onp,2011}$$

  - Weighted sum of region o and product n imports into the top 30 US ports (excluding port p) at month m, year y,
  - Monthly imports (\$, kg, Census Bureau, 2003 weights, $\geq$13 years lag) and increased US container trade boost port traffic.

Congestion Elasticity

	(1) OLS	(2) OLS	(3) First-Stage	(4) IV	(5) First-Stage	(6) IV
Port Traffic	0.09^{***}	0.10^{***}		0.26^{***}		0.24^{***}
	(0.01)	(0.01)		(0.10)		(0.09)
Port Trade Exposure			0.23^{***}		0.23^{***}	
			(0.01)		(0.01)	
Day-Month-Year FE	✓	✓	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓	✓	✓
Ship-Port FE		✓			✓	✓
Ship FE	✓		✓	✓		
Observations	90516	90516	90516	90516	90516	90516
First Stage KP-F				299.03		274.05

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robust standard errors in parentheses are two-way clustered by ship and port. All variables are in logs. Port traffic is the 28-day moving average of total daily net tonnage at the port. Weighted by ship net tonnage.

Balance test | Robustness - IV by value | Robustness - West Coast Ports and Pandemic | Multimodal Link | Comparison with Lit

Congestion Elasticity

1% ↑ in port traffic increases ship dwell times 0.24-0.26%.
Convert using Hummels and Schaur (2012) to $\lambda_2 = .37 * .26 = .0962$

	(1) OLS	(2) OLS	(3) First-Stage	(4) IV	(5) First-Stage	(6) IV
Port Traffic	0.09^{***}	0.10^{***}		0.26^{***}		0.24^{***}
	(0.01)	(0.01)		(0.10)		(0.09)
Port Trade Exposure			0.23^{***}		0.23^{***}	
			(0.01)		(0.01)	
Day-Month-Year FE	✓	✓	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓	✓	✓
Ship-Port FE		✓			✓	✓
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1. Estimate congestion at intermodal terminals (λ_m)
   - Elasticity of dwell time at ports (i.e. AIS) and intermodal terminals on traffic
2. Estimate modal elasticity of substitution (η) Details
   - Elasticity of modal mix (i.e. Rail-to-Road traffic) to highway placement (Duranton & Turner, 2012)

Modal Elasticity of Substitution (η)

- Revisiting: Direct Effect of Infrastructure on Traffic:
  - Estimated via Duranton & Turner (2011) using 3 historic IVs—1947 highway plan, 1898 railroads, and 1528–1850 exploration routes.
- GE & Identification:
  - Road improvement leads to (1) direct decrease in truck costs (partial equilibrium effect) and (2) indirect gains from improved market access for locations overall.
- Our approach:
  - Use IVs off-the-shelf, but...
  - ...evaluate the impact of enhanced road access on modal mix (rail-to-road traffic).
  - Differences out market access/induced demand effects.

Modal Complementarity and Substitution

$$\ln \text{Interstate Highway Lanes}_{cy} = \eta_2 \ln \text{Instruments}_c + \kappa C_{cy} + \iota_y + \nu_{cy}$$
$$\ln Y_{cy} = \eta_1 \ln \text{Interstate Highway Lanes}_{cy} + \phi C_{cy} + \iota_y + \mu_{cy}$$

where $\ln Y_{cy}$ is log traffic use outcome for city c in year t, $\ln \text{Instruments}_c$ is the three historic instruments discussed previously, $\ln \text{Interstate Highway Lanes}_{cy}$ is log number of interstate highway lanes through c proxying for its road infrastructure in year y. C_{jt} are city-specific time-varying controls including population, physical geography, census divisions, and socioeconomic characteristics that are taken from Duranton and Turner (2011), and ι_y is year fixed effects.

1. Replicate DT(2011) within 1 se using cities matched to rail data: Y_{cy} = truck traffic use results

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2. Estimate impact of road improvements on rail (noisy): Y_{cy} = rail traffic use results ratio

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3. Estimate impact of road improvements on rail relative to road: $Y_{cy} = \frac{\text{Rail}}{\text{Road}}$ traffic use

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   $\Rightarrow$ Ratio differences out indirect market access effects

Elasticity of Truck Traffic Use wrt Road Improvements

- OLS: Positive link between road access improvement and truck traffic use

Truck Traffic Use (vehicle-kms)	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Interstate Highway Lane KM	1.606***	1.616***	1.746***	2.083***	2.099***
	(0.328)	(0.338)	(0.427)	(0.483)	(0.530)
Population		0.967*	-0.278	-0.615	-0.484
		(0.550)	(0.303)	(0.376)	(0.393)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	663	663	663	663	663
R-squared	0.77	0.78	-	-	-
KP F-stat			13.48	10.08	10.02

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Truck traffic use (in vehicle-kilometers) and control variables are from Duranton and Turner (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

Elasticity of Truck Traffic Use wrt Road Improvements

- IV: 1% ↑ in road improvement increases truck traffic use by 1.7-2.1% (1 se of DT 2011)

Truck Traffic Use (vehicle-kms)	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Interstate Highway Lane KM	1.606***	1.616***	1.746***	2.083***	2.099***
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Elasticity of Rail Traffic Use wrt Road Improvements

- Noisy positive link between road improvement and rail traffic use (both direct substitution and indirect complementarity effects)

Rail Traffic Use	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Interstate Highway Lane KM	-0.103	-0.0993	0.434	0.254	0.401
	(0.173)	(0.175)	(0.314)	(0.337)	(0.315)
Population		0.346	0.695***	0.878***	0.757***
		(0.299)	(0.245)	(0.286)	(0.273)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	663	663	663	663	663
R-squared	0.94	0.94	0.39	0.55	0.57
KP F-stat			13.48	10.08	10.02

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- Compare relative change in rail to truck traffic use (Truck use: +1.7-2.1) first stage

Rail to Road Traffic Use	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Interstate Highway Lane KM	-1.432***	-1.432***	-0.867**	-1.249***	-1.099***
	(0.195)	(0.196)	(0.376)	(0.388)	(0.364)
Population		-0.150	0.699**	1.092***	0.891***
		(0.337)	(0.289)	(0.328)	(0.306)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	658	658	658	658	658
R-squared	0.88	0.88	-	-	-
KP F-stat			14.48	10.76	10.04

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- Compare relative change in rail to truck traffic use (Truck use: +1.7-2.1) first stage
- 1% $\uparrow$ in road improv decreases rail to truck use by 0.9-1.3% $\Rightarrow \eta = 1.099$

	(1)	(2)	(3)	(4)	(5)
Rail to Road Traffic Use	OLS	OLS	IV	IV	IV
Interstate Highway Lane KM	-1.432***	-1.432***	-0.867**	-1.249***	-1.099***
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Population		-0.150	0.699**	1.092***	0.891***
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MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
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Robustness

- Alternative measure of rail traffic use: rail weight-kms Results
- Similar magnitudes for outgoing vs incoming rail relative to truck traffic use Outgoing Incoming
- Similar magnitudes with 1835 exploration routes and 1947 planned interstate highways IV (dropping 1898 railroad) Carload Weight

Robustness

- Alternative measure of rail traffic use: rail weight-kms Results
- Similar magnitudes for outgoing vs incoming rail relative to truck traffic use Outgoing Incoming
- Similar magnitudes with 1835 exploration routes and 1947 planned interstate highways IV (dropping 1898 railroad) Carload Weight
- Comparison with existing substitution elasticities in trade and transportation literature:
  - Trade lit on ocean-air (Harrigan 2010; Hummels & Schaur 2013; Lugovskyy et al 2022), or ocean bulk-container (Cosar & Demir 2018): our estimates are lower, high costs of air shipping lead to a higher elasticity
  - Transport lit on rail-truck 0.6-1.6 within confidence interval of our estimate (Oum 1979; Oum 1989; Beuthe, Jourquin & Urbain 2014)

Outline of Talk

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2. Theory: QSM with Multiple Modes and Congestion
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Calibration and Validation

1. Build a QSM with multimodal network
    - Use geo-spatial and traffic data for roads, rail, waterways, ports, and terminals. Details
    - Use estimated elasticities for modal substitution ($\eta = 1.099$) and congestion ($\lambda_m = 0.096$).
    - Calibrate other parameters from existing literature. Details

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   - Use estimated elasticities for modal substitution ($\eta = 1.099$) and congestion ($\lambda_m = 0.096$).
   - Calibrate other parameters from existing literature. Details
2. Validate model predictions against data & literature
   - ☑ Predicted vs observed trade flows by mode (i.e. bilaterally and across distance)
   - ☑ Test gravity model implications on trade and trade costs.
   - ☑ Assess unimodal predictions (Allen & Arkolakis 2022)

Calibration Overview

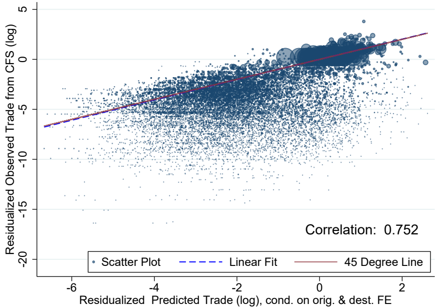
Parameter	Description	Value	Target/Source
Calibrated Externally			
$\alpha,\ \beta$	Productivity and amenity elasticities	$0.1,\ -0.3$	Allen & Arkolakis (2022)
θ	Route (sourcing) elasticity	8	Allen & Arkolakis (2022)
λ_1	Road-congestion elasticity	0.092	Allen & Arkolakis (2022)
σ	Elasticity of substitution over goods	4	Common in trade literature
Estimated			
η	Modal substitution elasticity	1.099	Section 4.1 (IV on rail & road)
λ_m	Terminal-congestion elasticity	0.096	Section 4.2 (AIS vessel data)
Calibrated in Equilibrium			
$A_i,\ u_i$	Location productivity and amenity	—	Match local outcomes (Y_i, L_i)
$t_{ij},\ t_{ij,m}$	Mode-specific link costs,	—	Match observed traffic & Aggregate traffic share: Waybill [Rail], HPMS [Road], USACE WCSC [Waterways], US Trade online [Export/Imports at Ports]
$Average(\omega_{ii})$	Domestic Trade Openness,	—	Tradable share of US GDP

Table: Parameter Values and Sources

Model Fit: Bilaterally and Across Distance

Model Fit: Bilaterally and Across Distance

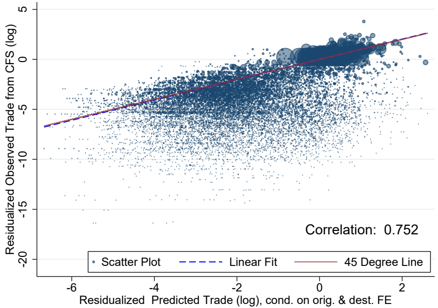
- Predicted and observed mode-specific flows (CFS) strongly correlated (absorb O+D FEs) Regressions

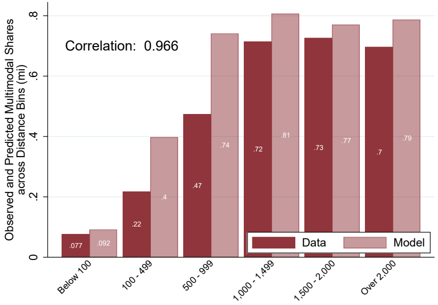


Left figure compares observed bilateral mode-specific trade flows data, from the 2012 Commodity Flow Survey (CFS), with flows predicted by the multimodal economic geography model based on observed traffic data along the network. Variables are in logs, residualized using origin and destination fixed effects, and circle sizes indicate trade weight in tons. Right figure compares observed shares of freight transported multimodally across various distances, from the Department of Transportation (DoT), with model predicted multimodal shares.

Model Fit: Bilaterally and Across Distance

- Predicted and observed mode-specific flows (CFS) strongly correlated (absorb O+D FEs) Regressions
- Matches mode-distance bins: High correlation across predicted and data (FAF) distance bins.





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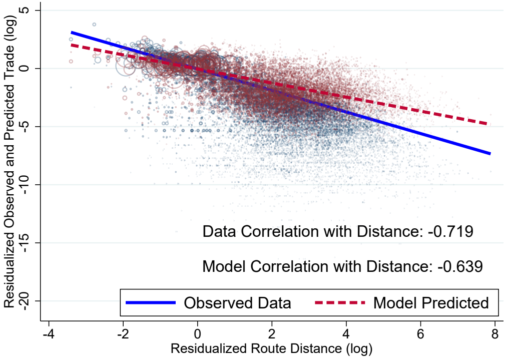
Gravity Model Implications

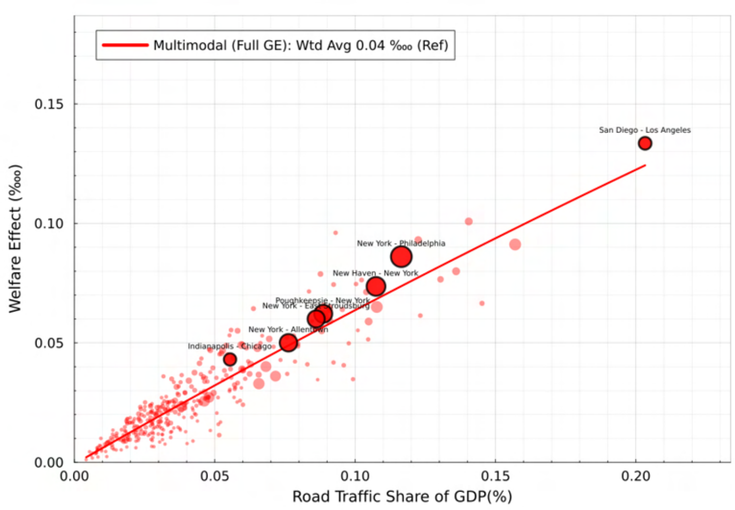
- Gravity Prediction: Corr(Trade,Distance) <0 for both data and model (absorb O+D FEs) Regressions



Comparison between observed and predicted bilateral trade flows against distance. Figure is in logs, residualized using origin and destination fixed effects, and circle sizes indicate trade weight in tons.

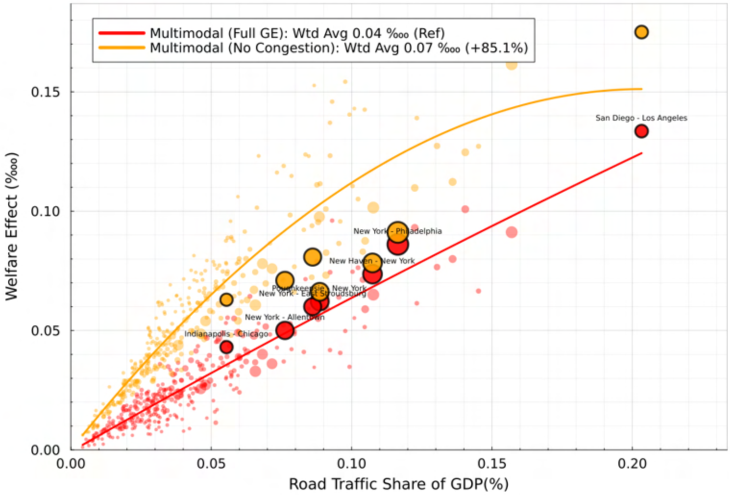
Previous Literature: Revisiting Highway Investments

- Our results capture additional qualitative channels:



Previous Literature: Revisiting Highway Investments

- Our results capture additional qualitative channels:
    - Omitting sources of modal congestion upward biases welfare results. (+44%) Removing terminal congestion



Previous Literature: Revisiting Highway Investments

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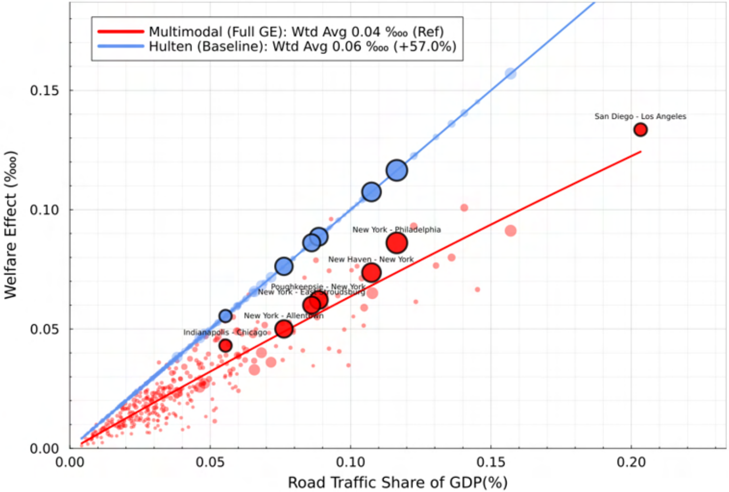

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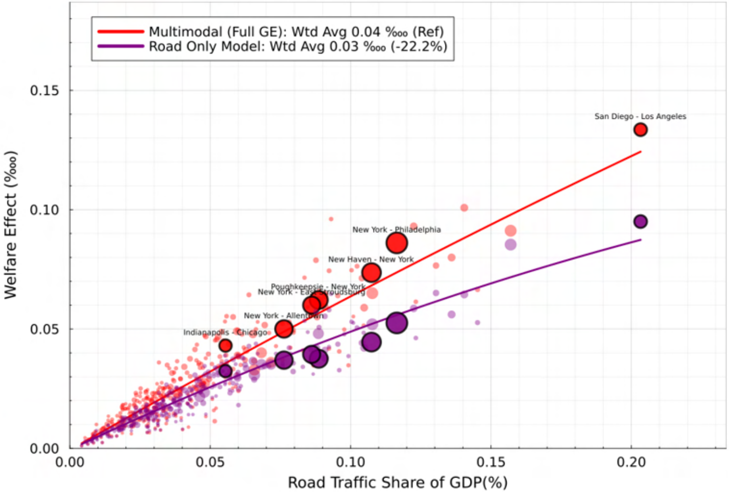
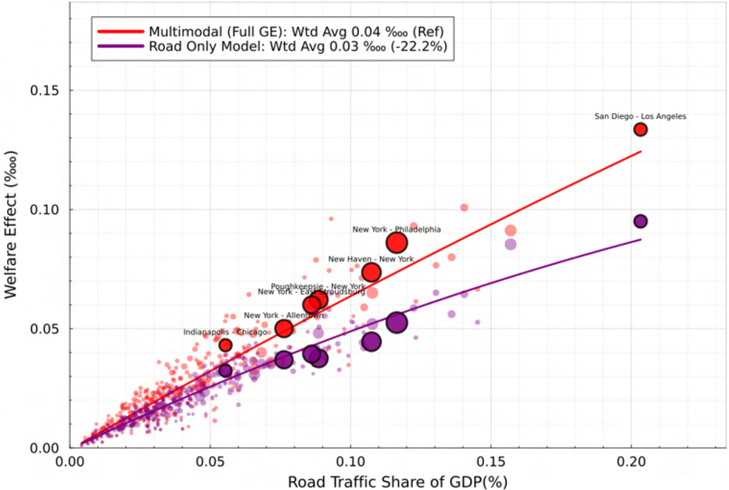


Previous Literature: Revisiting Highway Investments

- Our results capture additional qualitative channels:
  - Omitting modal substitution downward biases welfare results. (-23%)
  - Previous approaches (Allen & Arkolakis 2022) lack ΔW from modal complementarity.



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Counterfactual: Terminal Improvements & Network Disruptions

Counterfactual overview:

1. Terminal Improvements: Improve the level of integration within the US multimodal transport network
   - First evaluation of modal investments accounting for multimodal transport network and spatial equilibrium
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Welfare Effects of Intermodal Terminal Investments

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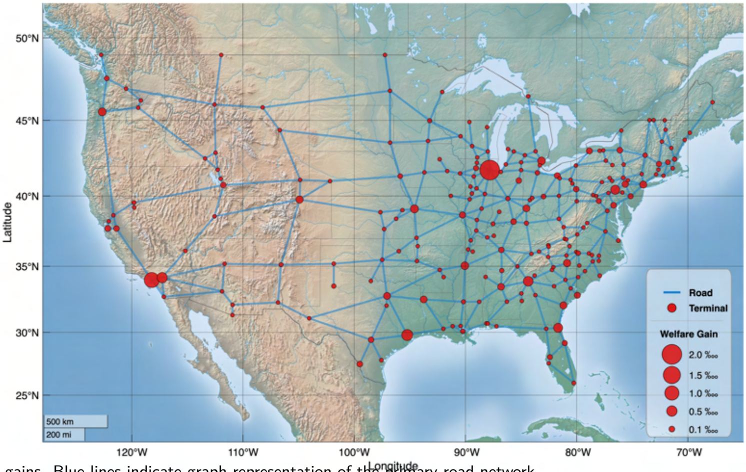

Larger dots indicate larger gains. Blue lines indicate graph representation of the primary road network.

Welfare Effects of Intermodal Terminal Investments: Top 10

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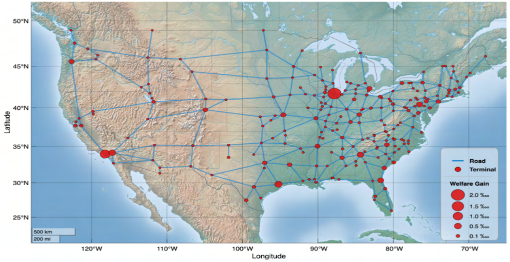
	(1) CBSA Name	(2) Population	(3) Terminals	(4) Throughput	(5) ROI	(6) Benefit ($m)	(7) Cost ($m)
1	Chicago-Joliet-Naperville, IL-IN-WI	9368268	88	10368684	3.730	3851	814
2	Los Angeles-Long Beach-Santa Ana, CA	9639715	38	6836640	3.039	2168	537
3	Houston-Sugar Land-Baytown, TX	3133212	27	630300	24.782	1086	42
4	Riverside-San Bernardino-Ontario, CA	2173638	14	761760	10.999	942	79
5	Atlanta-Sandy Springs-Marietta, GA	1627623	28	1830840	4.643	811	144
6	Lebanon, PA	655561	1	793920	10.194	698	62
7	Jacksonville, FL	936317	18	797880	17.252	689	38
8	Kansas City, MO-KS	1767872	55	1088760	5.335	510	81
9	Portland-Vancouver-Hillsboro, OR-WA	1641801	30	424296	16.349	492	28
10	Detroit-Warren-Livonia, MI	2732964	31	557760	11.799	463	36

Top ten terminals where one percent reduction of switching cost generates the highest benefit. The terminal's population & number of terminals is in Columns (2) and (3), as well as rail throughput in Column (4). Column (5) shows the imputed ROI, & Column (5) calculates how much 2012 US GDP would need to increase in order to match the overall welfare gain, while Column (6) presents the required cost of making this one percent improvement.

Welfare Effects of Intermodal Terminal Investments: Comparison

- Rel to unimodal network: largest gains from (1) coastal segments linking densely populated areas, like Boston-PHL & LA-San Diego, & (2) trade thoroughfares via Indiana

AA (2022) Fig 5(a): Highway links improvement



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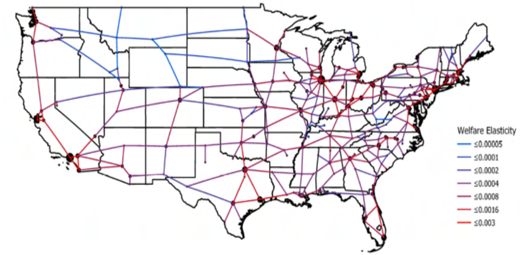

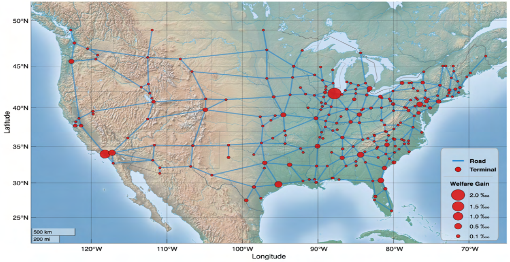

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Environmental Implications from Infrastructure Investments

- Modal Substitution: Improving Chicago's terminals decreases road traffic locally

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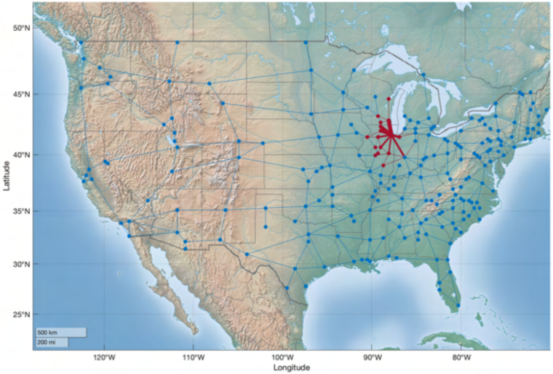
- Investments have environmental consequences due to varying emissions of each mode: Trucks emit 8 times more CO_2 per ton-mile than rail (CBO 2022)



Changes in road traffic due to 1% reduction in transport costs at Chicago. Red indicates decreases in traffic while blue indicates increases. Thicker lines indicate larger changes.

Environmental Effects of Intermodal Terminal Investments

- Improving terminals causes modal diversion: rail traffic $\uparrow$, truck traffic $\downarrow$

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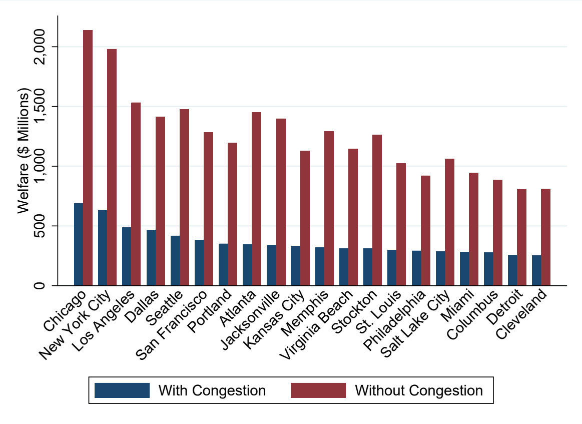
	(1) CBSA Name	(2) Benefit ($m)	(3) Cost ($m)	(4) Truck GHG (kt)	(5) Rail GHG (kt)	(6) GHG Benefit ($m)
1	Chicago-Joliet-Naperville, IL-IN-WI	3851	814	78.97	151.25	214.29
2	Los Angeles-Long Beach-Santa Ana, CA	2168	537	20.42	67.98	98.21
3	Houston-Sugar Land-Baytown, TX	1086	42	0.52	35.35	52.78
4	Riverside-San Bernardino-Ontario, CA	942	79	25.64	38.83	54.05
5	Atlanta-Sandy Springs-Marietta, GA	811	144	58.66	30.99	38.00
6	Lebanon, PA	698	62	11.84	38.47	55.46
7	Jacksonville, FL	689	38	22.83	30.71	43.01
8	Kansas City, MO-KS	510	81	11.26	14.97	21.01
9	Portland-Vancouver-Hillsboro, OR-WA	492	28	6.64	14.44	20.67
10	Detroit-Warren-Livonia, MI	463	36	9.63	12.43	17.29

Environmental impact from top ten terminals where transshipment cost decrease yields highest benefits. Column (2) calculates how much 2012 US GDP would need to increase in order to match the overall welfare gain, Column (3) presents the required cost of making this one percent improvement, Column (4) shows truck GHG emissions change due to road traffic flow change. Column (5) shows the change in rail emissions due to rail traffic change. Column (6) presents the net social cost or benefit from the changes in mode-specific GHG emissions. Waterway emissions are omitted here for brevity. Conclusion

Role of Congestion in Intermodal Terminal Improvements

- Benefits without congestion are 2.1x higher at Chicago, 2x Dallas, 3.2x Atlanta, 2.4x Kansas City
- Overall, welfare benefits are 2.5x higher without congestion for top 50 terminals Scatterplot



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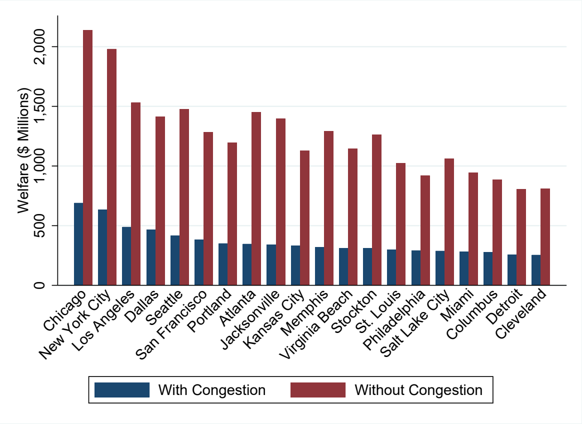
- Overall, welfare benefits are 2.5x higher without congestion for top 50 terminals Scatterplot
- Targeted investments at these intermodal terminal bottlenecks can generate large gains



Counterfactual: Infrastructure Investments in Terminals & Disruption Scenarios

Counterfactual overview:

1. Terminal Improvements: Improve the level of integration within the US multimodal transport network
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   - Evaluate (1) loss of railroad, (2) Jones Act removal, (3) decreased Panama Canal access

Evaluating Policy Relevant Scenarios

1. Value of the Class 1 Railroad Network: Losing access to railroads implies a welfare loss of $231bn
   - 40-54% of value of US highway (Jaworski et al 2021), 40% more than adjusted value of railroads to agricultural sector (Donaldson and Hornbeck 2016)
2. Value of the Panama Canal to the US: Decreasing access implies a welfare loss of 2.64bn USD
   - To the best our knowledge, first US estimate allowing for modal (incl ports) and route substitution
3. Removal of the Jones Act: Adjusting the efficiency of the domestic maritime linkages to match foreign merchant marine implies welfare increase by 3.03bn USD
   - Only for continental US and inclusive of long-run modal substitution patterns

Evaluating Policy Relevant Scenarios: Environmental Effects

Substitution across mode within the multimodal network generates additional environmental effects

1. Value of Class 1 Railroad Network: Rail loss moves cargo onto trucks, GHG emissions ↑
2. Jones Act repeal: Substitute away from truck and rail onto greener water, GHG emissions ↓
3. Value of Panama Canal to the US: Substitute to truck and rail, GHG emissions ↑

	(1) Scenario	(2) Truck GHG Change (kt)	(3) Rail GHG Change (kt)	(4) GHG Benefit ($bn)	(5) Benefit ($bn)
1	Railroad Strike	38947	-5171	-11.88	-230.46
2	Removal of the Jones Act	-589	-47	0.19	3.15
3	Panama Canal	1524	111	-0.45	-2.67

Environmental impact from each scenario. Column (2) shows truck GHG emissions change due to road traffic flow change. Column (3) shows the change in rail emissions due to rail traffic change. Column (4) presents the net social cost or benefit from the changes in mode-specific GHG emissions. Column (5) calculates the 2012 US GDP change in order to match overall welfare changes from each scenario. Waterway emissions are omitted here for brevity.

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  - Losing rail network access reduces GDP by $230b (factoring in modal substitution and GE effects)
- Rel to unimodal estimates: Our welfare estimates 1.5x higher from investments, highlighting the importance of taking into account the interactions across modes within multimodal networks

Recursive Routing and Sourcing

- Under perfect competition, consumers choose the lowest-cost route–source combination.
- The price at node j is given by

$$p_j = \mathbb{E}_\varepsilon \left[\min_{(k,i) \in \mathcal{B}(j) \times N} \frac{t_{kj}\, \tau_{ik}}{\varepsilon_{ikj}(\nu)}\, w_i \right],$$

  where shocks $\varepsilon_{ikj}(\nu)$ are i.i.d. Fréchet with scale parameter $1/A_i$ and node-specific shape θ_j.
- The joint routing–sourcing probability is decomposed as

$$\pi_{ij,k} = \pi_{ij} \times \pi_{ij}^{ik},$$

  where
  - π_{ij} is the sourcing probability based on bilateral transport cost τ_{ij},
  - π_{ij}^{ik} is the implicit route choice probability via neighboring node k.
- Under homogeneous substitution elasticities ($\theta_j = \theta$), the expected sourcing prices become recursive across the network.

back

Graph Representation of the US Freight Network

1. Income and road traffic data (Allen & Arkolakis 2022)
   - Preserve endpoints and intersections
   - Append income, population and traffic data (HPMS)
   - 228 cities (nodes: CBSAs $\geq$ 10,000 people plus adjacent commuting areas) and 704 links
2. Rail network and intermodal rail traffic (Census TIGER GIS info on Class 1 Multimodal rail)
   - Preserve endpoints and intersections
   - Include terminal locations connecting road and rail network (National Transportation Atlas)
   - Append rail traffic from STB's waybill sample
3. Waterbourne traffic: Barges and TEUs at ports (USACE Waterborne Commerce statistics)

Multimodal Network Graph back

Calibration of parameters

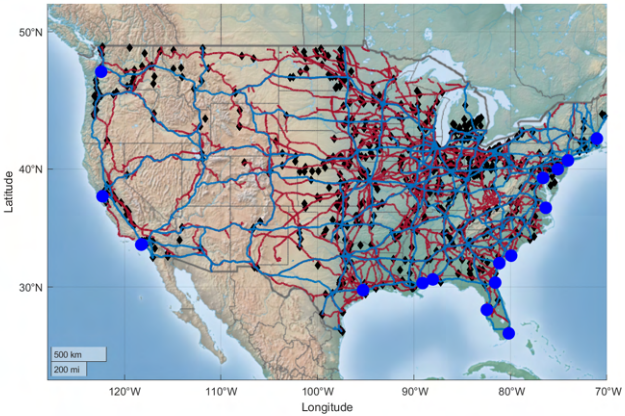
- Take key parameters from literature (Allen & Arkolakis, 2022):
  - Shape parameter $\theta = 8$
  - Local productivity spillovers $\alpha = 0.12$
  - Local amenity spillovers $\beta = -0.1$
- Road network congestion parameter is $\lambda_1 = 0.092$ (Allen & Arkolakis, 2022)
- Modal elasticity of substitution, $\eta = 1.0999$
- Multimodal network congestion parameter $\lambda_2 = 0.096$
  - Using time cost conversion from Hummels and Schaur (2013)

CFs EQM Theory

back

US Multimodal Freight Network

- Class I multimodal railroad (red lines), interstate highway (blue lines), intermodal terminals that allow road/rail switches (black diamonds), top ocean ports (blue circles), and waterways



GIS information from Topologically Integrated Geographic Encoding and Referencing (TIGER) Database, Census Bureau.

Substitution and Complementarity in Multimodal Networks

The impact of a change in mode m' cost $t_{kl,m'}$ on traffic flows $\Xi_{kl,m}$ for mode m on the same segment can be decomposed (no congestion):

$$\frac{d \ln \Xi_{kl,m}}{d \ln t_{kl,m'}} \approx \left[\underbrace{\eta}_{\text{Direct Substitution}} - \underbrace{\theta \left(1 + \left[\tilde{\Omega}^{t,P} \right]_{kl} + \left[\tilde{\Omega}^{t,\Pi} \right]_{kl} \right)}_{\text{Indirect Complementarity}} \right] \omega_{kl,m'}$$

[2] Through iterative improvements of the market access measures along the graph topology: $\tilde{\Omega}^{t,\Pi}$ and $\tilde{\Omega}^{t,P}$ are Leontief inverses of market access measures.

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1. **Direct effect:** Elasticity η, proportional to m' traffic share.
   - E.g., lower road costs shift traffic from rail to road.
2. **Indirect effect:** Lower aggregate kl costs boost traffic and improve market access[2]
   - Better roads raise demand across all modes, including rail.

back

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Counterfactual as Nested Fixed Point

Given data on traffic $(\Xi_{ik}, \Xi_{ik,m})$, income (Y_i), and calibrated parameters $\{\alpha, \beta, \{\theta_i\}, \eta, \lambda_1, \lambda_2\}$, solve for counterfactual $\left(\hat{y}_i, \hat{l}_i, \hat{\chi}\right)$ as the solution of a nested fixed point problem CF Eqm Calibration

- **Outer Fixed Point**: Solve for $\left(\hat{P}_i, \hat{\Pi}_i,\right)$ from hat algebra of equilibrium equations (Market Clearing)
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back

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$$\hat{P}_i^{-\theta_i} \hat{\Pi}_i^{-\theta_i} = \omega_{ii} \hat{\delta}_i + \sum_{k \in \mathcal{N}(i)} \omega_{ik} \hat{t}_{ik}^{-\theta_i} \hat{P}_i^{-\theta_i} \hat{\Pi}_k^{-\theta_i}$$

$$\hat{P}_i^{-\theta_i} \hat{\Pi}_i^{-\theta_i} = \omega_{ii} \hat{\gamma}_i + \sum_{k \in \mathcal{N}(i)} \omega_{ki} \hat{t}_{ki}^{-\theta_i} \hat{P}_k^{-\theta_i} \hat{\Pi}_i^{-\theta_i}$$

  - Hat algebra weights $(\omega_{ii}, \omega_{ik})$ constructed from aggregate traffic and income.
  - Market access terms in changes are given by $\hat{P}_i = \hat{y}_i \hat{l}_i^{\beta-1} \hat{W}^{-1}$, and $\hat{\Pi}_i = \hat{l}_i^{\alpha+1} \hat{y}_i^{-\frac{\theta+1}{\theta}}$

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back

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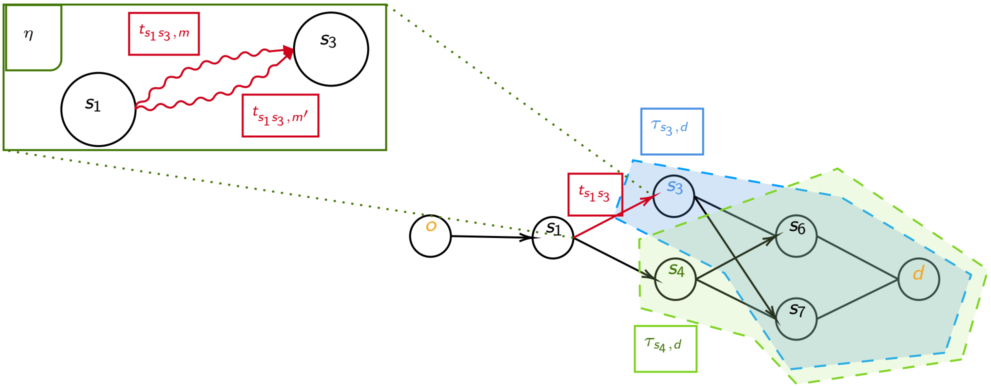
$$\hat{t}_{ik}^{-\theta} = \left(\sum_{m \in \mathcal{M}(i,k)} \omega_{ik,m} \hat{t}_{ik,m}^{-\eta}\right)^{\frac{\theta}{\eta}}$$

  - Weights $(\omega_{ik,m})$ constructed from modal and aggregate traffic.
  - Closed-form expressions for mode-specific endogenous transport cost as a function of market access terms $(\hat{t}_{ik,m})$

back

Example of Multimodal Transport Network from o to d

- Agents face a nested mode choice with modal substitution elasticity η.



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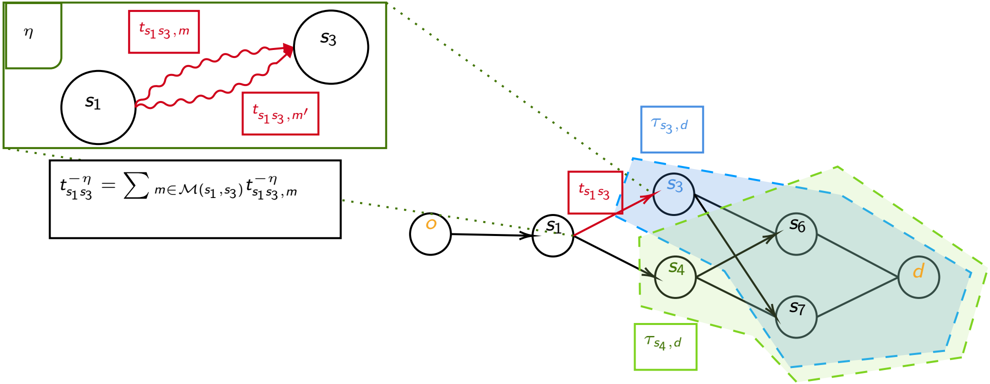
Example of Multimodal Transport Network from o to d

- Closed-form expression for aggregate transport cost.



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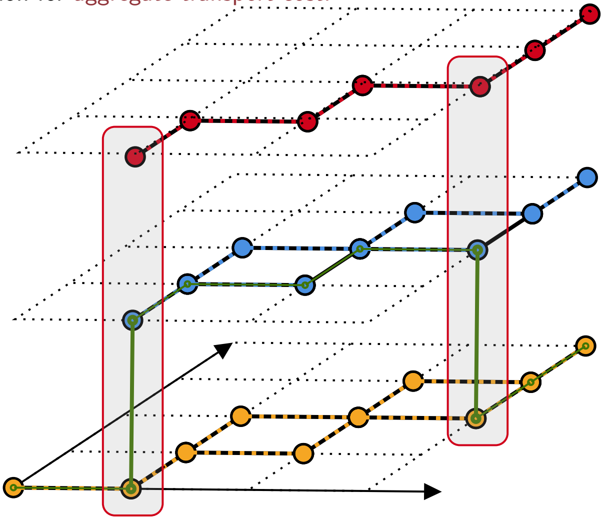

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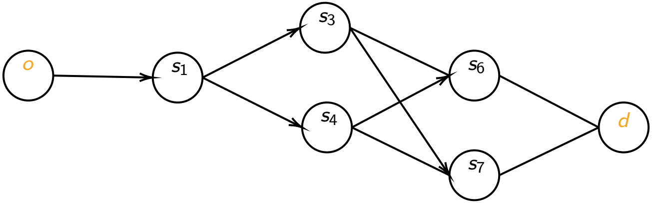
Example of Multimodal Transport Network from o to d

- Transportation from city o to city d requires choosing a route r



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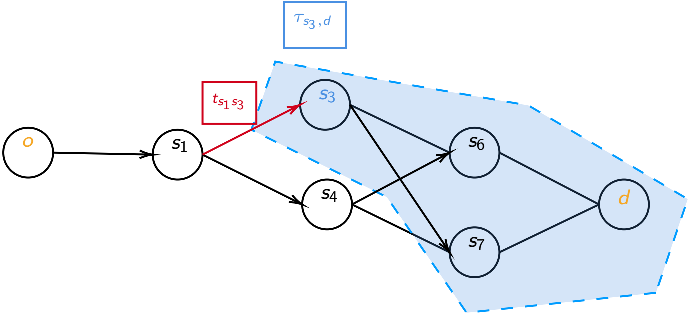
Example of Multimodal Transport Network from o to d

- Route is chosen recursively by comparing edge-specific costs (t_{s_1,s_3}) and continuation values $\tau_{s_3,d}$



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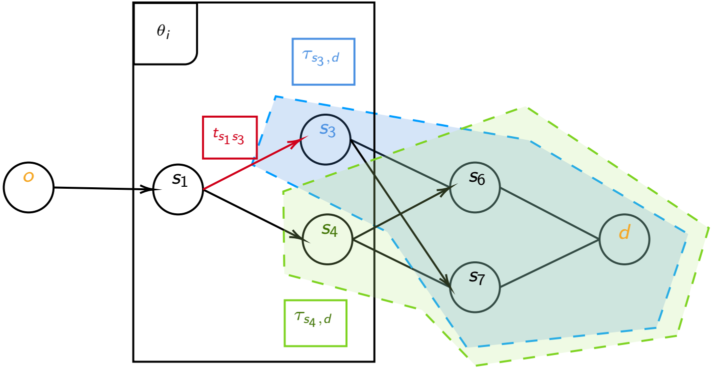
Example of Multimodal Transport Network from o to d

- Recursive choice is node-specific and compares neighboring options subject to a (possibly) node-specific elasticity of substitution.



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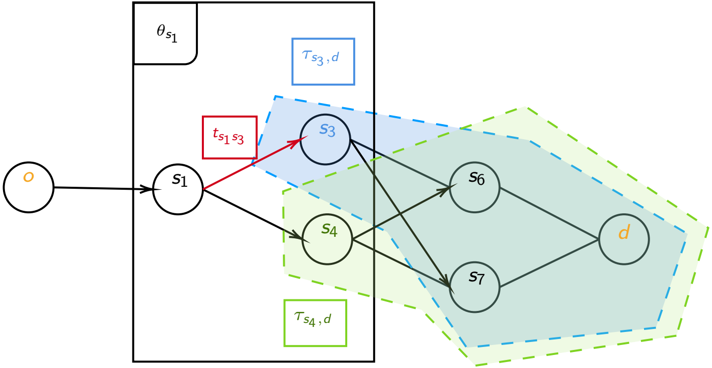
Example of Multimodal Transport Network from o to d

- Gives rise to a closed-form (recursive) formula for transportation costs.



$$\tau_{s_1,d}^{-\theta_{s_1}} = \sum_{k\in\mathcal{F}(s_1)} t_{s_1 k}^{-\theta_{s_1}} \tau_{kd}^{-\theta_{s_1}}$$

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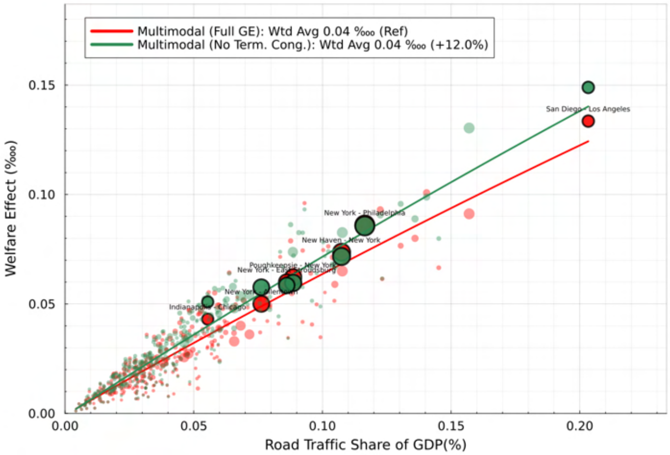
Recursive Routing

back

Previous Literature: Revisiting Highway Investments (Allen and Arkolakis, 2022)

- Our results capture additional qualitative channels:
  - Omitting terminal congestion upward biases welfare results. (+11%)



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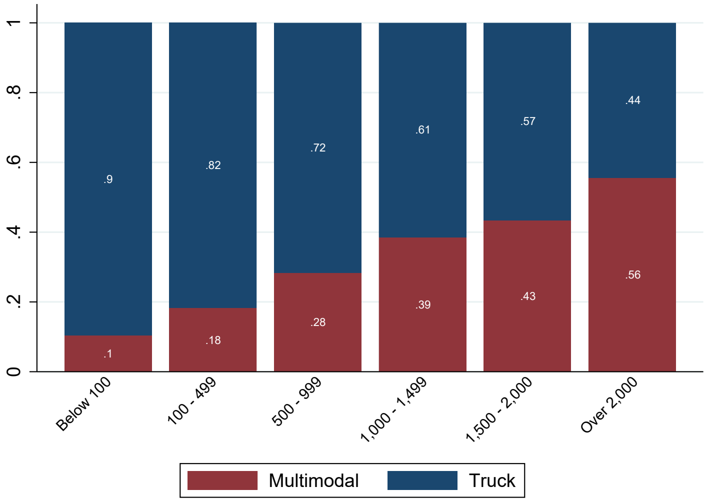
Modal Value Shares by Distance



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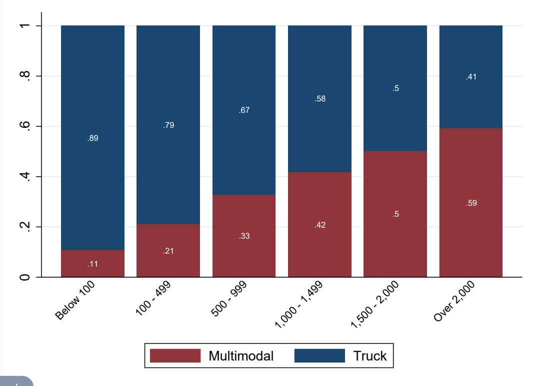
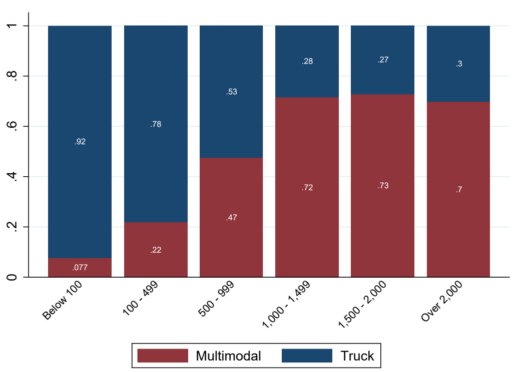
Modal Shares by Distance, including Air

Slightly higher multimodal shares by value (left) and barely any change by weight (right)





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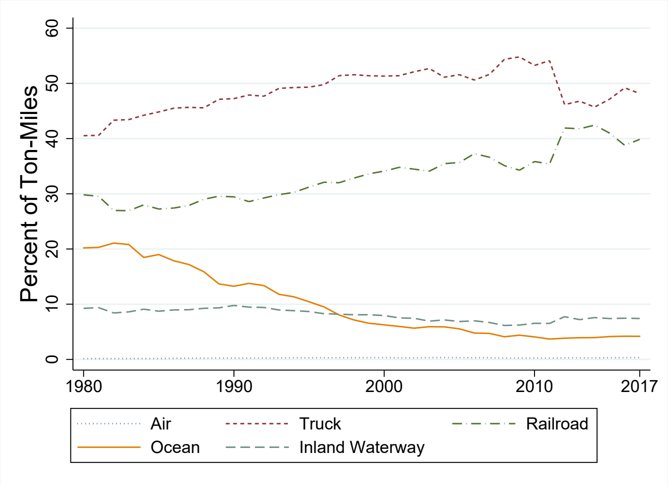
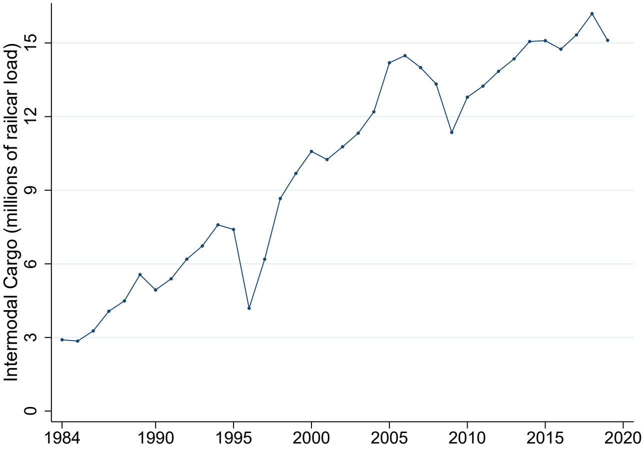
Freight Share 1980-2017



Data Multimodal Map

Intermodal Rail Cargo from 1984-2019



Transport within US | Data | Multimodal Map

Congestion at Intermodal Port Terminals

- AIS Vessel Traffic Data, June 2015 - December 2021 (Marine Cadastre)
  - Vessel location in US waters at 1-minute intervals (200 land-based receiving stations)
  - Vessel information (IMO & net tonnage capacity), lat/lon, speed, navigation status (moving, moored—held in position at pier, anchored)
  - **Ship dwell time** $\equiv$ time spent moored at zero speed
- Match ship location to geographic area of top 30 US ports (95% US container trade)
  - **Port Traffic** $\equiv$ daily sum of ship capacity moored $*$ % of day each ship spends at port
  - Calculate 28-day moving averages of daily port traffic (21-, 14-, 7-day av for robustness)

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OLS of Ship Dwell Times wrt Port Traffic

	(1)	(2)	(3)	(4)
Port Traffic	0.0926***	0.0995***		0.229***
	(0.0108)	(0.0104)		(0.0235)
Port Traffic × Before Mar 2020			0.0907***	
			(0.0105)	
Port Traffic × After Mar 2020			0.120***	
			(0.0123)	
Day-Month-Year FE	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓
Ship-Port FE		✓	✓	✓
Ship FE	✓			
West Coast Ports				✓
Observations	90516	90516	90516	22367
R^2	0.69	0.77	0.77	0.81
F	74.09	92.19	50.42	94.99

Robust standard errors in parentheses are clustered by port. All variables are in logs. Port traffic is the 28-day moving average of total daily net tonnage at the port. Weighted by ship net tonnage. Back

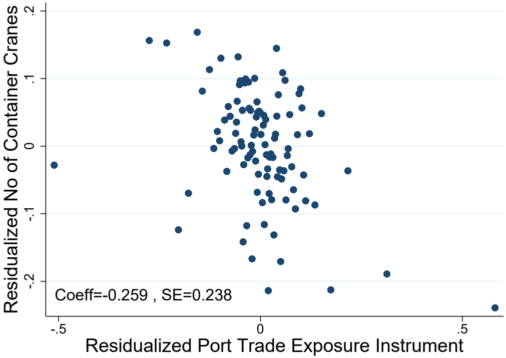
OLS of Ship Dwell Times wrt Port Traffic by Time Aggregation

	(1)	(2)	(3)	(4)
Port Traffic	0.0995***	0.0800***	0.0540***	0.0246***
	(0.0104)	(0.00850)	(0.0151)	(0.00692)
Day-Month-Year FE	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓
Ship-PortFE	✓	✓	✓	✓
Moving Average (Days)	28	21	14	7
Observations	90516	90516	90515	90492
R^2	0.77	0.77	0.77	0.77
F	92.19	88.54	12.82	12.68

Robust standard errors in parentheses are clustered by port. All variables are in logs. Port traffic is the 28-day moving average of total daily net tonnage at the port. Weighted by ship net tonnage. Back

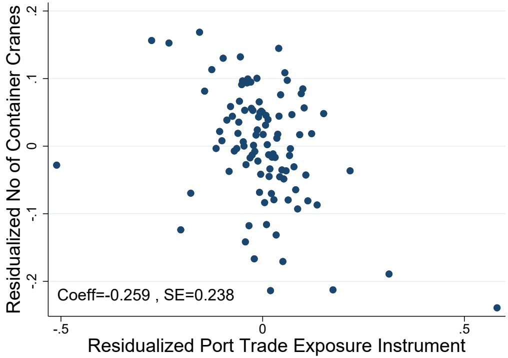
Balance Test

- IV validity: port trade exposure measure is generally uncorrelated with unobserved ship dwell time determinants ϵ_{spdmy} after accounting for all fixed effects
- Potential concern: time-varying ship-port interactions are outside the scope of our fixed effects
  - Example: Busier ports may invest in infrastructure to reduce containership dwell times, like cranes



Balance Test

- IV validity: port trade exposure measure is generally uncorrelated with unobserved ship dwell time determinants ϵ_{spdmy} after accounting for all fixed effects
- Potential concern: time-varying ship-port interactions are outside the scope of our fixed effects
  - Example: Busier ports may invest in infrastructure to reduce containership dwell times, like cranes
- Use annual container cranes data at port-level to proxy for time-varying ship-port-specific investments



Balance Test

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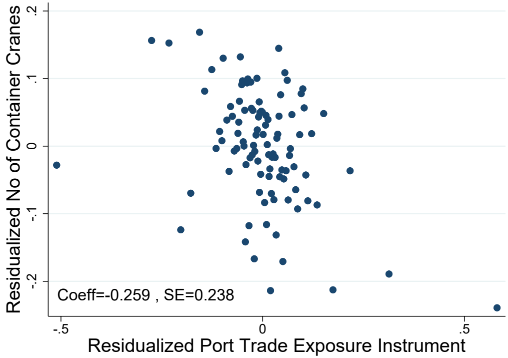


Lack of correlation suggests IV is unlikely systematically related to endogenous time-varying port investments aimed at particular ships

Congestion Elasticity - Robustness

With value-based IV, the congestion elasticity retains the same sign and is within a standard error of baseline results

	(1) OLS	(2) OLS	(3) First-Stage	(4) IV	(5) First-Stage	(6) IV
Port Traffic	0.09	0.10		0.25		0.19
	(0.04)	(0.04)		(0.28)		(0.31)
Port Trade Exposure by Value			0.11		0.11	
			(0.04)		(0.04)	
Day-Month-Year FE	✓	✓	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓	✓	✓
Ship-Port FE		✓			✓	✓
Ship FE	✓		✓	✓		
Observations	90516	90516	90516	90516	90516	90516
First Stage KP-F				8.53		8.51

Standard errors in parentheses

Robust standard errors in parentheses are two-way clustered by ship and port. All variables are in logs. Port traffic is the 28-day moving average of total daily net tonnage at the port. Weighted by ship net tonnage. Back

Congestion Elasticity - Robustness

Results are robust to restricting to West Coast ports, as well as pre- and post-pandemic periods

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Port Traffic	0.229		1.111	0.208	0.272
	(0.023)		(0.511)	(0.114)	(0.163)
Port Traffic $\times$ Before Mar 2020		0.091			
		(0.011)			
Port Traffic $\times$ After Mar 2020		0.120			
		(0.012)			
Day-Month-Year FE	✓	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓	✓
Ship-Port FE	✓	✓	✓	✓	✓
March 2020 Period				Before	After
West Coast Ports	✓		✓		
Observations	22367	90516	22367	69917	20084
First Stage KP-F			10.01	143.42	176.34

Robust standard errors in parentheses are two-way clustered by ship and port. All variables are in logs. Port traffic is the 28-day moving average of total daily net tonnage at the port. Weighted by ship net tonnage. Columns (4) and (5) are statistically significant at the 90% confidence level. Back

Multimodal Implications of Port Congestion

Using a limited dataset on how long rail cars spend at rail stations and matching them to nearest port, we can show how port congestion can impact the multimodal network

$$\ln \text{Rail Dwell Time}_{rpwy} = \beta_3 \ln \text{Port Traffic}_{pwy} + \gamma_{wy} + \phi_{rp} + \epsilon_{rpwy}$$

	(1)	(2)	(3)	(4)	(5)
Nearest Port Traffic (Net Tons)	0.05**		0.05**		0.03
	(0.02)		(0.02)		(0.02)
Nearest Port Traffic (Ships)		0.04**		0.04**	
		(0.01)		(0.01)	
Port Buffer Area	150km	150km	150km	150km	200km
Week-Year FE	✓	✓	✓	✓	✓
Rail Station-Port FE			✓	✓	
Port FE	✓	✓			
Rail Station FE	✓	✓			
Observations	3327	3327	3327	3327	4316
R^2	0.80	0.80	0.80	0.80	0.79
F	9.08	6.80	9.08	6.80	2.06

Robust standard errors in parentheses are clustered by port. All variables are in logs. Local railroads are determined by a 150km (6 ports, 11 rail stations) or 200km (9 ports, 16 rail stations) buffer area around the ports as indicated. Ship Dwell Data IV Results

Congestion Elasticity: Comparison with Literature

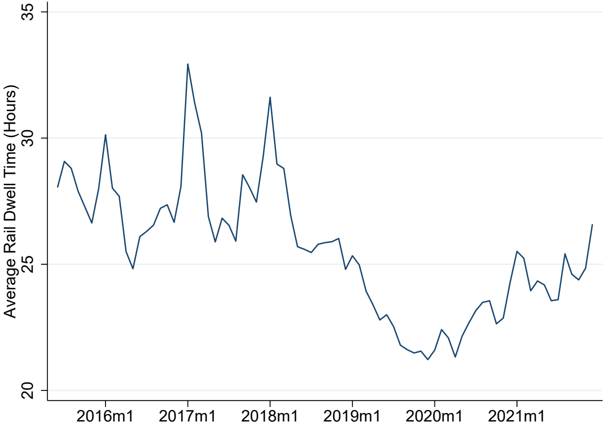
We find that 1% $\uparrow$ in port traffic increases ship dwell time by 0.24% (cost measure of $\lambda_m = 0.096$)

- Without directly comparable elasticities on intermodal terminal congestion, we compare our estimates to two strands of lit:
    - Trade Lit processing times at ports: Carballo, Graziano, Schaur, and Martincus (2021) estimates import processing cost elasticity of 0.06, within confidence interval of our baseline estimate
    - Urban Lit on road congestion in cities: US estimates 0.03-0.11 (Couture, Duranton & Turner 2018; Allen & Arkolakis 2022; Akbar et al 2023; Duranton & Puga 2023), within confidence interval of our baseline estimate

IV Results

Congestion at Intermodal Rail Terminals

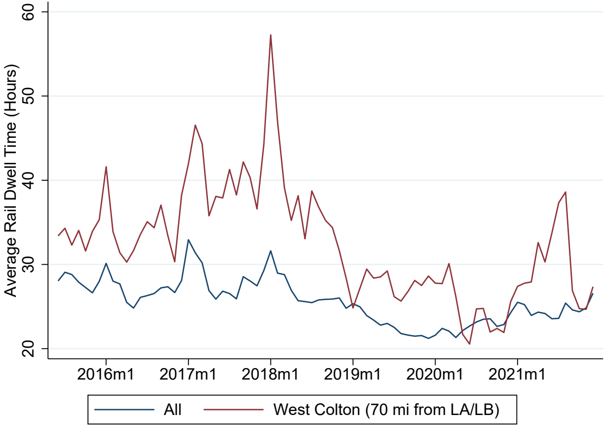
- Time a railcar spends at rail station (STB, 10 largest stations by Class I carriers)
  - Match stations to nearby ports using buffer area (150km buffer: 7 ports 12 rail stations)
  - Average of 25.8 hours per station (sd 2.7 hours)



Data Multimodal Map

Congestion at Intermodal Rail Terminals

- Time a railcar spends at rail station (STB, 10 largest stations by Class I carriers)
  - Match stations to nearby ports using buffer area (150km buffer: 7 ports 12 rail stations)
  - Average of 25.8 hours per station (sd 2.7 hours), 34.1 hours for stations close to LA/LB



Data Multimodal Map

Multimodal Impact of Port Congestion

- How much port traffic affect the amount of time a rail car spends at nearby rail stations

$$\ln \text{ Rail Dwell Time }_{rpwmy} = \beta_2 \ln \text{ Port Traffic }_{pwmy} + \gamma_{wmy} + \phi_{rpm} + \epsilon_{rpwmy}$$

where Rail Dwell Time_{rpwmy} is the average number of hours a rail car spends at a rail station r that is in the vicinity of port p for week w month m and year y, Port Traffic_{pwmy} is the total amount of port traffic at port p for week w month m and year y, γ_{wmy} is week-month-year fixed effects, and ϕ_{rpm} is rail station-port-month fixed effects.

  - β_2 captures the elasticity of rail dwell times with respect to port traffic
  - γ_{wmy} control for aggregate events. ϕ_{rpm} control for fixed (comparative adv/geography) and time-varying characteristics (technology changes) at the rail-port level

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Elasticity of Rail Dwell Times with respect to Port Traffic

	(1)	(2)	(3)	(4)	(5)
Nearest Port Traffic (Net Tons)	0.05**		0.05**		0.03
	(0.02)		(0.02)		(0.02)
Nearest Port Traffic (Ships)		0.04**		0.04**	
		(0.01)		(0.01)	
Port Buffer Area	150km	150km	150km	150km	200km
Week-Year FE	✓	✓	✓	✓	✓
Rail Station-Port FE			✓	✓	
Port FE	✓	✓			
Rail Station FE	✓	✓			
Observations	3327	3327	3327	3327	4316
R^2	0.80	0.80	0.80	0.80	0.79
F	9.08	6.80	9.08	6.80	2.06

Robust standard errors in parentheses are clustered by port. All variables are in logs.

1st Stage: Elasticity of Rail to Truck Traffic Use wrt Road Improvements

	(1)	(2)	(3)
1898 Railroads	0.102**	0.107**	0.129***
	(0.0445)	(0.0481)	(0.0478)
1947 Planned Interstates	0.148***	0.117***	0.108***
	(0.0317)	(0.0298)	(0.0274)
1835 Exploration Routes	0.0244**	0.0257**	0.0220*
	(0.0117)	(0.0124)	(0.0122)
Population	0.511***	0.597***	0.535***
	(0.0386)	(0.0474)	(0.0600)
Geography		✓	✓
Census Divisions		✓	✓
Socioeconomic Characteristics			✓
Year FE	✓	✓	✓
Observations	658	658	658
KP F-stat	14.48	10.76	10.04

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

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Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- Alternative measure of rail traffic use: rail weight-kms Back

	(1)	(2)	(3)	(4)	(5)
Rail to Truck Traffic Use	OLS	OLS	IV	IV	IV
Interstate Highway Lane KM	-1.473***	-1.472***	-0.930**	-1.373***	-1.203***
	(0.171)	(0.172)	(0.392)	(0.403)	(0.382)
Population		-0.101	0.524*	1.012***	0.774**
		(0.308)	(0.297)	(0.338)	(0.316)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	658	658	658	658	658
R-squared	0.89	0.89	-0.03	0.23	0.28
KP F-stat			14.48	10.76	10.04

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- Incoming rail traffic use rel to truck traffic use Back

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Inter-State Highway Lane KM	-1.060***	-1.061***	-1.101***	-1.210***	-0.999**
	(0.185)	(0.185)	(0.405)	(0.426)	(0.405)
Population		0.0605	1.132***	1.303***	1.145***
		(0.337)	(0.298)	(0.351)	(0.336)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	658	658	658	658	658
R-squared	0.89	0.89	0.04	0.21	0.24
KP F-stat			14.48	10.76	10.04

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- Outgoing rail traffic use rel to truck traffic use Back

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Inter-State Highway Lane KM	-1.075***	-1.075***	-0.635	-1.235***	-1.220***
	(0.207)	(0.207)	(0.468)	(0.451)	(0.444)
Population		-0.255	0.452	1.107***	1.000***
		(0.378)	(0.352)	(0.379)	(0.367)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	658	658	658	658	658
R-squared	0.90	0.90	-0.04	0.26	0.31
KP F-stat			14.48	10.76	10.04

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, 1898 railroad, and 1947 planned interstate highways.

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- IV: 1835 exploration routes & 1947 planned interstate highways (drop 1898 railroads)

Rail to Road Traffic Use	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV
Interstate Highway Lane KM	-1.432***	-1.432***	-1.015**	-1.622***	-1.593***
	(0.195)	(0.196)	(0.452)	(0.504)	(0.528)
Population		-0.150	0.802**	1.389***	1.267***
		(0.337)	(0.347)	(0.423)	(0.434)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	658	658	658	658	658
R-squared	0.88	0.88	-	-	-
KP F-stat			21.18	15.49	14.25

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, and 1947 planned interstate highways. Back

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

- IV: 1835 exploration routes & 1947 planned interstate highways (drop 1898 railroads)

	(1)	(2)	(3)	(4)	(5)
Rail to Road Traffic Use (Weight)	OLS	OLS	IV	IV	IV
Interstate Highway Lane KM	-1.473***	-1.472***	-1.090**	-1.747***	-1.703***
	(0.171)	(0.172)	(0.468)	(0.521)	(0.543)
Population		-0.101	0.635*	1.309***	1.155***
		(0.308)	(0.356)	(0.434)	(0.443)
Geography				✓	✓
Census Divisions				✓	✓
Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
Year FE	✓	✓	✓	✓	✓
Observations	658	658	658	658	658
R-squared	0.89	0.89	-	-	-
KP F-stat			21.18	15.49	14.25

Robust standard errors clustered by MSAs in parentheses. All variables in logs. Rail traffic use (in railcar-kilometers) is constructed using confidential rail waybill data. Truck traffic use and control variables from DT (2011). Instruments are 1835 exploration routes, and 1947 planned interstate highways. Back

Welfare Effects of Road Investments: Top 10

	o_cbsa_name	d_cbsa_name	Truck GHG	Rail GHG	Benefit	GHG Int	GHG Diff
1	Dallas	Balmorhea	-39.5	2.9	46.0	-2.1	-40.5
2	Los Angeles	San Diego	28.9	-0.5	32.5	1.4	25.7
3	San Diego	Los Angeles	35.7	-1.4	31.9	1.7	31.6
4	Raleigh	Fuquay-Varina	8.1	-1.4	30.9	0.2	4.0
5	Los Angeles	Riverside	21.9	-0.4	25.3	1.0	19.3
6	Riverside	Los Angeles	29.9	-0.2	24.6	1.5	27.7
7	Raleigh	Raleigh	20.8	-1.3	23.0	0.9	17.5
8	Concord	San Francisco	28.5	-0.7	22.8	1.4	25.8
9	Riverside	San Diego	25.1	-0.2	20.9	1.2	23.2
10	Providence	Boston	22.1	-1.0	20.7	1.0	19.4

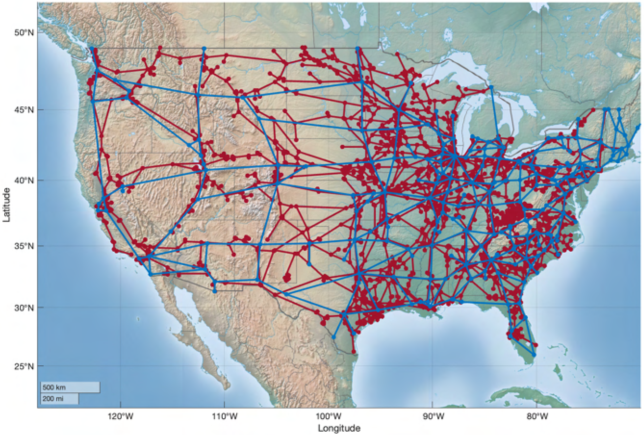
Robust standard errors in parentheses are clustered by port. All variables are in logs.

Graph Representation of the US Freight Network

1. Income and road traffic data following (Allen & Arkolakis 2022)
   - Preserve endpoints and intersections
   - Append income, population and traffic data (HPMS)
   - 228 nodes and and 704 edges
2. Rail network and rail traffic
   - Census' TIGER GIS information on Class 1 Multimodal Railroad network
   - Preserve intersections and endpoints
   - Use terminal locations connecting road and rail network (National Transportation Atlas)
   - Append rail traffic from STB's waybill sample
3. Append TEUs at Int'l Ports

back

Multimodal transport network



The figure shows the graph representation of the road (blue) and rail (red) network. Nodes are either population centers or intersections.

Calibration of parameters

- Take key parameters from literature:
  - Shape parameter $\theta = 8$
  - Local productivity spillovers $\alpha = 0.12$
  - Local amenity spillovers $\beta = -0.1$
- Road network congestion parameter is $\lambda_1 = 0.092$ (Allen & Arkolakis, 2022)
- Modal elasticity of substitution, $\eta = 1.09$
- Multimodal network congestion parameter $\lambda_2 = 0.206$
  - Using time cost conversion from Hummels and Schaur (2013)

CFs EQM Theory

Model Fit: Predicted vs Observed Mode-level Trade Flows

- Significantly positive correlations for all and individual modes (Columns (1) and (2))
- Rail coefficient slightly higher: may be due to CFS capturing all flows, while the model only predicts containerized flows Mode flows Gravity

	(1) Residualized Observed Trade	(2) Residualized Observed Trade	(3) Residualized Observed Trade	(4) Residualized Predicted Trade
Residualized Predicted Trade	1.02***			
	(0.02)			
Residualized Predicted Trade for Truck		0.91***		
		(0.03)		
Residualized Predicted Trade for Rail		1.65***		
		(0.05)		
Residualized Predicted Trade for Barges		0.86**		
		(0.26)		
Residualized Route Distance			-0.93***	-0.61***
			(0.05)	(0.02)
Conditional on origin and destination FE	✓	✓	✓	✓
Observations	14514	14514	14467	14467
R^2	0.57	0.60	0.52	0.41
F	1839.16	790.04	310.95	671.98

This table compares the observed bilateral origin to destination mode-specific trade flows with the mode-specific trade flows predicted by the multimodal economic geography model based on observed traffic data along the transport network. Both the observed and predicted trade flow measures are in logs and residualized using origin and destination fixed effects, allowing for the comparison to come from similarities at the origin-destination pair-level. Column (1) compares the aggregated observed and predicted trade flows while Column (2) compares the mode-specific observed and predicted trade flows for all three transport modes (truck, rail, and barges). Columns (3) and (4) examine the gravity model implications of the model by comparing the relationship between the observed trade flows and distance (Column (3)) to the relationship between the predicted trade flows and distance (Column (4)). The route distance measure is also in logs and residualized using origin and destination fixed effects. Robust standard errors in parentheses are clustered by origin and destination cities. Weighted by trade weight in tons.

Perfect Competition Assumption

- Simplifying assumption to focus on the multimodal network transport structure
- Multimodal container transport is generally more competitive relative to unimodal transport (Zgnoc, Tekavcic, and Jakcis 2019)
- Within rail transport, container transport is more competitive relative to non-containerized shipments (Surface Transportation Board 2009)

Back

Model Details

- CES preferences: rep agent in j supplies unit endowment of labor inelastically, earns wage w_j, and purchases continuum of goods, $\nu \in [0,1]$ with EoS $\sigma \geq 0$:

$$U_j = \left(\sum_{\nu} q_{ij}^{\frac{\sigma-1}{\sigma}}(\nu) \right)^{\frac{\sigma}{\sigma-1}}$$

- CRS Production: price of good ν in destination j from origin i along route $r \in \mathcal{R}_{ij}^{1} \cup \mathcal{R}_{ij}^{1,2}$

$$p_{ij,r}(\nu) = \frac{w_i}{A_i}\tau_{ij,r}(\nu) = \frac{w_i}{A_i}\frac{\prod_{k=1}^{K} t_{r_{k-1},r_k}}{\varepsilon_{ij,r}(\nu)}$$

MC in i is $\frac{w_i}{A_i}$, local wages w_i, and each worker produces A_i units of goods. Assume $\epsilon_{ij,r}(\nu)$ is iid Fréchet distributed across routes and goods with scale parameter $1/A_i$ where A_i captures origin-specific efficiency and shape parameter θ regulates the inverse of shock dispersion Back

Transport Cost over Multimodal Network

- Enumerating in matrix notation, where $\mathbf{A_1} = [a_{ij}] = \left[t_{ij}^{-\theta}\right]$ is $N^1 \times N^1$ adjacency matrix for road network, $\mathbf{A_2} = \left[a_{i'j'}\right] = \left[t_{i'j'}^{-\theta}\right]$ is $N^2 \times N^2$ adjacency matrix for multimodal network, $\mathbf{S} = [s_{ii'}]$ is diagonal matrix representing linkages between the two:

$$\tau_{ij}^{-\theta} = \left(\sum_{K=0}^{\infty}\left(\left(\sum_{K=0}^{\infty}\mathbf{A}_1^K\right)\left(\mathbf{S}\left(\sum_{K=0}^{\infty}\mathbf{A}_2^K\right)\mathbf{S}'\right)\right)^K\left(\sum_{K=0}^{\infty}\mathbf{A}_1^K\right)\right)_{ij} \tag{1}$$

- If spectral radius of matrices < 1, define $\mathbf{B} \equiv (\mathbf{I} - \mathbf{A}_1)^{-1}$ as geo sum of matrix $\mathbf{A}_1$ and $\mathbf{D} \equiv \mathbf{S}\left(\sum_{K=0}^{\infty}\mathbf{A}_2^K\right)\mathbf{S}'$ as geo sum of $\mathbf{A}_2$ inclusive of switching linkages between network $\mathbf{S}$
- Define the inverse of the Schur complement of the Laplacian of the partitioned infrastructure matrix for the multimodal transport network as $\mathbf{E} \equiv \left(\mathbf{B}^{-1} - \mathbf{D}\right)^{-1} \equiv S(\Omega)^{-1}$
- Apply definitions to (1) and invoke the recursive formula for inverse of sum of matrices

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Spatial Equilibrium

Assuming localized amenity and productivity spillovers, i.e.

$$A_i = \bar{A}_i L_i^{\alpha}, \quad u_i = \bar{u}_i L_i^{\beta} \tag{2}$$

We impose two market clearing conditions. First, good markets clear-total income in location i, Y_i, is equal to its total sales $\left(Y_i = \sum_{j=1}^{N} X_{ij}\right)$. Second, trade is balanced-total consumption expenditure in location j, E_j, is equal to its total imports ($E_j = \sum_{i=1}^{N} X_{ij}$). We obtain the following equilibrium system which solves for the endogenous variables, $\{y_j, l_j\}$, given the transport cost $\{\tau_{ij}\}$ as well as the geography of the economy, $\{\bar{a}_j, \bar{u}_j\}$

$$\Pi_i^{-\theta_i} = \left(t_{ii}^{-\theta_i}\right) \frac{\delta_i}{P_i^{-\theta_i}} + \sum_{k \in \mathcal{F}(i)} t_{ik}^{-\theta_i} \tilde{\Pi}_k^{-\theta_i}, \tag{3}$$

$$P_j^{-\theta_j} = \left(t_{ij}^{-\theta_j}\right) \frac{\gamma_j}{\Pi_j^{-\theta_j}} + \sum_{k \in B(j)} t_{kj}^{-\theta_j} P_k^{-\theta_j} \tag{4}$$

where consumer price index $P_j = \frac{1}{W} \bar{u}_j L_j^{\beta-1} Y_j$ and producer price index $\Pi_i = \bar{A}_i L_i^{1+\alpha} Y_i^{-\frac{e_i+1}{\theta_i}}$

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Transport Cost over Multimodal Network

- Adopt **"first and last mile"** feature of freight transportation: primary road network facilitates transport at start and end of route

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Transport Cost over Multimodal Network

- Adopt **"first and last mile"** feature of freight transportation: primary road network facilitates transport at start and end of route
- Expected transport cost from i to j is

$$\tau_{ij} = \int_{\mathcal{R}_{ij}^{1} \cup \mathcal{R}_{ij}^{1,2}} \tau_{ij,r}(\nu) dr$$

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Transport Cost over Multimodal Network

- Adopt **"first and last mile"** feature of freight transportation: primary road network facilitates transport at start and end of route
- Expected transport cost from i to j is the sum of separable sets of routes on road and multimodal network—where the multimodal route starts & ends on the road ($\mathcal{R}_{ij}^{1,2}$)

$$\tau_{ij} = \int_{\mathcal{R}_{ij}^{1} \cup \mathcal{R}_{ij}^{1,2}} \tau_{ij,r}(\nu) dr = \underbrace{\int_{\mathcal{R}_{ij}^{1}} \tau_{ij,r}(\nu) dr}_{\text{Road network}} + \underbrace{\int_{\mathcal{R}_{ij}^{1,2}} \tau_{ij,r}(\nu) dr}_{\text{Multimodal network}}$$

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- Introduce matrix notation (geo sum of road matrix **B**, intermodal linkages **S**, Schur comp. of multimodal matrix $S(\Omega)^{-1}$), apply formula for inverse of partitioned matrix Details

$$\tau_{ij}^{-\theta} = [\underbrace{\mathbf{B}}_{\substack{\text{Unimodal costs over} \\ \text{road network}}} + \underbrace{\mathbf{BS}\left(S(\Omega)^{-1}\right)\mathbf{S}'\mathbf{B}}_{\substack{\text{Multimodal costs over} \\ \text{road and secondary networks}}}]_{ij} = \left(\tau_{ij}^{1}\right)^{-\theta} + \left(\tau_{ij}^{1,2}\right)^{-\theta}$$

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Characterization of cost along multimodal routes *inclusive* of switching costs Back

Spatial Equilibrium with Road and Rail Traffic

The equilibrium system solves for the endogenous variables, $\{y_j, l_j\}$, given the uni- and multimodal transport cost $\{\tau_{ij}^{1}, \tau_{ij}^{1,2}\}$ as well as the geography of the economy, $\{\bar{A}_i, \bar{u}_i\}$

$$
\begin{aligned}
y_i^{\frac{1+\theta\lambda+\theta}{1+\theta\lambda}} l_i^{\frac{-\theta(1+\alpha+\theta\lambda(\alpha+\beta))}{1+\theta\lambda}} &= \chi \bar{A}_i^{\theta} \bar{u}_i^{\theta} y_i^{\frac{1+\theta\lambda+\theta}{1+\theta\lambda}} l_i^{\frac{\theta(\beta-1)}{1+\theta\lambda}} \\
&+ \chi^{\frac{\theta\lambda}{1+\theta\lambda}} \sum_j \left(\bar{t}_{ij} \bar{L}^{\lambda}\right)^{-\frac{\theta}{1+\theta\lambda}} \bar{A}_i^{\theta} \bar{u}_i^{\theta \frac{\theta\lambda}{1+\theta\lambda}} \bar{A}_j^{-\frac{\theta}{1+\theta\lambda}} y_j^{\frac{1+\theta}{1+\theta\lambda}} l_j^{-\frac{\theta(1+\alpha)}{1+\theta\lambda}} \\
&+ \sum_j s_{ii'}^{-\theta} \tau_{i'j'}^{-\theta} s_{j'j}^{-\theta} \bar{A}_j^{-\theta} y_j^{1+\theta} l_j^{-\theta(1+\alpha)} \bar{A}_i^{\theta} l_i^{-\theta(\beta-1)\frac{\theta\lambda}{1+\theta\lambda}} y_i^{-\theta\frac{\theta\lambda}{1+\theta\lambda}}
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
y_i^{-\frac{\theta(1-\lambda)}{1+\theta\lambda}} l_i^{\frac{\theta(1-\beta-\theta\lambda(\alpha+\beta))}{1+\theta\lambda}} &= \chi \bar{A}_i^{\theta} \bar{u}_i^{\theta} y_i^{-\frac{\theta(1-\lambda)}{1+\theta\lambda}} l_i^{\frac{\theta(\alpha+1)}{1+\theta\lambda}} \\
&+ \chi^{\frac{\theta\lambda}{1+\theta\lambda}} \sum_j \left(\bar{t}_{ji} \bar{L}^{\lambda}\right)^{-\frac{\theta}{1+\theta\lambda}} \bar{A}_i^{\theta\frac{\theta\lambda}{1+\theta\lambda}} \bar{u}_i^{\theta} \bar{u}_j^{-\frac{\theta}{1+\theta\lambda}} l_j^{\frac{\theta(1-\beta)}{1+\theta\lambda}} y_j^{-\frac{\theta}{1+\theta\lambda}} \\
&+ \sum_j s_{jj'}^{-\theta} \tau_{j'i'}^{-\theta} s_{i'i}^{-\theta} \bar{u}_j^{-\theta} y_j^{-\theta} l_j^{\theta(1-\beta)} \bar{u}_i^{\theta} l_i^{-\theta(1+\alpha)\frac{\theta\lambda}{1+\theta\lambda}} y_i^{\frac{\theta\lambda(1+\theta)}{1+\theta\lambda}}
\end{aligned}
\tag{6}
$$

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Counterfactual Equilibrium

Given observed traffic flows $\left(\Xi_{ij}^1, \Xi_{i'j'}^2\right)$, economic activity in the geography (Y_i, E_j), and parameters $\{\alpha, \beta, \theta, \lambda_1, \lambda_2, \nu\}$, the equilibrium change in economic outcomes $\left(\hat{y}_i, \hat{l}_i, \hat{\chi}\right)$ is the solution of the following system of equations:

$$
\begin{aligned}
\hat{l}_i^{\frac{-\theta(1+\alpha+\theta\lambda_1(\alpha+\beta))}{1+\theta\lambda_1}} \hat{y}_i^{\frac{-\theta(1-\lambda_1)}{1+\theta\lambda_1}} &= \hat{\chi}\left(\frac{Y_i}{Y_i + \sum_j \Xi_{ji}^1 + \sum_j \Xi_{ji}^2}\right) \hat{y}_i^{\frac{-\theta(1-\lambda_1)}{1+\theta\lambda_1}} \hat{l}_i^{\frac{\theta(\alpha+1)}{1+\theta\lambda_1}} \\
&+ \hat{\chi}^{\frac{\theta\lambda_1}{1+\theta\lambda_1}} \sum_j \left(\frac{\Xi_{ij}^1}{Y_i + \sum_j \Xi_{ji}^1 + \sum_j \Xi_{ji}^2}\right) \hat{\bar{t}}_{ji}^{-\frac{\theta}{1+\theta\lambda_1}} \hat{l}_j^{\frac{\theta(1-\beta)}{1+\theta\lambda_1}} \hat{y}_j^{-\frac{\theta}{1+\theta\lambda_1}} \\
&+ \hat{\chi}^{\frac{2\theta\lambda_2}{1+\theta\lambda_2}} \left(\hat{l}_i^{\alpha+1} \hat{y}_i^{-\frac{\theta+1}{\theta}}\right)^{\frac{\theta^2(\lambda_1-\lambda_2)}{(1+\theta\lambda_1)(1+\theta\lambda_2)}} \sum_j \left(\frac{\Xi_{ij}^2}{Y_i + \sum_j \Xi_{ji}^1 + \sum_j \Xi_{ji}^2}\right) \hat{\bar{s}}_{jj'}^{-\frac{\theta}{1+\theta\lambda_2}} \hat{\tau}_{j'i'}^{-\theta} \hat{\bar{s}}_{i'i}^{-\frac{\theta}{1+\theta\lambda_2}} \hat{l}_j^{\frac{\theta(1-\beta)}{1+\theta\lambda_2}} \hat{y}_j^{-\frac{\theta}{1+\theta\lambda_2}} \\
&\times \left(\sum_l \frac{\Xi_{i'l'}^2}{\sum_{l'} \Xi_{i'l'}^2} \hat{\tau}_{i'l'}^{-\theta} \hat{s}_{l'l}^{-\theta} \left(\hat{y}_l \hat{l}_l^{\beta-1}\right)^{-\theta}\right)^{-\frac{\theta\lambda_2}{1+\theta\lambda_2}} \left(\sum_l \frac{\Xi_{j'l'}^2}{\sum_{l'} \Xi_{j'l'}^2} \hat{\tau}_{j'l'}^{-\theta} \hat{s}_{l'l}^{-\theta} \left(\hat{l}_l^{\alpha+1} \hat{y}_l^{-\frac{\theta+1}{\theta}}\right)^{-\theta}\right)^{-\frac{\theta\lambda_2}{1+\theta\lambda_2}}
\end{aligned}
$$

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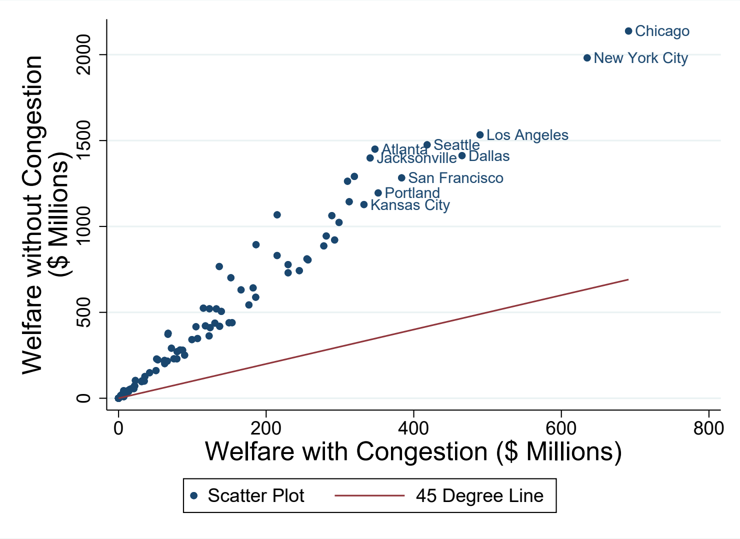
Scatter: Congestion in Intermodal Terminal Improvements



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