Multimodal Transport Networks

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Preliminary

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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

Where Are All the Truck Drivers? Shortage Adds to Delivery Delays

The trucking industry has long churned through drivers, and the pandemic has made the job even harder

Trucks line up to drop off containers in Carson, Calif. ALLISON ZAUCHA FOR THE WALL STREET JOURNAL

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    - Disruptions or improvements within the transport network can have large economic impacts
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- We study multimodal transport networks and their aggregate implications for infrastructure investments and disruptions

This Paper

- Develop spatial eqm model with multiple modes, intermodal terminals, and congestion
    - Introduce transport mode choice into optimal route choice model
    - Recursive generalized extreme value (GEV) choice along the topology of the network

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- Counterfactual: Welfare effects of improvements and disruptions within multimodal network
  - Terminal improvements: 1% cost reduction in top terminals generate welfare gains of $300-600m GDP
  - Disruptions: Losing railroad access, Decreased Panama Canal access, Repeal of the Jones Act

Related Literature and Contributions

- **Transportation networks in spatial equilibrium**: Add multi-modes & intermodal terminals
  - Infrastructure investment on road networks and congestion (Redding & Turner 2015, Fajgelbaum & Schaal 2017, Allen & Arkolakis 2022, Fan & Luo 2020, Fan, Lu, and Luo 2021)
  - Domestic transport cost and regional comparative advantage (Cosar & Demir 2016, Martincus et al 2017, Cosar & Fajgelbaum 2016, Cosar, Demir, Ghose, & Young 2020, Fajgelbaum & Redding 2020, Jaworski, Kitchens, & Nigai 2023, Bonadio 2022)
  - 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)

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- **Multimodal transport in transport lit**: Embed multimodal routing within GE framework
  - Estimation of freight transport price elasticities (Winston 1981, McFadden, Winston & Boersch-Supan 1986, Rich, Kveiborg & Hansen 2011, Beuthe, Jourquin & Urbain 2014)
  - Examining traffic assignment problems using stochastic user equilibrium (Bell 1995, Kitthamkesorn, Chen & Xu 2015, Boyles, Lownes & Unnikrishnan 2021, Li, Xie & Bao 2022)

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- **Environmental impact of transport**: Modal substitution 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

Data: Traffic and Geography of US Domestic Multimodal Freight Transportation

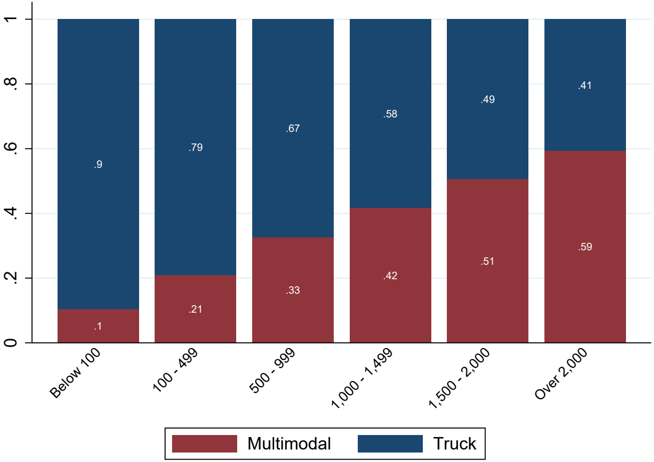
Theory: Spatial Eqm Model with Multiple Modes and Congestion

Theory to Data: Congestion, Modal Substitution, & Multimodal Network

Counterfactual: Infrastructure Investments in Terminals & Disruption Scenarios

Transportation within the US by Mode and Distance

- Trucks used for shorter distances (first & last mile), while multi-modal transport for longer (DOT)



by Weight

Including Air

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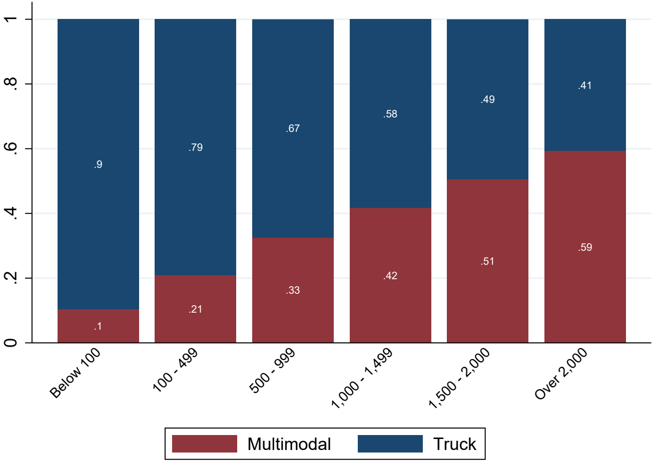

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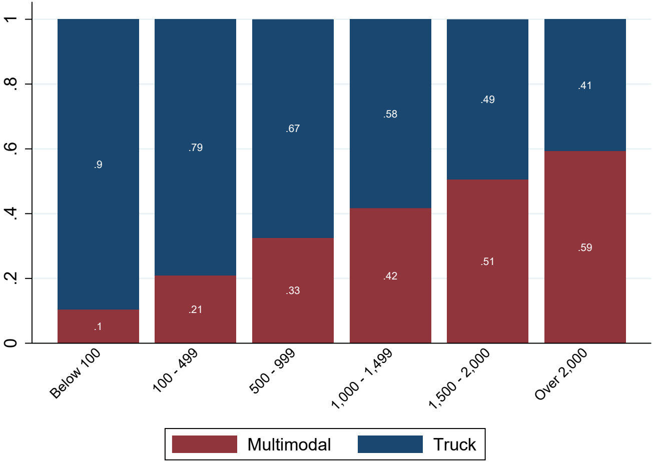

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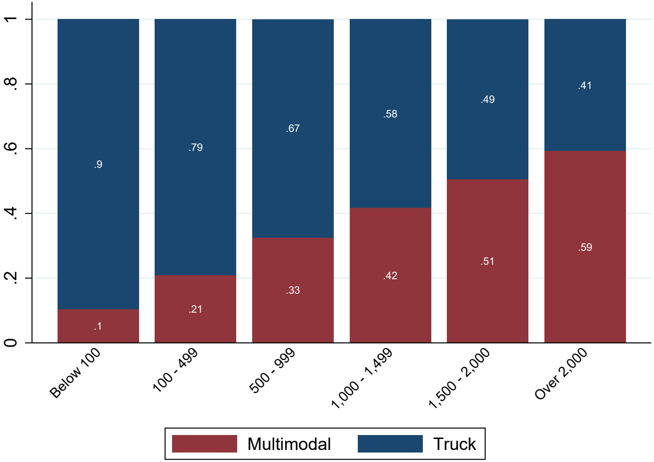


Multimodal share ↑ over time: container is fastest growing rail traffic segment: 5x in 1984-2019

by Weight

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)

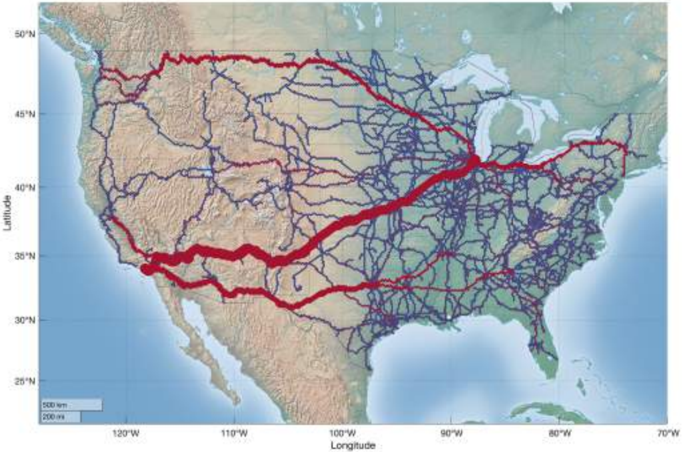
US Road Traffic

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
  - 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



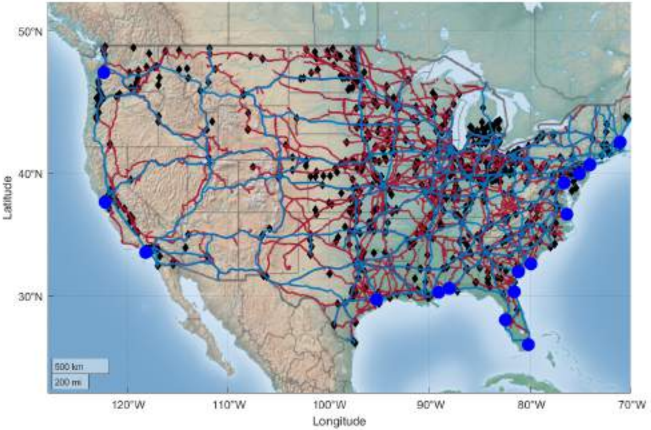
Domestic rail traffic data for Class I carriers (largest in US) conditional on intermodal capability. Shortest routes are imputed between origin, interchange stations, and destination to assign total tonnage to individual rail segments along the multimodal network.

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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Counterfactual: Infrastructure Investments in Terminals & Disruption Scenarios

Setup

- CES Consumption: Preferences over goods $\nu \in [0,1]$ (elasticity of substitution σ) Details
- CRS Production: Price of good ν in destination j from origin i along route r is

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

  with marginal cost $\frac{w_i}{A_i}$, origin-specific efficiency A_i & wages w_i, link-level transport costs t_{r_{k-1},r_k}

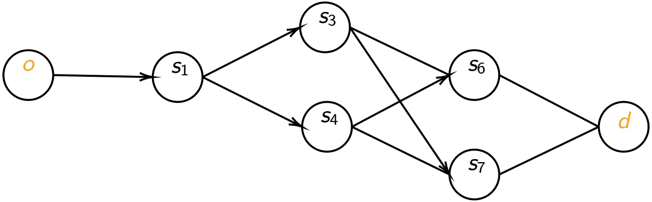
- Transport: Good ν transported to destination via any feasible route, modeled as a recursive choice subject to iid Frechet distributed preferences shocks. Competition

Model Overview

1. Recursive route choice
2. Nested transport mode choice
3. Equilibrium with congestion at intermodal terminals and along roads
4. Counterfactual equilibrium

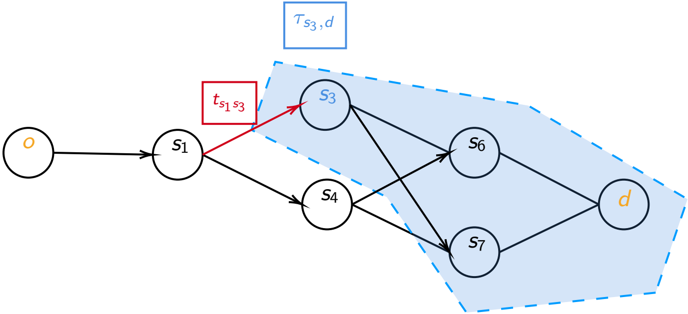
Example of Multimodal Transport Network from o to d

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



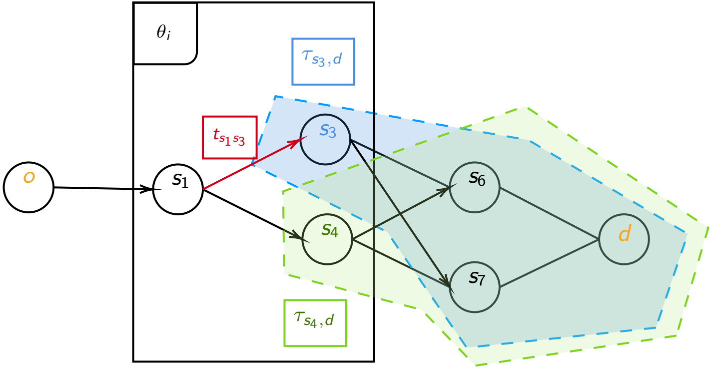
Example of Multimodal Transport Network from o to d

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



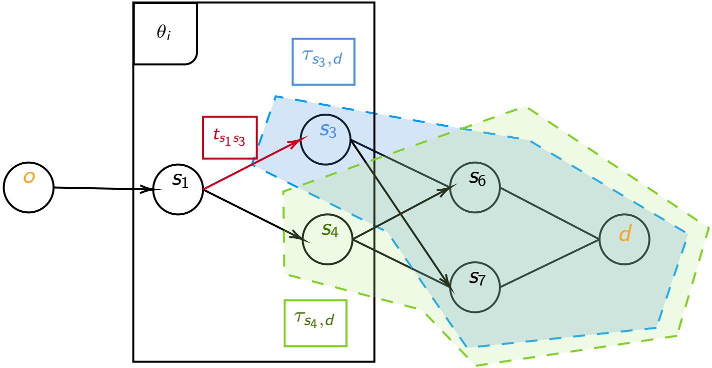
Example of Multimodal Transport Network from o to d

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



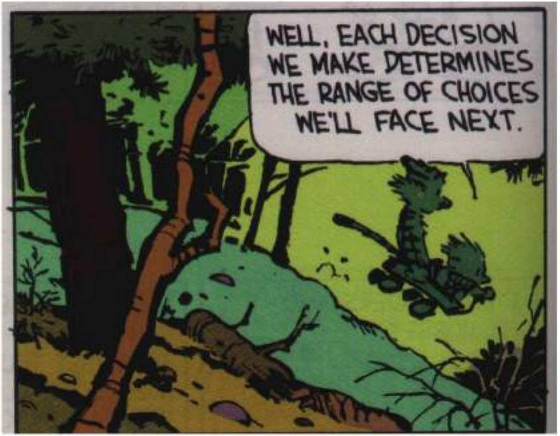
Example of Multimodal Transport Network from o to d

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



$$\tau_{s_1,d}^{-\theta_i} = \sum_{k\in\mathcal{N}(i)} t_{ik}^{-\theta_i}\tau_{kd}^{-\theta_i}$$

Recursive Routing



Recursive Routing

Expected transport cost τ_{ij} from i to j is

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

where the choice is between nodes in the neighborhood of node i, $k \in \mathcal{N}(i)$ (and the associated costs to go from each k to destination j), and $\varepsilon_{kj}(\nu)$ is a link-level iid Frechet distributed across routes with shape parameter θ_i

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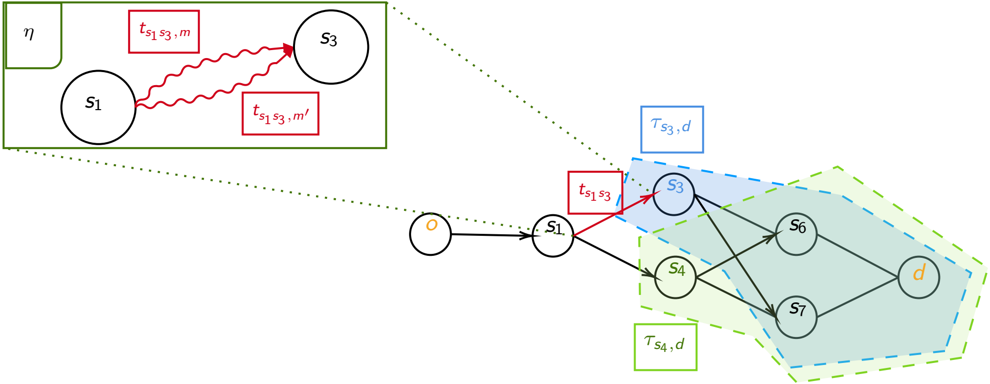
This allows us to characterize the market access terms (consumer and producer price indices) recursively along the network

Second, we introduce the choice of which transport mode to use

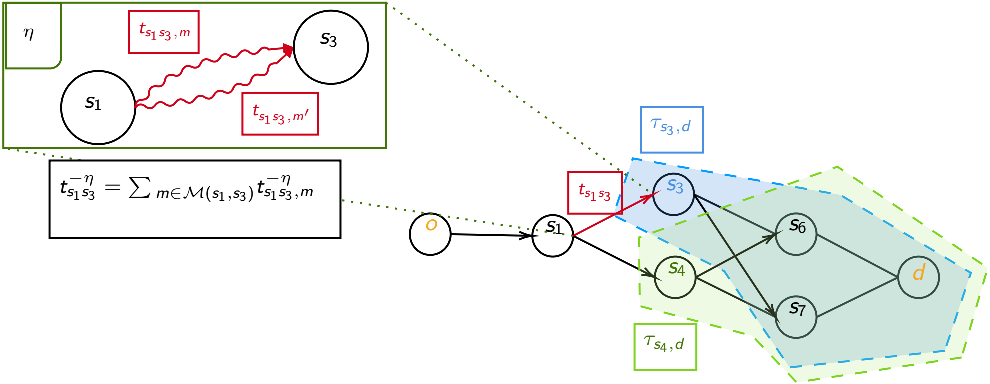
Example of Multimodal Transport Network from o to d

- Agents additionally face a nested mode choice between any two neighboring nodes (subject to modal elasticity of substitution η)



Example of Multimodal Transport Network from o to d

- Gives rise to a closed-form expression of the aggregate transport cost in terms of the mode-specific transport cost.



$$t_{s_1 s_3}^{-\eta} = \sum_{m\in\mathcal{M}(s_1,s_3)} t_{s_1 s_3,m}^{-\eta}$$

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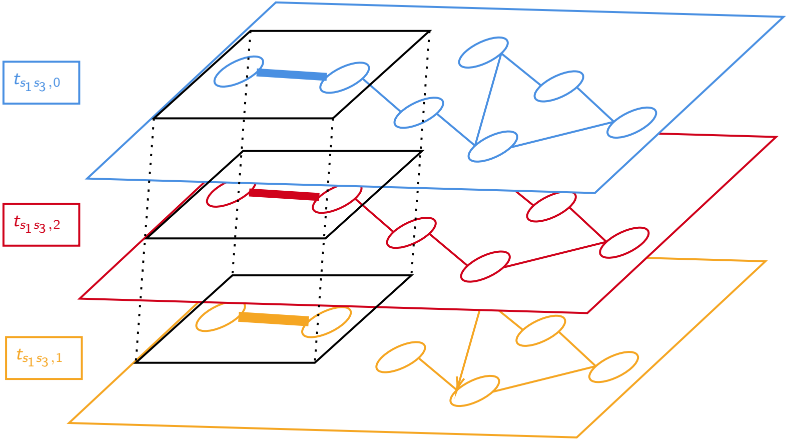

Nested Mode choice

- At the link or edge level, there is an additional choice of which transport mode to use:

$$t_{ik} = \mathbb{E}\left[\min_{m \in \mathcal{M}(i,k)} \left\{t_{ik,m}\varepsilon_{ik,m}\right\}\right] = \left(\sum_{m \in \mathcal{M}(i,k)} {t_{ik,m}}^{-\eta}\right)^{-\frac{1}{\eta}}$$

where the choice to go from i to k is over different transport modes m and the associated link-level mode cost $t_{ik,m}$, where $m \in \mathcal{M}(i,k)$, and $\varepsilon_{ik,m}$ is a mode-level iid Frechet distributed across links with dispersion parameter η

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Third, we introduce switching costs and congestion at intermodal terminals

Congestion

1. We incorporate mode-specific transport costs with switching costs at intermodal terminals,

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

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2. This allows us to introduce endogenous congestion at the intermodal terminals

$$s_{ii,m} = \bar{s}_{ii,m} \left(\Xi_{ii,m}\right)^{\lambda_2}$$

   where λ_2 is strength of congestion at terminals which we will estimate later on, $\bar{s}_{ii}$ is infrastructure of terminal connecting the two networks (exo)

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3. Also allow for endogenous congestion on road network following existing lit λ_1

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)
- **Inner Fixed Point**: Given $\left(\hat{P}_i, \hat{\Pi}_i\right)$, solve for modal choice and endogenous transport cost ($\hat{t}_{ki}^{-\theta}$)

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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 $\left(\hat{y}_i, \hat{l}_i, \hat{\chi}\right)$ CF Eqm Calibration

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

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

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

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

  - 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 $(\hat{t}_{ik,m})$

Contribution of this Framework

- Gives rise to an equilibrium system that is:
  - Equilibrium system that is recursive in market access terms,
  - Convenient separation of aggregate problem and transportation equilibrium at link-level
  - Is flexible with arbitrary substitution elasticities along the network (θ_i, in principle also η_i)
  - Isomorphic to Allen and Arkolakis (2022) with common iid Frechet distributed shocks ($\theta_i = \theta$) and single mode (or $\eta = \theta$)

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- Counterfactuals with 'low' data requirement:
  - Estimates for key elasticities $\{\alpha, \beta, \theta, \eta, \lambda_1, \lambda_2\}$
  - Aggregate and modal traffic ($\Xi_{ij}, \Xi_{ij,m}$) and data on economic activity (Y_i, E_j)

Contribution of this Framework

- Gives rise to an equilibrium system that is:
  - Equilibrium system that is recursive in market access terms,
  - Convenient separation of aggregate problem and transportation equilibrium at link-level
  - Is flexible with arbitrary substitution elasticities along the network (θ_i, in principle also η_i)
  - Isomorphic to Allen and Arkolakis (2022) with common iid Frechet distributed shocks ($\theta_i = \theta$) and single mode (or $\eta = \theta$)
- Counterfactuals with 'low' data requirement:
  - Estimates for key elasticities $\{\alpha, \beta, \theta, \eta, \lambda_1, \lambda_2\}$
  - Aggregate and modal traffic ($\Xi_{ij}, \Xi_{ij,m}$) and data on economic activity (Y_i, E_j)

Outline of Talk

Data: Traffic and Geography of US Domestic Multimodal Freight Transportation

Theory: Spatial Eqm Model with Multiple Modes and Congestion

Theory to Data: Congestion, Modal Substitution, & Multimodal Network

Counterfactual: Infrastructure Investments in Terminals & Disruption Scenarios

Theory to Data

1. **Estimate congestion at intermodal terminals (λ_2)**
2. Estimate modal elasticity of substitution (η)
3. Construct a multimodal transport network from detailed GIS data Details Graph

Data: 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)

Ship Dwell Time Calculation

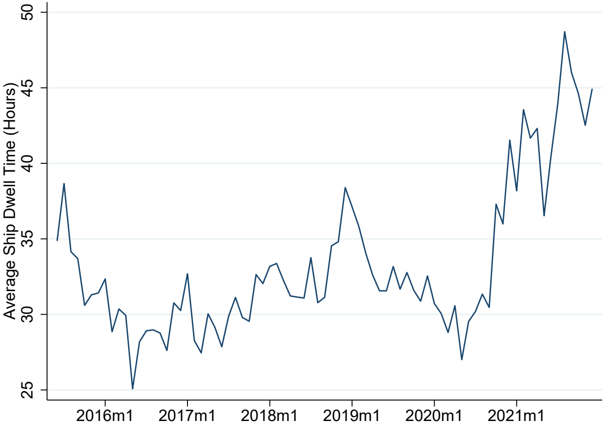
- Ship path indicated by line, redder color = slower speed. Darker regions are port areas

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

Guthorm Maersk (11k TEUs) at Port of Newark

Containership Dwell Times at Port

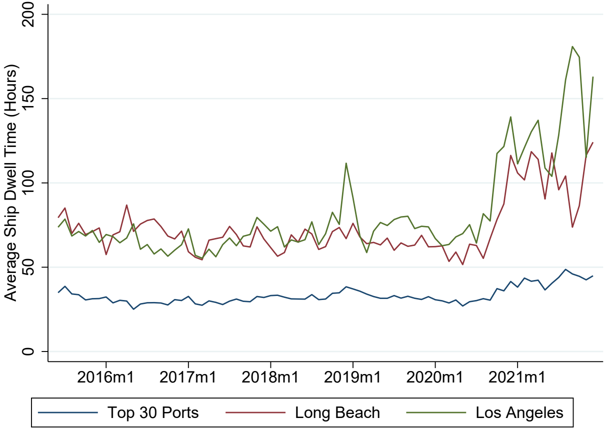
- 1,444 containerships: Average 33.3 hours per ship (sd 5 hours). Post 2021 av 42.8 hours



Weighted by ship net tonnage

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)



Weighted by ship net tonnage

Estimate intermodal congestion (λ_2)

$$\ln\ \text{Ship Dwell Time}_{spdmy} = \beta_1 \ln\ \text{Port Traffic}_{pdmy} + \delta_{dmy} + \alpha_{spm} + \epsilon_{spdmy}$$

where Ship Dwell Time$_{spdmy}$ is the hours ship s spent at port p on day of the week d month m and year y, Port Traffic$_{pdmy}$ is 28-day moving average amount of port traffic at port p ending on day d month m and year y, δ_{dmy} is day-month-year fixed effects, and α_{spm} is ship-port-month fixed effects

- β_1 captures the elasticity of ship dwell times with respect to port traffic OLS
- δ_{dmy} captures aggregate events that affect all ships, α_{spm} control for fixed ship-port characteristics (ship sizes, deep harbors, and their interaction), and time-varying port changes
- We find smaller magnitudes with shorter period of moving averages (21, 14, 7)—ship dwell times respond less to shorter period averages at port Details

Congestion Elasticity

- To establish impact of port traffic on ship dwell times, require demand shifter for port traffic that is uncorrelated with unobserved ship dwell times determinants ϵ_{spdmy}
- Shift share IV that predicts demand for port p: weighted sum of region o and product n imports into top 30 US ports excluding p at month m and year y

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

- Imports by \$ and kg at monthly-level (Census Bureau), 2003 weights lagged by ≥ 13 years
  - Weights sum to 1, low HHI
- All else equal, overall increases in region- and product-level US import demand for container trade exposes port p to more 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**
	(0.04)	(0.04)		(0.12)		(0.11)
Port Trade Exposure by Weight			0.23***		0.23***	
			(0.05)		(0.05)	
Day-Month-Year FE	✓	✓	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓	✓	✓
Ship-Port FE		✓			✓	✓
Ship FE	✓		✓	✓		
Observations	90516	90516	90516	90516	90516	90516
First Stage KP-F				18.27		18.19

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.

Robustness - IV by value Multimodal Link

Congestion Elasticity

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

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			(0.05)		(0.05)	
Day-Month-Year FE	✓	✓	✓	✓	✓	✓
Port-Year FE	✓	✓	✓	✓	✓	✓
Ship-Port FE		✓			✓	✓
Ship FE	✓		✓	✓		
Observations	90516	90516	90516	90516	90516	90516
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2. **Estimate modal elasticity of substitution (η)**
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Modal elasticity of substitution (η)

- Mode-specific infrastructure improvements have direct & indirect effects within GE multimodal framework: Road improvement will directly decrease truck costs

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- Estimate indirect effects using Duranton & Turner (2011): increasing interstate highways through cities increases road and truck traffic use
    - 3 historic IVs to predict stock of roads in cities: planned interstate highway from 1947 highway plan (Baum-Snow 2007, Michaels 2008), 1898 railroads, and 1528-1850 exploration routes

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- Aggregate rail data to cities, estimate impact of improved road access on rail traffic use (indirect effects (1) & (2)), and on rail to road traffic use

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.

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Modal Complementarity and Substitution

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

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.

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3. Estimate impact of road improvements on rail relative to road: $Y_{cy} = \frac{\text{Rail}}{\text{Road}}$ traffic use
   $\Rightarrow$ Negative Elasticity: Elasticity of Substitution across Transport Modes

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***			
	(0.328)	(0.338)			
Population		0.967*			
		(0.550)			
Geography					
Census Divisions					
Socioeconomic Characteristics		✓			
MSA FE	✓	✓			
Year FE	✓	✓			
Observations	663	663			
R-squared	0.77	0.78			
KP F-stat					

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***
	(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 Rail Traffic Use wrt Road Improvements

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

	(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	-	-	-
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% ↑ in road improv decreases rail to truck use by 0.9-1.3% $\Rightarrow \eta = 1.099$

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***
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Geography				✓	✓
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Socioeconomic Characteristics		✓			✓
MSA FE	✓	✓			
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Observations	658	658	658	658	658
R-squared	0.88	0.88	-	-	-
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Robustness

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

Theory to Data

1. Estimate congestion at intermodal terminals (λ_2)

2. Estimate modal elasticity of substitution (η)

3. **Construct a multimodal transport network from detailed GIS data** Details Graph

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 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 barge data (USACE Waterborne Commerce statistics)
4. Traffic volume at International Ports (TEUs, US Army Corps of Engineers)

Outline of Talk

Data: Traffic and Geography of US Domestic Multimodal Freight Transportation

Theory: Spatial Eqm Model with Multiple Modes and Congestion

Theory to Data: Congestion, Modal Substitution, & Multimodal Network

Counterfactual: Infrastructure Investments in Terminals & Disruption Scenarios

- While previous work has mostly focused on improving single modes like highway segments, less is known about improving the level of integration within US multimodal transport networks Calibration
    - Recent focus on contributions of highways and domestic roads to transport costs, and port access (Fan el al 2019, Fan and Luo 2020, Bonadio 2021, Jaworski et al 2023)

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- While there is focus on the impact of disruptions on supply chains and shipping, less is known about evaluating the impact of these disruptions taking the multimodal network into account

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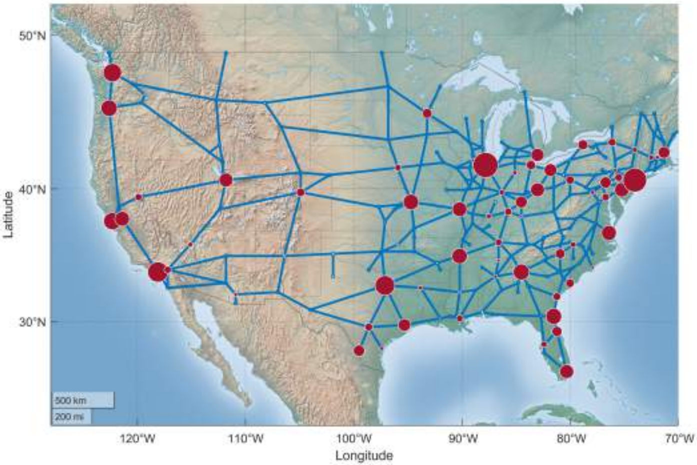
- **Estimate the aggregate welfare impact of a 1% cost reduction in accessing intermodal terminals—equivalent to adding a crane**
- While there is focus on the impact of disruptions on supply chains and shipping, less is known about evaluating the impact of these disruptions taking the multimodal network into account
- **Evaluate (1) loss of railroad, (2) Jones Act removal, (3) decreased Panama Canal access**

Welfare Effects of Intermodal Terminal Investments

- Intermodal terminals that generate the largest gains are in the center of US, highlighting the role of multimodal network transporting goods from coastal regions to the interior



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

Welfare Effects of Intermodal Terminal Investments: Top 10

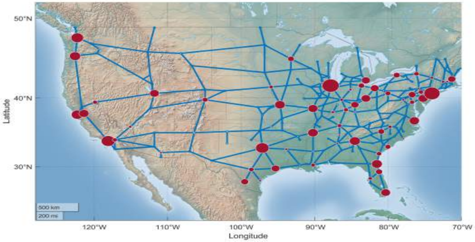
- Intermodal terminals that are substantive bottlenecks to the US transportation system, with associated welfare gains between $300-600m USD and high return on investment (ROIs)

	(1) CBSA Name	(2) Population	(3) Terminals	(4) Throughput	(5) ROI	(6) Benefit ($m)	(7) Cost ($m)
1	Chicago	9368268	88	3456228	0.249	691	553
2	New York City	14745610	29	497852	1.820	635	225
3	Los Angeles	9639715	38	2278880	-0.624	490	1301
4	Dallas	4513776	13	564160	4.581	465	83
5	Seattle	2189215	20	644052	1.917	418	143
6	San Francisco	3863536	14	104312	2.757	384	102
7	Portland	1641801	30	141432	8.891	352	36
8	Atlanta	1627623	28	610280	3.237	347	82
9	Jacksonville	936317	18	265960	6.995	341	43
10	Kansas City	1767872	55	362920	7.225	333	40

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) short coastal segments linking densely populated areas, like Boston-PHL & LA-San Diego, & (2) trade thoroughfares via Indiana

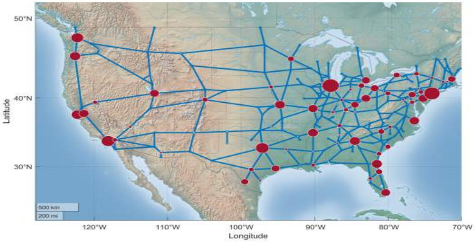


AA (2022) Fig 5(a): Highway links improvement

Welfare Effects of Intermodal Terminal Investments: Comparison

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

- Our gains are mostly in the center of the US: indicative of multimodal transportation taking place over longer distances and linking coastal to interior regions



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

Environmental Implications from Infrastructure Investments

- **Modal Substitution**: Improving Chicago's terminals decreases road traffic locally
- Investments have environmental consequences due to varying emissions of each mode: Trucks emit 8 times more $\mathrm{CO_2}$ 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 ↑, truck traffic ↓
- Trucks generate more GHG rel to rail, so improving terminals decrease rel GHG emissions

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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	691	553	-148.62	19.15	45.33
2	New York City	635	225	-148.09	19.05	45.13
3	Los Angeles	490	1301	-107.17	13.36	32.64
4	Dallas	465	83	-89.36	11.82	27.23
5	Seattle	418	143	-101.76	12.92	31.00
6	San Francisco	384	102	-100.82	12.97	30.73
7	Portland	352	36	-72.86	9.54	22.21
8	Atlanta	347	82	-82.83	11.12	25.24
9	Jacksonville	341	43	-81.10	10.37	24.74
10	Kansas City	333	40	-76.64	9.89	23.37

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. End

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

1. Value of Class 1 Railroad Network: Losing railroads implies welfare loss of $230bn
    - 40-54% of US highway value (Jaworski et al 2021), 40% more than rail value to agriculture (Donaldson & Hornbeck 2016)
2. Jones Act repeal: ↑ US maritime efficiency to match foreign ships implies welfare increase by $3bn
    - Low end of $2.8-$9.8bn USITC estimates: Only continental US + LR modal substitution patterns
3. Value of 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

	(1) Scenario	(2) Benefit ($bn)	(3) Benefit without Terminal Congestion ($bn)	(4) Benefit without All Congestion ($bn)
1	Railroad Strike	-230.46	-236.40	-278.94
2	Removal of the Jones Act	3.15	11.73	16.16
3	Panama Canal	-2.67	-7.64	-10.29

Welfare impact each of the three scenarios. Column (2) calculates the 2012 US GDP change in order to match overall welfare changes from each scenario. Column (3) is calculated like Column (2) with the removal of intermodal terminal congestion ($\lambda_2 = 0$). Column (4) is like Column (2) with the removal of terminal and road congestion ($\lambda_2 = 0$, $\lambda_1 = 0$).

Evaluating Policy Relevant Scenarios

1. Value of Class 1 Railroad Network: Losing railroads implies welfare loss of \$230bn
    - 40-54% of US highway value (Jaworski et al 2021), 40% more than rail value to agriculture (Donaldson & Hornbeck 2016)
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3. Value of 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

Congestion plays a compounding effect, depending on the transport modes affected

	(1) Scenario	(2) Benefit (\$bn)	(3) Benefit without Terminal Congestion (\$bn)	(4) Benefit without All Congestion (\$bn)
1	Railroad Strike	-230.46	-236.40	-278.94
2	Removal of the Jones Act	3.15	11.73	16.16
3	Panama Canal	-2.67	-7.64	-10.29

Welfare impact each of the three scenarios. Column (2) calculates the 2012 US GDP change in order to match overall welfare changes from each scenario. Column (3) is calculated like Column (2) with the removal of intermodal terminal congestion ($\lambda_2 = 0$). Column (4) is like Column (2) with the removal of terminal and road congestion ($\lambda_2 = 0$, $\lambda_1 = 0$).

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 ($bn)	(5) Benefit ($br
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.

Conclusion

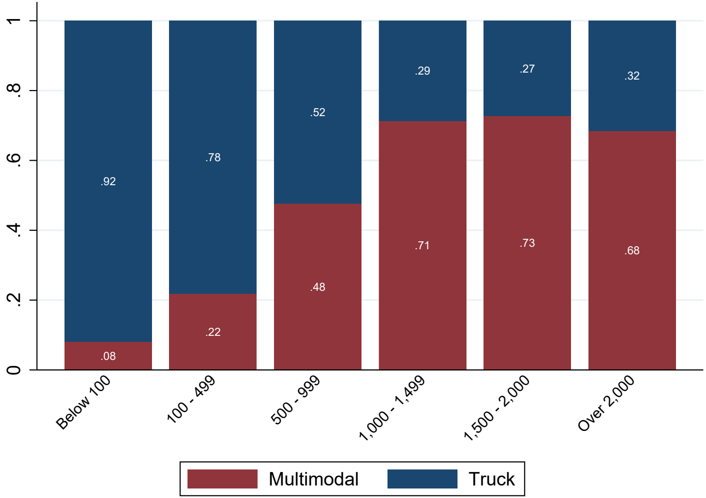
- This paper studies multimodal transport networks, and their welfare and environmental implications for infrastructure investments and disruptions

- Develop spatial eqm model with multiple modes, with switching and congestion at terminals
    - Introduce transport mode choice into optimal route choice model

- Estimate congestion elasticity at terminals and elasticity of substitution between modes

- Counterfactuals on intermodal terminal investments and policy-relevant scenarios
    - Intermodal terminals in center of US generate the largest welfare gains from investment
    - Modal substitution within multimodal network has environmental consequences, on top of welfare

Modal Weight Shares by Distance



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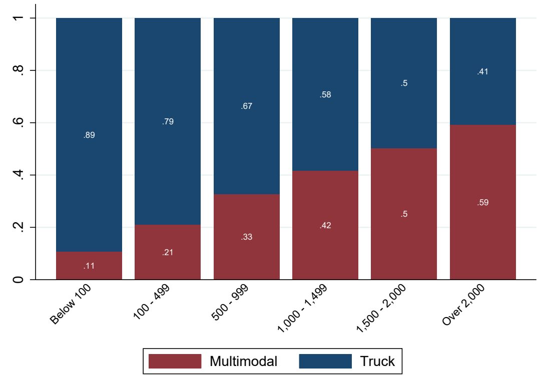
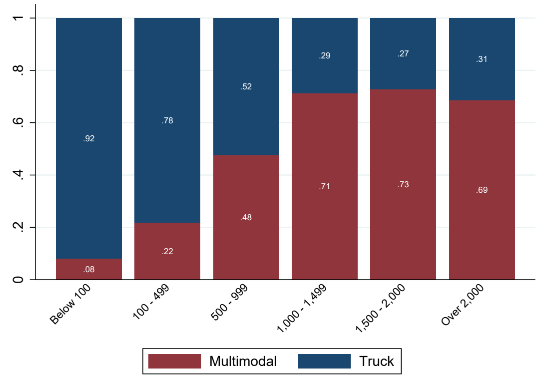
Modal Shares by Distance, including Air

Slightly smaller numbers by value (left figure) and no change by weight (right figure)





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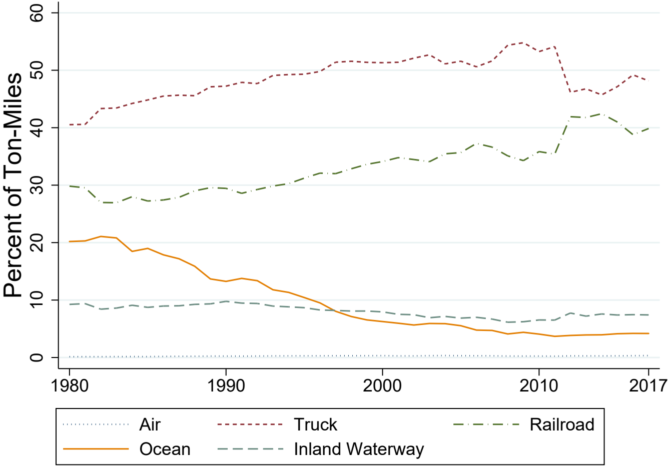
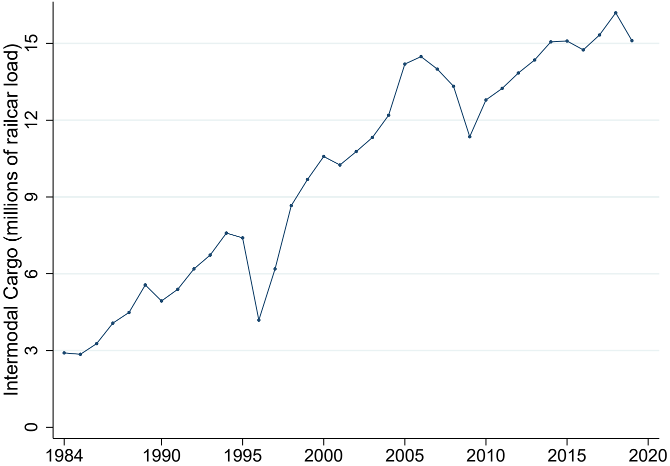
Freight Share 1980-2017



Data Multimodal Map

Intermodal Rail Cargo from 1984-2019



Transport within US Data Multimodal Map

US Rail Traffic

- Confidential waybill rail data, 1984-2019
    - Stratified sample of waybills representing 1-3% of all US rail traffic
    - Key Variables:
        - Origin-Interchanges-Destination at monthly level
        - Carloads, Tonnage, Weight, Freight Revenue
        - Product details: STCC (2 Digit) or HS
        - Car Type (intermodal vs not)

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)

back

OLS of Ship Dwell Times wrt Port Traffic

	(1)	(2)	(3)	(4)	(5)
Port Traffic	0.0955**	0.100**	0.103**		0.241***
	(0.0374)	(0.0399)	(0.0394)		(0.0534)
Port Traffic × Before Mar 2020				0.0955**	
				(0.0408)	
Port Traffic × After Mar 2020				0.122***	
				(0.0389)	
Day-Month-Year FE	✓	✓	✓	✓	✓
Ship-Port-Year FE			✓	✓	✓
Port-Year FE	✓	✓			
Ship-Port FE		✓			
Ship FE	✓				
West Coast Ports					✓
Observations	86094	86094	86094	86094	21205
R^2	0.70	0.78	0.83	0.83	0.87
F	6.53	6.29	6.85	5.60	20.35

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	0.103**	0.0848***	0.0527**	0.0266**
	(0.0394)	(0.0297)	(0.0203)	(0.0113)
Day-Month-Year FE	✓	✓	✓	✓
Ship-Port-Year FE	✓	✓	✓	✓
Moving Average (Days)	28	21	14	7
Observations	86094	86094	86092	86058
R^2	0.83	0.83	0.83	0.83
F	6.85	8.17	6.74	5.59

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

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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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. 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

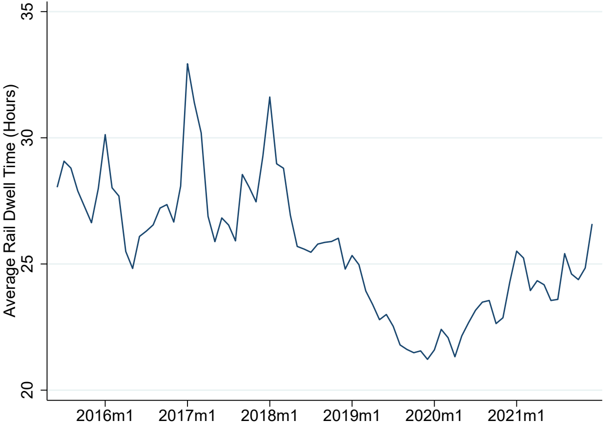
$$\ln \text{Rail Dwell Time}_{rpwy} = \beta_3 \ln \text{Port Traffic}_{pwy} + \gamma_{wy} + \phi_{rp} + \epsilon_{rpwy}$$

	(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. Back

Congestion at Intermodal Rail Terminals

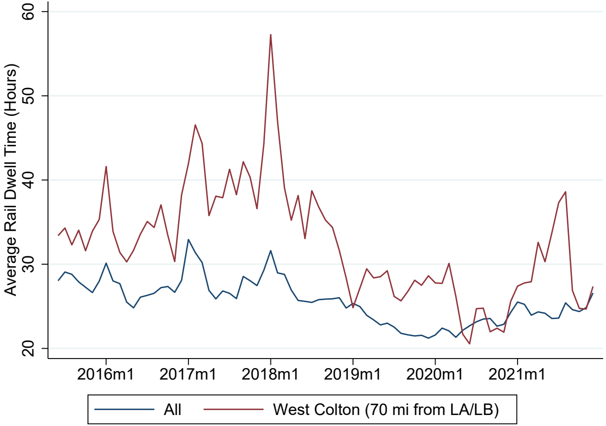
- Time a railcar spends at rail station (STB, 10 largest stations by Class I carriers)
  - Match stations to nearby ports using buffer area (150km buffer: 7 ports 12 rail stations)
  - Average of 25.8 hours per station (sd 2.7 hours)



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



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

back

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.

Back

Elasticity of Rail to Truck Traffic Use wrt Road Improvements

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

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) 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)

Rail to Road Traffic Use (Weight)	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) 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

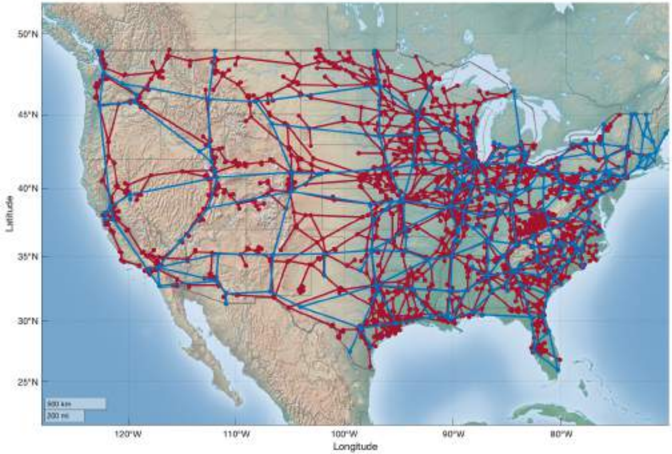
Robust standard errors in parentheses are clustered by port. All variables are in logs.

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.

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.

Data

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

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)

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, $\mathbf{A_2} = [a_{i'j'}] = \left[t_{i'j'}^{-\theta}\right]$ 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.

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

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, $\{\bar{a}_j, \bar{u}_j\}$

$$\bar{A}_i^{-\theta} y_i^{1+\theta} l_i^{-\theta(1+\alpha)} = \chi \sum_{j=1}^{N} \left(\tau_{ij}^{1}\right)^{-\theta} \bar{u}_j^{\theta} y_j^{1+\theta} l_j^{\theta(\beta-1)} + \chi \sum_{j=1}^{N} \left(\tau_{ij}^{1,2}\right)^{-\theta} \bar{u}_j^{\theta} y_j^{1+\theta} l_j^{\theta(\beta-1)} \tag{3}$$

$$\bar{u}_i^{-\theta} y_i^{-\theta} l_i^{\theta(1-\beta)} = \chi \sum_{j=1}^{N} \left(\tau_{ij}^{1}\right)^{-\theta} \bar{A}_j^{\theta} y_j^{-\theta} l_j^{\theta(\alpha+1)} + \chi \sum_{j=1}^{N} \left(\tau_{ij}^{1,2}\right)^{-\theta} \bar{A}_j^{\theta} y_j^{-\theta} l_j^{\theta(\alpha+1)} \tag{4}$$

where $\chi \equiv \left(\frac{L(\alpha+\beta)}{\bar{W}}\right)^{\theta}$ is an endogenous scalar that is inversely related to welfare.

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 $\mathbf{B}$, intermodal linkages $\mathbf{S}$, 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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Transport Cost over Multimodal Network

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

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 $\left(\Xi^1_{ij}, \Xi^2_{i'j'}\right)$, 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:

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

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