

Valuing Domestic Transport Infrastructure: A View from the Route Choice of Exporters

Jingting Fan (Pennsylvania State University)

Yi Lu (Tsinghua University)

Wenlan Luo (Tsinghua University)

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Inland trans. infrastructure investment

- Investment on inland trans. infrastructure: 850 billion/year in 47 major countries, half of which in China (2% GDP in 2000 ↗ 5% in 2010)
- **Blue:** Expressway network 1999. **Red:** Expressway network 2010



- What are the impacts of transportation infrastructure improvement on regional and aggregate economy
 - Early work: first-order based measurement (Fogel, 1964) or reduced-form (Banerjee et al., 2012)
 - GE in nature → necessitates a structural model
- Recent progress:
 - **Market access approach**: Donaldson and Hornbeck (2016), Alder (2016), Baum-Snow et al. (2018), ...
 - **Quantification via structural counterfactual**: Donaldson (2018a), Allen and Arkolakis (2014, 2016), Fajgelbaum and Schaal (2017), ...

Background

Key to both approaches: identify the trade cost elasticity

- travel distance $\xrightarrow{\text{trade cost elast.}}$ trade cost $\xrightarrow{\text{trade elast.}}$ trade flow \xrightarrow{GE} emp./wage
- How existing work recovers trade cost elast.
 - (1) external measure of freight rates: Baum-Snow et al. (2018)
 - (2) estimate using price gaps of homogeneous goods: Asturias et al. (2018), Atkin and Donaldson (2015), Donaldson (2018b)
 - (3) estimate using shipment flows: Allen and Arkolakis (2014, 2016)
- Approach (1) rules out the non-monetary component of trade cost
- (2) and (3) both demanding in data \rightarrow restricted to a small groups of products (thus one-sector models); trade cost elas. identified from cross-sectional variations in shipment flows

What we do

- A novel source of information to measure domestic shipment
 - export data from the Chinese customs 1999-2010
 - location of exporter, port of exit, volume and quantity \implies routing, price gap
- Combined with expressway expansion to estimate cost on expressway and regular roads
 - idea: A exports more through port a than port b $\implies \tau_{A,a} < \tau_{A,b}$
 - use **over-time variations** and an IV (Faber, 2014) to address various concerns
 - allow **trade cost heterogeneity** by weight-to-value ratio; discipline extent of heterogeneity using prices
- Parameterize a regional GE model
 - routing module from Allen and Arkolakis (2016)
 - idiosyncratic trucker preference over routes \implies tractable for characterization of the welfare effects
 - Caliendo and Parro (2015) with sector heterogeneity in trade costs

Main findings

- Transport costs parameters:
 - ad valorem for each 100 kilometer on regular road (7.4%) and expressway (5.5%)
 - doubling weight-to-value ratio increases cost by 23%

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 - doubling weight-to-value ratio increases cost by 23%
- Evaluate the return to expressway expansion: 1999-2010
 - 50,000 kilometer expressways built; total cost \$570 billion (10 % of 2010 GDP)
 - welfare gains 5.6%, or 180% net return to investment
 - return smaller if shut down *regional specialization* (15% less), *sector heterogeneity in cost* (30% less), and *intermediate linkages* (75% less)
 - ⇒ 0.74% welfare gains in one-sector model, or 63% negative return to investment

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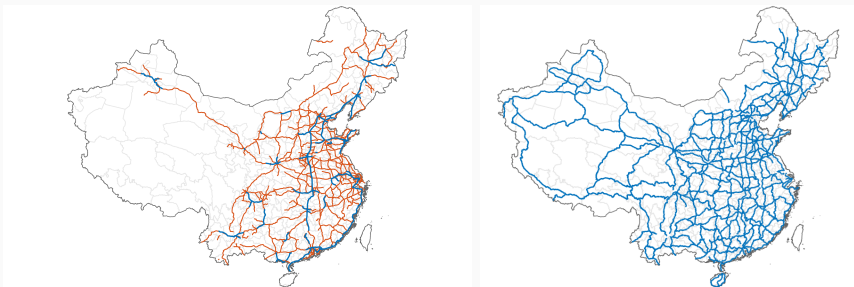
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 - ⇒ 0.74% welfare gains in one-sector model, or 63% negative return to investment
- The effects can be approximated accurately using a 2nd-order characterization
 - after the model is parameterized, no need for computing counterfactuals
 - not for today

- **Impacts of infrastructure projects on**
 - **regional development or growth** (Cosar et al., 2019, Fajgelbaum and Redding, 2014), **migration** (Morten and Oliveira, 2018), **within city activity** (Gu et al., 2018, Severen, 2018, Tsivanidis, 2018), **seller buyer match** (Xu, 2018), and **optimality for the aggregate economy** (Alder and Kondo, 2019, Allen and Arkolakis, 2016, Fajgelbaum and Schaal, 2019)
 - **difference: a new way of estimating trade cost elasticity**
- **Domestic trans. infra. promotes export**
 - using **country-level** (Limao and Venables, 2001) and **region-level** variations (Coşar and Demir, 2016 and Martincus et al., 2017)
 - **difference: focus are impact on trade cost and welfare, rather than export per se**
- **Chinese spatial economy.**
 - Fan (2019), Ma and Tang (2019), Tombe and Zhu (2019), Zi (2016),...
 - determine transport cost using **railway shipments** (account for only 10% of shipment; province level) or **regional input-output** table (imputed from railway)
 - **new: parameterize a domestic trade cost matrix**

- Data and Reduced-form Specification
- Model
 - Road network \rightarrow trade cost
 - Multi-sector EK
- Quantification and Counterfactuals

Data and Reduced-form Specifications

Data: transportation network (Baum-Snow et al., 2018)



- Left: expressways for 1999 and 2010
- Right: regular roads ('national' and 'provincial' roads) in 2007
- Find distance along the shortest path between o and d ,
 $\{\text{dist}_{od}^t : t = 1999, 2010\}$
 - necessary to take a stand on relative costs of expressway and regular road
 - for now: 1 km on expressway equals to 0.5 km on regular road
 - later: pinned down in full quantification

Reduced-form specification: routing

$$\ln(q_{(o,RoW),d}^t) = \beta_{od} + \beta_o^t + \beta_d^t + \gamma \cdot \text{dist}_{od}^t + \epsilon_{od}^t$$

- $q_{(o,RoW),d}^t$: quantity (tons) exported from city o via port d in year t
- dist_{od}^t : shortest effective distance from o to d : $0.5 \times \text{dist}_{o \rightarrow d,H}^t + \text{dist}_{o \rightarrow d,L}^t$
- γ : composite of $\kappa_L \times \theta^F$
 - κ_L : effective cost for regular roads; θ^F : elasticity of substitution between ports

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- Remarks
 - limit case of the structural equation w/o. trucker preference heterogeneity
 - omitting β_{od} leads to biased $\hat{\gamma}$
 - address endogeneity of road networks: (1) exclude major cities; (2) minimum-spanning tree IV; (3) sectoral-level specification

Exporting share elasticity w.r.t. distance

Table 1: Expressway and Routing of Export Shipments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS				PPML			
$dist_{o,d}$	-0.346*** (0.010)	-0.103*** (0.025)	-0.136*** (0.033)	-0.144*** (0.040)		-0.655*** (0.062)	-0.470*** (0.066)	
-on express					-0.082* (0.042)			-0.286** (0.117)
-on regular					-0.148*** (0.043)			-0.488*** (0.084)
Fixed Effects	<i>o, d, t</i>	<i>od, t</i>	<i>od, ot, dt</i>	<i>od, ot, dt</i>	<i>od, ot, dt</i>	<i>ot, dt</i>	<i>od, ot, dt</i>	<i>od, ot, dt</i>
Exclude major cities				yes	yes	yes	yes	yes
Observations	3625	2768	2738	2002	2002	2740	2002	2002
R ²	0.601	0.820	0.893	0.882	0.882	-	-	-

Notes: Standard errors are clustered at city-port level

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

Robustness test: IV and sectoral-level specification

Table 2: IV and Sectoral Results

	(1)	(2)	(3)	(4)	(5)
	Aggregate IV		Sectoral OLS		
$dist_{od,t}$	-0.156*** (0.050)		-0.092*** (0.030)	-0.110*** (0.037)	
-on express		-0.096 (0.067)			-0.088** (0.040)
-on national		-0.164*** (0.060)			-0.120*** (0.039)
Fixed Effects	<i>od, ot, dt</i>	<i>od, ot, dt</i>	<i>odi, ot, dt it</i>	<i>odi, oit, dit</i>	<i>odi, oit, dit</i>
Exclude major cities	yes	yes	yes	yes	yes
Observations	1926	1926	13006	11044	11044
R ²	-	-	0.839	0.896	0.896
First Stage KP-F statistic	1748.984	212.052			

Notes: Standard errors are clustered at city-port level

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Summary and Motivation for a routing model

- Reduced-form elasticity of routing w.r.t. effective distance around 15%
 - Using cross-sectional variations more than doubles the estimate
 - Needs to take a stand on the relative cost of express/national, for shortest path
 - Confounding with port choice elasticity and router preference heterogeneity

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 - Needs to take a stand on the relative cost of express/national, for shortest path
 - Confounding with port choice elasticity and router preference heterogeneity
- Extend the routing problem and embed into a GE model
 - allow truckers to have heterogeneous preference for routes \implies both regular roads and expressways used; identify $\theta_F, \kappa_L, \kappa_H$
 - incorporates alternative modes
 - use the GE structure to infer the level of cost; counterfactuals

Model

Routing block: from road network to domestic trade cost

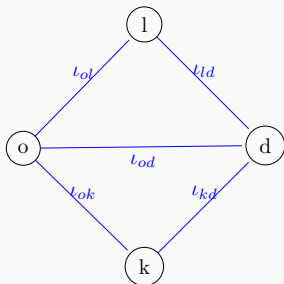


Figure 1: A trucker going from o to d

- iceberg cost $l_{ol} = \exp(\kappa_L \text{dist}_{ol})$
- Three direct paths; trucker draws a preference shock from Frechet for each
- if made choose among the three, the expected cost is:

$$\tau_{od,2} = \Gamma\left(\frac{\theta-1}{\theta}\right) \left([l_{od}]^{-\theta} + [l_{ol}l_{ld}]^{-\theta} + [l_{ok}l_{kd}]^{-\theta} \right)^{-\frac{1}{\theta}}, \quad o \neq d$$

Routing block: Matrix representation

$$\begin{array}{c}
 \begin{array}{cccc}
 & o & l & d & k \\
 o & \left(\begin{array}{cccc}
 0 & l_{ol}^{-\theta} & l_{od}^{-\theta} & l_{ok}^{-\theta} \\
 l_{lo}^{-\theta} & 0 & l_{ld}^{-\theta} & 0 \\
 l_{do}^{-\theta} & l_{dl}^{-\theta} & 0 & l_{dk}^{-\theta} \\
 l_{ko}^{-\theta} & 0 & l_{kd}^{-\theta} & 0
 \end{array} \right)
 \end{array}
 \end{array}$$

- $[\mathbb{L}_{(o,d)}]$ is (o, d) element of \mathbb{L} . $[\mathbb{L}_{(o,d)}^2]$ is (o, d) of \mathbb{L}^2
- $\tau_{od,2} = \Gamma\left(\frac{\theta-1}{\theta}\right) ([\mathbb{L}_{(o,d)}] + [\mathbb{L}_{(o,d)}^2])^{-\frac{1}{\theta}}$, $o \neq d$
- Allowing detours, expected cost among all path with less than N edges is:
 $\tau_{od,N} = \Gamma\left(\frac{\theta-1}{\theta}\right) \left(\sum_{s=1}^N [\mathbb{L}_{(o,d)}^s]\right)^{-\frac{1}{\theta}}$, $o \neq d$
- Allowing arbitrary detours:

$$\tau_{od} \equiv \lim_{N \rightarrow \infty} \tau_{od,N} = \Gamma\left(\frac{\theta-1}{\theta}\right) \left(\sum_{s=1}^{\infty} [\mathbb{L}_{(o,d)}^s]\right)^{-\frac{1}{\theta}} = \Gamma\left(\frac{\theta-1}{\theta}\right) ([\mathbb{I} - \mathbb{L}]_{(o,d)}^{-1})^{-\frac{1}{\theta}}.$$

Routing block: extension for quantification

- With both expressways \mathbb{H} and regular roads \mathbb{L} to choose from:
 - $\mathbb{A} \equiv \mathbb{H} + \mathbb{L}$, $\mathbb{B} \equiv (\mathbb{I} - \mathbb{A})^{-1}$.
 - $\tau_{od} \equiv \lim_{N \rightarrow \infty} \tau_{od,N} = \Gamma\left(\frac{\theta-1}{\theta}\right) \left(\sum_{s=1}^{\infty} [\mathbb{A}_{(o,d)}^s]\right)^{-\frac{1}{\theta}} = \Gamma\left(\frac{\theta-1}{\theta}\right) [\mathbb{B}_{(o,d)}]^{-\frac{1}{\theta}}$

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- With alternative transport **mode** and **export**:

$$\bar{\tau}_{od}^i \propto \exp(\bar{\kappa} \cdot \overline{\text{dist}}_{od}), \quad o \neq d$$

$$\tilde{\tau}_{od}^i \propto \begin{cases} [(\bar{\tau}_{od}^i)^{-\theta_M} + (\tau_{od}^i)^{-\theta_M}]^{-\frac{1}{\theta_M}}, & \text{if } d \neq \text{RoW} \\ \left\{ (\tau_{\text{RoW}}^i)^{-\theta_M} + \left(\left[\sum_{\text{ports } k} (\tau_{ok}^i \tau_{\text{RoW}}^i)^{-\theta_F} \right]^{-\frac{1}{\theta_F}} \right)^{-\theta_M} \right\}^{-\frac{1}{\theta_M}}, & \text{if } d = \text{RoW} \end{cases}$$

The rest of the model

- 323 regions (prefectures)+RoW, 25 sectors (2-digit). Regions differ by population and sector productivity
- Consumption: immobile workers with CB preference over sector final goods
- Intermediate good production: labor and sector final goods from other sectors
- Final good production: aggregate intermediate inputs within the sector across all source regions a la Armington

Quantification

Estimating the routing model

$$\log(q_{(o, RoW), d}^{i, t}) = \frac{\theta_F}{\theta} \log \left([\tilde{\mathbb{B}}_t(\kappa^H \theta, \kappa^L \theta)_{(o, d)}] \right) +$$

$$+ \text{cons}_i - \theta_F \log(\tau_{d, RoW}^i) - \log \left(\sum_{\text{All ports } k} \tau_{ok}^{-\theta_F} \cdot \tau_{k, RoW}^{-\theta_F} \right)$$

fixed effects: $f_o^{i, t} + f_d^{i, t} + f_{od}^{i, t}$

- Recall $\mathbb{B} = [\mathbb{I} - \mathbb{H} - \mathbb{L}]^{-1}$; write as function of $\kappa^H \theta$ and $\kappa^L \theta$ to highlight the dependence
- Estimate the following without solving model equilibrium:

$$\min_{\frac{\theta_F}{\theta}, \kappa^H \theta, \kappa^L \theta, \mathbf{fe}} \left[\frac{\theta_F}{\theta} \log \left([\tilde{\mathbb{B}}_t(\kappa^H \theta, \kappa^L \theta)_{(o, d)}] \right) + \mathbf{fe} - \log(q_{(o, RoW), d, t}) \right]^2$$

- Point estimates: $\kappa^H \theta = 4.44$, $\kappa^L \theta = 5.98$, $\frac{\theta_F}{\theta} = 0.03$

Estimating the routing model

$$\log(q_{(o, RoW), d}^{i, t}) = \frac{\theta_F}{\theta} \log \left([\tilde{\mathbb{B}}_t(\kappa^H \theta, \kappa^L \theta)_{(o, d)}] \right) +$$

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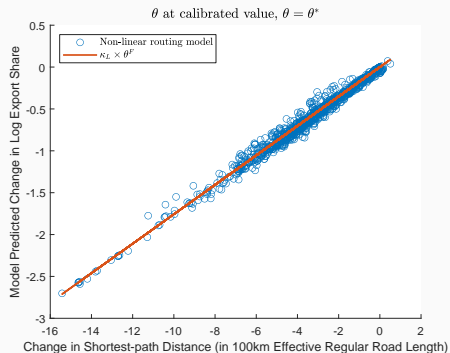
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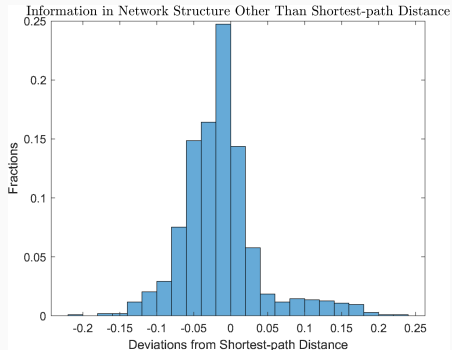
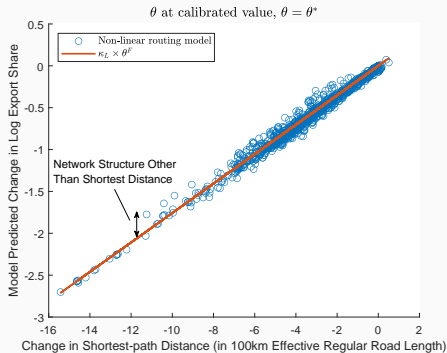
- Point estimates: $\kappa^H \theta = 4.44$, $\kappa^L \theta = 5.98$, $\frac{\theta_F}{\theta} = 0.03$
- Given κ_L , can identify κ^H / κ^L , θ_F , θ ; will use price-distance regression to separate κ_L and θ combining structural models

Identification for θ_F



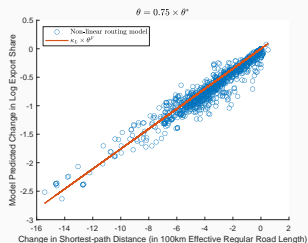
- Given κ_L and θ , θ_F is identified by the export share-distance elasticity

What is new to the nonlinear routing model?

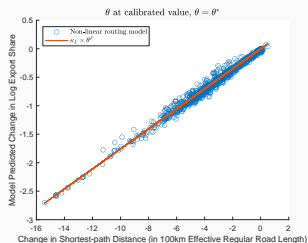


- The **deviation** of the nonlinear routing model from the linear model captures **other network structure** than the shortest-path distance

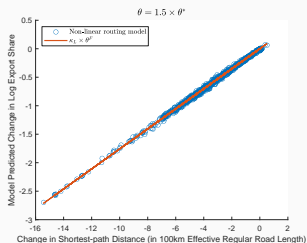
Varying θ affects how large this deviation contributes to model prediction



(a) $\theta = 0.75 \times \theta^*$



(b) $\theta = \theta^*$

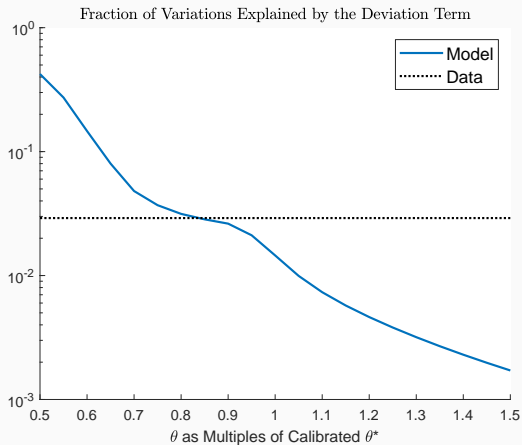


(c) $\theta = 1.5 \times \theta^*$

- Increasing θ brings the non-linear model closer to the linear model
 - converged to the linear model when $\theta \rightarrow \infty$

Identification for θ

- Identification: how much does **network structure other** than the shortest-path distance, measured by the **deviation term**, explain the data
- Compare $\frac{R^2_{\text{deviation}}}{R^2_{\text{shortest length}} + \text{deviation}}$ between model and data



Parameterize the rest of the model

Table 3: Parameter Values

Parameters	Descriptions	Value	Targets/Source
Parameters calibrated externally			
$\beta^i, \gamma^j, \alpha^j$	IO structure and consumption share	-	2007 IO table for China
L_d	Total employment	-	2010 Population Census
σ	Trade elasticity	6	
θ_M	Elasticity of substitution across modes	2.5	
Parameters calibrated in equilibrium			
θ	Routing elasticity	81.21	} joint estimate of $\kappa^H\theta = 4.44, \kappa^L\theta = 5.98, \frac{\theta_F}{\theta} = 0.03, \frac{\partial \log p}{\partial \text{dist}} = 0.06$
θ_F	Port choice elasticity	2.45	
κ_H	Expressway route cost	0.055	
κ_L	Regular route cost	0.074	
h_0	Trade cost level	1.295	Average ground shipment distance: 177 km
$\bar{\kappa}$	Alternative mode cost	0.210	Share of non-road shipment: 0.24
μ	Cost-weight to value elasticity	0.3	estimated
$\tau_{RoW}^i, \tau_{RoW}^j$	Export and import costs	-	Sectoral export and import
T_d^i	Region-sector productivity	-	City-sector sales in 2008 Economic Census

Price-distance Regression

Price-weight-to-value elasticity

Model validation



Figure 2: Model Predicted Shipment Flows

- Model predicts trans-shipment by city well, controlling for city size and prov. fe
- City-sector export change in the model due to expressway expansion between 1999-2010 correlates with actual export growth

Counterfactuals

The Effects of the Expressway Expansion, 1999-2010

Change in	Value
Aggregate welfare	0.056
Log(Domestic trade / GDP)	0.113
Log(Exports / GDP)	0.157
Std Log(real wage) across regions	-0.0288

- Numbers in perspective: between 1999 and 2010, aggregate TFP increased by **36%** (Penn World Table), trade/GDP increased by **70%**
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- Expressway expansion explains about **16%** of the former; **a quarter** of the latter
- Total cost: 10% of 2010 GDP. Assuming 10% depreciation rate (Bai and Qian, 2010), 10% return to capital (Bai et al., 2006) \implies 180% net return to investment

The role of sectors

	Baseline	Model (2)	Model (3)	Model (4)	Model (5)
International trade	✓				
Regional specialization	✓	✓			
Trade cost heterogeneity	✓	✓	✓		
Intermediate input	✓	✓	✓	✓	
Welfare gains	5.64%	5.27%	4.54%	3.18%	0.74%

Each model recalibrated to match the same sales by city ($\{T_d^i\}$) and average shipment distance (h_0).

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- (4) \rightarrow (5): inferred wrong sales/VA ratio (same as in international trade)

Evaluating mega projects



ID	Length	Cost/GDP (%)	Welfare gains	%Change in Export/GDP
G1	1533.61	0.3	0.52	0.94
G2	1768.29	0.38	0.45	1.28
G3	2513.38	0.54	0.79	4.37
G4	2924.88	0.65	0.4	1.12
G5	2829.75	0.73	0.26	0.51

Conclusion

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- Exploit over-time variations in city-to-port export to estimate the impact of transportation infrastructure on trade cost
 - construction of expressway reduces cost-distance elasticity by 25%
 - sectoral heterogeneity in cost levels that systematically correlates with weight-to-value ratios
- Accommodating regional specialization / sectoral heterogeneity / intermediate input is important
 - neglecting these underestimate the gains and turns positive NPV into negative
- Our approach requires data on sectoral production and is computational intensive. For future work useful to think about ways to
 - circumvent parameterizing the full model and computing counterfactuals
 - 2nd-order characterization quite accurate, but requires full information on shipment and routing
 - reduce the data requirement while retaining accuracy

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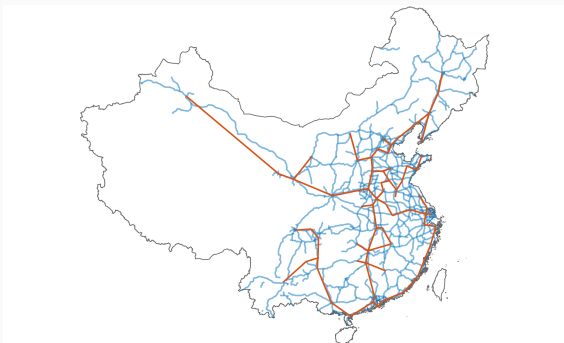
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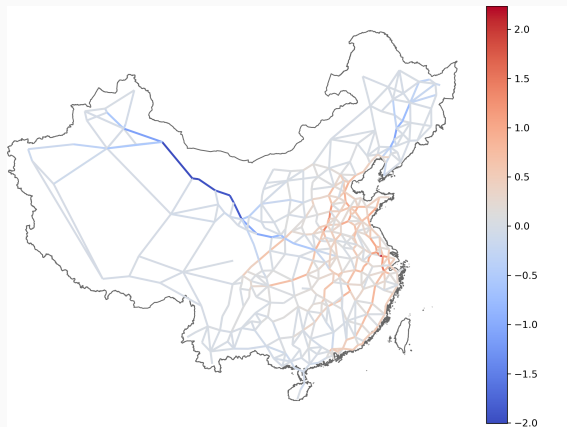
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The minimum-spanning tree IV (Faber, 2014)



- Red: min-distance network connecting 55 major cities; Blue: 2010 expressway
- IV for $dist_{ij}^{2010}$: Effective length of shortest-path along the (Blue) network
- IV for $dist_{ij}^{1999}$: $dist_{ij}^{1999}$
- Identification: National Trunk Highway System exogenous to small cities

Change in shipment flows between 3 and 2



Note: The numbers are the differences in shipment value/GDP between Model (2) and Model (3). Cold colors indicate that there is less shipment in Model (3) than in Model (2).

Price-distance regression

Table 4: Price Distance Regression

	(1)	(2)	(3)	(4)
	OLS		IV	
$dist_{od}$	0.055*** (0.013)	0.061*** (0.022)	0.053*** (0.012)	0.058*** (0.021)
Fixed Effects	<i>dci, oci</i>	<i>dci, oci</i>	<i>dci, oci</i>	<i>dci, oci</i>
Exclude major cities	yes	yes	yes	yes
Exclude differentiated goods		yes		yes
Observations	1829372	232609	1829372	232609
R ²	0.323	0.340	-	-
First Stage KP-F statistic			1515.787	1156.297

Notes: o , d , c , i stand for origin city, port, destination country, and HS-8 product fixed effects, respectively. Standard errors are clustered at city-port level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Price regression: estimate trade cost-weight elasticity

Table 5: Transport cost and weight-to-value ratio

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log price ratio				log price ratio		
Heaviness- HS2 Category	0.163*** (0.056)	0.161*** (0.056)	0.278*** (0.086)	0.199** (0.089)			
Heaviness- HS4 Category					0.303*** (0.044)	0.362*** (0.050)	0.253*** (0.043)
Fixed Effects	<i>o, d, c</i>	<i>odc</i>	<i>fdc</i>	<i>fdc</i>	<i>fdc, i</i>	<i>fdci</i>	<i>fdci</i>
Exclude major cities	yes	yes	yes	yes	yes	yes	yes
Exclude differentiated goods				yes			yes
Observations	1987140	1985946	1805563	190836	1805563	1126941	119077
R ²	0.063	0.074	0.375	0.481	0.417	0.596	0.639

Notes: *o, d, c, f, i* stand for origin city, port, destination country, firm, and HS2 category fixed effects, respectively.

Standard errors are clustered at HS2 category level (Columns 1-4) or HS4 category level (Columns 5-7). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.