

Entrepôt: Hubs, Scale, and Trade Costs

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- Notion that entrepôts are integral to trade network and engines of growth have been the impetus for policies aimed at attaining or maintaining entrepôt status
 - Saudi Arabia: \$7bn to be the “major east-west marine transshipment location.” (FT 2015)
 - India: \$5bn in new ports to compete with established hubs in Sri Lanka (Reuters 2016)
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 - Singapore: \$15bn to “stay ahead of the competition” as top maritime hub (WSJ 2021)
- We study entrepôts, the trade networks they form, and their impact on international trade

Contribution

1. Establish empirical evidence on how goods are shipped through the trade network
 - Merge customs & port call ship data to trace a shipment's journey from origin to destination
 - We observe *indirect trade*: shipment journeys that make stops with shipment either on-board or transshipped at additional countries (third-party countries)
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 - Previous work observed origin-destination trade or ship movements with solely port call data
 - The trade network is a hub and spoke system, where 80% of trade is shipped indirectly—nearly all via entrepôts

Contribution

2. Estimate trade costs that rationalize observed direct & indirect trade through the network
 - Build GE model of trade where optimal shipping routes and entrepôts emerge endogenously
 - Embed route selection model (Allen & Arkolakis 2019) in generalized Ricardian comparative advantage setting (Eaton & Kortum 2002)
 - Develop geography-based IV to estimate scale elasticity: 1% increase in traffic on a given leg reduces trade costs by 0.06%
 - Establish validity of modeling approach: tight match between estimates and external data

Contribution

3. Quantify trade & welfare impact of trade network: evaluate effects of (1) Country-level transport vs non-transport improvement, (2) Brexit, and (3) Opening of Arctic passage
 - Entrepôts are pivotal to trade network, have 10 times the global welfare impact from transport improvement rel to non-entrepôts, with scale amplifying the benefits concentration
 - Scale economies in transportation can be a source of agglomeration
 - Brexit: when accounting for interaction of network and scale, smaller countries like Ireland and Iceland that use the UK as entrepôt are disproportionately hurt
 - Arctic passage: network structure of trade distributes gains beyond directly impacted countries with pre-existing shipping routes, welfare impacts further tripled from scale effects

Related Literature

- Quantify trade and welfare impacts from technology underpinning trade fundamentals
 - Impact of containerization on trade (Bernhofen et al (2016), Cosar & Demir (2018), Wong (2020))
 - Shipping network and endogenous trade costs (Hummels (2007)): for containership movement with port call data (Heiland et al (2019)), for dry bulk ships (Brancaccio et al (2020))
 - Fit models with leg-level oligopoly, fixed costs, & endogenous entry (Sutton (1991)); abstract from market power through network (Hummels et al (2009), Grant & Startz (2020), Asturias (2020))
- Provide empirical evidence on role of trade networks
 - Extend (Allen and Arkolakis (2019)) Armington framework to multi-sector Ricardian setting
 - Trade cost changes and infrastructure investment at nodes (entrepôts) and with scale instead of congestion (Redding & Turner (2015), Fajgelbaum & Schaal (2017), Ducruet et al. (2019))
- Agglomeration and the role of localized scale economies
 - Scale in transportation can interact with trade network to concentrate economic activity (Allen & Arkolakis (2014), Allen & Donaldson (2018), Lashkaripour & Lugovskyy (2019), Bartelme et al (2019))
 - Micro-data on economies of scale (Alder (2015), Anderson et al (2016), Holmes and Singer (2018))

Data

Stylized Facts

Model: Overview

Trade Cost and Scale Elasticity Estimation

Comparison of Model-Predicted Estimates to Data

Counterfactual

Conclusion

Data: Container Trade

- Accounts for more than 60% of all seaborne trade values
- Occurs on set routes like buses, with published schedules and minimal search costs



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- Accounts for more than 60% of all seaborne trade values
- Occurs on set routes like buses, with published schedules and minimal search costs
- Larger ships are associated with lower per unit costs



Data

- We compile and combine two proprietary data sets in this project
 1. Containership movements globally (port of call): ship, water height, latitude and longitude
 2. All containerized imports into the US (bill of lading): shipment information, foreign origin, US destination, and location where it was loaded on US-bound ship
- Using data on ships, loading location, and dates, we match these shipments to their journeys on specific containerships
 - From origin location of these shipments to their US port of entry: 15m TEUs and 106m tons

Ports of Call

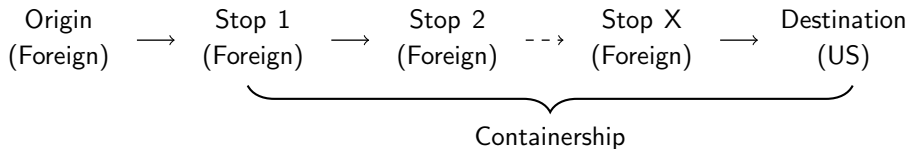
- Transponder information on (>90% of) containership entry and exit into 1,200 ports



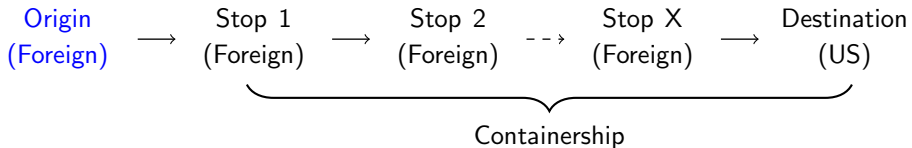
Dots represent the 1,203 ports (all important major, medium and small ports). Line represents the journeys of 4,986 containerships between port pairs.

- Containership movements do not necessarily capture the journey of container shipments

Combined Port of Call and Bill of Lading Data

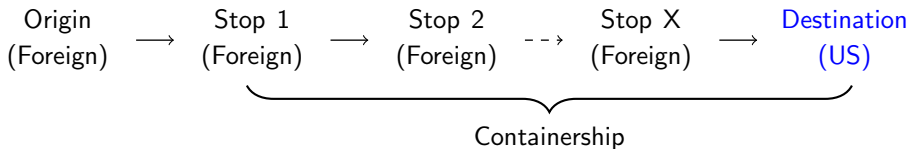


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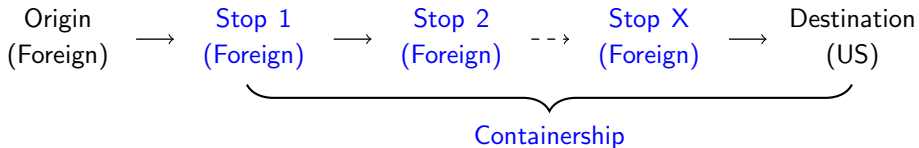
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- Origin: foreign location where shipment originated from
- Destination: US port where it was unloaded from containership

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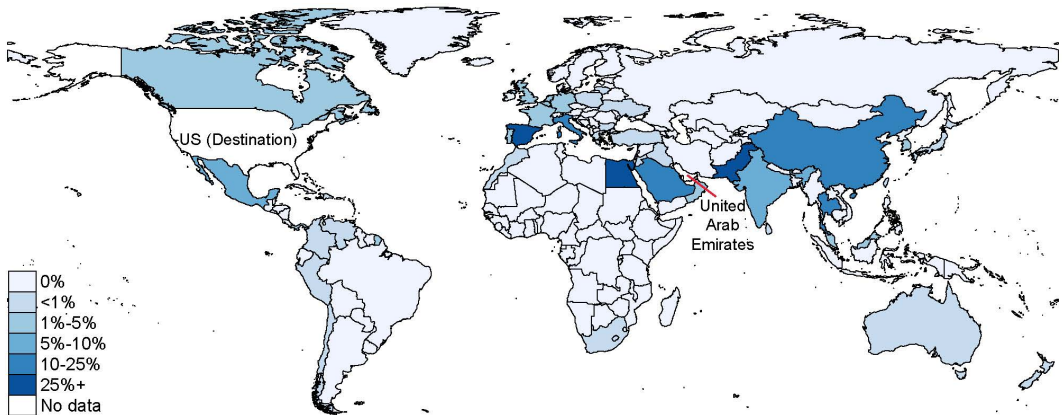
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- Origin: foreign location where shipment originated from
- In between: where loaded on containership bound for US (Stop 1) and subsequent stops
- Destination: US port where it was unloaded from containership
- Shipment information: weight, container TEUs, product, value
- We match 90% of incoming containers: 227 origin countries (April-October 2014)

Example: United Arab Emirates

Percent of UAE-US containers that stops in each country before US destination



Stops are by country and weighted by container volume.

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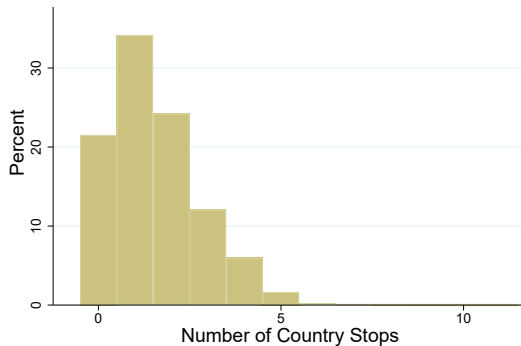
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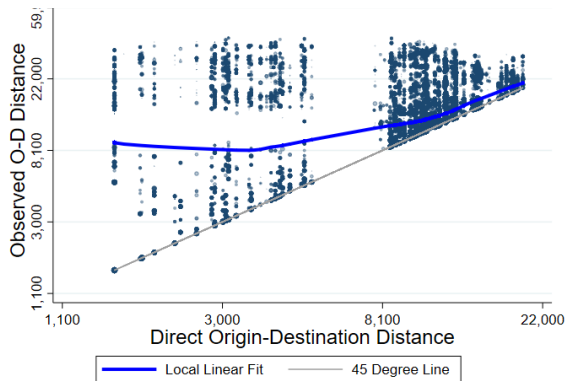
International trade network is indirect

- Average stops from foreign origin to US-destination (Direct = 0 stops)
 - Only 20% of containers exported to US are direct, av of 2 country stops [Wgt&Value](#) [Ports](#) [Map](#)
- Robust to alternative measure of indirectness: *transshipment*, when shipment origin is not the same as country where it was loaded onto US-bound containership [Data](#) [Hist](#)

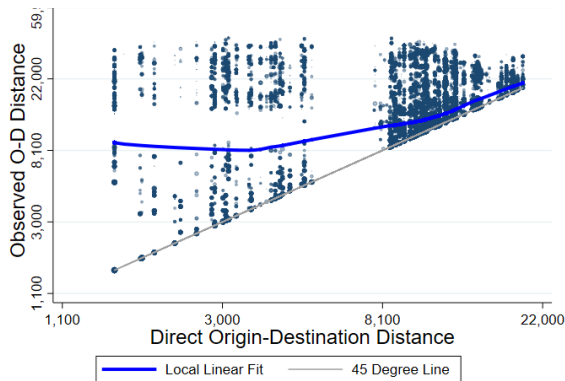


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Stylized Fact 1: *The majority of containerized trade into the US is indirect and results in a significant increase in shipping distance and time.*

Role of entrepôts in the trade network

- Hub-and-Spoke network (stops at hubs) vs Single Route (stops at every port/country)

Stylized Facts Summary

How do goods move from origins to destinations? How do entrepôts facilitate this move?

1. The majority of trade is indirect, indirectness increases shipping distance and time costs
2. Indirect trade are concentrated through entrepôts, trade occurs over hub-&-spoke network

Need a model to rationalize data and trade-off between indirectness (distance/time costs \uparrow) and concentration through entrepôts (costs \downarrow)

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Model: Overview

- Goal: model observed trade-off within global trading network that rationalizes indirectness
- Two observables: container traffic (Ξ) and trade volumes (X)
- Embed indirect trade in a Ricardian (EK 2002) setup
 1. Multilateral resistance
 2. Non-transportation trade costs
 3. Multiple industries with variable trade, tariff, and production costs

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 3. Multiple industries with variable trade, tariff, and production costs
- Back out trade costs for each link in network from the observed traffic and trade

Consumption and Production

- Consumers in country j consume goods $\omega_n \in \Omega_n$ from industries n
- Goods are produced with traded and nontraded inputs
- Equilibrium marginal cost of production is common to all products in industry

$$c_{in} \equiv c_{in}(z_{in}, W_i, P_{in})$$

where z_{in} is industry productivity, W_i is a vector of factor prices, P_{in} is a vector of intermediate good prices

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- To export to any j , competitive producers pay tariffs κ_{ijn} and iceberg transport cost $\tau_{nijr}(\omega)$ that depends on their chosen shipping route r :

$$p_{ijn}(\omega) = c_{in}\kappa_{ijn}\tau_{nijr}(\omega)$$

Endogenous Transport Costs (AA 2019)

- Total transport cost involves leg-specific costs t_{k_r-1,k_r} going from $k_r - 1$ to k_r on route r and a route-specific idiosyncratic cost shock ϵ Evidence for dispersion

$$\tau_{nijr}(\omega) = \prod_{k=1}^{K_r} t_{k_r-1,k_r}(\Xi, \varepsilon_{k_r-1,k_r}) \frac{1}{\epsilon_{ijnr}(\omega)}$$

where $t_{k_r-1,k_r}(\cdot)$ is a function of endogenous containerized traffic matrix Ξ over the entire network and ε_{k_r-1,k_r} reflects exogenous transport cost elements like distance

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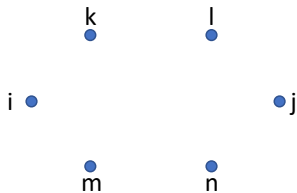
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- Multiplicative functional form allows for analytical solution: tight fits between estimates and external data help alleviate misspecification concerns
- Consistent with a host of mechanisms: agnostic to scale economies or dis-economies

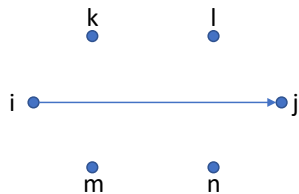
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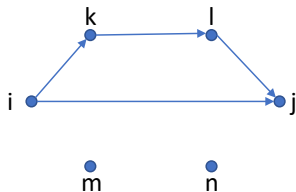
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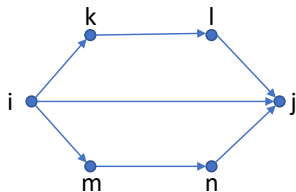


Route 1: $\tilde{t}_{ij1} = t_{ij}$

Route 2: $\tilde{t}_{ij2} = t_{ik} \times t_{kl} \times t_{lj}$

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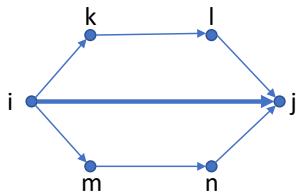
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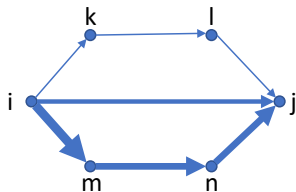
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Equilibrium Traffic

- Summing across routes r that goes through leg k, l , express share of exports in industry n from origin i to destination j that pass through leg k, l as

$$\pi_{ijn}^{kl} = [(c_{in}\kappa_{ijn}) \cdot \tau_{nik}t_{nkl}\tau_{nlj}]^{-\theta} \cdot \Phi_{jn}^{-1}$$

- τ_{nik} is the average cost to ship from i to k accounting for all possible routes
- Multilateral resistance $\Phi_{jn} = \sum_{i'} (c_{i'n}\kappa_{i'jn}\tau_{i'j})^{-\theta}$ accounts for costs and connectivity of all other competitors i'

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\Rightarrow Realized & observable share that we compare to microdata (& at higher aggregations)

- For a set of industries that share transport costs, total traffic between k and l :

$$\Xi_{kln} \equiv \sum_i \sum_j X_{ijn} \cdot [\tau_{ikn} t_{kln} \tau_{ljn} \tau_{ijn}^{-1}]^{-\theta} \quad \text{where} \quad X_{ijn} = \sum_{n \in N} X_{ijn}$$

\Rightarrow Identical to AA (2019). Intuition: Ricardian selection, tariffs, and Φ_{jn} affect trade from i to j proportionally on all routes

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Objective: Estimate (1) leg-level trade costs and (2) scale elasticity in shipping

- Scale elasticity suggested by stylized facts: causal impact of traffic volumes on trade cost
 - IV strategy based on geography-based instrument
- Leg-level trade cost: recover from O-D trade flows and leg-level traffic flows
 - Containerized global trade matrix (US Customs, CEPII, EORA I-O) and shipping network data
 - Extended AA (2019) model with Ricardian selection

Scale Estimation

- Stylized facts trace existence of scale economies (as opposed to congestion externalities)
 - Indirect trade concentrated via hubs appears by revealed preference to be cost-reducing
- Reduced Form Analog: Effect of traffic Ξ_{kl} on leg-level trade cost

$$\ln(t_{kl}^{\theta} - 1) = \alpha_0 + \alpha_1 \ln \Xi_{kl} + \alpha_2 \ln d_{kl} + \epsilon_{kl}$$

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- Traffic flows are endogenous to unobserved cost determinants for each leg kl
- Require a demand shifter for Ξ_{kl} that is uncorrelated with ϵ_{kl}

Geography-Based IV

- Geographic demand shifter: from origin i to destination j , link (k, l) is differentially attractive compared to link (m, o) because distances d_{ik}, d_{lj} are lower than d_{im}, d_{oj}

[Details](#)

$$z_{kl} = \sum_{i \setminus \{k, l\}} Pop_{i,1960} \sum_{j \setminus \{k, l\}} Pop_{j,1960} \frac{d_{ij}^2}{(d_{ik} + d_{lj})^2}$$

where d_{ij} is the sea distance between i and j , d_{ik} is sea distance for leg i, k , d_{lj} is sea distance for leg l, j and Pop is 1960 population at each i and j

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- All else equal for a leg that is more strategic: relative excess distance \downarrow , $z_{kl} \uparrow$ [First Stage](#)

Recovering Trade Costs

- Our model implies that the traffic flow at kl leg is:

$$\hat{\Xi}_{kl} \equiv \sum_i \sum_j X_{ij} \cdot \left[\tau_{ik} t_{kl} \tau_{lj} \tau_{ij}^{-1} \right]^{-\theta}$$

where trade cost t_{kl} is a function of τ and θ , and X_{ij} is origin-destination trade flows

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- Goal is to recover leg costs t_{kl} . X_{ij} and Ξ_{kl}^{data} are observed
- Limitation: underidentification stemming from unobserved overland traffic
- Solution: project t_{kl} on observables Y (**purely predictive**, including exogenous and endogenous factors) with coefficients β [Details](#)
- Compare Ξ_{kl}^{data} with $\hat{\Xi}_{kl}$ **for ocean routes**, model-predicted traffic flow is $\hat{\Xi}_{kl}(\beta|X, Y, \theta)$

Joint Estimation: GMM

- Criterion Function with two sets of moments

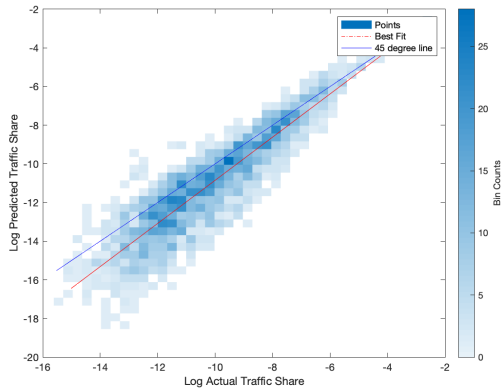
$$m_1(\alpha, \beta) = Z\epsilon(\alpha, \beta|X, Y, \theta)$$

$$m_2(\beta) = \left(\hat{\Xi}_{kl}(\beta|X, Y, \theta) \right) - \left(\Xi_{kl}^{data} \right)$$

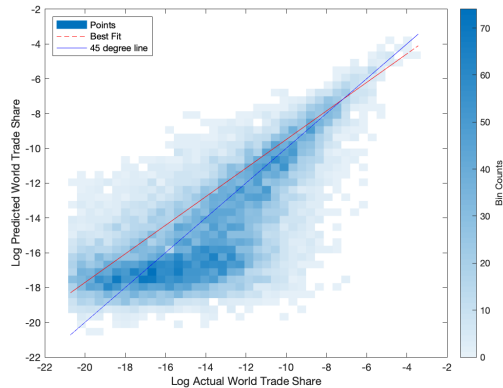
- m_1 accounts for the our causal estimates of scale
- m_2 rationalize trade costs t_{kl} conditional on world trade X and container traffic Ξ
- β is purely predictive: best attempt at recovering model-ideal values for t_{kl} .
- Inference is done only on α

Model Fit

Targeted: correlation of 0.97



Trade flows (untargeted): correlation of 0.73



Results: Two-stage GMM

| | (1) |
|-----------------------------|-----------------|
| | $\ln(c_{kl})$ |
| $\ln(\Xi_{kl})$ | -0.29 (0.13) |
| $\ln(\text{distance}_{kl})$ | 0.57 (0.03) |
| Constant | 4.24 (1.45) |

Scale elasticity: 1% increase in traffic on a leg reduces trade costs by about 0.06% ($\theta = 4.5$)

Median journey of 3 legs in microdata \Rightarrow 0.17% decrease in overall O-D trade costs

Direct Route Cost Estimates: Singapore



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How good are our estimates?

1. High correlation between cost estimates and container freight rates (Wong, 2020) [Results](#)
2. High correlation between model predicted US-bound shipments through trade network and US microdata [Results](#)
 - Robust to including links with zero traffic volumes in microdata

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Tight match between model estimates & observed data: Validity check of modeling approach

How good are our estimates?

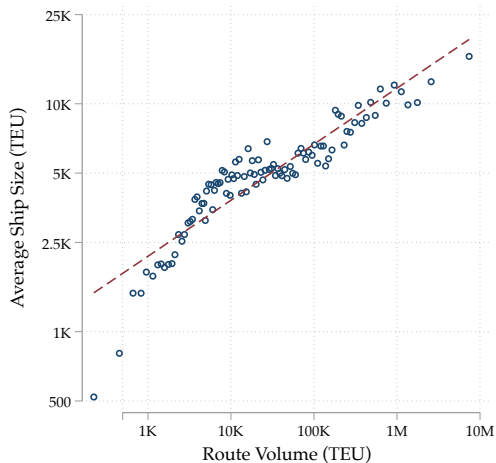
1. High correlation between cost estimates and container freight rates (Wong, 2020) Results
2. High correlation between model predicted US-bound shipments through trade network and US microdata Results
 - Robust to including links with zero traffic volumes in microdata

Tight match between model estimates & observed data: Validity check of modeling approach

3. Numerous mechanisms can generate cost reductions with trade concentration via hubs
 - Highlight scale economy mechanism using observed ship sizes (size \uparrow , cost estimates \downarrow)

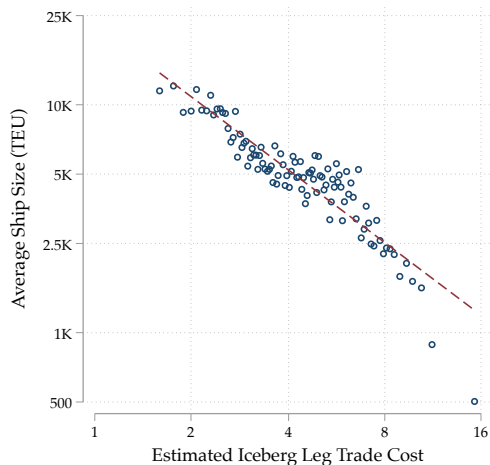
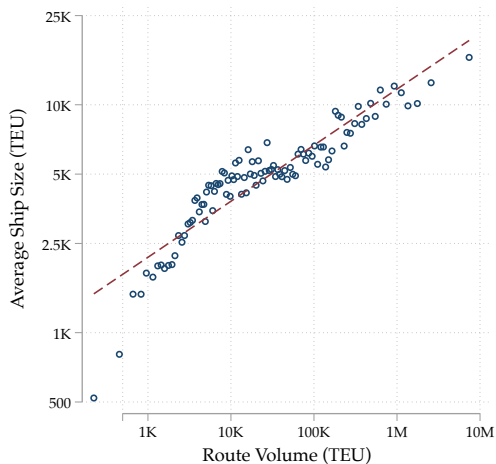
Mechanism for Scale Economy: Ship Size

- Routes with more traffic use larger ships



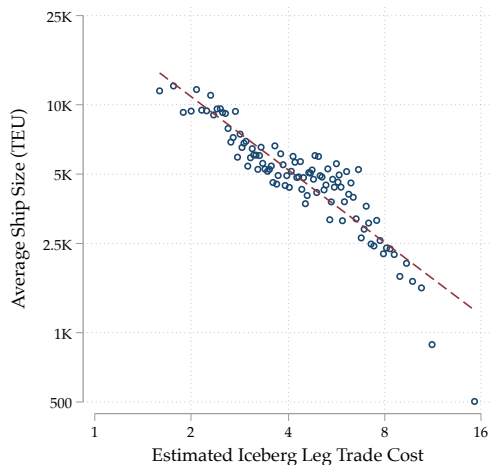
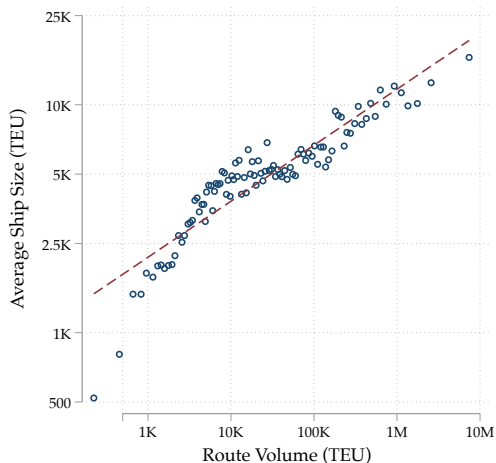
Mechanism for Scale Economy: Ship Size

- Routes with more traffic use larger ships; Routes with lower trade costs use larger ships



Mechanism for Scale Economy: Ship Size

- Routes with more traffic use larger ships; Routes with lower trade costs use larger ships
 - Goods from smaller origins routed through entrepôts also arrive on larger ships [Results](#)



Data

Stylized Facts

Model: Overview

Trade Cost and Scale Elasticity Estimation

Comparison of Model-Predicted Estimates to Data

Counterfactual

Conclusion

Counterfactuals

- Embed model into Caliendo and Parro (2015) with 3 sectors: (1) Containerized, (2) Non-containerized, (3) Non-traded and cross-border I-O linkages
- Calculate trade flow and welfare changes using hat algebra (Dekle, Eaton, & Kortum 2008)

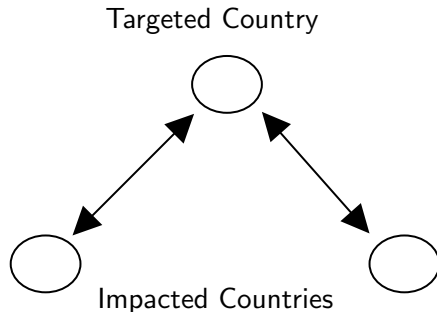
Counterfactuals

- Embed model into Caliendo and Parro (2015) with 3 sectors: (1) Containerized, (2) Non-containerized, (3) Non-traded and cross-border I-O linkages
- Calculate trade flow and welfare changes using hat algebra (Dekle, Eaton, & Kortum 2008)
- 3 CFs to illustrate short-to-medium term impact of entrepôts & trade network on welfare:
 1. Country-level transport vs non-transport improvements
 2. Brexit: 5% increase in tariffs for goods that originate or are destined for UK
 3. Arctic passage: Sea distance decrease between North America, Northern Europe, & East Asia

Transport vs Non-Transport Improvements

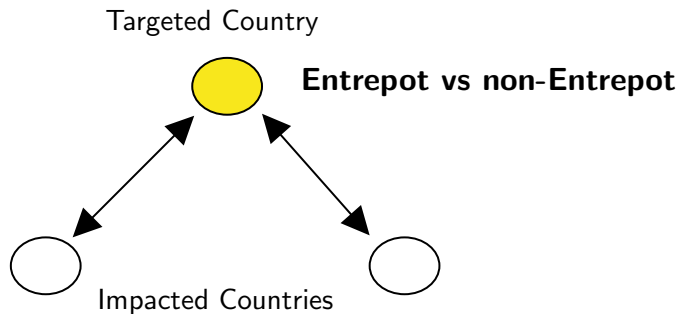
- For each targeted country, decrease transport costs by 1% (infrastructure improvement) vs non-transport trade costs by 1% (tariff liberalization)
- Evaluate eqm with & without scale impact (136 countries * 4 cases = 544 CFs)
 - Without scale, transport changes exogenously affects network while non-transport changes has no impact. Feedback loop with scale: as trade costs change, traffic volumes change

Details



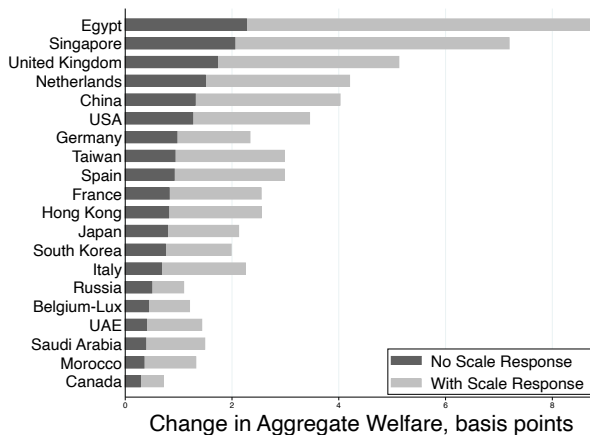
Which countries are pivotal to the trade network?

Calculate impact of changes at targeted country on global welfare excluding a country's own



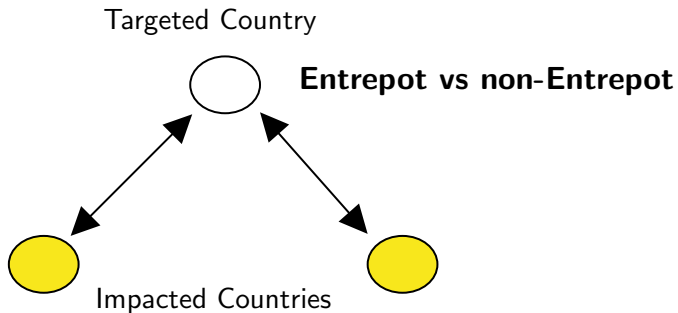
Which countries are pivotal to the trade network?

- Large world welfare impacts from transport improv in Egypt, Singapore, and Netherlands
 - Entrepôts generate 10 times the global welfare impact relative to elsewhere
- Tariff improvements on big trading countries have larger world welfare impact instead



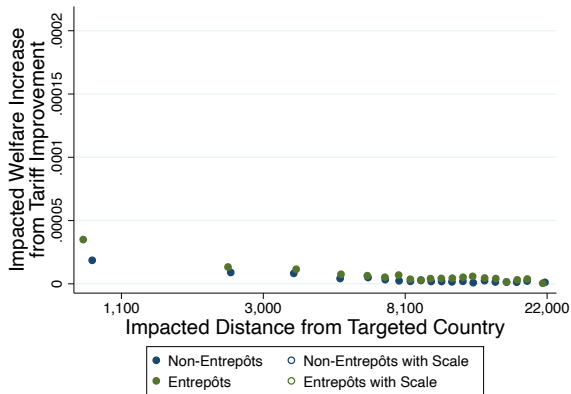
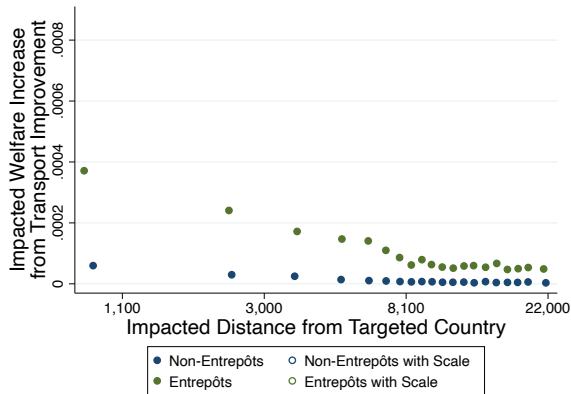
Impact of entrepôts are localized

Consider welfare on impacted country relative to distance from targeted country



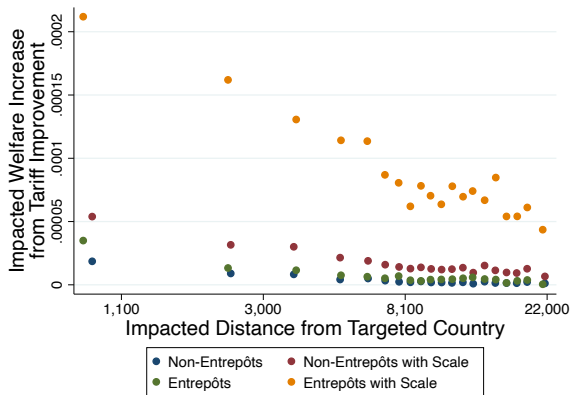
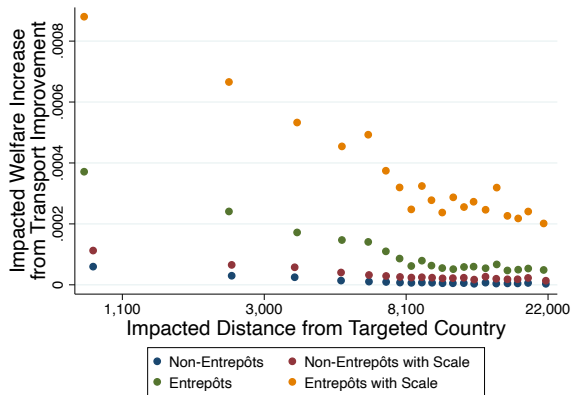
Impact of entrepôts are localized

- Impacted country welfare decrease with distance (gravity) away from targeted country
- Transport improvement at entrepôts have larger localized impact (green vs blue on left)



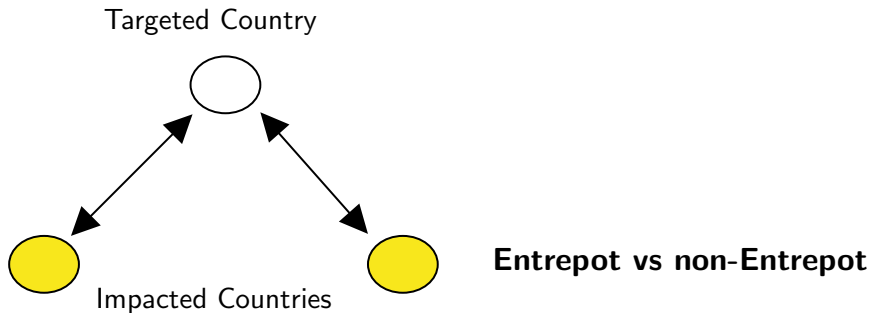
Impact of entrepôts are localized

- Impacted country welfare decrease with distance (gravity) away from targeted country
- Transport improvement at entrepôts have larger localized impact (green vs blue on left)
- Scale economies magnify the localization, especially for entrepôts (orange vs red dots)



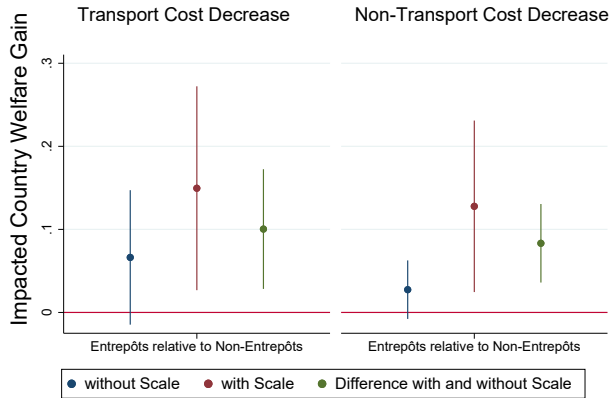
Scale economies concentrate gains to entrepôts

Consider how cost reductions affect impacted countries when they are entrepôts vs not



Scale economies concentrate gains to entrepôts

- With scale, impacted countries who are entrepôts are differentially affected
- Scale economies in transportation concentrate gains locally at and around entrepôts: highlight scale economies in transportation as a source of agglomeration

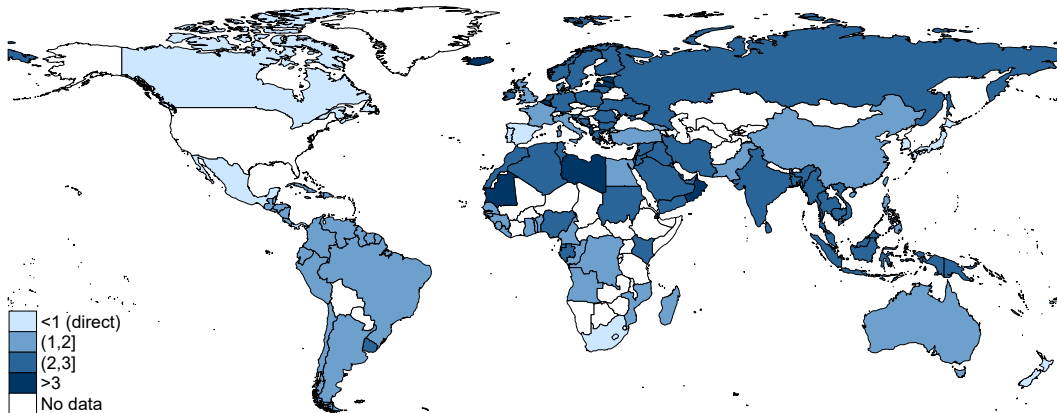


Conclusion

- We study entrepôts, the network they form, and their impact on international trade
- Novel empirical evidence: trade network is a hub and spoke system where majority (80%) of trade is indirect and concentrated through entrepôts
- Estimate new global trade costs from quantitative GE model with endogenous shipping routes and hub formation within Ricardian setting and scale economies
- Develop geography-based IV to estimate scale effect of traffic on shipping trade costs
- Entrepôts are pivotal to trade network, have 10 times global welfare impact from transport improvement rel to non-entrepôts, with scale amplifying the benefits concentration

How indirect is trade?

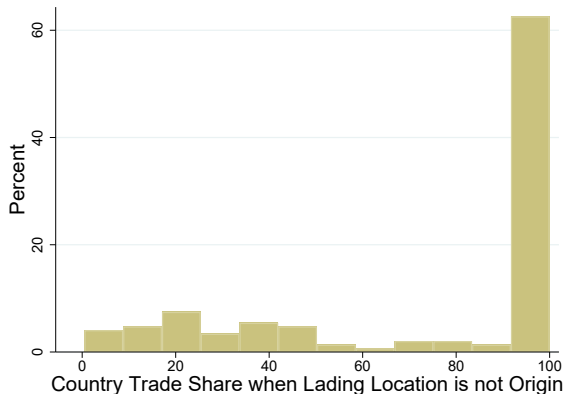
- Average number of stops on a container from foreign origin to US-destination
- 2 country stops on average (sd 1.3)



Landlocked countries are also not included since by definition they would need to stop at a coastal country (34, accounting for 1.6% of total TEUs).

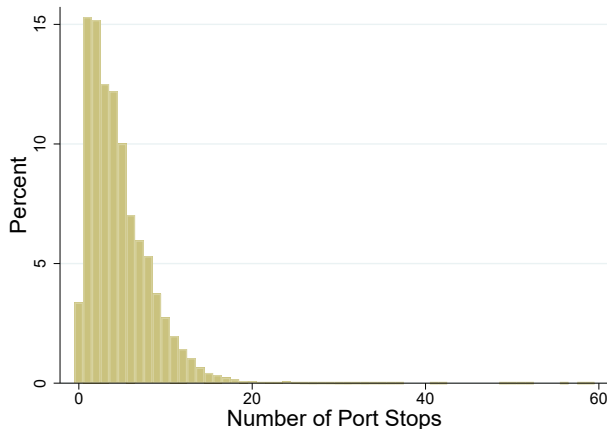
How indirect is trade?

- Alternative measure of indirectness: *transshipment*, when origin country of shipment is not the same as country where it was loaded onto US-bound containership
- > 60% of containers from origin countries are transshipped in third country



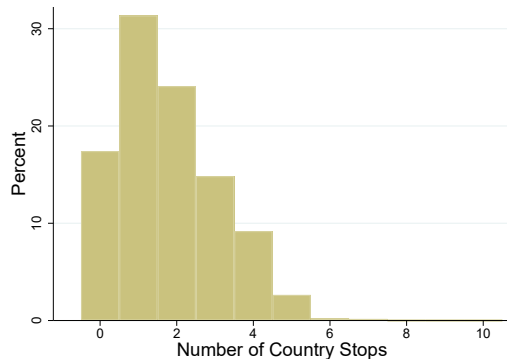
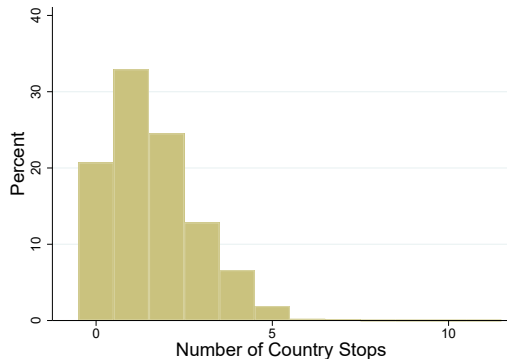
Indirectness of Trade

Number of port stops per TEU



About 15% of containers (TEUs) are direct, making no stops along the way, and the average number of port stops is 5.5 [Back](#)

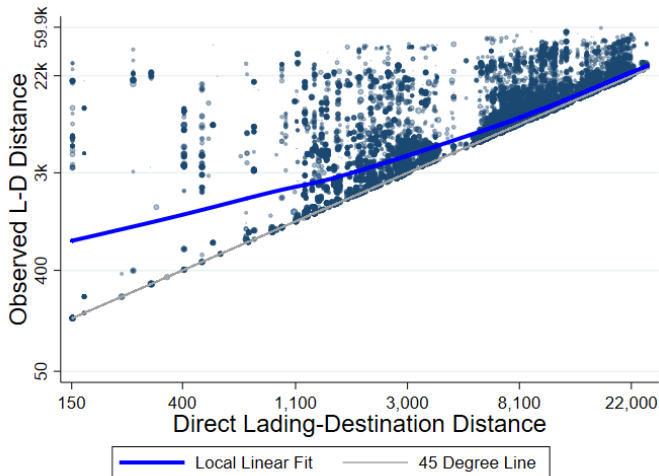
Indirectness of Trade by Weight and Value



About 70% of shipment weight and more than 80% of shipment value is indirect

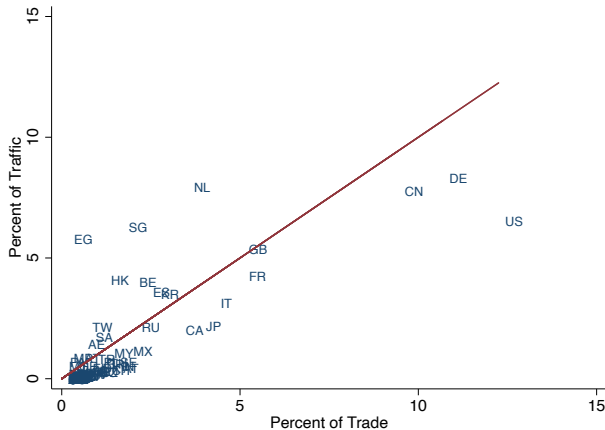
[Back](#)

- Actual traveled O-D distance is 31% more than direct, 14% for lading (Stop 1)-D



Global Data

Percent Transit Volume vs Percent Originated



Replicates microdata figure using global port of call and trade data with adjustments made for unobserved overland traffic [Back](#)

Definition of Entrepôts

Our measure entrepôt activity aims to capture the use of location l above and beyond its role as an exporter to j (top 15 countries):

$$Entrepôt_{l,j} \equiv \pi_j^l - \pi_{l,j}$$

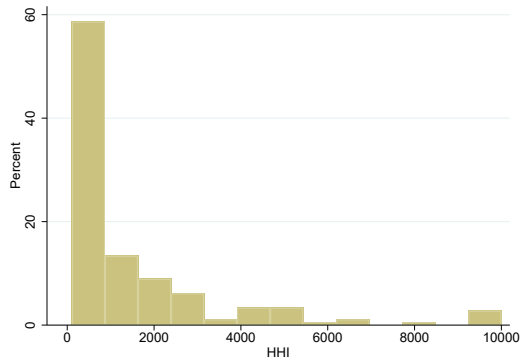
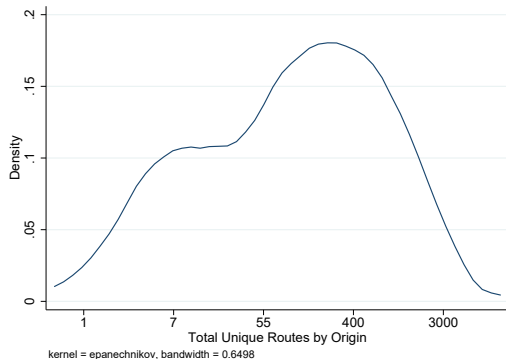
where country j 's usage of entrepôt l for its imports is the difference between π_j^l , the share of j 's imports flowing through l , and $\pi_{l,j}$ the share of j 's imports originating at l

These 15 entrepôts are Egypt, Singapore, Netherlands, Hong Kong, Belgium, Taiwan, Spain, Saudi Arabia, South Korea, the United Arab Emirates, Morocco, Panama, Malta, Portugal, and the United Kingdom

Variation in Trade Indirectness

Left Panel: Distribution in the number of unique routes to US by origin (mean 397, sd 681)

Right Panel: 70 percent of origin countries have low concentration of routes ($\text{HHI} < 1500$)



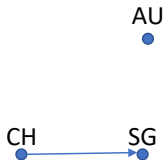
Geography-Based IV

Start with two possible legs: CH-SG and CH-AU



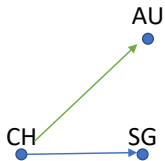
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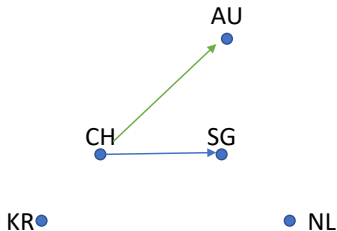


Geography-Based IV

Start with two possible legs: CH-SG and CH-AU

Intuition for IV:

Traffic flows from Origin KR to Dest NL are more likely to pass through CH-SG than CH-AU because CH-SG is closer to the direct KR-NL route



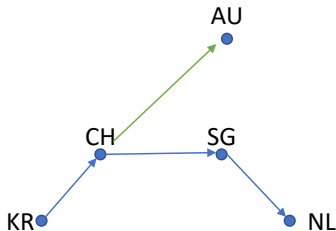
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KR-NL route that includes CH-SG is closer to direct KR-NL route



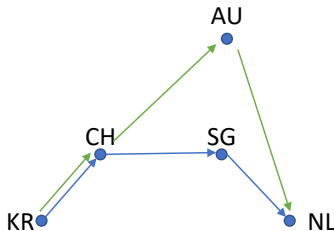
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KR-NL route that includes CH-SG is closer to direct KR-NL route compared to including CH-AU link, which is further away



Geography-Based IV

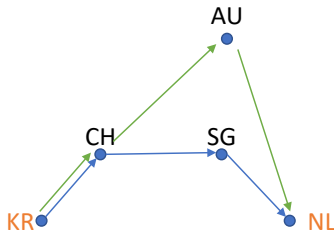
Start with two possible legs: CH-SG and CH-AU

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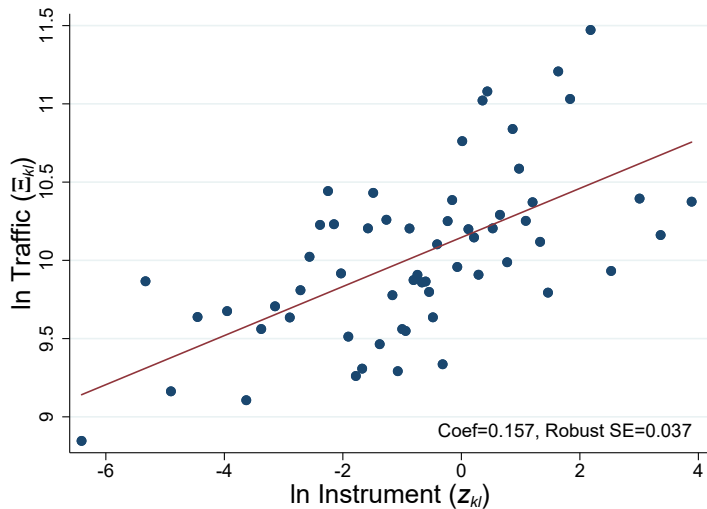
Traffic flows from Origin KR to Dest NL are more likely to pass through CH-SG than CH-AU because CH-SG is closer to the direct KR-NL route

KR-NL route that includes CH-SG is closer to direct KR-NL route compared to including CH-AU link, which is further away
Demand for CH-SG will be even higher, the bigger KR-NL is as a route

Being closer to “bigger” routes increases traffic demand



Residualized Plot of Correlation Between Instrument and Traffic



Estimation Details

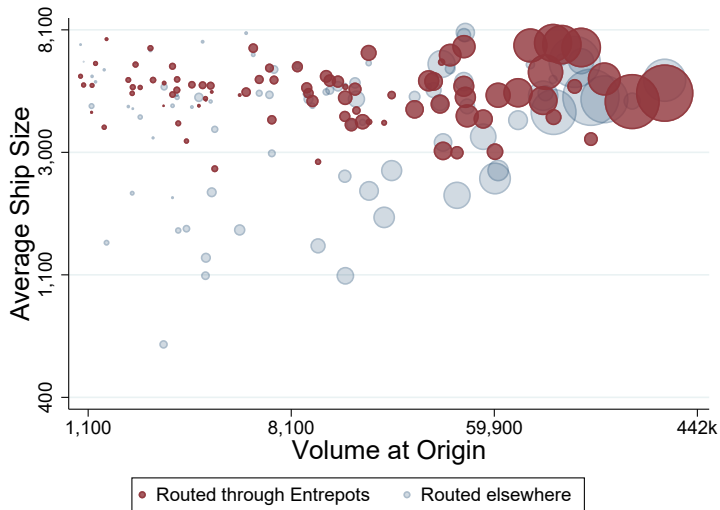
- Do not observe land based/within-country traffic: issue for contiguous countries
- Saturate variation in data to generate closest data prediction to estimates
- Functional form: $t_{kl}^{-\theta} = \frac{1}{1+\exp(Y\beta)} \in [0, 1]$
- Matrix Y is a vector of covariates defined as:

$$Y\beta = \beta_0 + \beta_1 \log \text{sea distance}_{ij} + \beta_2 \log \text{traffic}_{ij} + \beta_3 \log \text{traffic}_i \\ + \beta_4 \log \text{traffic}_j + \beta_5 \mathbb{1}_{\text{backhaul}} + \beta_6 \mathbb{1}_{\{i,j \in \text{Land Borders}\}}$$

where β_0 is an intercept, β_1 considers sea distance between the nearest principal port, and β_2 considers port-to-port traffic. β_3 and β_4 consider the total incoming and outgoing traffic at ports i and j respectively. β_5 considers the role of the backhaul problem from Wong (2020), where ship capacity is fixed by the shipping direction with the higher demand. The indicator variable simply consider if the traffic from i to j is more or less than the traffic from j to i . Finally β_6 consider an indicator variable for two countries that share a land border.

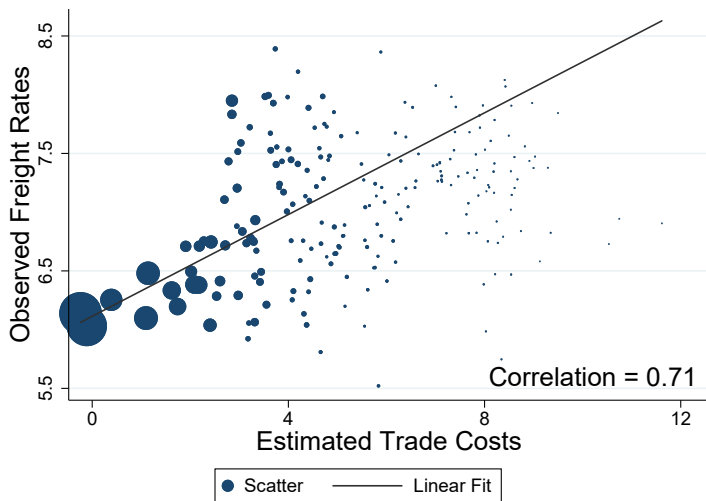
Link Between Indirect Trade and Ship Size

Larger origins transport goods to the US on larger ships. However, shipments from smaller origins routed through entrepôts also arrive on large ships.



How good are our estimates of global leg-level costs?

2. Compare trade cost estimates with actual freight rates paid by firms (Wong, 2020)



How good are our estimates of global leg-level costs?

2. Compare model predicted US-bound shipments through trade network with micro data

| | (1) $\widehat{\pi}_{iUS}^{kl}$ | (2) $\widehat{\Xi}^{kl}$ | (3) $\widehat{\pi}_{US}^I - \widehat{\pi}_{I,US}$ | (4) $\widehat{\pi}_{iUS}^{kl}$ | (5) $\widehat{\Xi}^{kl}$ | (6) $\widehat{\pi}_{US}^I - \widehat{\pi}_{I,US}$ |
|-------------------------------------|-----------------------------------|-----------------------------|--|-----------------------------------|-----------------------------|--|
| $\pi_{iUS,Data}^{kl}$ | 0.846 | | | | | |
| | (0.119) | | | | | |
| Ξ_{Data}^{kl} | | | | | | |
| $\pi_{US,Data}^I - \pi_{I,US,Data}$ | | | | | | |
| Observations | 13813 | | | | | |
| Data | | | | | | |
| R^2 | 0.513 | | | | | |
| F | 50.54 | | | | | |

Standard errors clustered by origin and destination countries.

Model predicted variables: $\widehat{\pi}_{iUS}^{kl}$ is share of goods from origin i to US destination through legs k and I , $\widehat{\Xi}^{kl}$ is the total US-bound traffic on legs k and I , $(\widehat{\pi}_{US}^I - \widehat{\pi}_{I,US})$ is the total US-bound traffic through node I subtracting i 's US exports—entrepôt usage of I for US-bound shipments. Corresponding observed variables in microdata has subscript *Data*.

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| $\pi_{iUS,Data}^{kl}$ | 0.846 (0.119) | | | | | |
| Ξ_{Data}^{kl} | | 1.224 (0.128) | | | | |
| $\pi_{US,Data}^I - \pi_{I,US,Data}$ | | | | | | |
| Observations | 13813 | 652 | | | | |
| Data | | | | | | |
| R^2 | 0.513 | 0.659 | | | | |
| F | 50.54 | 91.60 | | | | |

Standard errors clustered by origin and destination countries.

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| Ξ_{Data}^{kl} | | 1.224 (0.128) | | | | |
| $\pi_{US,Data}^I - \pi_{I,US,Data}$ | | | 0.945 (0.111) | | | |
| Observations | 13813 | 652 | 95 | | | |
| Data | | | | | | |
| R^2 | 0.513 | 0.659 | 0.410 | | | |
| F | 50.54 | 91.60 | 22.91 | | | |

Standard errors clustered by origin and destination countries.

Model predicted variables: $\widehat{\pi}_{iUS}^{kl}$ is share of goods from origin i to US destination through legs k and I , $\widehat{\Xi}^{kl}$ is the total US-bound traffic on legs k and I , $(\widehat{\pi}_{US}^I - \widehat{\pi}_{I,US})$ is the total US-bound traffic through node I subtracting i 's US exports—entrepôt usage of I for US-bound shipments. Corresponding observed variables in microdata has subscript *Data*.

How good are our estimates of global leg-level costs?

2. Compare model predicted US-bound shipments through trade network with micro data

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|-------------------------------------|-----------------------------------|-----------------------------|--|-----------------------------------|-----------------------------|--|
| $\pi_{iUS,Data}^{kl}$ | 0.846 (0.119) | | | 0.872 (0.121) | | |
| Ξ_{Data}^{kl} | | 1.224 (0.128) | | | 1.240 (0.126) | |
| $\pi_{US,Data}^l - \pi_{l,US,Data}$ | | | 0.945 (0.111) | | | 0.967 (0.115) |
| Observations | 13813 | 652 | 95 | 366010 | 2153 | 186 |
| Data | | | | All | All | All |
| R^2 | 0.513 | 0.659 | 0.410 | 0.513 | 0.669 | 0.415 |
| F | 50.54 | 91.60 | 22.91 | 51.75 | 96.88 | 22.53 |

Standard errors clustered by origin and destination countries.

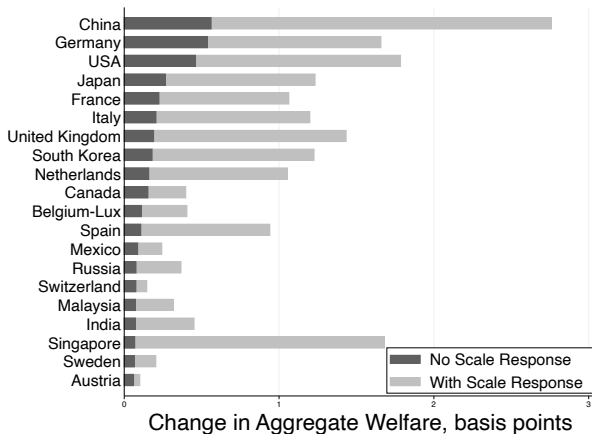
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Scale Counterfactual

Algorithm 1 Scale Counterfactual Algorithm

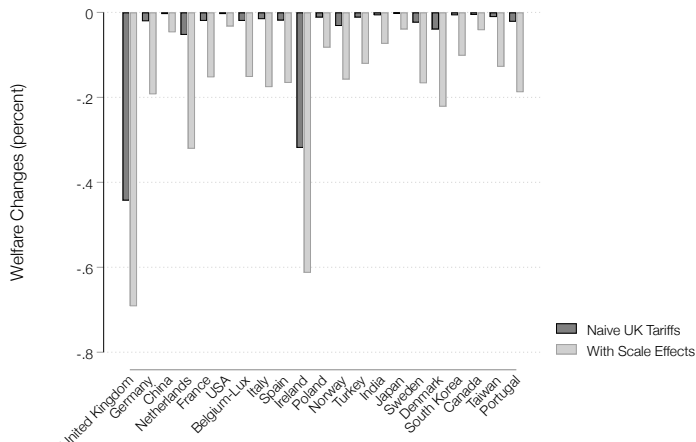
- 1: **procedure** WELFARE CHANGE(X_0, Ξ_0, \hat{t}) ▷ Find a new equilibrium
 - 2: Initialize current trade flows X_0 and traffic Ξ_0
 - 3: Initialize changes in cost fundamentals \hat{t} ▷ Example: shipping distances changes
 - 4: Compute $A_0 = A(\Xi_0; \hat{t})$ ▷ Following equation 12
 - 5: Compute $B_0 = (I - A_0)^{-1}$
 - 6: Initialize difference = ∞ , tolerance = ϵ
 - 7: **while** *difference* < *tolerance* **do**
 - 8: Update trade flows $X_1 = X(B_0)$ ▷ Solving 6.1.1
 - 9: Update traffic $\Xi_1 = \Xi(X_1, A_0, B_0)$ ▷ Following equation 10
 - 10: Update leg costs $A_1 = A(\Xi_1)$
 - 11: Update trade costs $B_1 = (I - A_1)^{-1}$
 - 12: Compute *difference* = $\sum_{ij} (B_1 - B_0)^2$
 - 13: Update $A_0 = A_1$ and $B_0 = B_1$
 - 14: Return final trade flows X_1
 - 15: Compare welfare and price index changes between X_1 and X_0 ▷ Solving 6.1.1
-

- Tariff improvements on big trading countries have larger world welfare impact instead



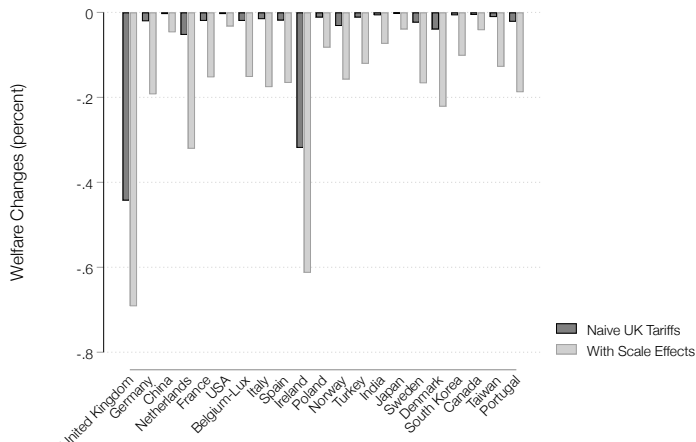
Brexit

- Naive Brexit: No spillover in costs to goods that stop/transship in UK
 - Irish exports to UK affected, Irish exports to US not affected (even if it goes via UK)

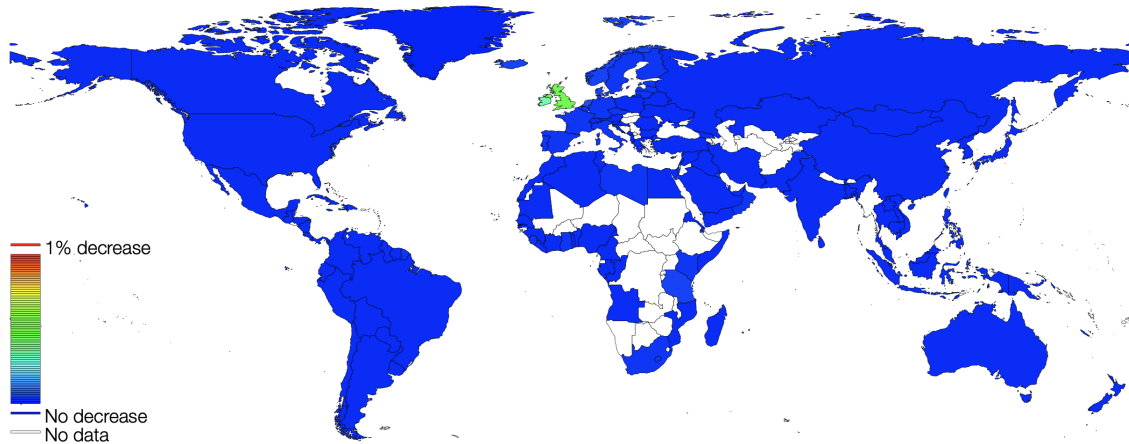


Brexit

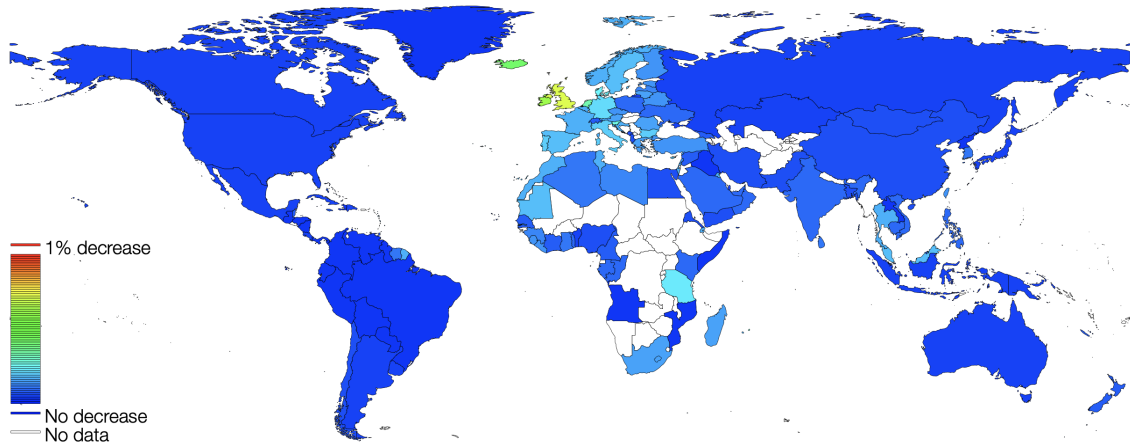
- Naive Brexit: No spillover in costs to goods that stop/transship in UK
 - Irish exports to UK affected, Irish exports to US not affected (even if it goes via UK)
- Scale and Networks: UK trade costs \uparrow , Irish exports to US now more expensive



Hard Brexit: Baseline

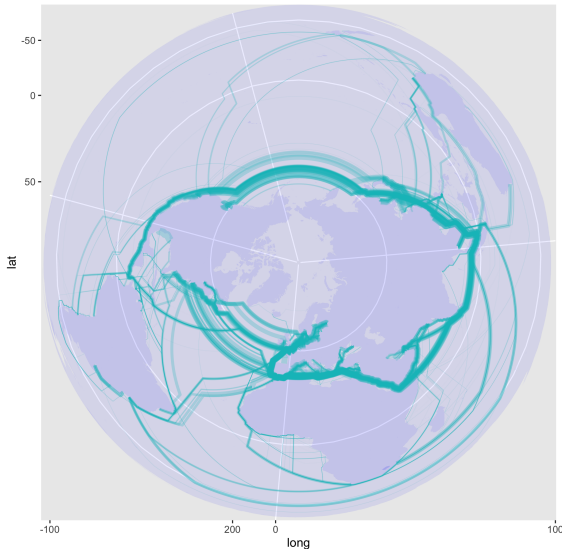


Hard Brexit: Scale and Network Effects



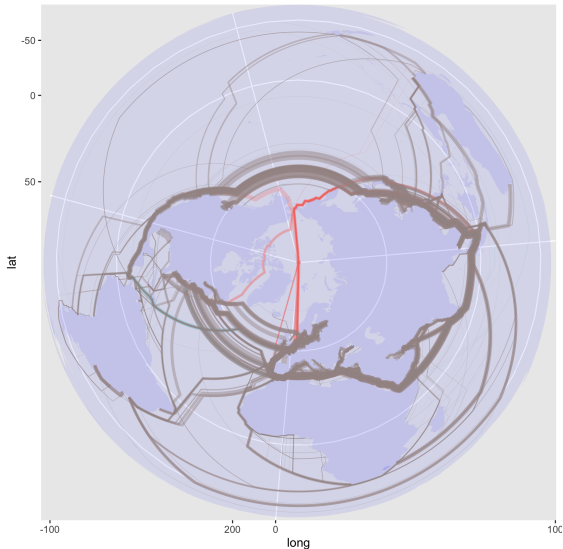
- Brexit effects are amplified throughout Europe
- Smaller countries who use UK as entrepôt are disproportionately hurt (Ireland & Iceland)

Arctic Passage



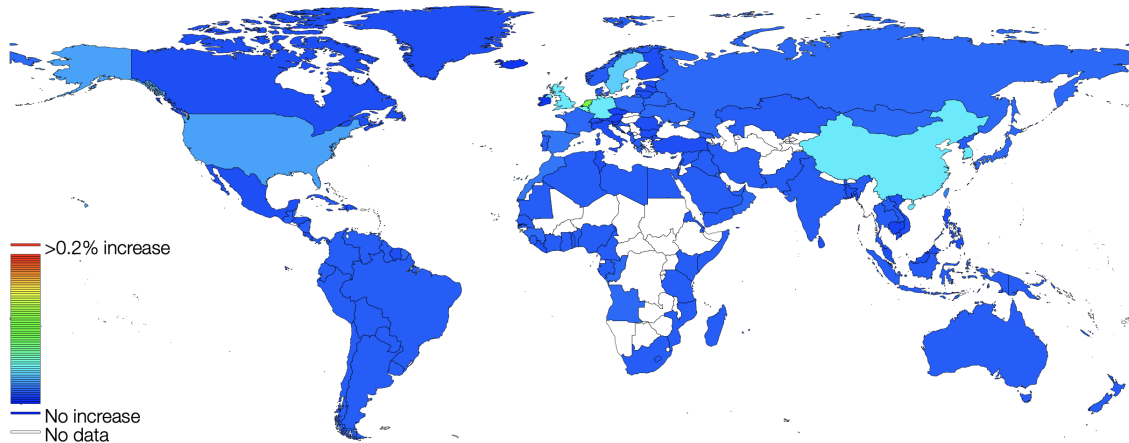
- Climate change has been melting polar ice caps and opening up previously inaccessible Arctic sea lanes
- Example: South Korea to Germany would take roughly 34 days via the Suez Canal but only 23 days via the Arctic Passage (the Economist, 2018)
- 30% reduction in average shipping distances for top routes

Arctic Passage



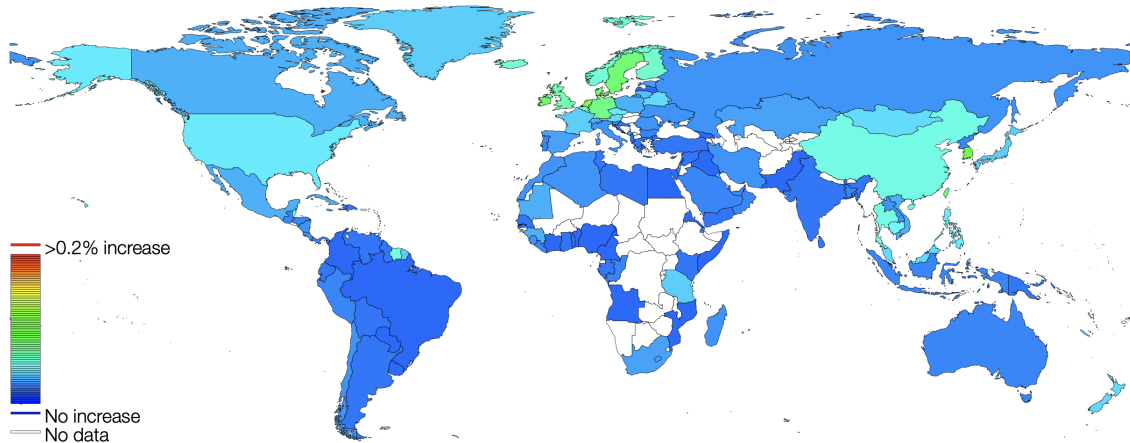
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Arctic Passage: Baseline



- Increase in trade between countries connected by the Arctic passage, very little spillover effects from classic multilateral resistance and value chain effects

Arctic Passage: Network Effects



- Allowing for indirect trade: spillovers to nearby countries
- Countries without direct transcontinental routes (who rely on entrepôts) benefit

