Trade and the Competition for Transport:

How (a Lack of) Competition in the Transportation Industry Affects Regional Trade Outcomes*

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Abstract

This paper seeks to understand how market structure for freight transportation affects domestic trade outcomes. I modify a standard Ricardian trade model to incorporate imperfectly-collusive transporters spanning multiple modes. Estimating the model's fundamentals reveals the expected per-mile iceberg trade cost for specific modes, the correlation of trade costs across disparate markets, and the ferocity of competition for freight transportation along individual segments of the domestic transit network. Calibrating the model to domestic trade flows, I find that: i) current losses due to non-competitive pricing are substantial, amounting to as much as 2% of U.S. GDP and suppressing international trade by as much as 70%; ii) these losses are concentrated in the Midwest, Southeast, and in urban centers aong the West Coast; iii) due to incomplete pass-through, imperfect freight competition mitigates the welfare impacts of exogenous shocks; iv) non-competitive markups genreate more geographically uniform impacts from exogenous shocks; and v) imperfect freight competition exacerbates the trade impacts international shocks.

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1 Introduction

Transportation is central to trade: how a good moves from its origin to its destination largely dictates its final price. Yet conventional trade models abstract away from the freight-service industry by assuming exogenous transport costs.[1] Recognizing this insufficiency, a raft of recent papers have sought to incorporate more realistic transportation sectors into canonical trade models (e.g. Fuchs and Wong, 2023; Allen and Arkolakis, 2022; Brancaccio et al., 2020). Sorely missing from this line of inquiry, however, is a comprehensive analysis of freight transporters' strategic price-setting behavior.

This paper seeks to understand how imperfect competition for freight services affects domestic trade outcomes. Towards this end, I modify an otherwise standard Ricardian trade model to allow for endogenous trade costs that respond to both the demand for transport as well as the degree of competition and/or collusion among transporters serving distinct markets (destinations). Building upon recent insights from the international trade literature, I further relax the strict independence assumptions which pervade conventional trade models, and allow correlation of trade costs across competing origins and routes. The model provides a straightforward framework to estimate: i) the state of competition among freight carriers within individual cities and modes throughout the mainland US; ii) expected trade costs along all major trade routes in the Lower-48; and iii) the correlation of these trade costs among distinct routes serving the same market. Beyond a descriptive tool, the model is useful for policy evaluation; I run a series of counterfactual simulations to estimate how imperfect competition for transport services exacerbates and/or mitigates the welfare impacts of domestic infrastructure investment as well as an international trade shock. The model thus provides a powerful framework to estimate the impact of imperfect competition for freight transport on the US economy.

A handful of trade papers have related market structure in the transportation industry to trade outcomes (Brancaccio et al., 2020; Atkin and Donaldson, 2015); none, however, model competition both within and across modes, as well as across space. Building upon longstanding insights from empirical IO, I summarize the ferocity of freight competition (or lack thereof) within each market-

[1] This strict exogeneity assumption stems from Samuelson (1954), who first proposed an exogenous iceberg trade cost formulation in order to generate a tractable expression of trade flows. While convenient, this assumption is undoubtedly an oversimplification

mode combination via a single parameter (Bresnahan, 1982). The power of this approach is that it does not assume a particular solution concept (e.g. Bertrand, Cournot, Nash bargaining, etc.). Rather, the theory permits a continuum of competitive outcomes; the prevailing equilibrium for each destination and mode is identified empirically. Moreover, this competition parameterization nests neatly within an otherwise standard iceberg trade cost formulation, thus retaining a simple gravity expression for trade flows. In other words, my model flexibly captures the competitive landscape for freight services among individual destinations and modes across the mainland US while maintaining the empirically tractable log-linear expression of trade flows that is the hallmark of conventional gravity models.

The model also reflects the multi-faceted and supremely dense nature of the US transit network. Between every origin and destination pairing, I allow not only a comprehensive set of modes,[2] but also multiple routes along each mode. This highly detailed choice structure is appealing first for its realism – instead of assuming a unique least-cost route between any two locations,[3] my model permits trade flows among alternate paths; these competing, parallel flows stem from unobserved, idiosyncratic efficiencies among transporters. Second, as demonstrated by Allen and Arkolakis (2022) as well as Fuchs and Wong (2023), modelling the transporter's route-choice problem allows me to express trade costs (and hence, trade flows) as a function of available infrastructure; the upshot of this approach in my model is that the estimated competition parameters reflect the density of the network.[4] Finally, this approach easily lends itself to a nested-logit formulation of trade shares (McFadden, 1984), which in turn offers a convenient and straightforward framework to evaluate the correlation of trade costs across competing routes serving the same destination.[5]

[2]Specifically, I analyse domestic freight movements via road, rail, inland and ocean waterways, air, as well as multi-modal movements. I exclude freight via pipeline, as it serves only a narrow subset of goods (i.e. crude oil, natural gas, and other petroleum products). The set of modes considered for any one origin-destination combination is determined by the presence of the relevant infrastructure. That is, I do not allow movements via – for example – water if no navigable waterway unites the two locations; the same logic applies to all modes. See section 3 for detail.

[3]Such a uniqueness assumption is usually made due to data constraints and/or for analytical convenience. See e.g. Allen and Arkolakis (2014), Donaldson and Hornbeck (2016), and Donaldson (2018), among others.

[4]Why should density matter for the transporters' pricing game? Routes serving the same origin-destination pairing are close substitutes. Sparse portions of the network thus imply a relative absence of close substitutes (or more precisely, the substitutes are less cost-competitive), which suggests greater opportunity to exploit market power. Indeed I find that current welfare losses due to non-competitive freight pricing are greatest among rural areas along relatively sparse portions of the network.

[5]Lind and Ramondo (2023) propose an Eaton and Kortum (EK) trade model with correlation of efficiencies across countries. They demonstrate that the conventional independence assumption is nontrivial, leading to vastly different welfare estimates than found using their correlation structure. I build upon their approach by allowing correlation of both production and transport efficiencies; these correlations, in turn, inform markups (see Section 2 for detail).

The model offers highly-granular, route-level insights; it is therefore notable that I estimate these fundamentals using exclusively public data. To elaborate, I populate potential trade routes utilizing detailed topographic information on the domestic transportation network from the National Transportation Atlas Databases (NTAD); I retrieve domestic trade flows in 2017 from the Freight Analysis Framework version 5 (FAF5). Both of these datasets are publicly-available from the Bureau of Transportation Statistics (BTS). However, the FAF5 data is aggregated by origin, destination, and mode; it does not provide route-level trade flows, which are necessary for estimation. I therefore rely on an expectation-maximization (EM) process – a well-known simulated method of moments strategy from the computer science literature, which has been used to some extent in the field of economics (e.g. Bonadio, 2021). No existing paper provides such a comprehensive and detailed view of the transportation sector using only public information.[6]

The model yields five, principal insights. First, I find that current losses due to non-competitive pricing in the freight sector are substantial, equalling approximately 2% of 2017 US GDP ($\sim$ \$393 billion). The lion's share of these losses stem from Air and Road freight – the former due to relatively high market concentration, and the latter due to substituion away from Air. Moreover, freight market concentration acts as a protectionist policy, reducing total U.S. imports and exports by as much as 70%. Second, I document significant regional heterogeneity in freight market power. Losses due to non-competitive markups are concentrated in the Midwest and Southeast, as well as in major urban centers along the West Coast; in turn, rural areas throughout the Great Plains, Mountain West, and New England, as well as urban centers along the Gulf of Mexico, *beneift* from trade dispersion sparked by non-competitive freight pricing. Third, due to incomplete cost pass-through, imperfect freight market competition mitigates the welfare impacts of exogenous shocks – this buffering is a two-way street, as it dampens the benefit of positive shocks like domestic infrastructure investment, but softens the blow from an exogenous cost shock. Fourth, non-competitive freight markets create more uniform impacts from exogenous shocks; this smoothing of geogrpahic heterogeneity stems from the transporter's profit motive. And finally, freight market concentration

[6] Other papers estimate detailed trade costs using confidential data. Most recently, Fuchs and Wong (2023) utilize the confidential waybill sample to estimate the impact of rail (as well as port) congestion throughout the domestic transport network; Brancaccio et al. (2020) estimate bargained freight rates using proprietary transaction data from Clarkson's Research. Others utilize public data, but narrow their focus to a a subset of modes – e.g. Allen and Arkolakis (2022) focus on roads; Donaldson (2018) focuses on rails; Ducruet et al. (2020) focuses on shipping networks.

exacerbates the trade impacts of an international shock.

This paper contributes to a growing body of trade papers, which explore the impact of freight transportation and infrastructure on trade outcomes. Recent papers along this line of inquiry have analysed the welfare effects of road and/or port congestion (Allen and Arkolakis, 2022; Bonadio, 2021;Fuchs and Wong, 2023), containerization (Coşar and Demir, 2018), and most popularly, network development/expansion (Jaworski et al., 2022; Ganapati et al., 2021; Donaldson, 2018; Ducruet et al., 2020; Donaldson and Hornbeck, 2016; Faber, 2014). However, all of these papers analyze only one or two modalities – e.g. roads, rail, or ports/ships. In contrast, I model all available modes simultaneously. Capturing the multi-faceted nature of the US transit network is important when studying the transporter's pricing decision, as competition weighs both within and across modes. Said differently, the consumer likely does not care *how* a good got to its destination, only that it arrived and its cheaper than all (quality-adjusted) alternatives. Thus, to stay cost-competitive, modes must compete with one another.[7] My primary contribution to this literature is to model competition among freight service providers, capturing price pressures both within and across modes.

The importance of multi-modal transport to domestic trade outcomes is highlighted in the parallel work by Fuchs and Wong (2023). In this important paper, the authors build upon a highly-tractable model of traffic flows (Allen and Arkolakis, 2022), to encompass multiple modes and costly transshipment. The upshot of this approach is that the authors may quantify how congestion along any one mode spills into the wider network; importantly, they identify key bottlenecks throughout the domestic transit network and estimate how even slight investments at these choke points create substantial gains throughout the nation. This paper underscores the importance of multi-modal shipping to domestic trade outcomes; however, the model treats transport costs (besides congestion) as exogenous. There is no consideration of competition for freight services within or across modes.

The present paper is most closely related to Brancaccio et al. (2020). In this work, the authors model the transport market with a matching function; freight rates are set via Nash bargaining. This paper is the first to model how transporters' strategic behavior impacts trade flows; however,

[7] Throughout the latter half of the 20th Century, domestic freight in the US was dominated by trucking. However, recent technological improvements, which facilitate near-seamless transshipment, have given new life to competing modes; multi-modal movements are now the second-most popular form of transit domestically (Bureau of Transportation Statistics and Federal Highway Administration, U.S. DOT, 2022).

their focus is solely on ships in the international freight market. In contrast, I focus on the multi-modal domestic transport network. Further, their matching function approach – which they utilize to explain ships' ballasting choices – assumes a Nash bargaining solution for freight-rates, which is governed by one, global bargaining parameter. In contrast, I evaluate the state of market power within distinct markets throughout the mainland US.

The rest of the paper is organized as follows. Section 2 develops my theoretical model, distinguishing between transport demand – equilibrium trade flows – and supply – a model of transporter's optimal pricing rule. Section 3 details my strategy for estimating the model fundamentals; it presents my data sources and expounds upon the EM algorithm, which exploits the structure of the model to estimate route-level trade costs from aggregated data. Section 4 discusses my estimated parameters and details the results of my counterfactual simulations. Section 5 concludes.

2 Theoretical Model

I develop a Ricardian trade model with a finite set of imperfectly-competitive transportation intermediaries. These intermediaries span multiple modes, and may pick among a selection of routes per mode. That is, transporters are not confined to the shortest path, but may elect more circuitous routes if they appear more profitable due to unobserved, exogenous costs. Further, transporters set markups endogenously to maximize profits; the key inputs into the transporter's problem include demand for freight transportation in their particular market (defined as trade between an origin, destination pairing ij), the costs incurred along the route r, and the ferocity of competition from other transporters serving the same market. Regarding competition: I do not take a stand a priori on a particular solution among competing trade routes, but adapt Bresnahan (1982)'s method to empirically estimate the state of competition. I now describe the model in detail.

2.1 Transportation Demand: Equilibrium Trade Flows

I begin with the familiar Eaton and Kortum (2002) framework. Trade in a unit-mass of goods Ω occurs amongst a discrete, finite set of locations $\mathcal{S}$. As my focus is on the domestic transit network, I distinguish between domestic locations $\mathcal{S}^d \subset \mathcal{S}$ and foreign markets $\mathcal{S}^f \subset \mathcal{S}$.[8] A further subset of

[8] I emphasize that these sets are disjoint, $\mathcal{S}^d \cap \mathcal{S}^x = \emptyset$.

domestic locations are international gates, $\mathcal{G} \subset \mathcal{S}^d$. All locations lie on a graph and are connected by a set of edges. A route between an origin and destination, $i, j \in \mathcal{S}$, comprises a set of edges that form an unbroken path between i and j. Routes need not be direct – a route may take a circuitous path spanning multiple edges. However, routes to an international destination *must* incorporate an international gate. Explicitly, transit to a foreign destination must pass through a port of exit $x \in \mathcal{G}$, while travel from a foreign origin must include a port of entry $e \in \mathcal{G}$. Let $\mathcal{R}_{ij}$ denote the set of all possible routes between i and j. Note that these routes are direction-dependent; that is, the set of edges forming a path from i to j is distinct from the same path moving from j to i. Further, the domestic network may be decomposed into distinct sub-graphs based on their mode. Let $\mathcal{M}$ denote the set of modes (e.g. Road, Rail, Water, Air, or Multi-modal), and let $\mathcal{R}_{ij}^m \subseteq \mathcal{R}_{ij}$ denote the subset of routes between i and j via mode $m \in \mathcal{M}$.[9] Figure 1 provides an illustrative example of the network.

Costs are incurred while traversing the network. Let $\tau_{r(i,e,x,j,m)}$ denote the cost of traversing route $r \in \mathcal{R}_{ij}^m$;[10] these transit costs take the standard iceberg formulation. I further assume that each location enjoys a uniform input cost c_i across all goods and employs constant returns to scale technology. Thus, the price of good ω, produced in i, taking route r to j is

$$p_{r(i,j)}(\omega) = \frac{c_i \tau_r}{\epsilon_r(\omega)} \tag{1}$$

where $\epsilon_r(\omega)$ is a composite production and transportation efficiency. It is worth highlighting that prices vary not only by their origin, but by the route taken en route to market. I assume perfect competition in the goods market such that the price paid by the consumer is the cheapest available alternative. That is:

$$p_j(\omega) = \min_{i \in \mathcal{S}} \left\{ \min_{r \in \mathcal{R}_{ij}} \{p_r(\omega)\} \right\}.$$

As in the traditional Eaton and Kortum model, I rely on a probabilistic representation of composite efficiencies to relate trade flows across locations and routes to a handful of easy-to-interpret parameters. Unlike the standard model, I follow McFadden (1984) to allow correlation of

[9] It is important to note that the set of modes is both exhaustive – such that $\mathcal{R}_{ij} = \cup_{m \in \mathcal{M}} \mathcal{R}_{ij}^m \ \forall\, i, j \in \mathcal{S}$ – and mutually exclusive – such that $\mathcal{R}_{ij}^m \cap \mathcal{R}_{ij}^{m'} = \emptyset \ \forall\, m, m' \in \mathcal{M}, m \neq m',$ and $\forall\, i, j \in \mathcal{S}$.

[10] Note that knowledge of the route implies knowledge of the origin i, destination j, domestic mode m, and ports entry e and exit x, if any. For ease of exposition, I will omit the extraneous subscripts where expedient.

efficiencies across the same origin and mode. Explicitly, the distribution function for the vector of log efficiencies in market j is given by:

$$F\begin{pmatrix}\ln\epsilon_1(\omega)\\ \ln\epsilon_2(\omega)\\ \vdots\end{pmatrix} = \exp\left(-\sum_{i\in\mathcal{S}}\left(\sum_{m\in\mathcal{M}}\left(\sum_{r\in\mathcal{R}_{ij}^m}\exp\left(\frac{-\ln A_i - \theta\ln\epsilon_r(\omega)}{\varphi\rho_j}\right)\right)^{\varphi}\right)^{\rho_j}\right). \tag{2}$$

In words, I assume a generalized extreme value distribution with location parameter A_i and scale parameter θ. The parameters $\rho_j, \varphi \in (0, 1]$ respectively govern the correlation of efficiencies from the same origin, mode;[11] a value of 1 implies no correlation across origins, modes; a value of 0 implies perfect correlation. Due to the correlation structure across nests, the interpretation of these parameters is altered somewhat from the original EK model. A_i governs absolute advantage, while θ, φ, and ρ_j jointly determine the prevalence of comparative advantage.[12]

Equation (2) is a generalization of the hallmark Fréchet assumption from the canonical Eaton and Kortum model. This formulation is attractive for two, key reasons. First, this logit model treats transport along different routes as differentiated services. Hence, different modes, as well as competing trade routes along the same mode, serve as imperfect substitutes. Second, the nesting structure dispenses with the assumption that efficiency shocks are independent across locations; rather, I allow correlation of these efficiencies across both origins and modes. This correlation structure relaxes the independence of irrelevant alternatives (IIA) assumption inherent in the standard logit model, which implies strict and often unrealistic substitution patterns. In this model, I require IIA to hold within, but not across nests.[13]

[11] In principle, I could allow ρ_j and φ to vary across origins, destinations, and in the case of the latter, modes. However, for reasons expounded in Section 3.2, I must fix φ to a constant value. In the case of ρ_j, identifying unique correlation coefficients for every origin, destination combination is computationally over-burdensome (see Section 3 for detail).

[12] See Lind and Ramondo (2023) for a complete discussion of the economic interpretation of these correlation parameters.

[13] To illustrate the potential pitfalls of IIA, consider the following, stylized example. Imagine that a transporter introduces a new rail route between an arbitrary origin and destination. Naturally, this new route will siphon traffic away from existing trade routes. IIA requires that the new route will draw from other routes in proportion to their trade shares, such that the ratio of trade shares among existing routes remains constant. However, it seems far more likely that the new rail line will dispraportionately draw trade away from other rail routes, and have less of an impact on trade via other modes. The nested structure of my model captures this more realistic substitution pattern.

I assume the following functional form for trade costs:

$$\tau_{r(i,e,x,j,m)} = \exp\Big(\underbrace{\mu_r}_{\text{markup}} + \underbrace{\kappa_r}_{\substack{\text{deterministic}\\ \text{costs}}} + \underbrace{u_r}_{\substack{\text{unobserved}\\ \text{quality}}} + \underbrace{\eta_{iem} + \nu_{xjm}}_{\substack{\text{international}\\ \text{trade cost}}} + \underbrace{\alpha_{im}}_{\substack{\text{first}\\ \text{mile}}} + \underbrace{\gamma_{jm}}_{\substack{\text{final}\\ \text{mile}}} \Big) \tag{3}$$

I now detail each component. The parameter μ_r is an endogenous markup set by the transporter, which reflects imperfect competition for freight services. Transporters set μ_r to maximize profit; the transporter's pricing rule naturally depends upon the state of competition for freight services within their market. I do not assume a particular solution to the transporter's pricing game; rather, I parameterize μ_r to flexibly capture a continuum of solution concepts (see Section 2.2 for detail). The deterministic component, κ_r, reflects the costs incurred per-mile while moving along a route – practically, this includes the cost of fuel, labor, and maintenance, and is taken as exogenous. The parameter u_r is unobservable route quality, which encompasses, e.g., infrastructure quality, congestion, and/or elevation gain. Following Berry (1994), I assume $u_r \sim N(0, v)$, and is drawn independently across routes. The parameters η_{iem} and ν_{xjm} capture costs incurred along the international leg of the journey (if any). Explicitly, η_{iem} presents the cost of travelling from an international origin i to a domestic port of entry e, while ν_{xjm} is the cost of travelling from a domestic port of exit x to a foreign destination j. For imports (exports), these parameters also capture costs incurred at the port of entry (exit). In the case of purely domestic shipments, both of these parameters are zero. Finally, the parameters α_{im} and γ_{jm} capture a wide array of otherwise unobserved location-by-mode-specific costs. These include the cost of entering/exiting a domestic location via mode m, and reflect, e.g., port, yard, and/or inner-city congestion. These parameters also capture stand-alone, mode-specific costs, such as loading times, product composition, network-wide congestion, and/or reliability.

The distributional assumption on composite efficiencies, coupled with perfect competition in the market for tradeable goods, yields a two-level nested logit[14] formulation for trade shares:[15]

$$\pi_{r|ijm} = \exp\left(-\theta[\mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{xjm}]/(\rho_j\varphi) - J_{ijm}\right) \tag{4}$$

$$\pi_{m|ij} = \exp\left(-\theta[\alpha_{im} + \gamma_{jm}]/\rho_j + \varphi J_{ijm} - I_{ij}\right) \tag{5}$$

[14] Note that if $\varphi = 1$, the model collapses to a one-level nested logit with origins as nests; if $\rho_j = 1$ then the model collapses to a one-level nested logit with origin, mode pairs as nests; if $\varphi = \rho_j = 1$, the model collapses to a standard (non-nested) logit, which yields market shares analogous to those derived in Eaton and Kortum (2002).

[15] See Train et al., 1987 for detailed derivations.

$$\pi_{i|j} = \exp\left(-\ln A_i - \theta \ln c_i + \rho_j I_{ij} - Q_j\right) \tag{6}$$

where

$$J_{ijm} = \ln \sum_{r \in \mathcal{R}_{ij}^m} \exp\left(-\theta[\mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{xjm}]/(\rho_j \varphi)\right) \tag{7}$$

$$I_{ij} = \ln \sum_{m \in \mathcal{M}} \exp\left(-\theta[\alpha_{im} + \gamma_{jm}]/\rho_j + \varphi J_{ijm}\right) \tag{8}$$

$$Q_j = \ln \sum_{i \in \mathcal{S}} \exp\left(-\ln A_i - \theta \ln c_i + \rho_j I_{ij}\right) \tag{9}$$

I combine these conditional probabilities to find the trade share along any one route:

$$\begin{aligned}
\pi_{r(i,e,x,j,m)} =& \pi_{r|ijm}\pi_{m|ij}\pi_{i|j} \\
=& \exp\Big(- \ln A_i - \theta\big[\ln c_i + (\mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{xjm})/(\rho_j\varphi) + (\alpha_{im} + \gamma_{jm})/\rho_j\big] \\
& - (1-\varphi)J_{ijm} - (1-\rho_j)I_{ij} - Q_j\Big).
\end{aligned}$$

Some straightforward (though tedious) algebra yields (see Appendix A.1 for detail):

$$\begin{aligned}
\pi_{r(i,e,x,j,m)} =& \exp\Big(- \ln A_i - \theta\big[\ln c_i + \mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{xjm} + \alpha_{im} + \gamma_{jm}\big] \\
& + (1-\rho_j\varphi)\ln \pi_{r|ijm} + (1-\rho_j)\ln \pi_{m|ij} - Q_j\Big).
\end{aligned} \tag{10}$$

Finally, consumers enjoy CES utility with elasticity parameter $\sigma \in (1, \theta + 1]$. Explicitly, consumers consume a quantity of each good, $q(\omega)$ to maximize $U = \left(\int_\Omega q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}}$ subject to a budget constraint that aggregates to a trade balance condition. That is, the sum total value of imports must equal the sum total value of exports in location j. The assumption of CES utility implies a CES price index in location j (see Appendix A.2 for detail). Further, I adhere to the structure laid out in Eaton and Kortum (2002) and assume a Cobb-Douglas aggregate of input costs, with labor having a constant share β. These conditions yield expressions for input costs, prices, and wages:

$$c_i = w_i^\beta p_i^{1-\beta} \tag{11}$$

$$p_j = \Gamma\left(\frac{\theta + 1 - \sigma}{\theta}\right)^{\frac{1}{1-\sigma}} Q_j^{-\frac{1}{\theta}} \tag{12}$$

$$L_i w_i = \sum_{k\in\mathcal{S}} \sum_{m\in\mathcal{M}} \sum_{r\in\mathcal{R}_{ik}^m} \pi_r L_k w_k \tag{13}$$

where w_i, L_i are the wage, population in location i, and Γ denotes the gamma function. Taken together, Equations (4) - (13) characterize a modified Ricardian model of trade, allowing for a multiplicity of trade routes between locations, imperfect modal substitution, and imperfect competition for freight transport services.

2.2 Transportation Supply: Setting Markups

A key component of trade costs is the route-level markup, μ_r. These markups reflect the level of competition for transportation services in a specific market ij, and are a critical insight of the model. I do not assume a particular solution concept to the transporter's pricing game within distinct markets and modes; instead, I follow Bresnahan (1982) to derive a simple expression for markups that encompasses a wide range of solution concepts (including the extreme cases of perfect competition and perfect oligopoly). I now describe the structure that yields this result.

Each route is served by a finite number of freight-service-providers, indexed by $t = 1, ..., T_r$. Denote the individual transporter's trade share by ψ_r^t; note that $\sum_{t=1}^{T_r} \psi_r^t = \pi_r$. It follows that total revenue and total cost for a transporter operating along a given route r will be:

$$\begin{aligned} TR_r^t =& B_j \psi_r^t \big(\exp\left(\mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{xjm} + \alpha_{im} + \gamma_{jm}\right) - 1 \big) \\ TC_r^t =& B_j \psi_r \big(\exp\left(\kappa_r + u_r + \eta_{iem} + \nu_{xjm} + \alpha_{im} + \gamma_{jm}\right) - 1 \big) \end{aligned}$$

where B_j is the total expenditure of destination j. The transporter's pricing rule obviously depends upon the state of competition: a perfectly competitive transporter will set price equal to marginal cost, while a monopolist (or perfect oligopoly) will set prices such that marginal demand equals marginal cost. Following Bresnahan (1982), I characterize *perceived* marginal revenue, which neatly encompasses the transporter's marginal revenue over a continuum of solution concepts, including the extremes of perfect competition and monopoly:

$$\begin{aligned} PMR_r^t =& B_j \big(\exp(\mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{jxm} + \alpha_{im} + \gamma_{jm}) - 1 \big) + \\ & \lambda_r B_j \psi_r^t \exp(\mu_r + \kappa_r + u_r + \eta_{iem} + \nu_{jxm} + \alpha_{im} + \gamma_{jm}) (\partial \mu_r / \partial \psi_r^t) \end{aligned}$$

where $\lambda_r \in [0,1]$ captures the state of competition along a particular route. The transporter's marginal cost takes a similar formulation:

$$MC_r = B_j\big(\exp(\kappa_r + u_r + \eta_{iem} + \nu_{jxm} + \alpha_{im} + \gamma_{jm}) - 1\big).$$

Setting perceived marginal revenue to marginal cost yields the following pricing rule:

$$\mu_r = -\ln\big(1 + \lambda_{ijm}\psi_r^t(\partial\mu_r/\partial\psi_r^t)\big).$$

It will prove expedient to define:

$$\delta_{r(i,j,m)} = -\theta\pi_{ijm}\frac{\partial\mu_r}{\partial\pi_r}\frac{\partial\pi_r}{\partial\psi_r^t} = \frac{\varphi\rho_j\pi_{ijm}}{\pi_r(1-(1-\varphi)\pi_{r|ijm} - (1-\rho_j)\varphi\pi_{m|ij}\pi_{r|ijm} - \varphi\rho_j\pi_r)}. \tag{14}$$

The pricing rule is thus:

$$\begin{aligned}\mu_r &= -\ln\left(1 - \lambda_{ijm}\left(\frac{\psi_r^t\delta_r}{\theta\pi_{ijm}}\right)\right)\\ &\approx \lambda_{ijm}\left(\frac{\psi_r^t\delta_r}{\theta\pi_{ijm}}\right)\end{aligned}$$

where this last step follows from a first-order Taylor Series expansion about 1.

I now shift my attention to the transporter's trade share, ψ_r^t. Unfortunately, absent transaction-level data on individual freight movements, I cannot identify trade shares more refined than the route-level. I therefore impose the following structure. Let $T_{ijm} \in \mathbb{Z}_{++}$ denote the number of transporters serving market ij via mode m. I assume Cournot competition among transporters serving the same market,[16] such that

$$\psi_r^t = \frac{\pi_{ijm}}{T_{ijm}}.$$

With this expression for the transporter's trade share, I may define markups based solely on observable data:

$$\begin{aligned}\mu_r &\approx \left(\frac{1}{\theta}\right)\lambda_r\left(\frac{\pi_{ijm}}{Z_{ijm}}\right)\left(\frac{\delta_r}{\pi_{jm}}\right)\\ &= \left(\frac{1}{\theta}\right)\left(\frac{\lambda_{ijm}}{Z_{ijm}}\right)\delta_r\end{aligned}$$

[16]It is important to stress that, while I assume a Cournot equilibrium *within* each market, I do not take a stand on the nature of compeition *between* distinct origins. Thus, my model captures competition for freight services across competing corridors.

$$= \left(\frac{1}{\theta}\right) \tilde{\lambda}_{ijm}\delta_r. \quad (15)$$

3 Empirical Strategy

Having laid out the theory, I turn my attention to estimating the model fundamentals. In this section, I demonstrate how the structure developed through Section 2 yields a simple, linear estimating equation that identifies: i) expected trade costs per mile, by mode; ii) the severity of freight competition among individual markets and modes, and consequently, route-specific markups; and iii) the correlation parameter ρ_j. I also detail the data used to estimate the model. Notably, my model characterizes trade along individual routes, while the data are aggregated by origin, destination, port of entry/exit (if any), and mode; I thus develop a method to estimate the model fundamentals from aggregated data.

3.1 Data

I utilize domestic trade data from the Freight Analysis Framework, version 5 (FAF5), compiled by the Bureau of Transportation Statistics (BTS) and Federal Highway Administration (FHA). This dataset lists total annual trade volumes in 2017 disaggregated by mode among major metropolitan areas in the U.S. and the following international regions: Canada, Mexico, Rest of Americas, Europe, Africa, Southwest and Central Asia, Eastern Asia, Southeast Asia, and Oceania.[17] The FAF also encompasses large, rural areas in each state. Figure 2 displays the domestic regions. I restrict my analysis of mode and route choice to the mainland U.S. due to the significant natural and political boundaries facing Hawaii and Alaska. For the same reasons, I do not model mode or route choice for the international portions of a journey. I thus analyse transportation among 129 domestic locations, as well as the eight international regions. The data are aggregated by origin, port of entry (for imports), port of exit (for exports), destination, and mode.[18] I restrict my analysis to five domestic modes: Road, Rail, Water, Air, and Multi-Modal; I do not consider freight movements via pipeline or with an unknown domestic mode. I also remove trade flows valued at less

[17] Unfortunately, the FAF does not offer more granular international geographies.

[18] It is important to note that the air freight included in the FAF5 encompasses shipments that are serviced by both road and air. The reason for this aggregation is that air typically cannot perform final-mile services, and thus relies on trucks to complete the trip. This aggregation is not a problem when estimating my model, as I account for final-mile costs via destination × mode fixed effects.

than \$1,000 total in 2017, to ensure enough variation in each origin-destination pairing to reliably identify the parameters of interest.

Second, I utilize detailed geographic information on the domestic transit network from the National Transportation Atlas Database (NTAD). The NTAD provides highly granular detail on domestic roadways, rail lines, navigable waterways, airports, and intermodal exchanges. I assume that travel may occur directly between any airport. Along the roadway, I limit my attention to arterial roads and interstates, as these carry the most interstate commerce. From these disparate modal networks, I create a graphical representation of a single, multi-modal transport network in PostgreSQL. Importantly, exchanges between modes may only occur at designated intermodal exchanges. Figure 1 provides a simplified example of my geography; Figure 3 displays a map of my network (excluding routes via international waters).

3.2 Estimation & Identification

I parameterize the deterministic component of trade costs as follows:

$$\kappa_r = Miles_r \beta_m, \tag{16}$$

where $Miles_r$ is the length of the route in thousands of miles, and β_m captures the expected cost per-mile along a particular mode. Plugging Equations (15) and (16) into Equation (10) yields the following log-linear expression:

$$\begin{aligned}\pi_{r(i,e,x,j,m)} = \exp\Big(& -\ln A_i - \tilde{\lambda}_{ijm}\delta_r - \theta\big[\ln c_i + Miles_r\beta_m + u_r + \eta_{iem} + \nu_{xjm} + \alpha_{im} + \gamma_{jm}\big] \\ & + (1-\rho_j\varphi)\ln \pi_{r|ijm} + (1-\rho_j)\ln \pi_{m|ij} - Q_j\Big). \end{aligned} \tag{17}$$

Given appropriate data, this expression provides a convenient, linear framework to estimate the model parameters.

However, before detailing my estimation procedure, I must emphasize a few points regarding identification. First, it should be noted that, because $\ln \pi_{r|ijm}$ and $\ln \pi_{m|ij}$ are included to identify the correlation coefficients, the cost and conduct parameters, β_m and $\tilde{\lambda}_{ijm}$, are identified by variation in trade shares across origins, which is observed, not simulated; similarly, ρ_j is identified by variation in trade shares across modes (also observed). The parameter φ, however, cannot be identified, as it depends entirely on simulated variation; it does not reflect any observable variation in the data. Thus, I cannot empirically evaluate φ, but must fix it at the outset. Currently, I set this value to 1, implying zero correlation of transport efficiencies within origin, mode pairs. In future drafts, I will show how the results change with lower values of φ (i.e. non-zero correlations among routes of the same origin, mode).

Second, Equation (17) makes evident that all cost coefficients are identified up to scale; I cannot separately identify θ. This scaling is not strictly a problem in the context of my model, but requires that I rely on estimates of θ from the literature when calibrating wages and performing counterfactual analysis.

Third, there is the obvious issue of endogeneity. Markups – and hence, estimates of λ_{ijm} – are endogenous for two reasons: i) the pricing rule laid out in Section 2.2 makes clear that μ_r is structurally correlated with u_r;[19] and ii) the linear approximation of markups introduces further error into the regression equation, which will necessarily be correlated with δ_r. I overcome these identification problems with a classic instrumental variables strategy.

As an instrument, I propose the production cost of related goods, which, in this case, is the distance of alternate routes. Specifically, I utilize the length of competing routes serving the same market along alternate modes and of the same relative routing sequence for their respective mode. So, markups on the shortest path via Road are instrumented by the distances of the shortest paths by Rail, Water, Air, and Multi-Modal serving the same market; markups along the second-shortest path by Road are instrumented by the distances of the second-shortest paths via these alternate modes; and so on. The same logic applies to all modes. Explicitly, these instruments are given by:

$$Z_r = \begin{bmatrix} Z_{ij\,Road(1)} \\ Z_{ij\,Road(2)} \\ \vdots \\ Z_{ij\,Rail(1)} \\ \vdots \end{bmatrix} = \begin{bmatrix} 0 & Miles_{ij\,Rail(1)} & Miles_{ij\,Water(1)} & Miles_{ij\,Air(1)} & Miles_{ij\,Multi(1)} \\ 0 & Miles_{ij\,Rail(2)} & Miles_{ij\,Water(2)} & Miles_{ij\,Air(2)} & Miles_{ij\,Multi(2)} \\ & & \vdots & & \\ Miles_{ij\,Road(1)} & 0 & Miles_{ij\,Water(1)} & Miles_{ij\,Air(1)} & Miles_{ij\,Multi(1)} \\ & & \vdots & & \end{bmatrix}$$

where *Road*(1) denotes the shortest path via Road, *Road*(2) denotes the second-shortest path via Road, and so on.

Of course, for my IV estimates to be valid, these instruments must satisfy the exclusion re-

[19] Explicitly, Equation (4) demonstrates that lower draws of u_r imply higher values of $\pi_{r|ijm}$, which in turn leads to higher markups per Equations (14) and (15).

striction and relevance assumptions. Regarding the former: the exclusion restriction is satisfied so long as trade flows today are independent of the trade flows that influenced the planning and development of the disparate modal networks decades (or in some cases, centuries) ago. Given my focus on short-run outcomes, this assumption is reasonable. The relevance assumption holds so long as modes compete in prices and respond strategically to one another. While this strategic pricing behavior is guaranteed by construction in my model, it may not hold in reality. Different modes carry highly differentiated products, implying segmented freight markets; moreover, their transport services are not identical – each modal network is characterized by a different speed, reliability, and capacity, creating differentiation of freight transport services not fully reflected in my logit demand framework. The relevance of my proposed instruments may therefore be suspect – however, I may empirically evaluate the relevance of the instrument via the first-stage F-statistic (detailed in Table 2).

My first-stage regression equation is given below:

$$\delta_r = Z_r \zeta + Miles_r \phi_m + \lambda \ln \pi_{r|ijm} + \varrho \ln \pi_{m|ij} + \vartheta_{iem} + \vartheta_{xjm} + \varepsilon_r \tag{18}$$

where ϑ denote the corresponding fixed-effects and ε is assumed normal, iid across routes. The fitted values from this first-stage equation are utilized to identify $\tilde{\lambda}_{ijm}$.

Given route-level data on domestic trade as well as knowledge of δ_r, it would be straight-forward to estimate my model parameters via 2SLS. However, my data fails on both of these counts. As made evident by Equation (14), δ_r is a nonlinear function of φ and ρ_j, which I aim to estimate in the same equation. Second, and much more problematic, I do not observe route-level trade shares; rather, my data only reports aggregate trade flows for an origin, destination, port of entry/exit (where relevant), and mode. I thus rely on a simulated method of moments strategy to overcome these data shortcomings.

As a first step, I populate the set $\mathcal{R}_{ij}$ by mapping successively longer paths between i and j along each mode; in the case of international origins/destinations, I map to the port of entry/exit.[20] I also remove the first and last 25 miles from each journey, as these are the most-expensive parts of the trip and should be captured by the α_{im} and γ_{jm} parameters.[21] Theoretically, I could repeat this

[20] I require these paths to be substantially different, so that the changes to the distance are meaningful. Table 1 demonstrates the average evolution of mileage across these paths.

[21] This truncation, as well as the fact that I cannot route within a region, means that I hold $\kappa_r = 0$ for all routes

process almost infinitely; practically, I consider only the 10 shortest paths for each mode. I have two, main reasons for stopping at this threshold: i) computation time grows with each additional route, becoming excessive after 10, and ii) routes outside of this set seem sufficiently circuitous to be cost-prohibitive, and therefore add little information to my analysis. This mapping process generates a set of 10 distinct routes – as well as the corresponding mileage – for each origin/port of entry, destination/port of exit, and mode combination.

Table 1 describes the evolution of average mileage across these subsequently longer routes for each mode. To construct this table, I scale the distance of each routing by the shortest distance for every origin, port of entry, port of exit, destination, and mode pairing. I then average these scaled distances across origin-destination combinations to find the average, scaled distance for every routing. Columns (1) and (2) demonstrate that, on average, the second-shortest routing via Road is approximately 4.4% longer than the shortest path on the Road; the third-shortest path is 7.4% larger than the shortest path, and 2.8% larger than the second-shortest path; and so on. Notably, for Roads, Rails, and Multi-modal, the marginal increase in mileage along each route generally shrinks as the number of routes increases; I attribute this trend to the relative density of these networks: as routes become more and more circuitous, the marginal increase in mileage becomes less and less. Likewise, the marginal increase in Air distance with each route is consistently small and stable; this trend owes to the fact that I allow a straight-line path between all freight airports, making the Air network the most dense by far. Finally, the increases in routed distance over Water are somewhat erratic, reflecting the relative sparsity of the water network. The last, notable takeaway from this table is the sizeable difference between the shortest path and the tenth-shortest path: for Roads and for Multi-modal, the tenth-shortest path is about 19% longer than the shortest path on average; this number hovers around 25% for the Rail and Water networks. For Air, the tenth-shortest path is only 2.9% greater than the shortest trip on average, again reflecting the unique ability of Air to travel in a straight line, anywhere.

The routed mileage identifies the per-mile cost parameters, β_m. The question now becomes how to estimate route-level costs (and markups), from aggregated data. Towards this end, I employ an Expectation-Maximization (EM) algorithm. The algorithm proceeds accordingly:

1. Take an initial guess at the model parameters, $\tilde{\lambda}_{ijm}^{(0)}, \beta_m^{(0)}, \rho_j^{(0)}, \varphi^{(0)},$ and $\upsilon^{(0)}$

that start and end in the same region.

2. (Expectation Step) Simulate $\mathbb{E}\left[\pi_{r|ijm}\middle|\tilde{\lambda}^{(0)}_{ijm}, \beta^{(0)}_m, \rho^{(0)}_j, \varphi^{(0)}, v^{(0)}\right]$ according to Equation (4) under the assumption that $u_r \sim N(0, v^{(0)})$. Denote this conditional probability $\pi^{(0)}_{r|ijm}$.

3. Calculate $\pi^{(0)}_{r(i,j,m)} = \pi^{(0)}_{r|ijm}\pi_{m|ij}\pi_{i|j}$. Note that these last two conditional probabilities are observed in the data.

4. Calculate $\delta^{(0)}_r$ as described by Equation (14).

5. Estimate the first-stage regression equation via OLS, utilizing Z_r to instrument for the endogenous regressor $\delta^{(0)}_r$:

$$\delta^{(0)}_r = Z_r\zeta + Miles_r\phi_m + \lambda \ln \pi^{(0)}_{r|ijm} + \varrho \ln \pi_{m|ij} + \vartheta_{iem} + \vartheta_{xjm} + \varepsilon_r \tag{19}$$

   Denote the fitted values from this regression $\hat{\delta}^{(0)}_r$.

6. (Maximization Step) Estimate the second-stage via OLS:

$$\begin{aligned}\ln \pi^{(0)}_{r(i,e,x,j,m)} = & -\tilde{\lambda}_{ijm}\hat{\delta}^{(0)}_r - \theta Miles_r\beta_m + (1-\rho_j)(\ln \pi^{(0)}_{r|ijm} + \ln \pi_{m|ij}) - \theta u_r + \\ & \underbrace{\text{Importer} \times \text{Port} \times \text{Mode FEs}}_{-\theta(\nu_{xjm}+\gamma_{jm})-Q_j} + \underbrace{\text{Exporter} \times \text{Port} \times \text{Mode FEs}}_{-\ln A_i - \theta(\ln c_i + \eta_{iem} + \alpha_{im})}\end{aligned} \tag{20}$$

   Denote the new set of parameter estimates $\tilde{\lambda}^{(1)}_{ijm}, \beta^{(1)}_m, \rho^{(1)}_j, \varphi^{(1)},$ and $v^{(1)}$.[22]

7. Return to step 2, and repeat the process with the new parameter estimates. Continue until the estimates converge.

Under standard assumptions required for a linear regression model, the parameter estimates of the EM process converge to the (local) maximum-likelihood estimates. See Appendix A.3 for detail.

4 Results

I split my results into two, broad categories. The first is descriptive: these describe the estimated trade costs along individual modes (captured by the β_m parameters), correlations of these costs among routes serving the same destination (ρ_j parameters), and the current state of freight competition among distinct market-mode combinations throughout the mainland US ($\tilde{\lambda}_{ijm}$ parameters).

[22] It should be noted that, while I do not immediately estimate $v^{(1)}$ via OLS, I can estimate $v^{(1)} = \text{Var}(\hat{u}_r)$.

These results include reduced-form parameter estimates, as well as current, calibrated losses due to non-competitive pricing in the transport sector. The second category estimates the impact of counterfactual shocks. Explicitly, I simulate how a lack of competition in the market for transport exacerbates and/or mitigates the real-wage impacts of domestic infrastructure investment (modelled as a reduction in per-mile trade costs via the β_m parameters), as well as an international trade shock (modeled as an increase in the η_{iem} and ν_{xjm} parameters). I now describe my results in detail.

4.1 Descriptive Estimates

The EM process described in Section 3.2 yields estimates of per-mile iceberg costs for each mode, β_m. As mentioned at the outset, a novel feature of my model is that I dispense with the assumption of a single, least-cost path between an origin and destination. To assess the impact of allowing a wider expanse of route options per mode, I re-run the EM process over varying dimensions of $\mathcal{R}_{ij}$; the results of this analysis are listed in Table 2. Each column restricts the dimensionality of $\mathcal{R}_{ij}$, such that all traffic via the specified mode must travel along a subset of routes. Column (1) allows only the shortest the path; column (2) allows the two shortest paths; and so on up to 10 unique routes for each mode between every origin/port of entry, destination/port of exit, and mode combination. Panel (a) reports the estimated coefficients, along with bootstrapped standard errors. Notably, all coefficients are statistically different from zero. For Road, Water, and Multi-modal exchanges, the estimated coefficient on distance decreases with the number of routings. For Rail, the estimated coefficient increases somewhat initially, but decline slightly as I consider up to 10 distinct trade routes. The estimated coefficient on Air-miles remains relatively constant. None of the differences across specifications are statistically significant.

Due to the scaling of these estimates by the (unobserved) trade elasticity θ, as well as the exponential form of τ_r, immediate interpretation of these coefficients is somewhat involved. Thus, in Panel (b), I provide the iceberg cost of a 1,000 mile journey (or in the case of Multi-modal, the iceberg cost of 1 modal exchange) assuming a trade elasticity of four.[23] Road is consistently the most expensive option, accounting for approximately 19.0 to 20.2% of a good's original value, depending on the number of distinct routings. The finding that Road is the most expensive mode

[23]Please note that the costs reported in Panel B exclude route-invariant costs (e.g. $\alpha_{im}, \gamma_{jm}, \eta_{iem}$, and ν_{xjm}).

per-mile is not surprising given its relatively high fuel consumption, labor intensity, and insurance costs. After Road comes Rail and Water: 1,000 miles on rails runs about 11.3 to 11.9% of the good's original value, while the same distance on water costs between 12.1 and 18.0%.

Notably, when restricting travel to the shortest possible path, Rail movements are estimated to be substantially cheaper than Water shipments by approximately 6.7 percentage points. This difference declines as I expand the set of parallel routings. When considering 10 distinct trade routes in column (5), the difference in the iceberg cost of Water and Rail shrinks to 0.5 percentage points; this decline is driven largely by a drop in the estimated per-mile cost of Water transit. The sensitivity of this coefficient to the number of available routes suggests that, more than any other mode, Water is most likely to deviate from its shortest path.

Air is estimated to be the cheapest standalone mode: 1,000 miles of Air travel costs approximately 5.8% of a good's factory-gate price; this estimate barely changes with the dimensionality of $\mathcal{R}_{ij}^{m}$. The finding that Air is cheaper than competing modes is initially surprising, given Air's extremely high fuel consumption and maintenance requirements. However, Air is also much, much quicker than any alternative; the high cost of fuel is offset by its ability to span the entire country in a handful of hours. Also, keep in mind that these estimates reflect per-mile costs; any costs incurred at airports or freight terminals (e.g. congestion, loading, and/or unloading) are not reflected in this table. Moreover, this finding accords with previous estimates in the literature (Allen and Arkolakis, 2014). Finally, a single modal exchange is estimated to account for 1.1 to 2.3% of a good's initial value.

Table 2 also lists my first-stage F statistic, which indicates the power of my proposed instrument Z_r. Notably, the F-statistic equals only 1.087 when restricting movements to the shortest available path in column (1), but rises steadily as I consider more routes, and equals about 61 as I consider 10 parallel routings along each mode for every domestic freight market. Some of this growth is partially attributable to the 10-fold increase in degrees of freedom as I move from column (1) to column (5) – however, the near-60 fold jump in the F-statistic suggests that the relevance of the instrument is also increasing. This substantial gain in explanatory power suggests that, as the set of routes becomes broader, transporters respond more stringently to competition from competing modes; this trend may be attributable to transporters enjoying more flexibility to price competitively with multiple routes available. Regardless of the explanation, the high F-statistic among the wider set of routings suggests allays concerns of a weak instrument.

Another key estimate from my model is the structural correlation parameter, ρ_j. This coefficient captures the correlation of composite efficiencies across distinct locations – recall that values close to zero imply near-perfect correlation, while values close to 1 imply little-to-no correlation. Figure 4 presents a histogram of these estimates. As displayed by the figure, my estimates of ρ_j range from 0.01 to 0.32, with a mean and median of about 0.20. These estimates imply a correlation of efficiencies (and hence, trade costs) from the same origin that span 0.9 to 0.99, with a mean and median correlation of approximately 0.96.[24] This exceptionally high correlation reinforces my choice of a nested-logit trade structure, as a traditional EK model – which assumes independence of efficiencies across locations – would fail to capture any correlation of trade costs.[25] In future drafts, I will evaluate the sensitivity of my estimates to alternate nesting structures. [26]

The final, and arguably most-important, estimate from my descriptive analysis is the conduct parameter, λ_{ijm}. Unfortunately, the scalar approximation of μ_r (as detailed by Equation (15)) obfuscates immediate interpretation of my estimated parameter. That is, λ_{ijm} is not point-identified by my model, so I cannot directly interpret my estimate. However, I may still describe the state of competition for freight transport in distinct markets by estimating current income losses due to non-competitive pricing. Specifically, I calibrate the model to domestic trade flows in 2017 utilizing 10 parallel routes[27] for every market-mode combination. For this calibration, as well as for all future simulations, I assume a trade elasticity of 4, an elasticity of substitution (across varieties) of 4, and a labor-share of 0.5. I then simulate trade flows under the counterfactual scenario, in which freight markets are perfectly competitive (i.e $\lambda_{ijm} = 0$ for all markets and modes). These simulated earnings changes reveal potential welfare gains from elimination of markups, which are indicative of the current state of competition – higher potential gains suggest more exploitation of market power, ceteris paribus. This exercise produces the first principal finding of my analysis.

[24] Per Heiss (2002), the correlation coefficient is given by $1 - \rho_j^2$.

[25] Finding substantial correlation of trade costs across disparate origins reinforces recent findings by Lind and Ramondo, 2023, who focus on an international trade setting.

[26] Explicitly, I will allow for non-zero correlation of trade costs across origins and modes (i.e. $\varphi > 0$), as well as re-estimate the model assuming zero correlation of trade costs across origins.

[27] Table 2 makes clear that my coefficient estimates are relatively stable across the varying dimensions of $\mathcal{R}_{ij}^m$. Thus, for my counterfactual simulations, I utilize the specification with the highest-possible F-statistics and the most realistic routing behavior.

Finding # 1: Current Losses due to Non-Competitive Freight Pricing are Substantial, Particularly for International Trade

Panel (a) of Table 3 lists the simulated change in GDP resulting from elimination of market power in the transport sector. As displayed by the final line of Columns (4) and (5), enforcing perfect competition in freight markets increases national income by approximately 2% ($\sim$ \$393 billion in 2017 U.S. dollars). The table further disaggregates these real income changes by mode of transport. Column (4) lists the total change in freight volume along each mode; Air accounts for all gains in national trade, while the remaining modes see *decreases* in total domestic volume from elimination of markups. However, these aggregate shifts encompass both income and substitution effects; I thus disentangle these two effects in Columns (2) and (3).[28]

Focusing on the first of these, approximately half of total income gains are concentrated in Air; Road and Rail also garner substantial income gains. Notably, Multi-modal reports a sizeable, negative income effect. It is unclear from this aggregate statistic whether this result is a function of preferences or network composition: poorer, remote locations along sparse portions of the transit network may more frequently elect multi-modal due simply to a dearth of alternatives. Thus, in subsequent analysis, I analyse the geographic distribution of these income effects.

Switching focus to Column (3), I find sizeable substitution of freight across modes. Elimination of non-competitive markups spurs Air to accumulate from competing modes additional trade volume equaling nearly 5% of national GDP. Almost 64% of this new volume draws from Road; over 20% comes from Rail. The large substitution into Air freight suggests that this mode accounts for the lion's share of non-competitive freight pricing nationally.

Beyond total income, I also evaluate the effects of competition on the United States' international trade position. The transport sector handles all goods trade in the U.S.; hence, inflated trade costs due to a lack of competition for domestic freight transport reduces market access across the nation. Panels (b) and (c) of Table 3 report the total changes in U.S. imports and exports to/from foreign markets, as well as the associated income an substitution effects. The listed modes correspond to the domestic legs of the journey; I do not consider travel from the port of exit (entry) to its final, international destination (origin).

[28] Because the shocks I analyse are not uniform across locations, I calculate aggregate income effects along each mode that are different from the aggregate trade shares. That is, different locations have distinct modal compositions, which generate aggregate effects distinct from the aggregate trade shares.

At first glance, it is immediately apparent from this table that the effects on international trade are profound. Elimination of markups would increase total imports and exports by almost 70% (respectively \$2 trillion and \$1.6 trillion). This exaggerated effect on trade suggests that markups weigh more heavily on international shipments, where trade costs are higher, alternatives limited, and reliance on the transport sector is central. As displayed by Column (2) of the table, these changes are driven by a large income effect for both Road and Air. That is, about 70%[29] of the increase in trade (both imports and exports) from enforcing perfect competition in domestic freight markets stems from gains along the Roadway. As in the income results, there is a substantial substitution away from Air, as displayed by Column (3). This result reinforces the conclusion that market power is most concentrated within Air freight; this substitution effect is more pronounced for imports over exports, suggesting that the markets most heavily served by Air also rely more on international sources.

The careful observer will note that the increase in exports listed in Panel (c) of Table 3 far outweighs the increase in income reported in Panel (a). Focusing on Column (5), total U.S. exports increase by \$1.6 trillion, yet GDP increases by only \$400 billion (approximately). This means that "domestic exports" – goods produced and consumed within U.S. borders – decline by almost \$1.2 trillion (about 8% of baseline levels). Thus, imperfect competition in the transport industry acts as a protectionist measure, reducing international trade in favor of domestic products.

While these aggregate figures are striking, they shed no light on the geographic composition of freight competition. Moreover, I suspect that the effects on international trade will be more pronounced for inland regions, which require greater interaction with the domestic transit network to reach international markets. I thus estimate the aggregate welfare, import, and export changes accruing to each FAF region; this analysis sheds light on how network composition impacts freight market power. This analysis yields my second, key finding:

Finding # 2: Losses are Geographically Heterogeneous and Driven Largely by Air and Road

Panel (a) of Figure 5 provides a heatmap of GDP changes as a percentage of each region's GDP. As displayed by the figure, the Midwest and Southeastern United States, as well as in major

[29] $48.9\%/69\% \approx 70\%$; $45.8\%/70\% \approx 70\%$.

metropolitan areas along the West Coast and Texas, stand the most to gain from elimination of markups. On the flip side, rural areas in the center of the country and New England, as well as urban centers along the Gulf of Mexico, *lose* GDP from elimination of markups. These losses are driven by equilibrium benefits under imperfect competition: high trade costs driven by non-competitive freight rates in the Southeast, Midwest, and West Coast divert trade to these more remote areas. However, it should be noted that the scale of potential gains is nearly double the scale of potential losses.

Panels (b) and (c) of Figure 5 provide similar heatmaps for imports and exports. Notably, the the import changes correlate largely with income changes– that is, the areas that see highest gains also see the largest jump in imports; in some cases, this increase is dramatic– rural Pennsylvania and Ohio see over 300% increases in their total imports. Rural regions in the center of the country as well as New England see modest declines in imports. Shifting focus to Panel (c), the same overall pattern holds for exports. However, the declines in exports among rural regions are much more pronounced, in some dropping by more than half.

To delve deeper into these results, I further decompose these welfare regional effects into their modal components. I should stress that there are two, distinct channels, by which markups along a particular mode affect domestic trade flows. The first is an income effect, and concerns the composition of trading partners: if one, single mode is highly concentrated and thus enjoys high markups, then locations that more heavily rely on that mode will become more attractive trading partners under the perfect-competition scenario; this effect determines aggregate trade – and thus, welfare – within each region. The second impact is a substitution effect: changing the relative price of modes will shift the composition of trade, holding the total volume within each market (origin-destination combination) constant. This second effect reveals the modes that have the highest relative prices within each region. In Figures 6 - 10, I isolate both effects for each mode: the income effect in Panel (a), and the substitution effect in Panel (b).

These figures reveal that the aggregate income impacts displayed in Figure 5 are driven almost entirely by the Road; competing modes produce at-best mild income effects. Broadly speaking, the income effects over Rail and Water reinforce the same geographic pattern as Road: the Southeast, Midwest, and urban centers on the West Coast and Texas see the largest potential income gains, while the remainder of the country sees moderate losses. The remaining modes generate much more uniform income effects. Analysis of the substitution effects reveals the following:

a) markups along the Road are concentrated in the Midwest and Southeast, mimicking the income effect;

b) California, Chicago, and Kentucky see an over-reliance on trucking, as evidenced by the sharp decline in Road's trade volume due to elimination of markups;

c) this reliance on Road is spurred by non-competitive markups from other modes, namely Air;

c) losses via Rail are concentrated in the Washington, D.C. area

d) losses due to multi-modal market power are concentrated in the Midwest, with mild losses also reported along the West Coast;

e) Water is largely competitive.

These findings paint a rather nuanced picture of market power in the freight industry. While total losses due to non-competitive freight pricing are driven largely by the Roadway – a fact attributable to its outsize importance in carrying nearly 80% of domestic trade – market power is most concentrated within Air, relative to other modes. This concentration of market power causes certain regions – namely, California, Chicago, IL, Seattle, WA, and certain parts of Kentucky and Tennessee – to rely more heavily on road transport. This finding has wide implications, not only for trade but also for domestic infrastructure, social, and environmental policy. Evaluating the effects of these alternate perspectives, however, is beyond the scope of this paper.

4.2 Policy Simulations

Having established the current state of freight competition in the mainland U.S., I now move on to my policy-focused results. I simulate two macroeconomic shocks, and evaluate how non-competitive freight rates exacerbate/mitigate their welfare impacts throughout the Lower-48. Specifically, I simulate: i) a reduction in domestic trade costs designed to mimic recent and forthcoming domestic infrastructure investment, and ii) an increase in international trade costs designed to replicate recent supply-chain bottlenecks. In each case, I simulate the shock twice: first assuming the current state of imperfect competition for freight services, and then assuming perfect competition. I may thus quantify how non-competitive freight rates exacerbate or mitigate the real income and trade impacts of each shock. I now describe the results of each simulation in turn.

Shock #1: Reduction in Domestic Trade Costs

For this exercise, I simulate the effects of proposed infrastructure investment. Utilizing summary measures from the recently-passed Bipartisan Infrastructure Law, I reduce costs along each modal network to reflect the increase in spending over historic levels stipulated in the Law for each mode. According to a reports prepared by McKinsey & Company and the Union Pacific Railroad, spending on road and railways will increase by approximately 14.7%; spending on train yards and intermodal terminals will increase by about 20%; and spending on ports and airports will increase by approximately 35% relative to historic averages (McKinsey & Company, 2021;Union Pacific Railroad, 2022). For the purpose of this exercise, I assume a perfect relationship betwen these spending increases and cost savings.[30] To operationalize these planned cost reductions, I reduce my estimated cost parameters by the stated percentage. On average, across all available trade routes serving all domestic markets, these infrastructure investments lead to about a 16% drop in trade costs.[31]

As stated previously, I simulate the shock with and without non-competitive markups in the freight sector. To quantify the difference in the welfare impacts across these shocks, I calculate real incomes gains relative to the status quo, and real income gains relative to the perfect-competition scenario. Comparison of these two categories yields a "cannibalization rate" – that is, how much of the potential benefit (or loss, as the case may be) of the exogenous shock is cannibalized by the endogenous pricing response of the imperfectly competitive transportation sector.[32] Throughout this exercise, I focus on income effects – the change in aggregate trade volumes among distinct locations which lead to changes in welfare, but hold modal compositions within each market constant. In future analysis, I will also analyse substitution effects, which reveal how markups change in response to the cost shock.

[30] A logical consequence of this assumption is that, absent any increase in infrastructure spending, trade costs remain static. This assumption seems dubious over the long-run, but appears more reasonable over my 1-year horizon.

[31] As of this draft, I do not model any heterogeneity in investment, but assume a uniform reduction of costs across each mode's national network; in future drafts, I will refine this counterfactual simulation to reflect specific investment projects proposed.

[32] The notion of incomplete pass-through of exogenous cost shocks under imperfect competition is not novel – what differentiates my notion of cannibalization is that I focus not on the final price charged to consumers, but on welfare outcomes which reflect general equilibrium effects. Hence, my cannibalization rate is not bounded below by 0 or above by 100%.

This analysis yields my third principal finding.

Finding # 3: Non-competitive Freight Rates Disproportionately Mitigate the Impacts of Domestic Shocks

In response to the domestic infrastructure investment, I find that national welfare improves by approximately 25.4% when allowing imperfectly-competitive freight pricing; this benefit increases to 28.5% when asserting perfect competition for freight services, implying a cannibalization rate of approximately 10.8%. In words, the total benefit to U.S. consumers following domestic investment is about 10.8% lower due to higher freight rates charged in the transport industry cannibalization rate under the counterfactual equilibrium. This welfare cannibalization is strikingly large, especially in light of the 2% welfare losses reported under the status quo (see Table 3). Thus, the domestic impact of exogenous shocks is mitigated beyond even what we would expect form current losses due to freight market concentration.

These aggregate cannibalization rates are more pronounced when considering international trade, but perhaps less than expected relative to current non-competitive losses to imports and exports. Total U.S. imports rise by approximately 156% in response to domestic infrastructure investment under the status-quo pricing regime; the gain in imports climbs to approximately 182% when enforcing perfect competition, implying a cannibalization rate of about 16%. Similarly, total U.S. exports increase by approximately 168% when allowing non-competitive freight pricing; this gain climbs to 201% under perfect freight competition, yielding a 33% cannibalization rate. While undeniably large, current import and export suppression due to non-competitive freight pricing equals about 70%; thus, these aggregate impacts are somewhere between one-half and one-quarter of the cannibalization suggested by naive expectation. However, the shock I analyze in this context is purely domestic; a muted response along international freight movements is therefore less surprising.

As before, I delve further into these aggregate numbers to see how cannibalization affects each region. I quantify welfare, import, and export cannibalization to each FAF region in mainland U.S.; results of this analysis are displayed in Figures 11 - 13. Panel (a) of each figure details changes to income, imports, or exports under perfect competition; panel (b) details the cannibalization rate. A common trend occurs amongst all three figures: cannibalization is highest among regions that stand to gain from the exogenous shock; regions that benefit least from the shock see the highest, positive cannibalization. Thus I arrive at my fourth main finding:

Finding # 4: Welfare Cannibalization Smooths the Geographic Consequences of Exogenous Shocks

I now delve into the specifics of these figures in detail. Panel (a) of Figure 11 makes clear that, under perfect competition, urban centers along the California coast and in Texas see the largest gains from domestic infrastructure investment; the Midwest, Great Plains, Southeast, and upstate New York see the least benefit. However, as illustrated in panel (b), those regions that stand the most to gain from the shock see the largest cannibalization rates, while those states that saw the least gain from the shock see dramatic, positive cannibalization rates. Thus, transporter's profit-maximizing motive balances trade flows across the country.

Shifting focus to Figures 12 and 13, I see a similar trend. Domestic infrastructure investment produces dramatic increases (over 300%) for most regions West of the Missouri river. Benefits to the Midwest and Southeast are relatively muted (approximately 20-40%). However, imperfect competition smooths these disparate benefits. As displayed by panel (b) of each figure: cannibalization rates are positive among regions that stand to benefit the least from the shock.

Shock #2: Increase in Foreign Trade Costs

My final counterfactual simulation mimics recent supply chain bottlenecks sparked by the Covid-19 pandemic. At the peak of the crisis, dwell times at major international gates rose between 40 and 80% according to the U.S. International Trade Commission (United States International Trade Commission (USITC), 2021). To replicate this shock, I increase costs along the international legs of any shipment by 60%, which I achieve by raising the associated international trade parameters. This modification results in an average 10.7% increase in τ_r along international trade routes (inclusive of the domestic sections of the trip); purely domestic routes are unaffected. This simulation reveals the short-run impacts of supply chain bottlenecks at international gates. In future drafts, I will mimic cost increases at specific ports during the Covid-19 pandemic; for now, I present the results a blanket, 60% increase in international trade costs. As before, I simulate the shock with and without non-competitive markups for freight services; I compare these simulated welfare losses to quantify GDP cannibalization– the level of potential losses which are lost or exacerbated by a lack of competition in the freight market. I again focus solely on income effects: the aggregate welfare changes spurred by changes of trading partners in response to the shock and holding constant modal composition within each market (origin-destination combination).[33]

The real welfare impacts of this shock reinforce Principal Findings 3 and 4: non-competitive freight pricing softens the blow of an exogenous shock; this cannibalization is strongest among the otherwise worst-impacted areas, smoothing the geographic distribution of the shock. I now detail the impacts of this international trade sock.

I find welfare cannibalization of approximately 33%. While this cannibalization was a negative in the case of domestic infrastructure investment, it is a positive in the case of an international trade shock: total income losses under perfect freight competition are about 1.9% of U.S. GDP (∼\$383 billion); under imperfect competition, these losses decline to approximately 1.3% of GDP (∼\$252 billion). In Figure 14, I display the geographic distribution of these shocks.

The story is substantially different for international trade. In terms of total U.S. imports, I find a *positive* cannibalization rate of 15.9%— imports decline nationwide by approximately 30.5% under the status-quo pricing regime, but only by 26.3% when imposing perfect freight competition. Results for U.S. exports are similar: real exports decline by roughly 29% allowing transporters to price non-competitively, and by only 25% under perfect competition, yielding a *positive* cannibalization rate of approximately 13%. Thus, I arrive at my final, main result:

Finding # 5: Non-competitive Freight Rates Exacerbate the Trade Impacts of International Shocks

Why is this the case? By making international trade more expensive, domestic trade becomes relatively cheaper. Hence, the negative international shock is a boon for domestic exports. Indeed, I find that domestic exports – goods created and consumed within U.S. borders – increase by as much as 4.5% under the perfect competition scenario. However, thanks to incomplete pass-through under imperfect competition, domestic exports increase by only 2.9% under the status-quo pricing regime. That is, approximately 35% of the gain to domestic exports is cannibalized by non-competitive freight rates. This cannibalization reduces the purchasing power of U.S. consumers,

[33] In future drafts, I will analyze modal composition, which reveals how markups respond to the international trade shock; presumably, locations with higher freight market concentration will see a greater response.

causing them to substitute away from already expensive foreign goods.

Figures 15 and 16 shed some light on the geographic composition of the import and export consequences of the shock. As with the income results, comparison of panels (a) and (b) reveals that cannibalization correlates with potential gains under perfect competition. These results confirm my previous conclusion: non-competitive freight rates smooth the geographically heterogeneous impacts of exogenous trade shocks. On the import side, most of the additional gains (or rather, foregone losses) are concentrated in rural areas– major urban centers see sight gains or moderate to substantial additional losses. For exports, very few regions benefit from imperfect pass through; additional losses, on the other hand, are concentrated in a handful of regions throughout the country. There is no discernable geographic trend to these additional losses.

5 Conclusion

This paper quantifies the impact of imperfect competition in the freight market on domestic trade outcomes. I modify a standard Ricardian trade model to account for multiple modes, a multiplicity of routes along each mode, imperfect modal substitution, and imperfect competition among transporters. The net result of these refinements is a highly realistic model of the transportation industry, as well as its effect on domestic trade. Specifically, I may link non-competitive outcomes in the transport industry to trade flows (and their consequences) nation-wide.

Estimation of the model fundamentals yields a detailed account of per-mile trade costs along specific modes through the domestic U.S., as well as a measure of non-competitive pricing along individual trade routes. To evaluate the extent of freight market concentration, I simulate trade flows under perfect competition for freight services. This exercise yields my first two, main findings: i) current losses due to a lack of competition in transport markets is substantial, costing U.S. consumers as much as 2% of GDP; and ii) these losses are geographically disparate, and are concentrated in the Midwest, Southeast, and among urban areas along the West Coast. Notably, non-competitive losses are driven primarily by Air and Road–the former because of high market concentration, and the latter due to high transport volume, all the larger due to substitution away from Air. The remaining modes appear relatively competitive, and are responsible for minor losses throughout the mainland U.S., with some exceptions. Moreover, the effects of imperfect freight competition on international trade are profound– total U.S. imports and exports would increase by as much as 70% from their current levels due to elimination of markups in the transport sector. As with income, these international trade impacts are geographically heterogeneous.

Having established the current state of competition for freight services, I shift my attention to two counterfactual scenarios, meant to emulate recent and forthcoming macroeconomic shocks. Specifically, I simulate domestic trade flows under infrastructure improvements proposed by the Bipartisan Infrastructure Law, and under supply-chain bottlenecks that became binding during the Covid-19 pandemic. I estimate the impact of each shock under two, distinct scenarios: assuming status-quo freight market concentration, and imposing perfect competition for freight services. Analysis of these scenarios yields three principal findings: i) due to incomplete cost pass-through, imperfectly-competitive freight markets mitigate the welfare impacts of exogenous shocks, and this welfare cannibalization is even larger than suggested by current losses; ii) non-competitive freight rates smooth the geographic heterogeneity of these impacts; and iii) non-competitive freight rates exacerbate the trade impacts of an international trade shock. As before, these impacts are geographically heterogeneous, with the greatest impacts concentrated in the Midwest and Southeast, as well as rural Pennsylvania and upstate New York.

In light of these descriptive findings, there remains one, obvious question: what are the policy recommendations? However, creating a policy prescription is tricky due to competing objectives. On the one hand, imposing perfect competition for freight services will benefit U.S. consumers as a whole; these benefits will be substantial. On the other, the lion's share of these gains will accrue mainly to consumers in the Midwest and Southeast, as well as in urban centers along the West Coast. Consumers in rural areas throughout the center of the country, as well as in New England and urban centers along the Gulf of Mexico, will be harmed. Thus, the question becomes whether the aggregate gains compensate the increase in inequality. Moreover, freight market power acts as somewhat of an insurance policy: incomplete cost pass through can be beneficial to consumers in the case of a negative shock. There are also political considerations concerning the U.S. trade position. Reducing freight market power will greatly increase international trade, both imports and exports, yet this new reliance on trade will undoubtedly impact U.S. production. Eliminating freight market power is decidedly not a "Buy American" prescription. Beyond even these simple welfare considerations, there are concerns for environmental and social policy: enforcing increased competition will drastically affect the modal composition of domestic freight, which has much wider consideration beyond economic efficiency. Hence, the question of what do about freight market power is rather nuanced; the answer is not clear-cut.

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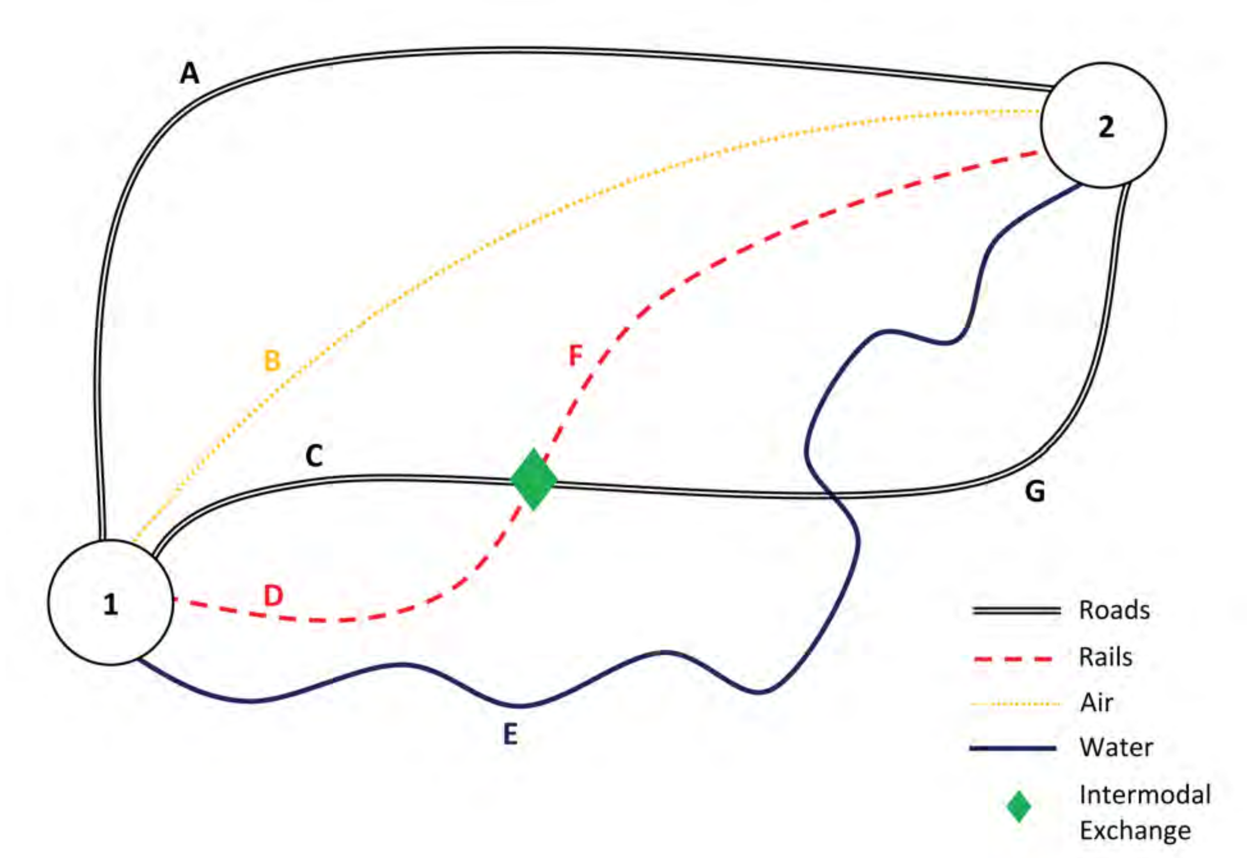
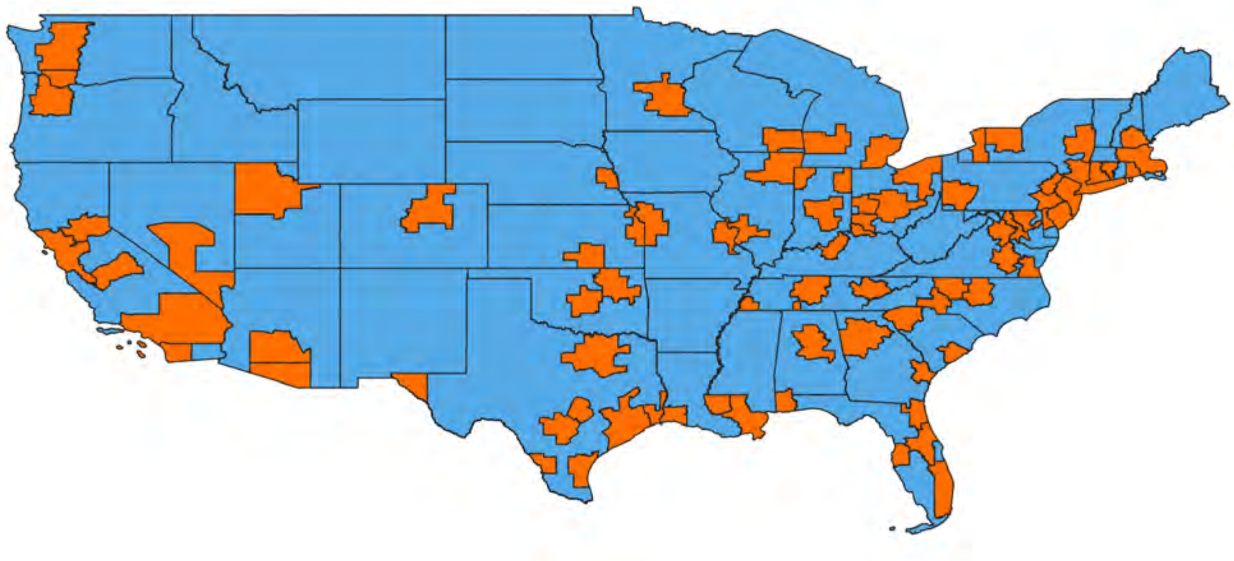
6 Figures & Tables

Figure 1: A Simple Network



Notes: The above figure displays a simplified transport network to illustrate the basic logic of my setup. In this case, $\mathcal{S} = \{1, 2\}$, and the sets of simple (non-repeating) routes along each mode are given by: $\mathcal{R}_{ij}^{Road} = \{A, CG\}$, $\mathcal{R}_{ij}^{Rail} = \{DF\}$, $\mathcal{R}_{ij}^{Air} = \{B\}$, $\mathcal{R}_{ij}^{Water} = \{E\}$, and $\mathcal{R}_{ij}^{Multi-modal} = \{A, CF, CG, DF, DG\}$. An important point regarding multi-modal: intermodal transshipment may only occur at designated intermodal exchanges (e.g. the green diamond); hence, even though the road network crosses a waterway, an exchange is not possible at this point. Additionally, multi-modal routes need not utilize the intermodal exchange. The defining feature of multi-modal is the *ability* to move across multiple networks, but not a requirement. This feature is appealing given how multi-modal shipments are recorded in the data (see Appendix **??** for detail).

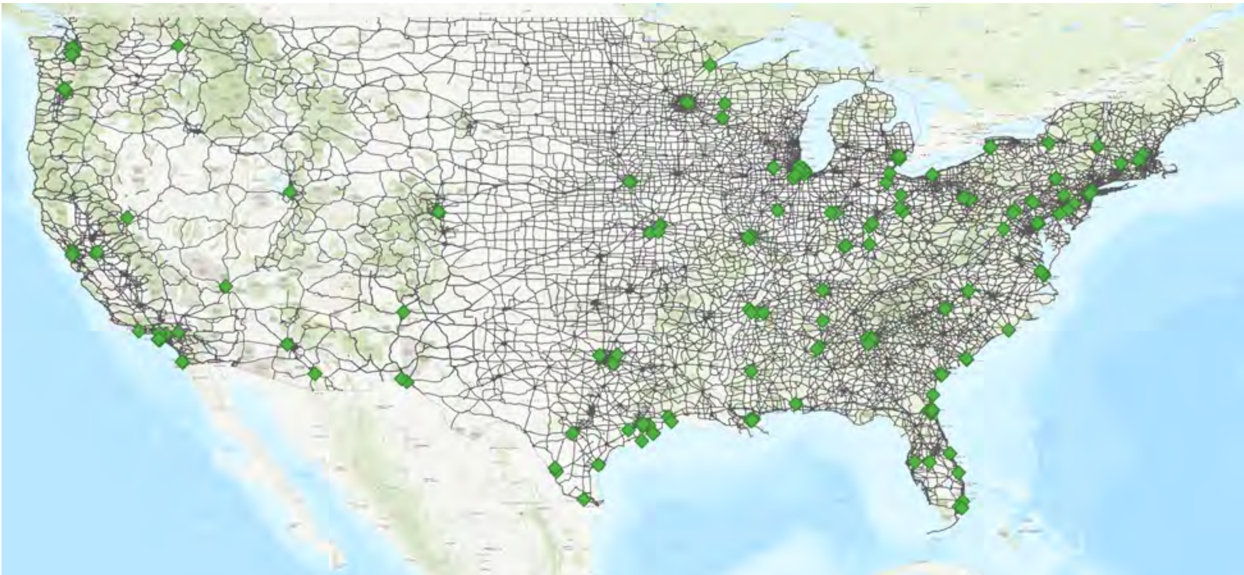
Figure 2: FAF Regions



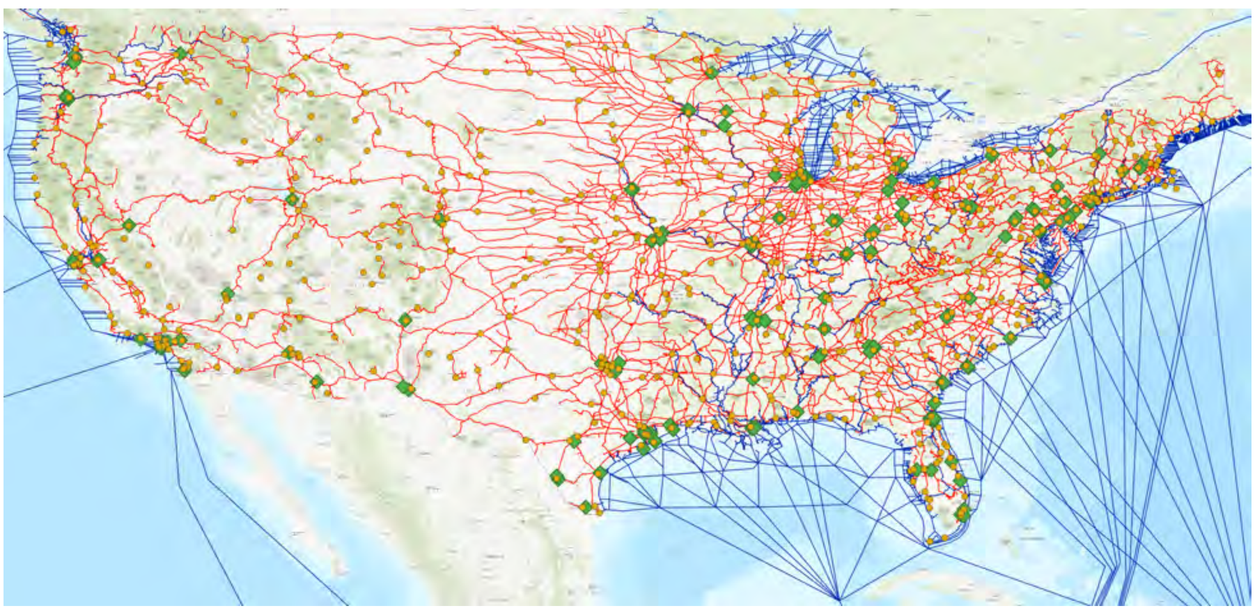
Notes: Black lines denote boundaries between regions. Bright orange areas denote major metropolitan areas. Light blue areas encompass large, rural areas. Note that there is at least one large, rural swath per state; rural areas are distinguished by their state.

Figure 3: National Transport Network

(a) **Roads & Intermodal**



(b) **Rail, Water, Air, & Intermodal**



Notes: This figure displays the domestic transport network in the mainland U.S.. Roads are depicted in dark grey, rails in red, navigable waterways in dark blue, airports accepting freight as golden-yellow points, and intermodal exchanges as green diamonds. Panels are split to make the separate networks clearer. Multi-model transshipment may only occur at designated intermodal exchanges. I assume that travel may occur in a straight line between airports. Background map provided by ESRI World Topographical map.

Table 1: Evolution of Routed Mileage by Mode

	Road		Rail		Water		Air		Multi-modal	
Route	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	1	–	1	–	1	–	1	–	1	–
2	1.044	*+4.4%*	1.056	*+5.6%*	1.042	*+4.2%*	1.002	*+0.2%*	1.043	*+4.3%*
3	1.074	*+2.8%*	1.096	*+3.8%*	1.066	*+2.3%*	1.005	*+0.3%*	1.069	*+2.5%*
4	1.099	*+2.3%*	1.122	*+2.4%*	1.135	*+6.5%*	1.009	*+0.4%*	1.093	*+2.2%*
5	1.119	*+1.8%*	1.155	*+2.9%*	1.153	*+1.6%*	1.013	*+0.4%*	1.114	*+1.9%*
6	1.135	*+1.5%*	1.173	*+1.6%*	1.157	*+0.4%*	1.018	*+0.5%*	1.127	*+1.2%*
7	1.152	*+1.5%*	1.194	*+1.8%*	1.221	*+5.5%*	1.019	*+0.1%*	1.143	*+1.5%*
8	1.166	*+1.3%*	1.216	*+1.9%*	1.242	*+1.7%*	1.023	*+0.4%*	1.16	*+1.4%*
9	1.18	*+1.1%*	1.229	*+1.1%*	1.255	*+1%*	1.027	*+0.4%*	1.174	*+1.2%*
10	1.189	*+0.8%*	1.247	*+1.4%*	1.262	*+0.6%*	1.029	*+0.1%*	1.186	*+1%*

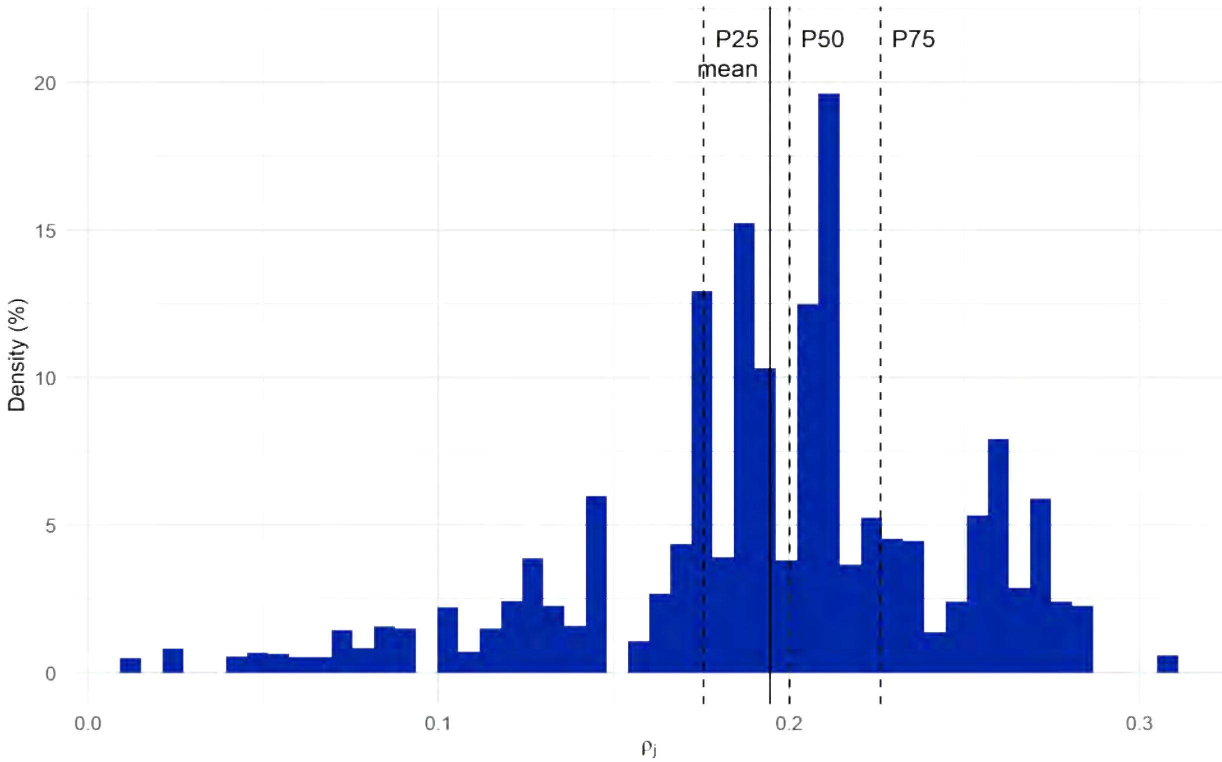
Notes: This table displays the average evolution of mileage along each route across all origin-destination pairs by mode. The odd-numbered columns display the average, scaled mileage per route; the shortest path takes a value of 1 for all origin-destination pairs. The even-numbered columns display the incremental percentage change in this average, scaled mileage.

Table 2: Reduced-Form Estimates: Sensitivity to $\mathcal{R}_{ij}^m$

Dep. Var:	No. of Routes				
$\ln \pi_{r(i,j,m)}$	1	2	3	5	10
	(1)	(2)	(3)	(4)	(5)
A. Estimated Coefficients (per 1,000 miles or 1 Modal Exchange)					
Road	0.736***	0.726***	0.722***	0.712***	0.695***
	(0.087)	(0.083)	(0.082)	(0.079)	(0.076)
Rail	0.430***	0.439***	0.446***	0.451***	0.439***
	(0.083)	(0.084)	(0.083)	(0.079)	(0.074)
Water	0.661***	0.646***	0.640***	0.562***	0.458***
	(0.194)	(0.179)	(0.172)	(0.145)	(0.105)
Air	0.226***	0.226***	0.226***	0.226***	0.226***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Intermodal	0.091***	0.063***	0.046***	0.050***	0.042***
	(0.024)	(0.017)	(0.014)	(0.012)	(0.009)
B. Iceberg Cost of 1,000 miles (excl. first/final mile, etc.)					
Road	1.202	1.199	1.198	1.195	1.190
Rail	1.113	1.116	1.118	1.119	1.116
Water	1.180	1.175	1.174	1.151	1.121
Air	1.058	1.058	1.058	1.058	1.058
Intermodal	1.023	1.016	1.012	1.013	1.011
N	145,974	291,948	437,922	729,870	1,459,740
Adj. R^2	0.866	0.869	0.870	0.872	0.873
First-Stage F-Stat	1.087	5.553	10.327	20.30	60.994

Notes: Panel A displays estimated cost coefficients resulting from the EM process, utilizing Equation (20). The parameter φ is held constant at 1. Each column restricts the size of $\mathcal{R}_{ij}^m$: column (1) allows only the shortest path between an origin and destination; column (2) allows the 2 shortest paths; column (5) allows 10 unique routes between an origin and destination. Bootstrapped standard errors (from 500 iterations) are presented in parentheses. Panel B reports the iceberg trade cost of traversing 1,000 miles along the specified mode, assuming a trade elasticity of 4. Note that the iceberg costs in Panel B exclude route-invariant costs (e.g. $\eta_{iem}, \nu_{xjm}, \alpha_{im}$, and γ_{jm}).

Figure 4: Distribution of ρ_j



Notes: This figure presents the distribution of the estimated origin correlation parameters. The mean, median, 25th percentile, and 75th percentile are also marked with vertical lines.

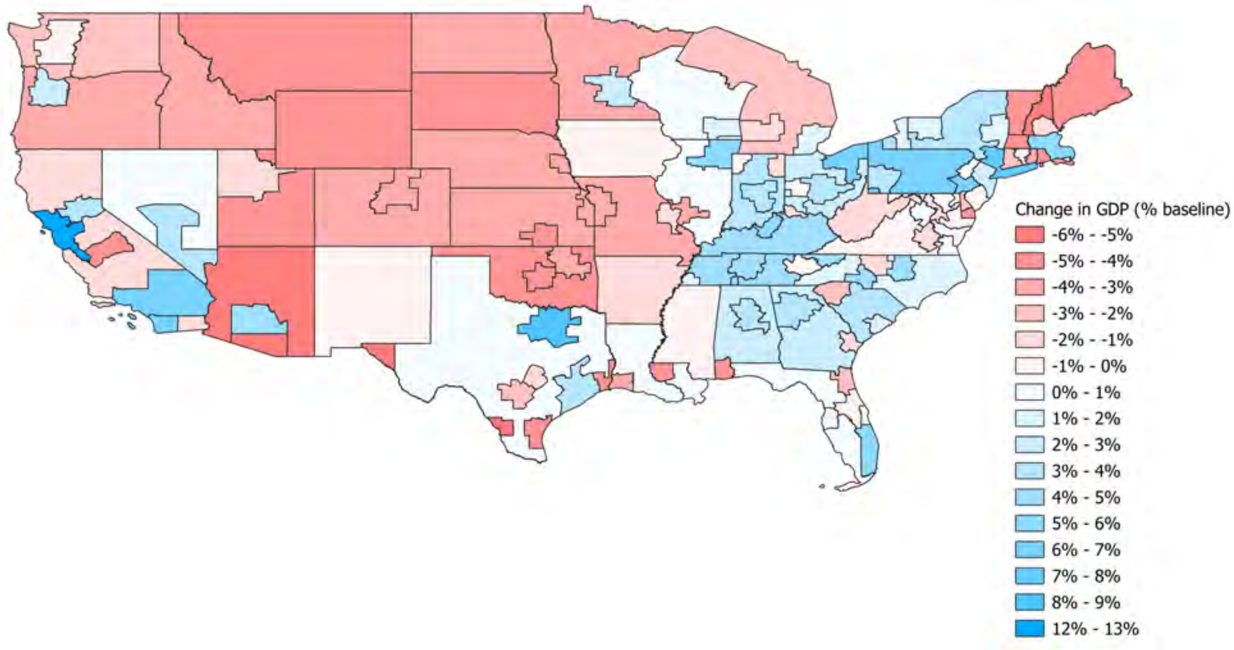
Table 3: Change in GDP, Imports, and Exports under Perfect Competition

	Baseline Trade Share (%)	Income Effect (% Baseline)	Subs. Effect (% Baseline)	Total Change % Baseline	Total Change $ billion
	(1)	(2)	(3)	(4)	(5)
A. National Income					
Road	78.32	0.85	-3.13	-2.28	-442
Rail	2.69	0.50	-1.03	-0.53	-103
Water	1.57	0.06	-0.19	-0.13	-25
Air	2.20	1.01	4.92	5.93	1,151
Multi	15.23	-0.40	-0.57	-0.97	-189
Total	100.00	2.02	0.00	2.02	393
B. Imports					
Road	68.94	48.90	-24.82	24.08	697
Rail	9.55	4.72	-8.17	-3.45	-100
Water	2.24	0.98	-1.53	-0.55	-16
Air	10.30	8.63	39.03	47.66	1,380
Multi	8.97	5.99	-4.51	1.48	43
Total	100.00	69.21	0.00	69.21	2,004
C. Exports					
Road	65.41	45.81	-14.41	31.39	731
Rail	6.65	3.98	-5.66	-1.68	-39
Water	4.22	1.59	-3.04	-1.46	-34
Air	17.55	15.08	27.36	42.44	989
Multi	6.18	3.79	-4.24	-0.45	-11
Total	100.00	70.24	0.00	70.24	1,636

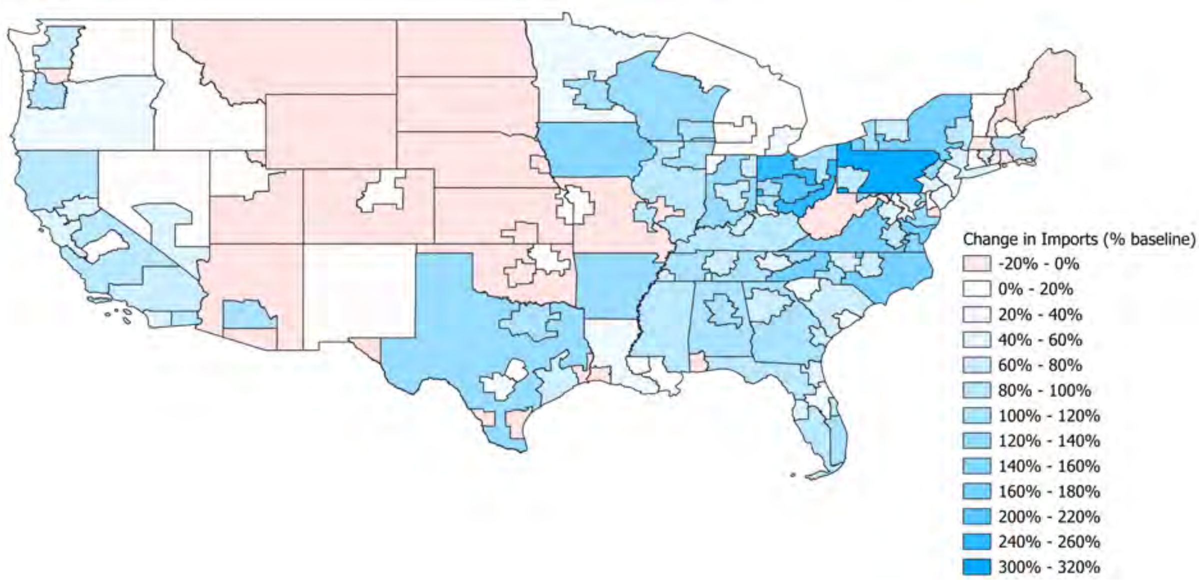
Notes: This table displays national income changes brought by elimination of non-competitive pricing in the transport sector. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in total domestic trade volume (as a percent of national GDP) as a result of eliminating markups, holding trade shares constant; Column (3) lists the change in volume stemming from substitution of freight across modes; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national GDP) along each mode; Column (5) lists the dollar amount in billions amount associated with Column (4). The simulated changes are calculated using 10 potential routings for each mode-market combination.

Figure 5: Real Changes from Elimination of Non-Competitive Markups

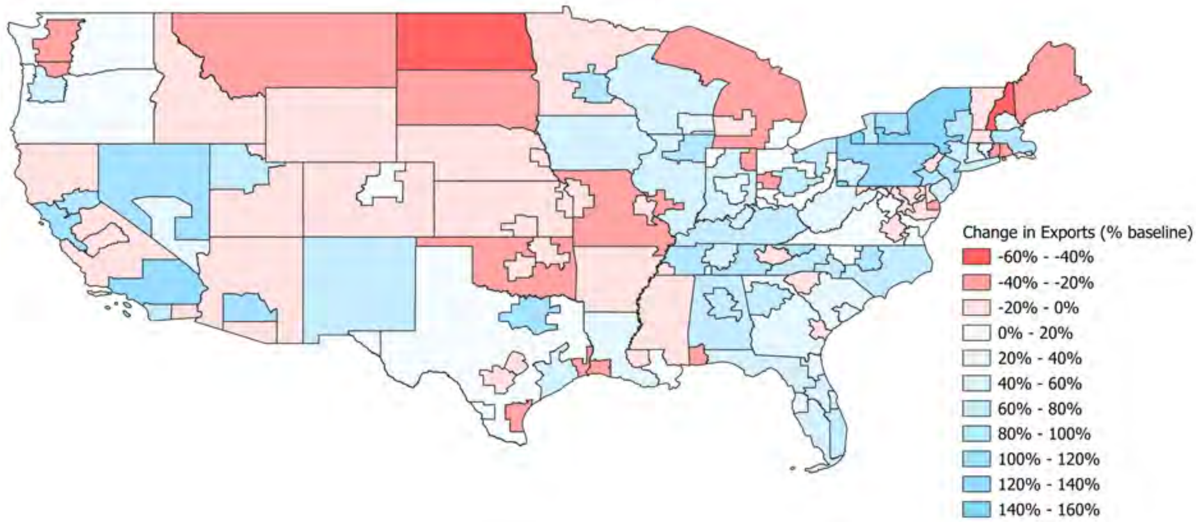
(a) **Welfare**



(b) **Imports**



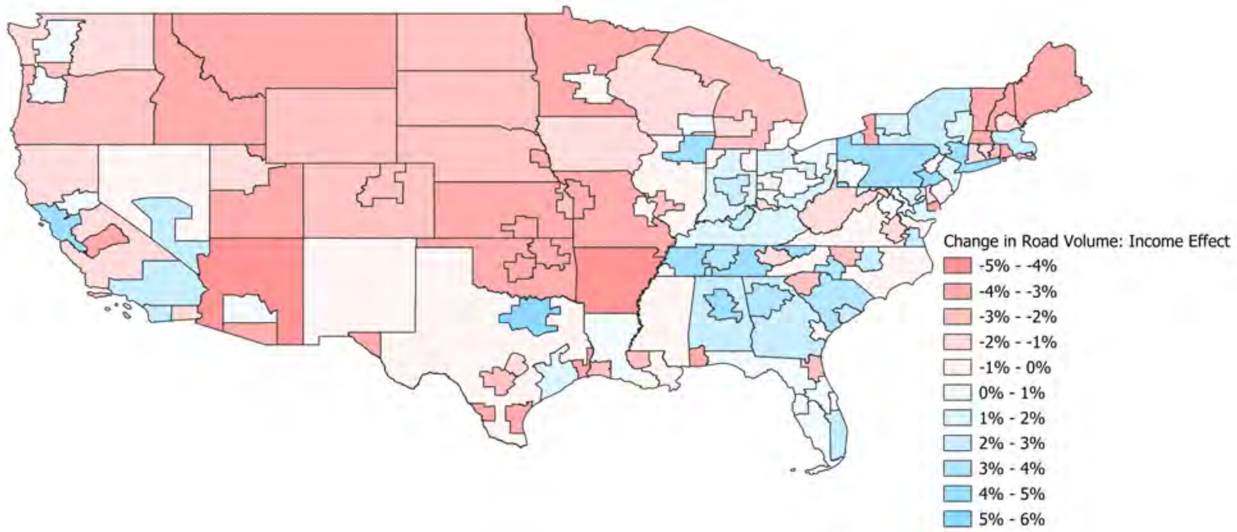
(c) **Exports**



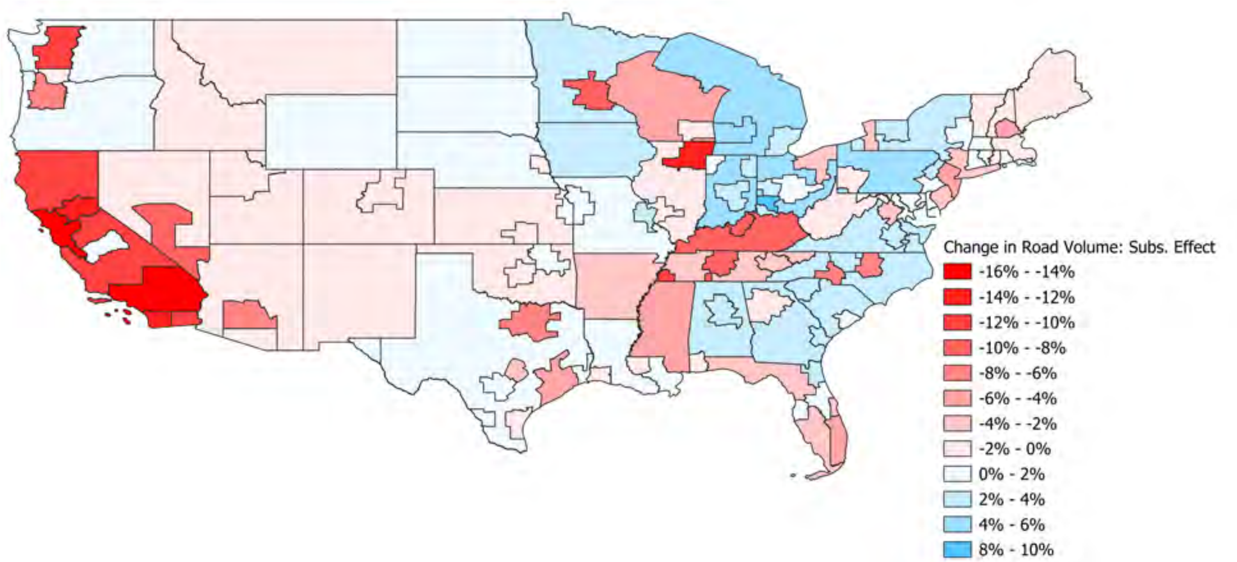
Notes: This figure presents potential change in real income, imports, and exports from imposing perfect competition in the transportation sector. These welfare gains are calculated as the percentage increase in real income when eliminating markups over real income under the status quo. Darker colors signify greater changes– red denotes a decline in income, while blue denotes a gain.

Figure 6: Changes in Trade Volume by Mode: Roadway

(a) **Income Effect**



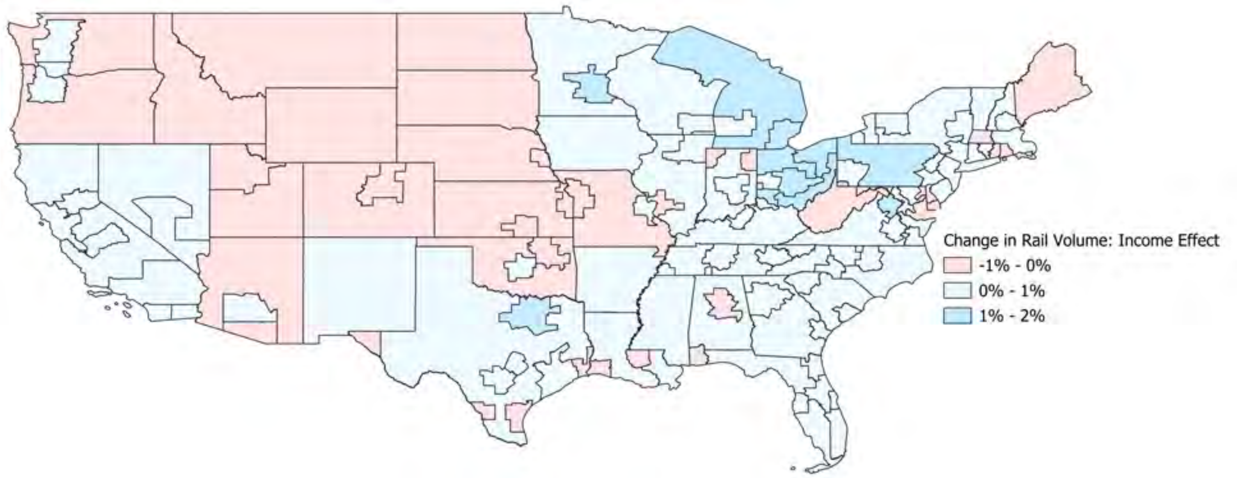
(b) **Substitution Effect**



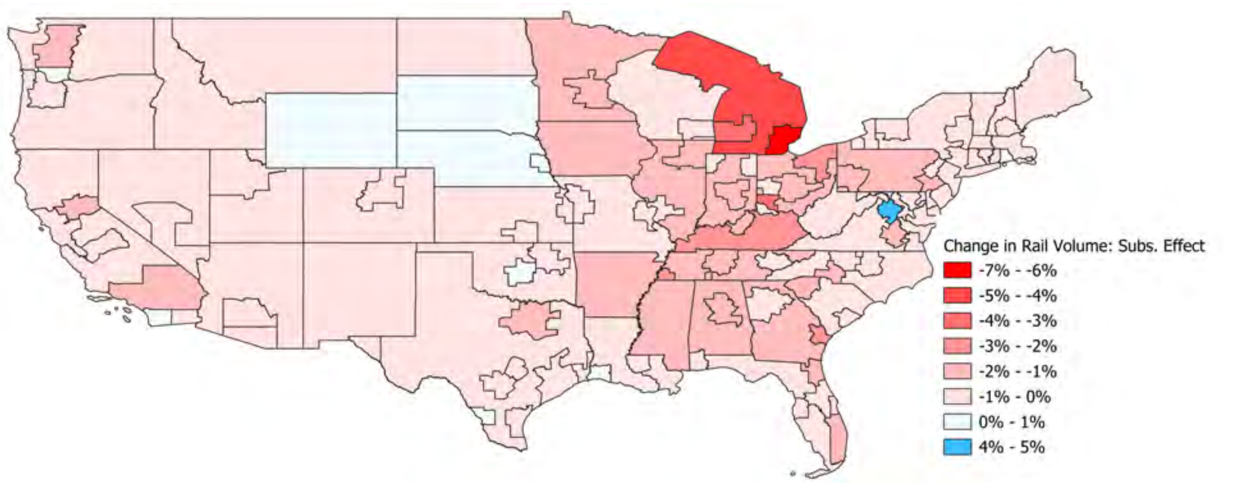
Notes: This figure presents potential change in trade volume along the roadway from imposing perfect competition in freight markets. The top panel reports the income effect, which stems from changes in trading partners. The bottom panel reports the modal substitution effect, which reveals changes in trade volume on the road, holding aggregate income constant.

Figure 7: Changes in Trade Volume by Mode: Rail

(a) **Income Effect**



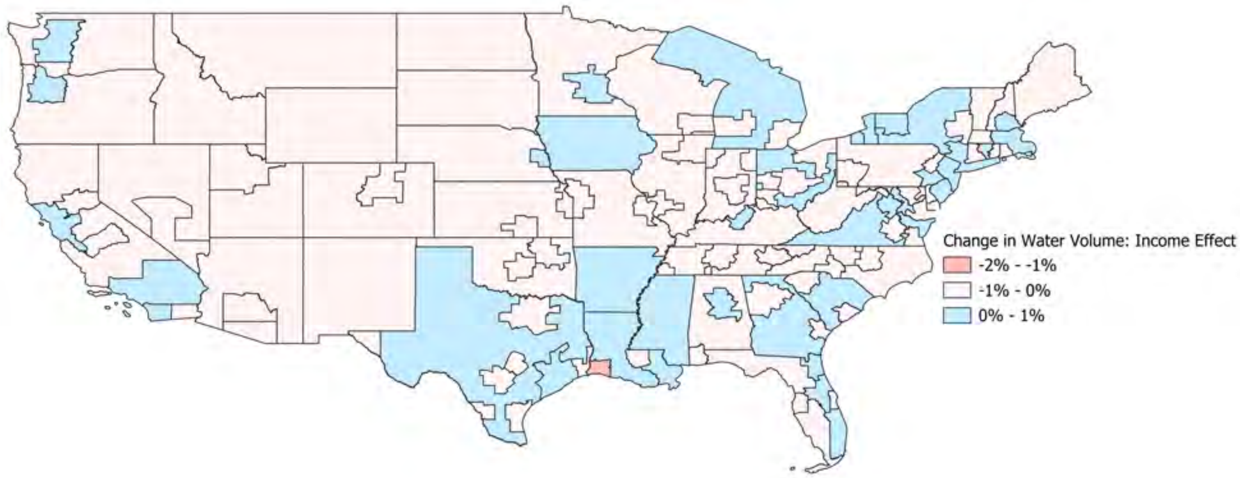
(b) **Substitution Effect**



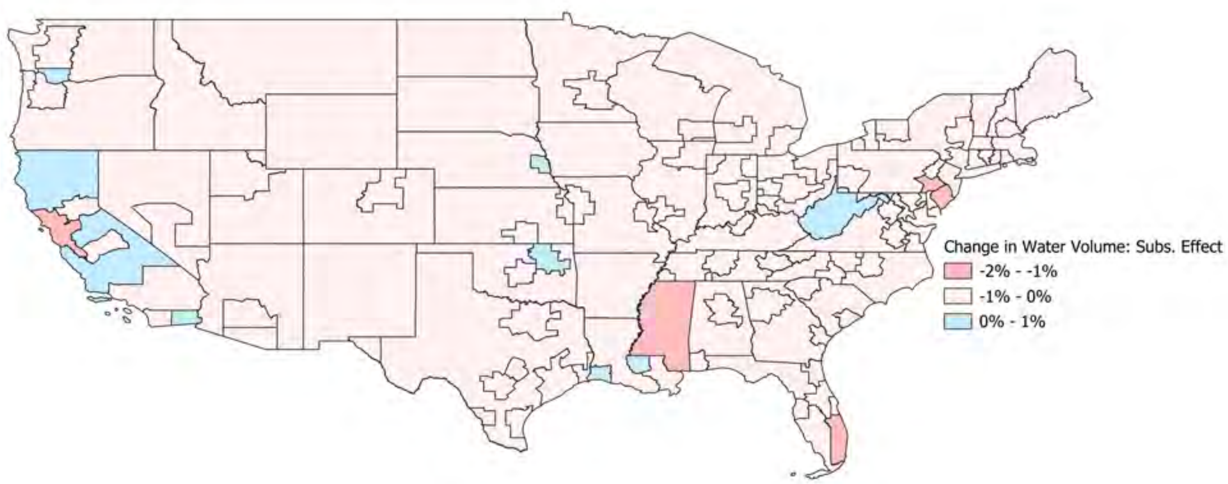
Notes: This figure presents potential change in trade volume along the railway from imposing perfect competition in freight markets. The top panel reports the income effect, which stems from changes in trading partners. The bottom panel reports the modal substitution effect, which reveals changes in trade volume on the Rail, holding aggregate income constant.

Figure 8: Changes in Trade Volume by Mode: Water

(a) **Income Effect**



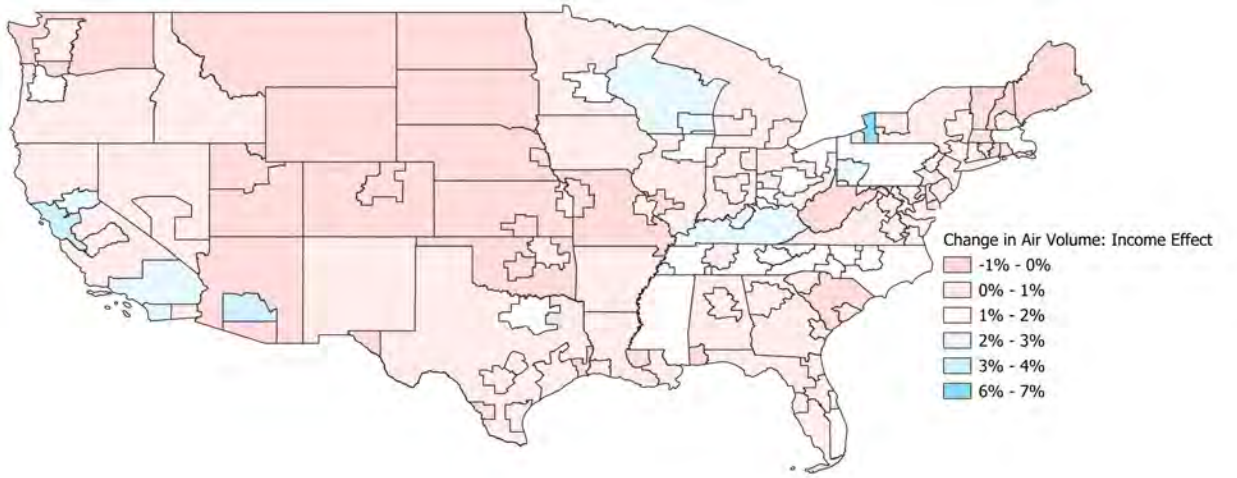
(b) **Substitution Effect**



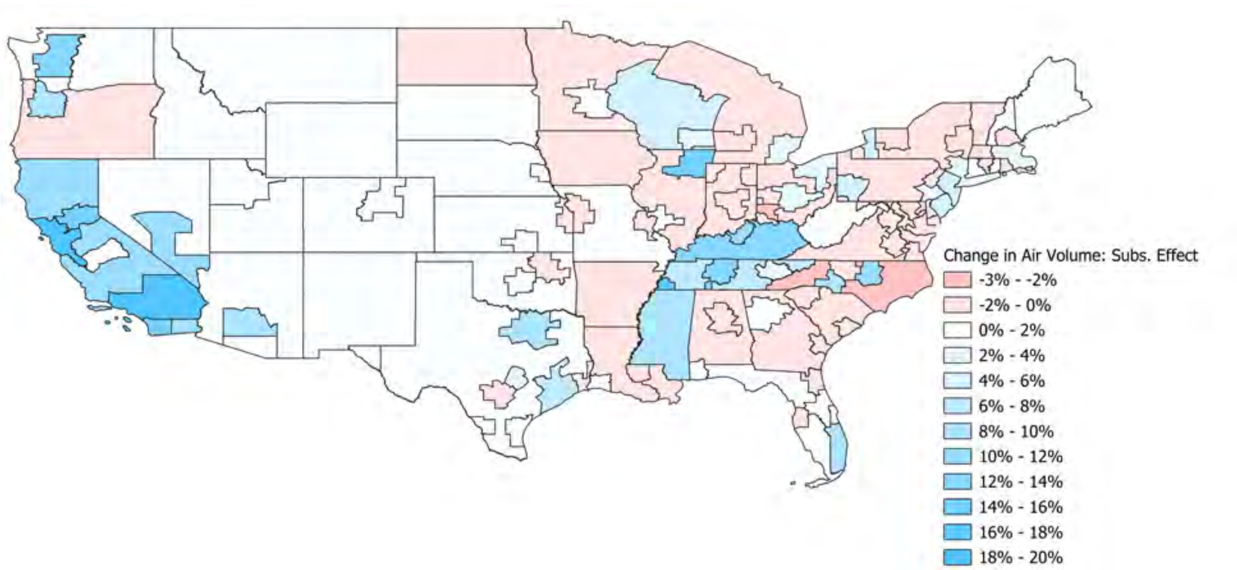
Notes: This figure presents potential change in trade volume along the Water from imposing perfect competition in freight markets. The top panel reports the income effect, which stems from changes in trading partners. The bottom panel reports the modal substitution effect, which reveals changes in trade volume on the Water, holding aggregate income constant.

Figure 9: Changes in Trade Volume by Mode: Air

(a) **Income Effect**



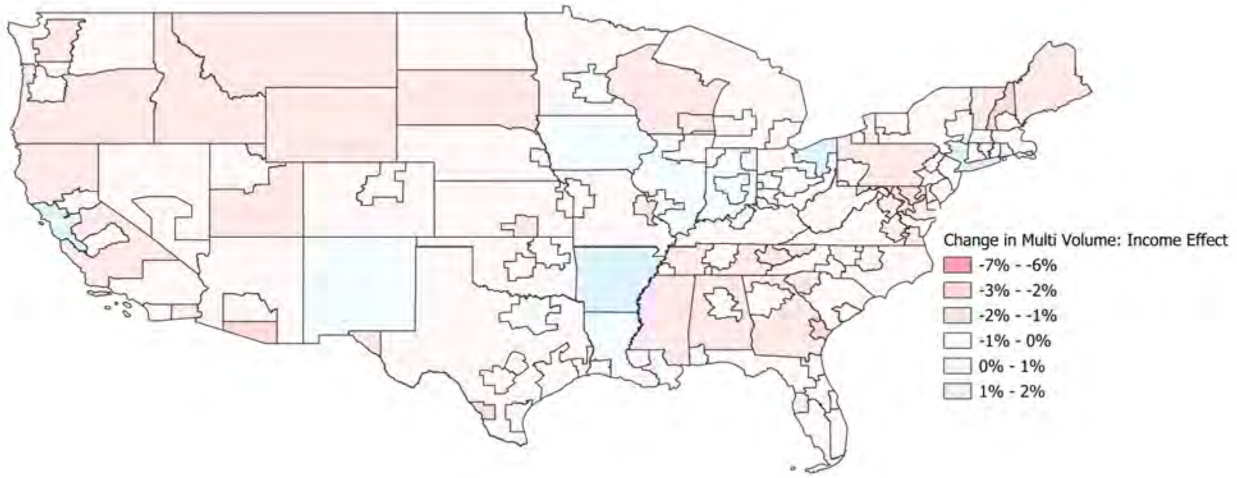
(b) **Substitution Effect**



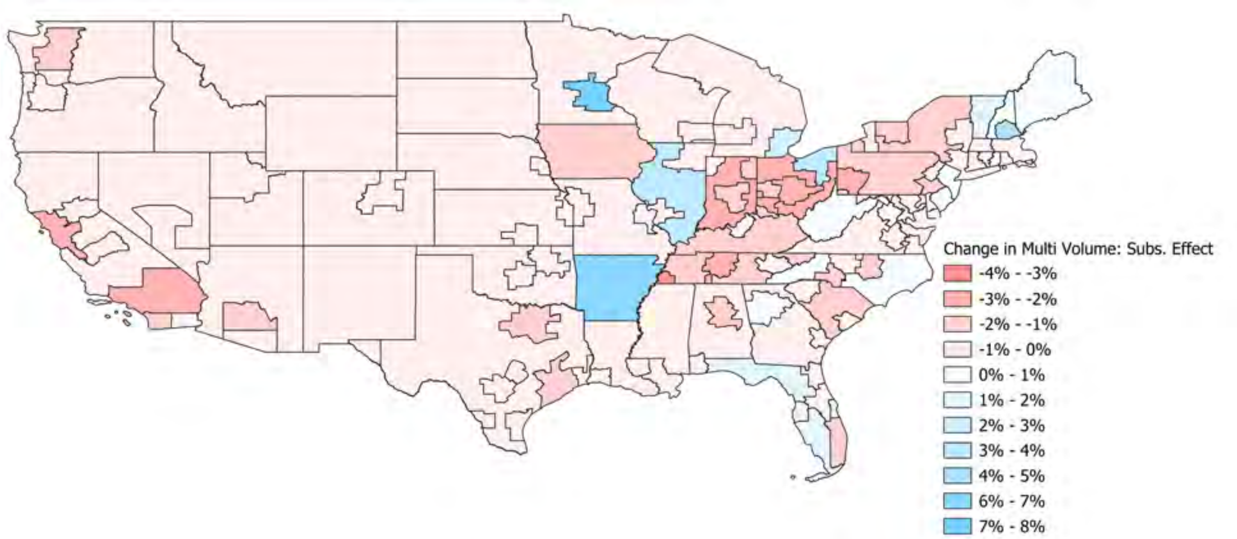
Notes: This figure presents potential change in trade volume along Air from imposing perfect competition in freight markets. The top panel reports the income effect, which stems from changes in trading partners. The bottom panel reports the modal substitution effect, which reveals changes in trade volume via Air, holding aggregate income constant.

Figure 10: Changes in Trade Volume by Mode: Multi-Modal

(a) **Income Effect**



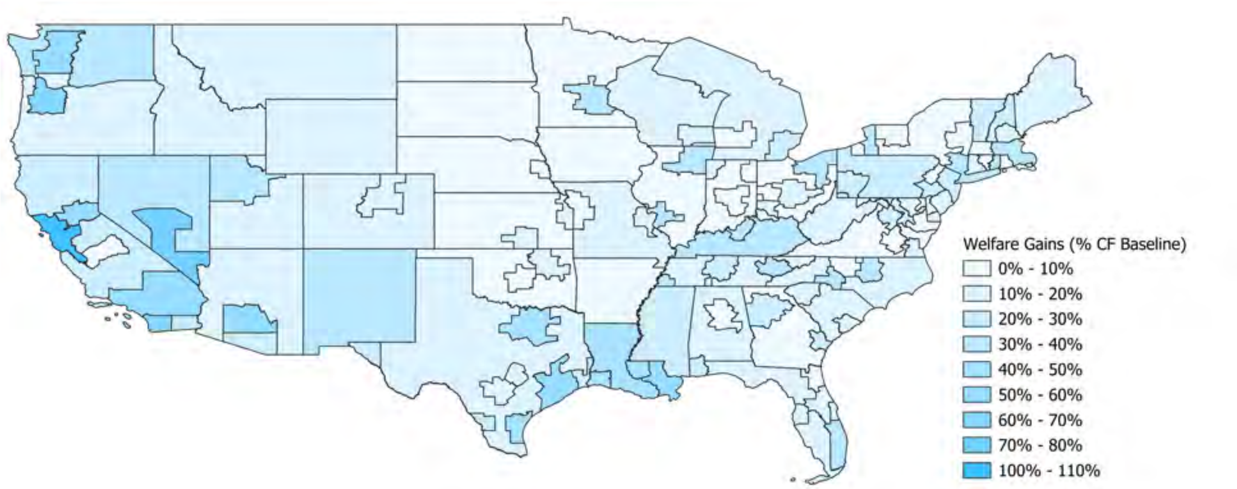
(b) **Substitution Effect**



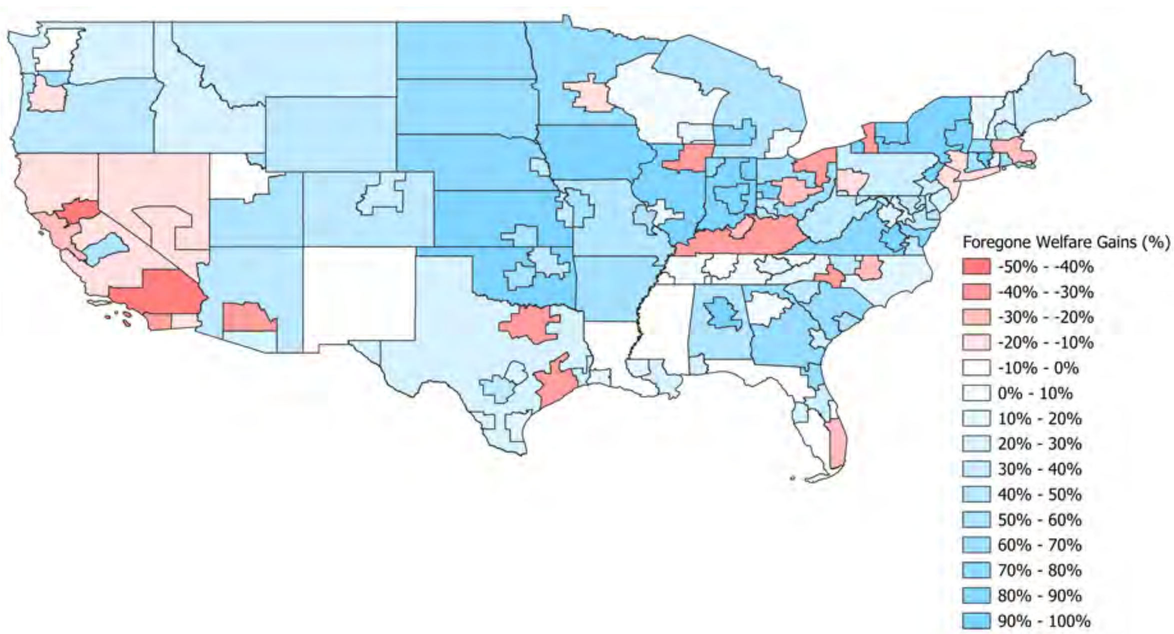
Notes: This figure presents potential change in trade volume along Multi-Modal from imposing perfect competition in freight markets. The top panel reports the income effect, which stems from changes in trading partners. The bottom panel reports the modal substitution effect, which reveals changes in trade volume along Multi-Modal, holding aggregate income constant.

Figure 11: Changes in Income Resulting from Domestic Infrastructure Investment

(a) **Income Gains under Perfect Competition**



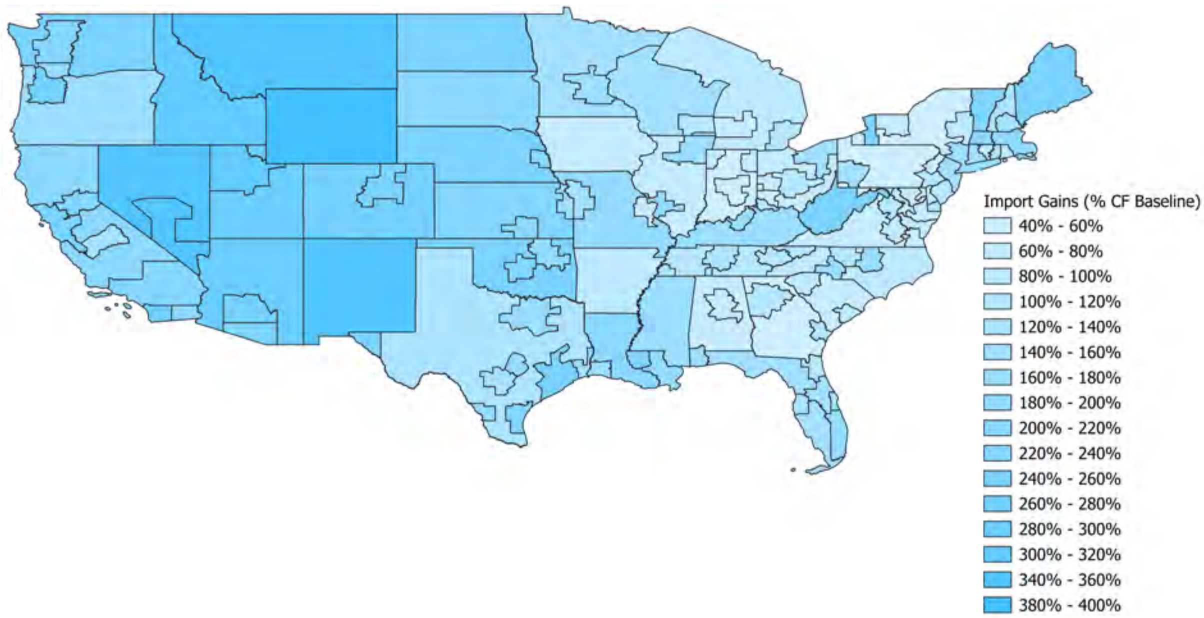
(b) **Income Cannibalization**



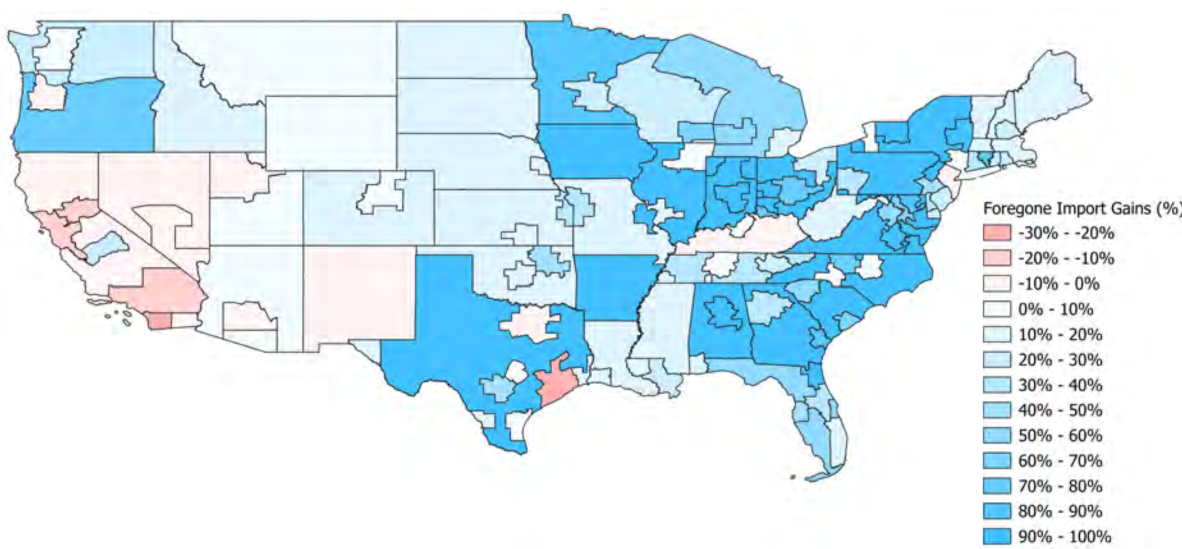
Notes: This figure summarizes income changes resulting from counterfactual domestic infrastructure investment. Panel (a) presents the change in welfare resulting from the shock under perfect competition (as a percentage of each region's baseline GDP). Panel (b) presents cannibalization rates – that is, the percent change in the estimated impact as a result on non-competitive freight pricing.

Figure 12: Changes in Imports Resulting from Domestic Infrastructure Investment

(a) **Import Changes under Perfect Competition**



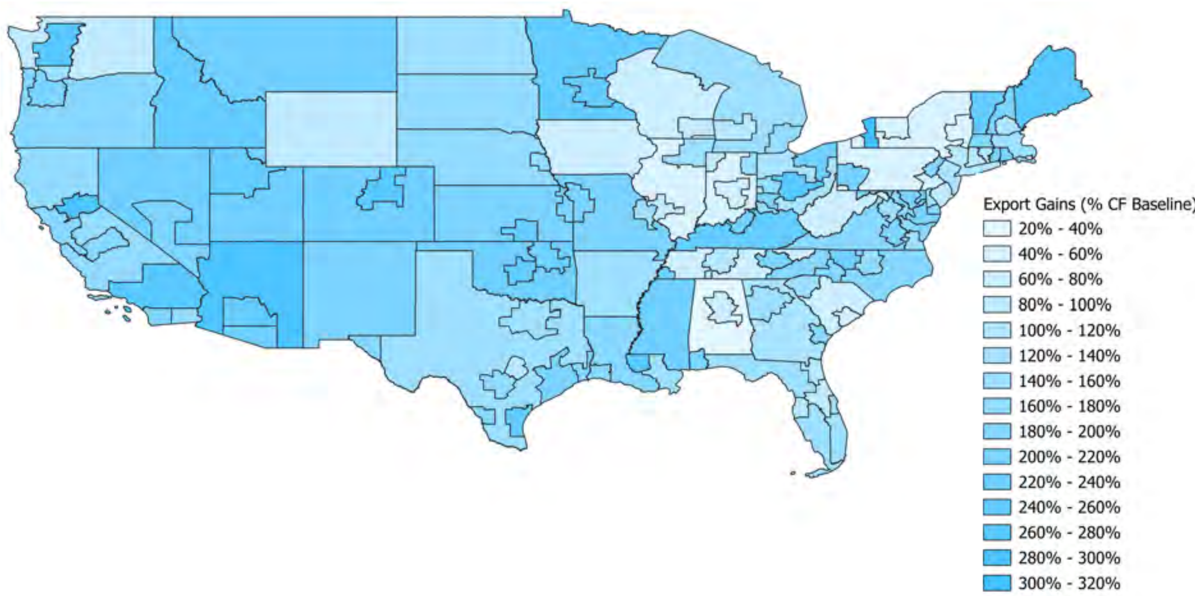
(b) **Import Cannibalization**



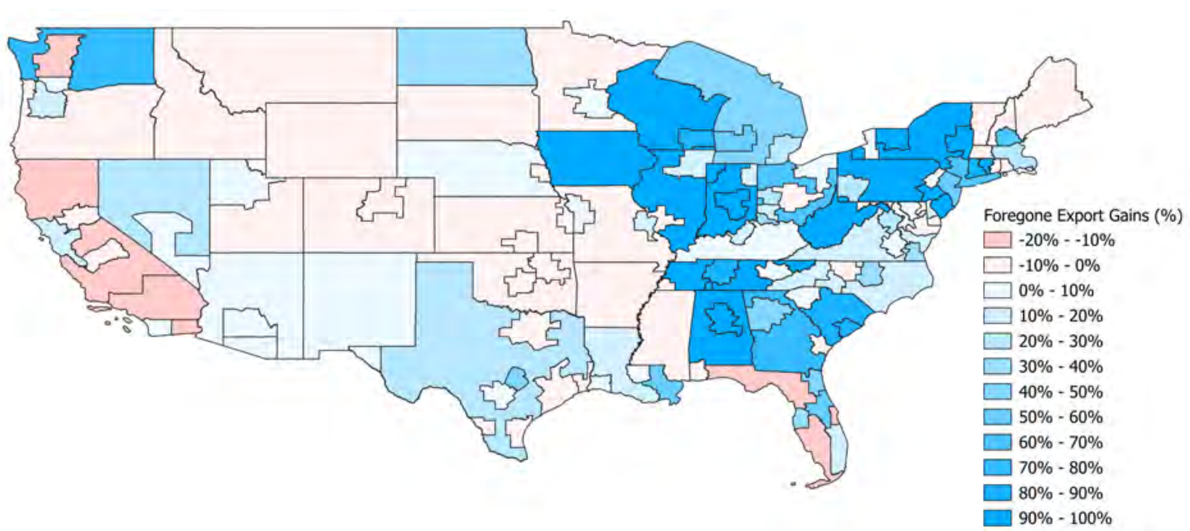
Notes: This figure summarizes real import changes resulting from counterfactual domestic infrastructure investment. Panel (a) presents the change in imports resulting from the shock under perfect competition (as a percentage of each region's baseline imports). Panel (b) presents cannibalization rates – that is, the percent change in the estimated impact as a result on non-competitive freight pricing.

Figure 13: Changes in Exports Resulting from Domestic Infrastructure Investment

(a) **Export Changes under Perfect Competition**



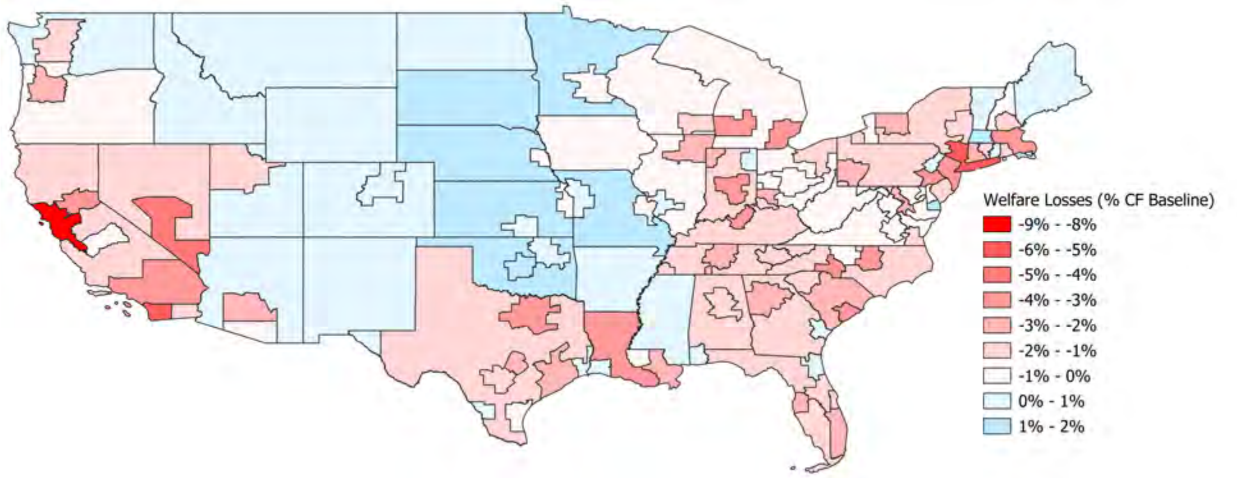
(b) **Export Cannibalization**



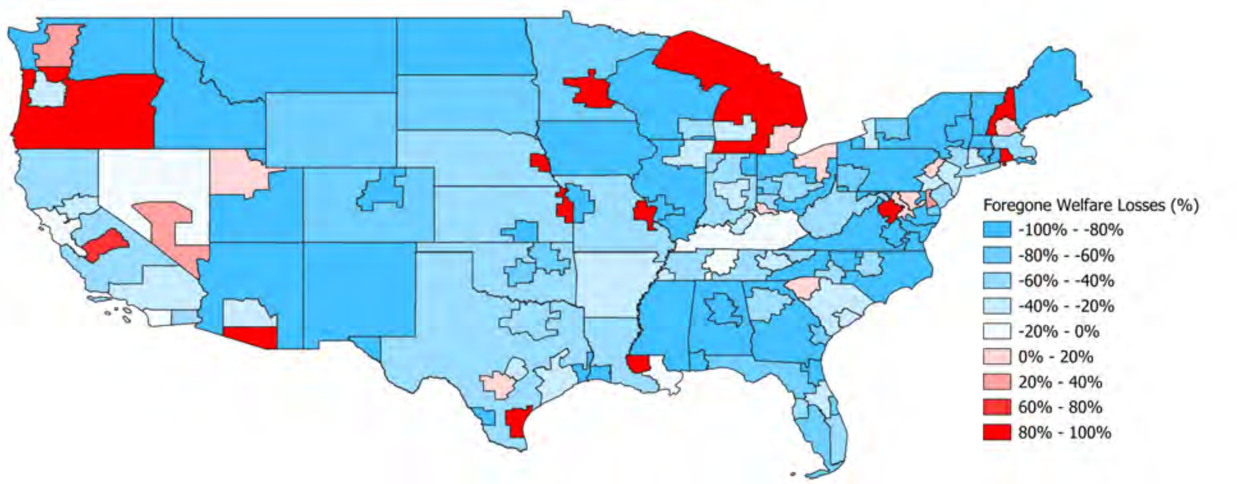
Notes: This figure summarizes real export changes resulting from counterfactual domestic infrastructure investment. Panel (a) presents the change in exports resulting from the shock under perfect competition (as a percentage of each region's baseline exports). Panel (b) presents cannibalization rates – that is, the percent change in the estimated impact as a result on non-competitive freight pricing.

Figure 14: Changes in Income Resulting from an International Trade Shock

(a) **Income Gains under Perfect Competition**



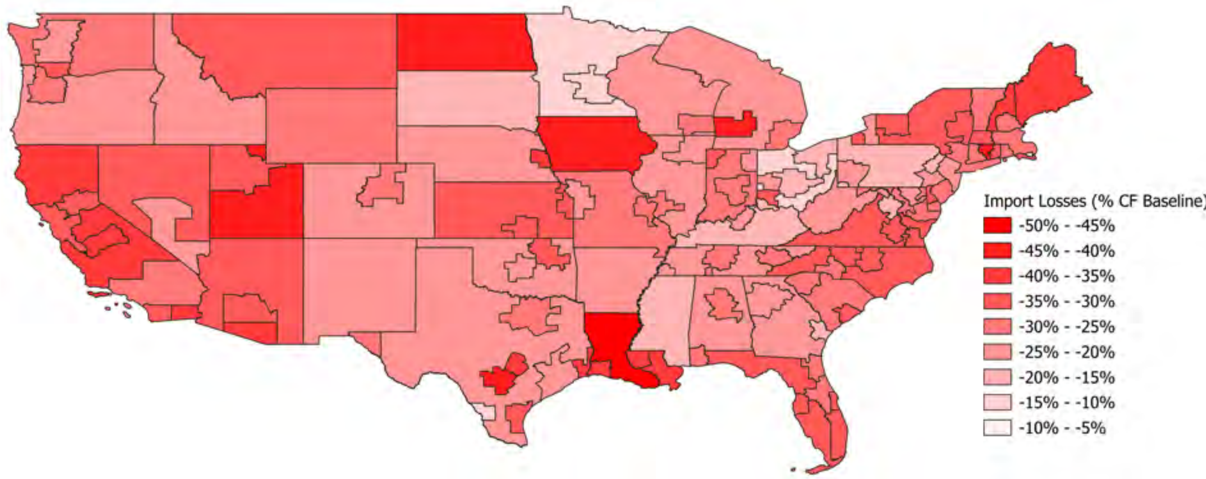
(b) **Income Cannibalization**



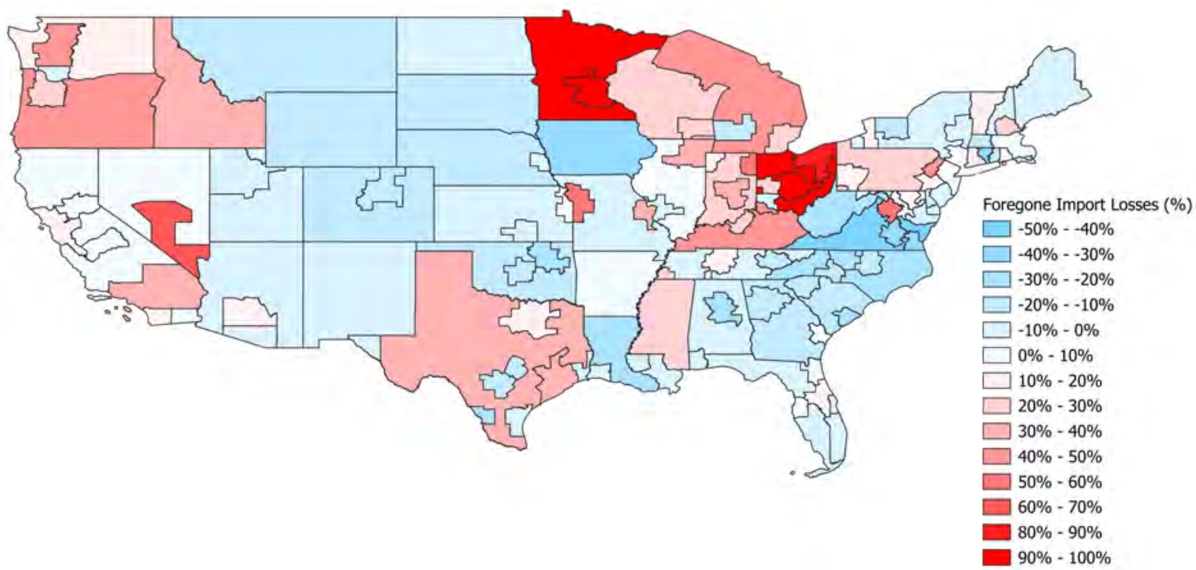
Notes: This figure summarizes income changes resulting from a counterfactual international trade shock. Panel (a) presents the change in welfare resulting from the shock under perfect competition (as a percentage of each region's baseline GDP). Panel (b) presents cannibalization rates – that is, the percent change in the estimated impact as a result on non-competitive freight pricing.

Figure 15: Changes in Imports Resulting from an International Trade Shock

(a) **Import Changes under Perfect Competition**



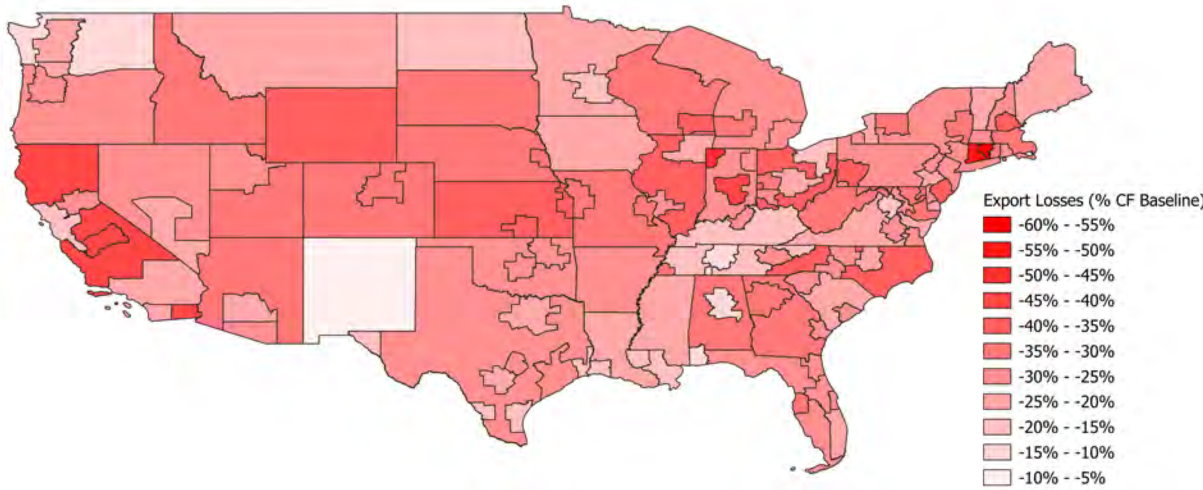
(b) **Import Cannibalization**



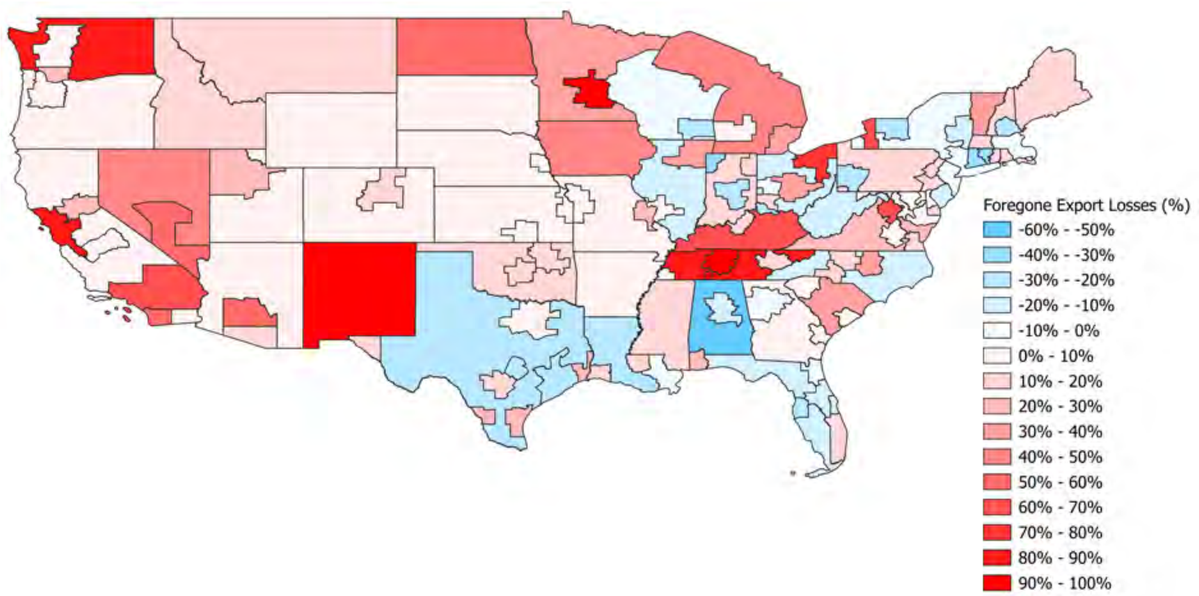
Notes: This figure summarizes real import changes resulting from a counterfactual international trade shock. Panel (a) presents the change in imports resulting from the shock under perfect competition (as a percentage of each region's baseline imports). Panel (b) presents cannibalization rates – that is, the percent change in the estimated impact as a result on non-competitive freight pricing.

Figure 16: Changes in Exports Resulting from an International Trade Shock

(a) **Export Changes under Perfect Competition**



(b) **Export Cannibalization**



Notes: This figure summarizes real export changes resulting from a counterfactual international trade shock. Panel (a) presents the change in exports resulting from the shock under perfect competition (as a percentage of each region's baseline exports). Panel (b) presents cannibalization rates – that is, the percent change in the estimated impact as a result on non-competitive freight pricing.

A Mathematical Appendix

A.1 Simplifying Trade Shares

I begin with the trade shares from the nested logit structure:

$$\pi_{r(i,e,x,j,m)} = \exp\Big(-\ln A_i - \theta\big[\ln c_i + (\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r)/(\rho_j\varphi) + (\alpha_{im} + \gamma_{jm})/\rho_j\big] \\ - (1-\varphi)J_{ijm} - (1-\rho_j)I_{ij} - Q_j\Big).$$

Unfortunately, this formulation is not a tenable regression specification. The inclusive values used to identify the correlation coefficients – J_{ijm} and I_{ij} – are not directly observed in the data; they could be calculated, though at substantial effort. Fixed effects do not offer a viable solution, as the origin-by-destination-by-mode fixed effect required to capture J_{ijm} would absorb all of the non-simulated variation present in the data. However, some simple manipulation yields a much more tractable specification:

$$\begin{aligned}
\pi_{r(i,e,x,j,m)} = &\exp\Big(-\ln A_i - \theta\big[\ln c_i + (\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r)/(\rho_j\varphi) + (\alpha_{im} + \gamma_{jm})/\rho_j\big] \\
&+ \theta\big[\alpha_{im} + \gamma_{jm}\big] - \theta\big[\alpha_{im} + \gamma_{jm}\big] + \rho_j\varphi J_{ijm} - \rho_j\varphi J_{ijm} \\
&- (1-\varphi)J_{ijm} - (1-\rho_j)I_{ij} - Q_j\Big) \\
= &\exp\Big(-\ln A_i - \theta\big[\ln c_i + (\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r)/(\rho_j\varphi) + \alpha_{im} + \gamma_{jm}\big] \\
&+ (1-\rho_j)\big[\theta(\alpha_{im} + \gamma_{jm})/\rho_j + \varphi J_{ijm} - I_{ij}\big] - (1-\rho_j\varphi)J_{ijm} - Q_j\Big) \\
= &\exp\Big(-\ln A_i - \theta\big[\ln c_i + (\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r)/(\rho_j\varphi) + \alpha_{im} + \gamma_{jm}\big] \\
&+ (1-\rho_j)\ln\pi_{m|ij} - (1-\rho_j\varphi)J_{ijm} - Q_j\Big) \\
= &\exp\Big(-\ln A_i - \theta\big[\ln c_i + (\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r)/(\rho_j\varphi) + \alpha_{im} + \gamma_{jm}\big] \\
&+ \theta\big[\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r\big] - \theta\big[\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r\big] \\
&+ (1-\rho_j)\ln\pi_{m|ij} - (1-\rho_j\varphi)J_{ijm} - Q_j\Big) \\
= &\exp\Big(-\ln A_i - \theta\big[\ln c_i + \mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r + \alpha_{im} + \gamma_{jm}\big] \\
&+ (1-\rho_j\varphi)\big[\theta(\mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r)/(\rho_j\varphi) - J_{ijm}\big] \\
&+ (1-\rho_j)\ln\pi_{m|ij} - Q_j\Big)
\end{aligned}$$

$$
\begin{aligned}
&= \exp\Big(-\ln A_i - \theta\big[\ln c_i + \mu_r + \kappa_r + \eta_{iem} + \nu_{jxm} + u_r + \alpha_{im} + \gamma_{jm}\big] \\
&\qquad + (1-\rho_j\varphi)\ln \pi_{r|ijm} + (1-\rho_j)\ln \pi_{m|ij} - Q_j\Big).
\end{aligned}
$$

A.2 Price Index

I now provide a detailed derivation of Equation (12). Let $p(\omega)$ be the vector of prices for good ω in market j, where each entry of $p(\omega)$ gives $p_{r(i,j,m)}(\omega)$; define similarly the vectors c, τ, and $\epsilon(\omega)$. Let the scalar $z \in \mathbb{R}_{++}$. Define the function:

$$
\begin{aligned}
G_j(z) &= \Pr\left(p(\omega) \leq z\right) \\
&= \Pr\left(\frac{c\tau}{\epsilon(\omega)} \leq z\right) \\
&= \Pr\left(\frac{c\tau}{z} \leq \epsilon(\omega)\right) \\
&= \Pr\left(\ln c + \ln \tau - \ln z \leq \ln \epsilon(\omega)\right) \\
&= 1 - \Pr\left(\ln c + \ln \tau - \ln z \geq \ln \epsilon(\omega)\right) \\
&= 1 - F\left(\ln c + \ln \tau - \ln z\right) \\
&= 1 - \exp\left[-\sum_{i\in\mathcal{S}} \left(\sum_{m\in\mathcal{M}} \left(\sum_{r\in\mathcal{R}_{ij}^m} \exp\left(\frac{-\ln A_i - \theta\left[\ln c_i + \ln \tau_r - \ln z\right]}{\varphi\rho_j} \right) \right)^{\varphi} \right)^{\rho_j} \right] \\
&= 1 - \exp\left[-z^{\theta} \sum_{i\in\mathcal{S}} \left(\sum_{m\in\mathcal{M}} \left(\sum_{r\in\mathcal{R}_{ij}^m} \exp\left(\frac{-\ln A_i - \theta\left[\ln c_i + \ln \tau_r\right]}{\varphi\rho_j} \right) \right)^{\varphi} \right)^{\rho_j} \right] \\
&= 1 - \exp\left(-z^{\theta} Q_j\right).
\end{aligned}
$$

From the CES utility assumption, it follows,

$$
\begin{aligned}
p_j &= \left(\int_{\Omega} p_j(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}} \\
p_j^{1-\sigma} &= \int_0^1 z^{1-\sigma} dG_j(z) \\
p_j^{1-\sigma} &= \int_{\mathbb{R}_{++}} z^{\theta-\sigma} \exp\left(-z^{\theta} Q_j\right) \theta Q_j dz \\
p_j^{1-\sigma} &= \Gamma\left(\frac{\theta+1-\sigma}{\theta}\right) Q_j^{\frac{\sigma-1}{\theta}} \\
p_j &= \Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)^{\frac{1}{1-\sigma}} Q_j^{-\frac{1}{\theta}}.
\end{aligned}
$$

A.3 Proof of Convergence of the EM Algorithm

It will be convenient to define the following matrices:

$$\phi^{\top} = \begin{bmatrix} \lambda_j & \beta_m & 1-\rho_j & 1-\rho_j\varphi \end{bmatrix}$$
$$X = \begin{bmatrix} \delta & Miles \times \mathbb{I}(m) & \ln\pi_{m|ij} \times \mathbb{I}(j) & \ln\pi_{r|ijm} \times \mathbb{I}(j) \end{bmatrix}$$

where $\mathbb{I}$ denotes the indicator function. This formulation implies the following estimating equation:

$$\ln\pi = X\phi + u. \tag{21}$$

Obviously, Equation (21) denotes the complete-information estimating equation. Unfortunately, elements of X, as well as $\ln\pi$, are unobserved. I therefore rely on the incomplete-information formulation:

$$\ln\pi^{(p)} = X^{(p)}\phi + u, \tag{22}$$

where $\ln\pi^{(p)}$ and $X^{(p)}$ respectively denote the expected values of $\ln\pi$ and X conditional on $\phi^{(p)}$ and the observed modal and trade shares, $\pi_{m|ij}$ and $\pi_{i|j}$. Estimating Equation (22) via OLS[34] yields the next entry in the EM sequence, $\phi^{(p+1)}$. Note also that $u^{(p+1)} = \ln\pi^{(p)} - X^{(p)}\phi^{(p+1)}$, is simply the estimated residual. From here, define the likelihood function:

$$Q\left(\phi^{(p+1)}|\phi^{(p)}\right) = \mathbb{E}\left[\ln f\left(X|\phi^{(p+1)}\right)|\pi_{m|ij}, \pi_{i|j}, \phi^{p}\right]$$

where f is the probability of X given ϕ. In words, $Q\left(\phi^{(p+1)}|\phi^{(p)}\right)$ defines the log-likelihood of observing $\phi^{(p+1)}$ given $\phi^{(p)}$.

Per Wu (1983), a sufficient condition for convergence of the EM process is the existence of a forcing function $c > 0$ such that

$$Q\left(\phi^{(p+1)}|\phi^{(p)}\right) - Q\left(\phi^{(p)}|\phi^{(p)}\right) \geq c\left\|\phi^{(p+1)} - \phi^{(p)}\right\| \;\forall p. \tag{23}$$

Note that this inequality holds trivially when $\phi^{(p+1)} = \phi^{(p)}$. I now focus on the case $\phi^{(p+1)} \neq \phi^{(p)}$.

[34] Note that OLS estimation satisfies the criteria of the EM process, as OLS estimates are also maximum-likelihood estimates.

Given the assumption that $u \sim N(0, v)$, it follows that

$$Q\left(\phi^{(p+1)}|\phi^{(p)}\right) = -(n/2)\ln(2\pi) - (n/2)\ln v - \big(1/(2v)\big)u^{(p+1)^\top}u^{(p+1)}, \tag{24}$$

where n is the number of rows in X. Similarly, define

$$\phi^{(p+1)} = \left(X^{(p)^\top}X^{(p)}\right)^{-1}\left(X^{(p)^\top}\ln\pi^{(p)}\right). \tag{25}$$

Combining equations (23) - (25) yields a characterization for c that satisfies Wu's criterion:

$$\frac{\left(u^{(p+1)^\top}u^{(p+1)} - u^{(p)^\top}u^{(p)}\right)}{2v\left\|\left(X^{(p)^\top}X^{(p)}\right)^{-1}\left(X^{(p)^\top}\ln\pi^{(p)}\right) - \phi^{(p)}\right\|} \geq c > 0. \tag{26}$$

The existence of c therefore hinges on three conditions: i) v must be non-zero and finite; ii) $X^{(p)^\top}X^{(p)}$ must be invertible (in other words, X must have non-zero variance); and iii) $X^{(p)}$ and $\ln\pi^{(p)}$ must have non-zero, finite covariance. That is, the same conditions required for OLS estimation guarantee convergence of the EM process.