

**Three Essays on Market Concentration in Markets for
Mobility**

by

Charles Adam Pfander

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Committee Members:

Jeronimo Carballo, Chair

Richard Mansfield

Taylor Jaworski

Wolfgang Keller

Jaehee Song

Pfander, Charles Adam (Ph.D., Economics)

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Thesis directed by Associate Professor Jeronimo Carballo

- (a) Chapter 1 - this paper seeks to understand how market structure for freight transportation affects domestic trade and its outcomes. I modify a 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 geographically distinct locations, and the intensity 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 5% of baseline welfare; ii) the exercise of freight market power has an outsized impact on exports relative to imports; iii) these impacts are concentrated in rural areas throughout the Southeast and Mountain West, as well as small urban areas in the Midwest and Gulf states; iv) exercise of freight market power exacerbates the impact of mode-specific shocks; and v) non-competitive freight pricing does little to attenuate international trade shocks, due to the concentration of freight market power away from international gates.
- (b) Chapter 2 - multi-establishment firms account for around 60% of U.S. workers' primary employers, providing ample opportunity for workers to change their work location without changing their employer. Using U.S. matched employer-employee data, this paper analyzes workers' access to and use of such between-establishment job transitions, and estimates the effect on workers' earnings growth of greater access, as measured by proximity of employment at other within-firm establishments. While establishment transitions are not perfectly observed, we estimate that within-firm establishment transitions account for 7.8% percent of all job transitions and 18.2% of transitions originating from the largest firms. Using

variation in workers' establishment locations within their firms' establishment network, we show that having a greater share of the firm's jobs in nearby establishments generates meaningful increases in workers' earnings: a worker at the 90th percentile of earnings gains from more proximate within-firm job opportunities can expect to enjoy 2% higher average earnings over the following five years than a worker at the 10th percentile with the same baseline earnings.

- (c) Chapter 3 - this paper seeks to understand how freight market concentration changes the impact of domestic market access improvements throughout the late 19th and early 20th Century. I modify a multi-sector Ricardian trade model to allow for endogenous transport costs set by a profit-maximizing freight monopolist. This framework yields a modified market access term that accounts not only for exogenous bilateral frictions, but endogenous bilateral markups. Reduced-form analysis reveals that omitting endogenous freight prices from the calculation of market access reduces the estimated impact by as much as half. I further document marked convexity in this treatment effect by initial output: smaller, remote counties stand the most to gain from market access improvements, which also means these counties are the most at-risk from the exercise of freight market power. I show that, over time, the most-affected counties move west along the American Frontier.

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Chapter 1

Trade and the Competition for Transport: How (a Lack of) Competition for Freight Transport Affects Domestic Trade Outcomes

1.1 Introduction

Transportation is central to trade —how a good moves from its origin to its destination greatly influences 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 has sought to incorporate more realistic transportation sectors into canonical trade models. Specifically, these recent works model route-choice ([Allen and Arkolakis, 2022, 2014](#)), mode-choice ([Fuchs and Wong, 2023](#)), and port-choice ([Brancaccio et al., 2020](#)) to generate trade costs as a function of existing infrastructure. However, the role of transporters’ strategic price-setting behavior remains unexplored. Hence, in this paper, I analyse the domestic trade impacts of market power among freight service providers.

I develop a Ricardian trade model, in which each origin-destination combination is served by a representative freight transporter of a particular mode. Multiple modes – namely, Trucking (or, “Road”), Rail, Water, Air, and Multi-Modal – service each origin-destination pairing,² and each of these intermediaries may pick among a selection of routes per mode. Transporters need not take the shortest path, but may elect more circuitous routes if they appear more profitable due to unobserved, exogenous cost components. Further, transporters set markups endogenously to maximize profits; the key inputs into the transporter’s problem include demand for freight transport between any origin-destination pairing, the costs incurred en-route, and the degree of freight-market compe-

¹This 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

²I emphasize that the set feasible of modes into any one location is determined by available infrastructure – Water transport is not possible without a navigable Waterway.

tition in their geographic region. Regarding competition among transporters: I do not take a stand a priori on a particular solution to the transporter’s pricing game, but adapt [Bresnahan \(1982\)](#)’s method to develop a pricing rule that admits a wide array of competitive outcomes, including the extremes of perfect competition and perfect monopoly.³ Additionally, to accurately model demand for freight transport, I follow [Lind and Ramondo \(2023\)](#) to incorporate correlation of prices across competing origins, modes, and routes, which permits more realistic substitution patterns across competing trade routes.⁴ The model thus provides a tractable framework to both estimate the extent of freight market power, and to evaluate how both trade flows and transport prices adjust to exogenous shocks.

The model yields five principal insights, three of which are descriptive. First, I find that current losses due to non-competitive freight pricing are substantial, equaling approximately 5% of baseline welfare. The lion’s share of these losses stem from the Road, a finding supported by anecdotal evidence of pervasive bottlenecks throughout the trucking industry, which lend market power to available operators. Second, I document significant geographic heterogeneity in the exercise of freight market power. Potential welfare gains from elimination of freight market power are concentrated in rural areas in the Southeast and Mountain West, as well as small urban areas throughout the Midwest and along the Gulf of Mexico; major international gates stand the least to gain from a perfectly-competitive freight market, as these markets currently exhibit the least concentration of market power. Third, the exercise of freight market power has an outsized influence on exports; imposing perfectly-competitive freight pricing may increase exports by as much as 20% but imports only 7%. This result suggests that managing non-competitive freight pricing offers a new lever to influence the U.S. trade deficit, which is of substantial interest to politicians and policy makers. Together, these results demonstrate how the current exercise of freight market power shapes domestic trade outcomes.

My final two principal results pertain to the simulated impact of exogenous transport shocks. Specifically, my fourth finding demonstrates that shutting down a single mode – perhaps due to a labor strike – sparks dramatic welfare losses; the pricing response among remaining modes exacerbates these losses.⁵ This result implies that, in the event of national, mode-specific shocks, we

³A more recent application of a conduct-parameter approach is [Miller and Weinberg \(2017\)](#).

⁴The assumption of perfectly independent trade costs, made originally for analytical convenience ([Eaton and Kortum, 2002](#)), implies unrealistic substitution patterns, and thus undermines the reliability of counterfactual simulations ([Train et al., 1987](#)). See [Lind and Ramondo \(2023\)](#) for a discussion of correlated prices in Ricardian models.

⁵The analysis that yields this result is inspired by the narrowly-avoided Rail strike of 2022, which would have halted all Rail traffic and the vast majority of multi-modal movements.

should expect a substantial pricing response from competing modes. Finally, due to the concentration of freight market power away from heavily-trading regions, I report near-perfect pass-through of a negative international trade shock; inland areas along sparse portions of the network see the greatest (relative) losses. This result is important, as it underscores that one of the few potential benefits of a concentrated freight market – namely, imperfect pass-through of exogenous shocks – remains unrealized in the case of international shocks. Coupled with the large welfare losses reported in baseline, as well as the exacerbating effect of mode-specific shocks, I conclude that freight market power offers little upside at substantial cost.

The natural question, then, is what is the appropriate policy response; the model offers some insight here as well. I document that market power is concentrated along trucking and within rural and small, urban areas. This finding accords with anecdotal evidence of pervasive bottlenecks throughout the trucking industry, granting market power to available operators ([Costello and Karickhoff, 2019](#)).⁶ Moreover, I demonstrate that multi-modal transport is trucking’s closest competitor; expanding the availability of multi-modal transshipment exchanges will offset the market-power of road transport. These interventions should be targeted to remote areas along sparse portions of the domestic transit network, where market power is concentrated.

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 using 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 are 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 popular in computer science, 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.⁷

⁶The American Trucking Associations points specifically to a severe shortage of qualified drivers causing disruptions throughout the industry. They also outline specific interventions designed to increase the supply of drivers, including: i) increasing recruitment and retention of women among the driving workforce; ii) relaxing strict drug-screening requirements; iii) lowering the minimum age required to drive freight across state lines; iv) increasing time at-home for long-haul truckers; v) increasing available parking stops and decreasing congestion at truck stops along major freight corridors; and vi) relaxing high standards as regards to driving records and criminal histories ([ATA, October 25, 2021](#)).

⁷Other papers estimate detailed trade costs using confidential data. Most recently, [Fuchs and Wong \(2023\)](#) utilize

This paper contributes to a growing body of research that explores 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., 2023a; 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. Put differently, the consumer likely does not care **how** a good got to its destination, only that it arrived and it is cheaper than all (quality-adjusted) alternatives. To stay cost-competitive, modes must engage with one another.⁸ 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 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 welfare gains throughout the nation. This paper underscores the importance of multi-modal shipping to domestic trade outcomes; however, the authors do not consider the role of competition in setting freight rates. I build upon their framework by incorporating the transporter’s strategic pricing decision.

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

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 subset of modes – for example, Allen and Arkolakis (2022) focus on roads; Donaldson (2018) focus on Rails; Ducruet et al. (2020) focus on shipping networks.

⁸Throughout 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 – is governed by one, global bargaining parameter. In contrast, I evaluate the state of market power within distinct markets throughout the mainland U.S.. My model thus offers a highly-granular assessment of how competition for transport within individual locations affects trade locally, and nationally.

The rest of the paper is organized as follows. Section 1.2 develops my theoretical model, distinguishing between transport demand – equilibrium trade flows – and supply – a model of transporter’s optimal pricing rule. Section 1.3 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 1.4 discusses my estimated parameters, model validation exercises, and robustness checks. Section 1.5 details my counterfactual simulations. Section 1.6 concludes.

1.2 Model

My theoretical model may be described simply as a general equilibrium model for freight transport services. On the demand side, I modify a standard Ricardian trade model to account for: i) multiple modes serving every origin-destination pairing; ii) multiple routes per mode; iii) correlation of prices across origins, modes, and routes; and iv) an endogenously-determined transportation markup set by freight-service firms. The trade flows implied by this model constitute the demand for freight transportation. On the supply-side, I develop an approximately linear pricing rule that expresses these markups as a function of (observable) trade shares and (estimable) correlation parameters. I now detail the model.

1.2.1 Transportation Demand: Equilibrium Trade Flows

I begin with the familiar [Eaton and Kortum \(2002\)](#) framework, henceforth termed “EK”. Trade in a unit-mass of goods Ω occurs amongst a discrete, finite set of locations $\mathcal{S}$; let $i, j \in \mathcal{S}$ denote the ultimate origin, destination. I further distinguish between domestic locations $\mathcal{S}^d \subset \mathcal{S}$ and foreign locations $\mathcal{S}^f \subset \mathcal{S}$, noting that $\mathcal{S}^d \cap \mathcal{S}^f = \emptyset$. Let $e, x \in \mathcal{S}^d$ denote a shipment’s domestic origin, destination; in the case of international trade, this will denote the shipment’s port of entry,

exit.⁹

All domestic locations lie on a graph and are connected by a set of edges. A route between a domestic origin and destination, $e, x \in \mathcal{S}^d$, comprises a set of edges that form an unbroken path between e and x . Routes need not be direct, but I do require them to be simple – that is, a route may take a circuitous path on its way from e to x , but no repeating edges.¹⁰ Let $\mathcal{R}_{ex}$ denote the set of all routes linking e to x . I further decompose this set by mode of transport. Let $\mathcal{M} = \{Road, Rail, Water, Air, Multi-modal\}$ denote the set of available modes and let $\mathcal{R}_{ex}^m \subseteq \mathcal{R}_{ex}$ denote the subset of routes between e and x via mode $m \in \mathcal{M}$.¹¹ Figure 1.1 provides an illustrative example of the domestic transit network.

Traversing the network is costly. Let $\tau_{ir(e,x,m)j}$ denote the cost of traversing route $r \in \mathcal{R}_{ex}^m$ between i and j ;¹² these transit costs take the standard iceberg formulation. I further assume that each origin enjoys a uniform input cost c_i and employs constant returns to scale technology. Finally, I impose perfect competition in the goods market, such that the price of good ω , produced in i , consumed in j , and taking route r via mode m between the two is given by

$$p_{irj}(\omega) = \frac{c_i \tau_{irj} \mu_{irj}}{\epsilon_{irj}(\omega)}, \quad (1.1)$$

where μ_{irj} is an endogenous markup set by the transporter, and $\epsilon_{irj}(\omega)$ is a composite production and transportation efficiency, which I will elaborate shortly. But first, I want to highlight that prices vary not only by their origin, but also by the route taken to market. Thanks to perfect competition in the market for tradeable goods, the price paid by the consumer is the cheapest available alternative. That is:

$$p_j(\omega) = \min_{i \in \mathcal{S}} \left\{ \min_{e, x \in \mathcal{S}^d} \left\{ \min_{m \in \mathcal{M}} \left\{ \min_{r \in \mathcal{R}_{ex}^m} p_{irj}(\omega) \right\} \right\} \right\}.$$

As in the traditional EK 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 efficiencies within

⁹Note that, for domestic origins (destinations), the choice of port of entry (exit) is degenerate.

¹⁰Note also that routes are direction-dependent: the set of edges forming a path from e to x is distinct from the same path moving from x to e , though their observable characteristics are identical.

¹¹It is important to note that the set of modes is exhaustive, such that $\mathcal{R}_{ex} = \cup_{m \in \mathcal{M}} \mathcal{R}_{ex}^m \forall e, x \in \mathcal{S}^d$. Additionally, with the exception of Multi-modal transport, these paths are mutually exclusive, $\mathcal{R}_{ex}^m \cap \mathcal{R}_{ex}^{m'} = \emptyset \forall m, m' \in \mathcal{M} \setminus \{Multi-Modal\}, m \neq m'$, and $\forall i, j \in \mathcal{S}$.

¹²Note that knowledge of the route implies knowledge of the domestic origin e , destination x , and mode m . For ease of exposition, I will omit the extraneous subscripts where expedient.

distinct destinations, origins, ports of entry/exit, and modes. Explicitly, the joint distribution function for the vector of log efficiencies is given by:

$$F_j \begin{pmatrix} \ln \epsilon(\omega)_1 \\ \ln \epsilon(\omega)_2 \\ \vdots \end{pmatrix} = \exp \left(- \sum_{i \in \mathcal{S}} \left(\sum_{e, x \in \mathcal{S}^d} \left(\sum_{m \in \mathcal{M}} \left(\sum_{r \in \mathcal{R}_{ex}^m} \exp \left(\frac{-\ln A_i - \theta \ln \epsilon_r(\omega)}{\varphi \rho \zeta} \right) \right) \right)^\varphi \right)^\rho \right)^\zeta \right). \quad (1.2)$$

In words, I assume a generalized extreme value distribution with location parameter A_i and scale parameter θ . The parameters φ, ρ , and $\zeta \in (0, 1]$ respectively govern the correlation of efficiencies within distinct nests— respectively, modes, ports of entry/exit, and origins. A value of 1 implies no correlation among these efficiencies within a given nest, while 0 implies perfect correlation. Due to this correlation structure, the interpretation of parameters is somewhat altered from the original EK model. A_i governs absolute advantage, while φ, ρ , and ζ , along with θ jointly determine the prevalence of comparative advantage.¹³ An illustration of the nesting structure are presented in Figure 1.2.

Equation (1.2) 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 demand formulation treats transport along different routes as differentiated services. Hence, trade from competing origins, modes, and even different routes serving the same market, function as imperfect substitutes. Second, the nesting structure dispenses with the assumption that efficiency shocks are independent across locations; rather, the model permits a highly flexible correlation structure across destinations, origins, ports of entry/exit, 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.¹⁴

¹³See [Lind and Ramondo \(2023\)](#) for a complete discussion of how allowing correlation of efficiencies changes the interpretation of the EK model.

¹⁴To 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 disproportionately 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:

$$\tau_{ir(e,x,m)j} = \exp \left(\underbrace{\mu_{irj}}_{\text{markup}} + \underbrace{\kappa_r}_{\text{deterministic costs}} + \underbrace{u_{irj}}_{\text{unobserved quality}} + \underbrace{\eta_{ie} + \nu_{xj}}_{\text{international trade cost}} + \underbrace{\alpha_{iem}}_{\text{first mile}} + \underbrace{\gamma_{xmj}}_{\text{final mile}} \right) \quad (1.3)$$

I now detail each component. Transporters set μ_{irj} to maximize profit, based on the demand and competition for transport services in geographically distinct markets (see Section 1.2.2 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_{irj} is a structural error term and reflects unobserved route quality. Following [Berry \(1994\)](#), I assume $u_r \sim N(0, v)$, and is drawn independently across routes. The parameters η_{ie} and ν_{xj} capture costs incurred along the international leg of the journey (if any). Explicitly, η_{ie} presents the cost of travelling from an international origin i to a domestic port of entry e , while ν_{xj} is the cost of travelling from a domestic port of exit x to a foreign destination j . Finally, the parameters α_{iem} and γ_{xmj} 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 nested logit¹⁵ formulation for trade shares within each market j :¹⁶

$$\pi_{r|iexmj} = \exp \left(-\theta[\mu_{irj} + \kappa_r + u_{irj}]/(\varphi\rho\zeta) - J_{iexmj} \right) \quad (1.4)$$

$$\pi_{m|ie xj} = \exp \left(-\theta[\alpha_{iem} + \gamma_{mxj}]/(\rho\zeta) + \varphi J_{iexmj} - V_{ie xj} \right) \quad (1.5)$$

$$\pi_{ex|ij} = \exp \left(-\theta[\eta_{ie} + \nu_{xj}]/\zeta + \rho V_{ie xj} - I_{ij} \right) \quad (1.6)$$

$$\pi_{i|j} = \exp \left(-\ln A_i - \theta \ln c_i + \zeta I_{ij} - Q_j \right) \quad (1.7)$$

¹⁵Note that if any one correlation parameter equals 1, then that nest effectively dissolves and is absorbed into the higher nest; if $\varphi = \rho = \zeta = 1$, the model collapses to a standard EK trade model with trade elasticity θ ([McFadden, 1984](#); [Eaton and Kortum, 2002](#)).

¹⁶See [Train et al. \(1987\)](#) for detailed derivations.

where

$$J_{iexmj} = \ln \sum_{r \in \mathcal{R}_{ex}^m} \exp \left(-\theta [\mu_{irj} + \kappa_r + u_{irj}] / (\varphi \rho \zeta) \right) \quad (1.8)$$

$$V_{ie xj} = \ln \sum_{m \in \mathcal{M}} \exp \left(-\theta [\alpha_{iem} + \gamma_{jxm}] / (\rho \zeta) + \varphi J_{ie xmj} \right) \quad (1.9)$$

$$I_{ij} = \ln \sum_{e, x \in \mathcal{S}^d} \exp \left(-\theta [\eta_{ie} + \nu_{xj}] / \zeta + \rho V_{ie xj} \right) \quad (1.10)$$

$$Q_j = \ln \sum_{i \in \mathcal{S}} \exp \left(-\ln A_i - \theta \ln c_i + \zeta I_{ij} \right). \quad (1.11)$$

Combining these conditional probabilities yields the following log-linear expression for the trade share along any one route:

$$\begin{aligned} \pi_{ir(e,x,m)|j} &= \pi_{r|ie xmj} \pi_{m|ie xmj} \pi_{ex|ij} \pi_{i|j} \\ &= \exp \left(-\ln A_i - \theta [\ln c_i + (\mu_{irj} + \kappa_r + u_{irj}) / (\varphi \rho \zeta) + (\alpha_{iem} + \gamma_{xmj}) / (\rho \zeta) + (\eta_{ie} + \nu_{xj}) / \zeta] \right. \\ &\quad \left. - (1 - \varphi) J_{ie xmj} - (1 - \rho) V_{ie xj} - (1 - \zeta) I_{ij} - Q_j \right). \end{aligned}$$

Some algebra yields:¹⁷

$$\begin{aligned} \pi_{ir(e,x,m)|j} &= \exp \left(-\ln A_i - \theta [\ln c_i + \mu_{irj} + \kappa_r + u_{irj} + \alpha_{iem} + \gamma_{xmj} + \eta_{ie} + \nu_{xj}] \right. \\ &\quad \left. + (1 - \varphi \rho \zeta) \ln \pi_{r|ie xmj} + (1 - \rho \zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - Q_j \right). \end{aligned} \quad (1.12)$$

Finally, consumers enjoy CES utility with elasticity parameter $\sigma \in (1, \theta + 1]$. Explicitly, consumers demand 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 B 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:

$$c_i = w_i^\beta p_i^{1-\beta} \quad (1.13)$$

¹⁷see Appendix A for detail.

$$p_j = \Gamma \left(\frac{\theta + 1 - \sigma}{\theta} \right)^{\frac{1}{1-\sigma}} Q_j^{-\frac{1}{\theta}} \quad (1.14)$$

$$L_i w_i = \sum_{k \in \mathcal{S}} \sum_{e, x \in \mathcal{S}} \sum_{r \in \mathcal{R}_{ex}} \pi_{ir|k} L_k w_k \quad (1.15)$$

where w_i , L_i are the wage, population in location i , and Γ denotes the gamma function. Taken together, Equations (1.4) - (1.15) 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.

1.2.2 Transportation Supply: Setting Markups

Given appropriate data, estimating Equation (1.12) is straightforward. However, nationally-representative data on costs and/or prices in the freight industry are not publicly available (see Section 1.3.1 for detail), meaning route-level markups μ_{irj} are unknown ex-ante. I thus impose additional structure on the transporter's pricing decision, the goal of which is to parameterize μ_{irj} such that: i) markups are a function of observable data; and ii) I do not assume a particular solution to the transporter's pricing game, but permit a wide array of potential equilibria, including the extremes of perfect competition and perfect monopoly. Research in empirical IO provides such a framework (Bresnahan, 1982; Miller and Weinberg, 2017); I now detail the structure that yields this result.

A representative transporter of mode m serves an origin-destination pairing ij . Given the scale of the transporter's problem, it is convenient to characterize its total profit in matrix notation. Accordingly, define $\boldsymbol{\pi}_{imj}^\top = [\pi_{ir_1|j} \ \pi_{ir_2|j} \ \dots]$, $\boldsymbol{\mu}_{imj}^\top = [\mu_{ir_1j} \ \mu_{ir_2j} \ \dots]$, and $\boldsymbol{\tau}_{imj}^\top = [\tau_{ir_2j} \ \tau_{ir_2j} \ \dots]$, the vectors of market shares, markups, and iceberg trade costs along all routes carrying freight from i to j via m . Total profits are thus:

$$\Pi_{imj} = B_j \boldsymbol{\pi}_{imj}^\top [(\boldsymbol{\mu}_{imj} - \mathbf{1}) \circ \boldsymbol{\tau}_{imj}]$$

where B_j is the total spending of destination j , which the transporter treats as exogenous, and $\circ$ denotes the element-wise matrix product. It follows that the transporter's marginal profit with respect to its vector of markups $\boldsymbol{\mu}_{imj}$ is given by:

$$\nabla \Pi_{imj} = \frac{\partial \Pi_{imj}(\pi_{ir_1|j}, \pi_{ir_2|j}, \dots)}{\partial (\mu_{ir_1j}, \mu_{ir_2j}, \dots)}$$

$$\begin{aligned}
&= \left(\frac{\partial(\ln \mu_{ir1j}, \ln \mu_{ir2j}, \dots)}{\partial(\mu_{ir1j}, \mu_{ir2j}, \dots)} \right) \left(\frac{\partial \Pi_{imj}(\pi_{ir1|j}, \pi_{ir2|j}, \dots)}{\partial(\ln \mu_{ir1j}, \ln \mu_{ir2j}, \dots)} \right) \\
&= B_j \left(\mathbf{DS}_{imj}^\top (\boldsymbol{\mu}_{imj} - \mathbf{1}) + \lambda_i \boldsymbol{\pi}_{imj} \right) \circ \frac{\boldsymbol{\tau}_{imj}}{\boldsymbol{\mu}_{imj}}
\end{aligned}$$

where $\mathbf{DS}^\top = \begin{bmatrix} \frac{\partial \pi_{ir1|j}}{\partial(\ln \mu_{ir1j}, \ln \mu_{ir2j}, \dots)} & \frac{\partial \pi_{ir2|j}}{\partial(\ln \mu_{ir1j}, \ln \mu_{ir2j}, \dots)} & \dots \end{bmatrix}$ is the Jacobian matrix of trade shares with respect to the vector of log markups, while $\lambda_i \in [0, 1]$ captures the transporter's pricing conduct. This λ_i parameter reflects the level of freight market competition for transport services out of i . $\lambda_i = 0$ corresponds to Bertrand competition: freight markets are perfectly competitive and markups as a percent of marginal cost go to 1. In contrast, λ_i parameters different from zero point to deviations from Bertrand competition, suggesting exercise of freight market power; at the extreme, $\lambda_i = 1$ corresponds to a perfect monopoly (oligopoly) in market i . This parameterization of the transporter's profit-maximizing behavior thus permits a wide variety of solution concepts.

Manipulating the transporter's first-order condition yields the pricing rule:

$$\begin{aligned}
\mathbf{0} &= B_j \left(\mathbf{DS}_{imj}^\top (\boldsymbol{\mu}_{imj} - \mathbf{1}) + \lambda_i \boldsymbol{\pi}_{imj} \right) \circ \frac{\boldsymbol{\tau}_{imj}}{\boldsymbol{\mu}_{imj}} \\
\boldsymbol{\mu}_{imj} &= \mathbf{1} - \lambda_i (\mathbf{DS}_{imj}^\top)^{-1} \boldsymbol{\pi}_{imj} \\
\ln \boldsymbol{\mu}_{imj} &\approx -\lambda_i (\mathbf{DS}_{imj}^\top)^{-1} \boldsymbol{\pi}_{imj}
\end{aligned}$$

where this last step follows from a first-order Taylor series expansion about the perfectly-competitive equilibrium.¹⁸ It will prove expedient to define:

$$\boldsymbol{\delta}_{imj} = \begin{bmatrix} \delta_{ir1j} \\ \delta_{ir2j} \\ \vdots \end{bmatrix} = -\theta (\mathbf{DS}_{imj}^\top)^{-1} \boldsymbol{\pi}_{imj} \quad (1.16)$$

Thanks to the logit-demand structure, the $\mathbf{DS}_{imj}^\top$ matrix may be easily calculated from the (observable) trade shares and correlation parameters; see Appendix C for detail. Markups along an individual route are given by

$$\ln \mu_{irj} \approx (\lambda_i / \theta) \delta_{irj}. \quad (1.17)$$

I thus arrive at a simple, linear expression for markups that encompasses a wide array of solution

¹⁸To be clear, the perfectly-competitive outcome corresponds to $\mu_{imj} = 1$.

concepts. Importantly, the linear markup input δ_{irj} may be easily calculated from observable data.

1.3 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 1.2 yields a simple, linear estimating equation that identifies: i) expected trade costs per mile, by mode; ii) the current severity of freight-market competition within and across distinct modes; and iii) the structural correlation parameters ρ and ζ . 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 and detail a method to estimate model fundamentals from aggregated data.

1.3.1 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.¹⁹ The FAF also encompasses large, rural areas in each state. Figure 1.3 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.²⁰ 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 than \$1 million total in 2017, to ensure enough variation in each origin-destination pairing to reliably identify the parameters of interest. In summary, the FAF provides total annual

¹⁹Unfortunately, the FAF does not offer more granular international geographies.

²⁰It 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 $\times$ mode fixed effects.

domestic trade flows in 2017, disaggregated by origin, destination, port of entry/exit (if any), and mode.

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. Importantly, exchanges between modes may only occur at designated intermodal exchanges. Figure 1.1 provides a simplified example of my geography; Figure 1.4 displays a map of my network (excluding routes via international Waters).

1.3.2 Estimating Model Parameters

I begin with my ideal regression specification. I parameterize the deterministic component of trade costs as follows:

$$\kappa_{r(m)} = Miles_r \beta_m, \quad (1.18)$$

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 (1.17) and (1.18) into Equation (1.12) yields the following log-linear expression:

$$\begin{aligned} \pi_{ir(e,x,m)|j} = \exp \Big(& -\ln A_i - \lambda_i \delta_{irj} - \theta [\ln c_i + Miles_r \beta_m + u_{irj} + \eta_{ie} + \nu_{xj} + \alpha_{iem} + \gamma_{xmj}] \\ & + (1 - \varphi \rho \zeta) \ln \pi_{r|iexmj} + (1 - \rho \zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - Q_j \Big). \end{aligned} \quad (1.19)$$

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

1.3.2.1 Identification

Before detailing my estimation procedure, I must emphasize a few points regarding identification. First, because the log conditional probabilities $\ln \pi_{r|ie xmj}$, $\ln \pi_{m|ie xj}$, and $\ln \pi_{ex|ij}$ are included to identify the correlation coefficients, the cost and conduct parameters, β_m and λ_i , are

identified by observed variation in trade shares across origins and destinations; similarly, ρ and ζ are respectively identified by observed variation in conditional trade shares across modes, domestic ports of entry. The parameter φ , however, cannot be estimated, as I do not observed trade flows at the route-level in my data.²¹ I thus fix this parameter to 1 at the outset, implying zero correlation of transport efficiencies within origin, mode pairs. In Section 1.4.2, I show how the results change with lower values of φ (i.e. non-zero correlations among routes of the same origin, mode).

Second, Equation (1.19) 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. Henceforth, I assume a standard trade elasticity of 4 (Simonovska and Waugh, 2014).²²

Third, there is the natural issue of endogeneity of the markup term δ_{irj} . This regressor is endogenous for two reasons: i) the pricing rule laid out in Equations (1.16) and (1.17) makes clear that δ_{irj} is structurally correlated with u_{irj} , and ii) the linear approximation of markups introduces further error into the regression equation, which will necessarily be correlated with δ_{irj} . I overcome these identification problems with an instrumental variables strategy.

To instrument the endogenous markup com, I propose the cost of competing transport services, which, in this context, is a log-linear function of the distance of routes along competing modes. Explicitly, I utilize the following instruments:

$$\mathbf{Z}_{ir(e,x,m)j} = \left[\sum_{r' \in \mathcal{R}_{ex}^{m'}} \mathbb{1}(k(r) = k(r')) \text{Miles}_{r'} \quad \dots \right] \quad (1.20)$$

for $m' \neq m$, and where $\mathbb{1}()$ is the indicator function and $k(r)$ denotes the relative ordering of the route. In words, I utilize the mileage along competing modes carrying freight from i to j of the same relative ordering as r – so, the shortest path on Rail from e to x is instrumented by the shortest path on Road, Water, Air, and Multi-Modal making the same trip; the second-shortest path on Rail is instrumented by the second-shortest path on Road, Water, Air, and Multi-Modal; while the shortest path on Water is instrumented by the shortest path on Road, Rail, Air, and Multi-modal.²³

²¹I estimate my route-level model using a simulated method of moments strategy; see Section 1.3.2.2 for detail.

²²Note that a well-known result in the trade literature is that varying the trade elasticity will scale the estimated parameters accordingly (Anderson and van Wincoop, 2003).

²³It should be noted that I have four instruments for every mode, leading to an over-identified model. I include all available instruments in my empirical specification as I am agnostic about which mode is likely to be most relevant

For my IV estimates to be valid, these instruments must satisfy the exclusion restriction and relevance assumptions. Regarding the former: the exclusion restriction is satisfied so long as routed miles along alternate modes are independent of the error term for a given trade route. This strict exogeneity holds by assumption in my theoretical context, and is valid in reality if 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. Moreover, many modal networks were built for reasons distinct from the efficient movement of goods: transportation of people, as well as national defense resources, are a major motivation underlying many transit networks, particularly the interstate highway system. Hence, my independence assumption seems reasonable. The relevance assumption holds so long as freight firms compete with one another. This assumption holds so long as distinct modes compete, which seems reasonable a priori. However, absent any price data from the transport industry, it is difficult to verify. 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 Panel D of Table 1.2). Reassuringly, all estimated F-statistics suggest that my instruments are relevant.

1.3.2.2 Estimation

Given route-level data on domestic trade as well as knowledge of the profit input δ_{irj} , it would be straight-forward to estimate my model parameters via 2SLS. However, this cannot be achieved with publicly-available data. As made evident by Equation (1.16) as well as Appendix C, δ_{irj} is a nonlinear function of φ and ρ , 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 $\mathcal{R}_{ij}^m$ by mapping successively longer paths between e and x along each mode.²⁴ 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_{iem} and γ_{jxm} parameters.²⁵ Theoretically, I could repeat this process almost infinitely; practically, I consider only the 5 shortest for the pricing of another mode.

²⁴I require these paths to be substantially different, so that the changes to the distance are meaningful. Table 1.1 demonstrates the average evolution of mileage across these paths.

²⁵This truncation, as well as the fact that I cannot route within a region, means that I hold $\kappa_r = 0$ for all routes that start and end in the same region.

paths for each mode. I have two main reasons for stopping at this threshold: i) routes outside of this set seem sufficiently circuitous to be cost-prohibitive, and therefore add little information to my analysis, and ii) computation time grows with each additional route, becoming excessive after 5.²⁶ This mapping process generates a set of 5 distinct routes – as well as the corresponding mileage – for domestic origin, destination, and mode combination.

Table 1.1 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 domestic origin, 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 distance of the third-shortest path is 7.4% long 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 key takeaway from this table is the sizeable difference between the shortest path and the fifth-shortest path: for Roads and for Multi-modal, the fifth-shortest path is approximately 11-12% longer than the shortest path on average; this number hovers around 15% for the Rail and Water networks. For Air, the fifth-shortest path is only 1.3% 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, $\lambda_i^{(0)}$, $\beta_m^{(0)}$, $\zeta^{(0)}$, $\rho^{(0)}$, and $v^{(0)}$. Keep in mind that I have already fixed the parameters φ and θ .

²⁶Estimated using a custom-built desktop, whose computing power (RAM, threads, and graphics card) exceeds most commercially-available desktops and is on-par with low- to mid-range cloud solutions; exact specifications are available upon request. In Section 1.4.2, I demonstrate the sensitivity of my estimates to different numbers of potential routings – in general, my estimates remain stable.

- (2) (Expectation Step) Simulate $\mathbb{E} \left[\pi_{r|iexmj} \mid \lambda_i^{(0)}, \beta_m^{(0)}, \zeta^{(0)}, \rho^{(0)}, v^{(0)}, \varphi, \theta \right]$ according to Equation (1.4) under the assumption that $u_{irj} \sim N(0, v^{(0)})$. Denote this conditional probability $\pi_{r|iexmj}^{(0)}$.
- (3) Calculate $\pi_{ir|j}^{(0)} = \pi_{r|iexmj}^{(0)} \pi_{m|ie xj} \pi_{ex|ij} \pi_{i|j}$. Note that only the first of these conditional probabilities is simulated; the rest are observed in the data.
- (4) Calculate the markup term $\delta_{irj}^{(0)}$ as described by Equation (1.16) and Appendix C.
- (5) Estimate the first stage via OLS:

$$\delta_{irj}^{(0)} = \mathbf{Z}_{irj} \zeta_m + Miles_r \phi_m + \vartheta_{iem} + \vartheta_{jxm} + \varepsilon_{irj}$$

where ϑ_{iem} and ϑ_{jxm} are fixed effects. Denote the fitted values from this regression $\hat{\delta}_{irj}^{(0)}$.

- (6) Define $y_{irj}^{(0)} = \ln \pi_{ir|j}^{(0)} - (1 - \varphi \rho^{(0)} \zeta^{(0)}) \ln \pi_{r|iexmj}^{(0)}$.
- (7) (Maximization Step) Estimate the second stage via OLS:

$$y_{irj}^{(0)} = -\theta Miles_r \beta_m - \lambda_i \hat{\delta}_{irj}^{(0)} + (1 - \rho \zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - \theta u_{irj} + \underbrace{\text{Origin} \times \text{Port} \times \text{Mode FEs}}_{-\theta(\nu_{xj} + \gamma_{xjm}) - Q_j} + \underbrace{\text{Destination} \times \text{Port} \times \text{Mode FEs}}_{-\ln A_i - \theta(\ln c_i + \eta_{ie} + \alpha_{iem})} \quad (1.21)$$

Denote the new set of parameter estimates $\lambda_i^{(1)}, \beta_m^{(1)}, \zeta^{(1)}, \rho^{(1)}$, and $v^{(1)}$.²⁷

- (8) 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 D for further detail.

1.4 Descriptive Results

The end result of the EM process just laid out in Section 1.3.2 are estimated model fundamentals. Namely, these encompass per-mile iceberg cost coefficients β_m , the correlation parameters

²⁷It should be noted that, while I do not immediately estimate $v^{(1)}$ via OLS, I can estimate $v^{(1)} = \text{Var}(\hat{u}_{irj})$.

ρ and ζ , as well as the conduct parameters λ_i , which in turn inform route-level markups μ_{irj} . Table 1.2 summarizes the results of my main specification; additional robustness checks and model validation exercises are discussed in Section 1.4.2.

1.4.1 Primary Specification

I begin discussion of my reduced-form estimates with Panel A of Table 1.2. This panel reports the parameter estimates that inform geographic costs in my trade model. I breakout per-mile costs by mode of transport, or – in the case of multi-modal – the cost of a single transshipment. As these coefficients inform iceberg trade costs, interpretation is somewhat involved.²⁸ However, their magnitude and relative ordering align with similar estimates in the literature (Allen and Arkolakis, 2014; Donaldson, 2018; Allen and Arkolakis, 2022). Importantly, Road is estimated as the most expensive mode per-mile, followed by Rail and Water, which have similar magnitudes. Air is estimated as cheapest mode per-mile, which may prove initially surprising, given Air’s high fuel intensity and maintenance requirements. However, bear in mind that these estimated coefficients exclude first- and final-mile costs, as well as any costs accrued at a destination or origins.²⁹ The final reported coefficient in Panel A is rarely estimated: the cost of transshipment across modes. I estimate that the cost of a single transshipment accounts for approximately 1.1% of the final value of a good. Note that this effect compounds across multiple exchanges.

I now shift focus to the estimated correlation coefficients listed in Panel B of Table 1.2. Note that these are inverse correlation coefficients: higher values of ρ, ζ imply lower correlations among composite efficiencies among modes, origins. In particular, the real correlation may be calculated as 1 minus the square of the estimated coefficient (Heiss, 2002). My estimate of the modal correlation parameter ρ thus implies that, on average, transportation efficiencies – and hence, prices – across domestic modes enjoy a correlation of $1 - 0.596^2 = 0.645$; production efficiencies across domestic locations report a correlation of $1 - 0.379^2 = 0.856$. Both of these estimates are statistically distinct from 1, which implies zero correlation. These substantial correlation estimates underscore the importance of allowing correlation in my model. In Section 1.4.2, I explore the consequences of imposing zero correlation, as is common the conventional EK setting.

Panel C summarizes the distribution of estimated non-competitive markups $\hat{\mu}_{irj} = \hat{\lambda}_i \delta_{irj}$. I

²⁸Interpreting the first reported coefficient: 1,000 additional miles on road increases iceberg trade costs, τ_{irj} , by $\exp(0.197) \approx 1.218$, or about 21.8%. Interpretation of the remaining coefficients is analogous.

²⁹These route-invariant costs are estimated via fixed-effects in my regression specification. See Section 1.3 for detail.

focus on the distribution of markups – as opposed to the distribution of conduct parameters λ_i – due to ease of interpretability.³⁰ The table demonstrates that, across all domestic trade routes, markups average 3% above marginal cost. The distribution is slightly skew right; the highest estimated markup is approximately 13% above marginal cost.³¹ These estimated markups are fairly low, suggesting that, in general, freight markets are highly competitive. However, due to the necessary centrality of the transport industry, even a small exercise of market power could have a profound influence on national welfare.³²

1.4.2 Model Validation & Robustness Checks

In Table 1.3, I evaluate my reduced-form estimates relative to those implied by simpler modelling approaches. Column (1) of this table re-states my reduced-form estimates under my main specification: estimating freight market power, allowing correlation of prices across both modes and geographies, and encompassing 5 distinct routings per-mode along every domestic origin-destination pairing.³³ Column (2) re-estimates my geographic cost and correlation coefficients, imposing perfectly-competitive freight markets (i.e. $\lambda_i = 0 \forall i$). Comparison of these first two columns reveals that assuming perfect freight competition (as is common in the trade literature) results in very minor changes to estimated fundamentals. This stability is unsurprising in light of my finding that freight markets are, generally, near-perfectly competitive. Column (3) further restricts the model by assuming zero correlation of prices across markets; these estimates correspond to the parameters implied by a conventional EK framework. My cost estimates remain fairly stable: estimated Road and Air coefficients increase slightly, while the coefficients on Rail and Water drop. The largest change comes from Multi-Modal transshipment, whose coefficient drops by nearly half. Finally, in Column (4), I re-run the model using only one routing per-mode; substitution across parallel trade routes in this model is impossible.³⁴ This change causes the estimated coefficient on Road to again increase, while the coefficients on Rail and Water decreases slightly. Overall, this exercise reveals that simpler models induce very limited bias in estimated

³⁰While the extreme cases of $\lambda_i = 1$ and $\lambda_i = 0$ are easily interpretable as perfect monopoly and perfect competition, intermediate values are more obscure. I thus focus discussion of my reduced-form results on the distribution of markups, as opposed to the conduct parameters themselves. A histogram of the estimated λ_i parameters is presented in Figure 1.5.

³¹I will analyze the geographic distribution of these markups – or rather, their consequences – in Section 1.5.

³²Indeed, I demonstrate in Section 1.5.1 that even these moderate markups produce aggregate welfare losses equal to approximately 5% of total perfectly-competitive welfare.

³³The numbers reported in this column are identical to those reported in Table 1.2.

³⁴This constrained model most closely resembles the routing logic utilized in [Allen and Arkolakis \(2014\)](#).

fundamental parameters.³⁵

I also run the model through a battery of robustness checks, summarized in Tables 1.4 - 1.6. First, I re-estimate my primary specification allowing for non-zero correlation of prices across parallel trade routes, which I achieve by setting the route-correlation parameter φ to values less than 1. Results of this exercise are displayed in Table 1.4. Column (1) re-states my main results; each subsequent column displays analogous estimates assuming an intermediate value of φ . Across these alternate specifications, there is no discernable difference in my estimated coefficients. This stability stems from the fact that my parameters are identified by observed variation in trade shares at the origin-destination level, which is independent of the simulated route-level variation (see Section 1.3.2 for detail). Hence, Table 1.4 confirms that my model is insensitive to the values of the route-level correlation parameter φ .

In my next battery of robustness checks, I re-estimate my primary specification with amended or different data; results of these checks are reported in Table 1.5. As before, Column (1) re-states my main results. Column (2) restricts the set of commodities, from which I generate aggregate trade flows, to those that are easily transported by any mode.³⁶ Results of this exercise reveal generally similar parameter estimates; notably, the distribution of markups is slightly higher than those reported in baseline. These results suggest that I may under-estimate market power in my primary specification. Next, in Column (3) I re-estimate the model excluding Air and Water, which account for a small share of domestic trade and do not enjoy wide geographic representation. Reassuringly, my estimates are largely the same. The distribution of markups is again slightly larger relative to my main specification; however, as I elaborate in Section 1.5.1, Air and Water report relatively little exercise of market power, and I expect the distribution of markups to shift right when removing two relatively competitive modes. In Column (4), I re-estimate the model using only urban areas. Reported cost coefficients are slightly smaller, but of a similar magnitude, while the distribution of markups compresses slightly. Again, this result accords with expectation, based on the geographic distribution of markups (see Section 1.5.1 for detail). Finally, in Columns (5) and (6) I address external validity concerns by re-estimating the data in 2012 and in 2022.³⁷

³⁵I should emphasize that, while my complex modelling framework does not lead to drastic differences in estimated fundamentals, the welfare consequences of freight market power are still profound (see Section 1.5).

³⁶I achieve this by restricting my trade data to the subset of commodities that report at least \$10 million in total volume within the U.S. across all modes in 2017. These commodities include: cereal grains and seed, agricultural products (excluding grains, feed, and forage), alcoholic beverages, coal, crude petroleum, other coal and petroleum products, raw chemicals, other chemical products and preparations, plastics and rubber, base metals in a semi-finished form or basic shape, machinery, motorized and other vehicles, and transport equipment not elsewhere defined.

³⁷I elect these years to create an even interval about my estimation year, 2017. Moreover, these are years, in which

Reassuringly, the estimated cost and correlation parameters are similar. Notably, markups are declining over time—there is a steady, approximately linear downward trend in the distribution of markups as I move from 2012 to 2022. This decline is striking, but further investigation is beyond the scope of this paper. Overall, these results demonstrate the stability of my estimates to different data-cleaning decisions.

Finally, I analyse the impact of different starting values in my EM algorithm; results of this exercise are reported in Table 1.6. In my main specification, I elect $\beta_m = \mathbf{1}$ as my starting value, which implies that each mode has the same cost per-mile at the outset of the EM process; results stemming from these starting values are reported in Column (1). In the subsequent Columns, I change my starting values to equal 1 for a particular mode, and zero for the remaining; hence, in these alternate specifications, one mode is particularly costly to traverse, while the others are free (outside of the first- and final-mile). Reassuringly, the model converges to the exact same parameter estimates.

1.5 Counterfactual Simulations

Having estimated the fundamental parameters, I calibrate the model to domestic trade flows in 2017; I then run three counterfactual simulations, designed to highlight the role of freight transport in impacting domestic trade. The first such exercise investigates which regions and modes are most or least impacted by imperfect competition in the market for freight transport. Explicitly, I compare calibrated welfare under a counterfactual, perfectly-competitive pricing regime to calibrated welfare under the status-quo; this juxtaposition reveals where and along what modes current non-competitive losses are concentrated. My second counterfactual evaluates the welfare consequences of removing an entire mode of transport from the domestic transit network: specifically, Rail and (consequently) multi-modal.³⁸ This simulation is inspired by the proposed Rail strike of 2022, which was narrowly avoided at the eleventh hour by federal intervention, and to some controversy ([Shepardson and Baertlein, November 29, 2022](#)). My model sheds light on the potential impacts of such a strike, how trade would have moved to competing modes, and how freight market power may amplify or attenuate downstream welfare losses to consumers. My final

the Commodity Flow Survey (CFS) is conducted. The FAF data I use is based on the CFS, and is most accurate in survey years.

³⁸Why multi-modal as well? The lion's share of domestic multi-modal movement's encompass the Rail network (of [American Railroads](#), AAR); hence, removing Rail also vastly limits the scope for multi-modal travel. For the purpose of my counterfactual simulation, I make the simplifying assumption that, if Rail shuts down, multi-modal movements disappear as well.

counterfactual simulates an international trade shock: specifically, a sharp increase in trade costs at international gates, meant to emulate supply chain bottlenecks sparked by the Covid-19 pandemic. This counterfactual reveals how strategic pricing across a geographically dispersed, multi-modal network exacerbates or mitigates an exogenous, geographically concentrated trade shock. Together, these three scenarios highlight how the transport sector influences domestic trade outcomes.

It is important to emphasize that my model is agnostic about the source of market power: I cannot differentiate between non-competitive pricing stemming from collusion or from barriers to entry. However, with the notable exception of Rail, freight markets are typically saturated with multiple service providers,³⁹ while fixed-costs in the industry are exceptionally high.⁴⁰ It thus appears likely a-priori that barriers to entry, coupled with inelastic demand for freight transport along specific modes, are the culprit for exercise of freight market-power; accordingly, I direct my policy discussion towards lowering barriers to entry, as opposed to anti-trust enforcement.

I now detail the results of my counterfactual simulations.

1.5.1 Simulating a Perfectly Competitive Freight Market

For this counterfactual exercise, I set (log) markups to zero across all domestic trade routes; I then utilize Equations (1.4) - (1.17) to simulate trade flows and prices with this perfectly-competitive freight market. Comparing calibrated welfare under the status-quo and counterfactual pricing regimes reveals current losses due to non-competitive freight pricing. I further decompose these aggregate effects by mode and geography in Table 1.7 and Figure 1.6, respectively. The former exploits my logit structure to simulate substitution patterns across competing modes; the latter reveals what locations enjoy the greatest/least concentrations of freight market power, and thus stand the most/least to gain from an erosion of that pricing power. I now discuss these results in detail.

³⁹In 2021, approximately 600 thousand for-hire interstate trucking companies operated in the United States (FMCSA, 2021); approximately 543 Air cargo carriers (FAA, 2021), 37 U.S.-flagged maritime carriers (MARAD, September, 2022), and just 7 Class-1 freight Railroads operated in the U.S. concurrently.

⁴⁰Trucking has the lowest entry cost: a new Semi truck runs between \$100 and \$200 thousand, with an additional \$50 thousand for a new trailer on average; this estimate excludes (substantial) insurance and licensing costs, as well as the cost of any sophisticated trailer – e.g., refrigeration, logging, HAZMAT, etc.. (Harris, 2021). The remaining modes enjoy much higher fixed costs: a new diesel locomotive costs between \$1.5 to \$2 million on average (World Wide Rails, 2023), while a new Rail car runs between \$100 and \$150 thousand (Blaze, 2019); a new cargo plane averages between \$49 and \$77 million, but can reach over \$400 million, depending on capacity and technology (Walsh, 2023); and a newly-constructed container ship costs between \$14 and \$300 million, again depending on capacity and technology (UNCTAD, 2010). In addition, while roads, Waterways, and Airways are (generally) free-to-use, Rail companies must create and maintain their own infrastructure.

I find that, as a result of removing freight market power, real welfare in the U.S. increases by approximately 5.04%; Panel A of Table 1.7 details total welfare changes accruing to each mode and overall. Column (1) of the table lists the baseline share of real trade volumes; Column (4) details the percentage change in this trade share brought about by the imposition of perfect freight competition. Columns (2) and (3) decompose this aggregate change into a modal substitution and income effect. The former effect is calculated by simulating the change in trade volumes, holding constant income in each region;⁴¹ the latter effect is calculated by simulating the change in aggregate trade volumes to each region, holding constant the distribution of trade across modes.⁴² The sum of these effects equals the total change in trade volume.

Analysis of Panel A, Column (2) reveals that, holding real incomes in each region constant, elimination of freight markups shifts trade away from multi-modal transport and onto the road. This result may be initially surprising, as it suggests road transport currently enjoys the **highest** markups, despite having by-far the highest market concentration and barriers to entry. One potential explanation for this perhaps counter-intuitive outcome is the unique ability of truck transport to complete the first- and final-mile. This supreme routing flexibility limits the scope for cross-modal competition: no alternative save multi-modal can offer comparable services. Indeed, Column (2) displays that the vast majority of this new trucking volume comes from multi-modal; very little crosses over from Rail, Water, or Air.⁴³ In summary, Column (2) displays the imperfect substitution of trade across modes: price decreases that mainly affect the Road draw trade primarily from multi-modal.

I now shift attention to Panel A, Columns (3) and (4). The former isolates the income effect: the change in welfare brought about by making certain regions wealthier via a reduction in trade costs. This column aligns with expectation: all modes see an increase in real trade volumes, and the relative distribution of these increases roughly corresponds to the baseline trade allocation displayed in Column (1).⁴⁴ Finally, Column (4) presents the aggregate change in welfare accruing to each mode. Notably, the income effect dominates for all modes except multi-modal. Hence, the

⁴¹If markups were uniformly distributed across modes, then the substitution effect would simply equal the change trade costs multiplied by the baseline trade share of each mode.

⁴²If markups were uniformly distributed across geography, then the income effect would simply equal the change in income multiplied by the baseline trade share.

⁴³A more complete evaluation of this “final-mile hypothesis” requires more refined geographic data, which is not publicly-available at a national scale.

⁴⁴Note that this relative distribution does not perfectly correspond to Column (1) due to geographic heterogeneity: as just discussed, the largest gains from this counterfactual are concentrated on the roadway; areas that trade more heavily in the road will see the largest income gains. Figure 1.6 provides a more detailed geographic analysis.

lion's share of welfare improvements accruing to each mode stems from these income gains following the reduction in trade costs.

Panels B and C of Table 1.7 repeat much the same exercise, focusing instead on imports and exports; the outcomes reported in these panels largely mirror the effects on domestic welfare. Focusing first on Column (2), roadways see the largest relative benefit holding income in each region constant. Among imports, these newfound roadway flows again draw primarily from multi-modal; among exports, this substitution effect pulls primarily from Rail. In general, Rail, Air, and Water see much higher substitution effects among these international movements than among domestic trade, a trend likely attributable to their higher baseline trade volumes (see Column (1)). Column (3) demonstrates that, for both imports and exports, trucking is again the largest benefactor from the income effect; however, among exports, all modes report substantial increase in volume due to increasing incomes. Finally, in Column (4), I report aggregate changes: roadways again see the largest change in total imports and exports, driven largely the income effect reported in Column (3). Total imports increase by 7.52%, while exports climb by nearly 20%. This outsized effect on exports is striking, and suggests that managing freight market power is a powerful policy tool to influence the international trade balance.

Finally, in Figure 1.6, I breakout the geographic incidence of removing non-competitive freight rates. Panel A reports real welfare impacts: generally, the largest welfare gains accrue to rural areas in the Southeast and Mountain West, as well as to small urban areas in the Midwest and along the Gulf of Mexico. Strikingly, major international gates, including Los Angeles/Long Beach, CA, San Francisco/Oakland, CA, New York, NY, Chicago, IL, Baltimore, MD, Norfolk, VA, Atlanta, GA, and Ft. Lauderdale, FL, are among the **least** affected areas. While this result aligns with expectation – high trade volumes should attract more shippers, thereby reducing market power – it suggests that the aggregate impact of removing freight market power will be muted relative to the local impact in rural regions. Indeed, the Panel A of Figure 1.6 reveals that local impacts range from 2 to 11% of baseline welfare.

Panels B and C of Figure 1.6 report the geographic incidence among imports and exports, respectively. I begin with imports, where the largest gains accrue mostly to the coasts, as well as the northern Midwest and Great Plains. Regions up the middle of the country – including Lake Charles, LA, Austin, TX, Laredo, TX, East St. Louis, IL, Rural Georgia, Rural Indiana, most regions in Appalachia, and all of Michigan – experience modest increases or even **declines**

in imports. Notably, these areas also saw substantial welfare gains due to elimination of markups; this pattern suggests that, thanks to the alleviation of freight market power, these regions import relatively less from abroad as domestic goods become cheaper. Switching focus to Panel C, increases in real exports accrue primarily to the regions bordering the Gulf of Mexico, as well as rural areas up the east coast and in the Northwest. There is not a discernable geographic relationship between welfare changes and export increases.

In summary, my first simulation explores the welfare consequences of removing freight market power. Most of these welfare gains accrue to the Road, and shift domestic trade away primarily from multi-modal, and to a lesser extent, Rail. This substitution pattern suggests that market power is currently concentrated along the roadway—an initially counter-intuitive finding that is somewhat supported by anecdotal evidence of a pervasive shortage of qualified truck drivers. Effects on international trade are similar, but larger. Most strikingly, real U.S. exports increase by nearly 20%, relative to only a 7.5% increase in real imports. Geographically, gains from the simulation are concentrated in rural and small, urban areas throughout the Southeast, Midwest, and Gulf states; major international gates see the smallest welfare impacts. Notably, areas that see large welfare gains report the smallest gains or even modest declines in imports as a result of removing freight market power. This latter trend is likely the result of domestic freight becoming cheaper, leading to a lower reliance on imports.

1.5.2 Simulating a Rail Closure

The counterfactual detailed in this Section is primarily policy-focused. Explicitly, I simulate the effect of removing Rail and multi-modal transport from the domestic transit network – this simulation emulates the narrowly-avoided Rail strike of 2022. To highlight the role of freight-market concentration in determining domestic welfare, I simulate the shock twice: once under status-quo freight pricing and once imposing perfect competition. Comparison of calibrated welfare under these two scenarios reveals how the downstream impacts of this exogenous shock are amplified/attenuated by market power in the freight industry.

Table 1.8 reports the impacts to domestic welfare as a result of removing Rail and multi-modal. Panel A reports simulated welfare changes under status-quo freight pricing; Panel B reports the same under perfect freight market competition. Comparison of these results reveals a key conclusion: removal of the Railway (and consequently, multi-modal) leads to substantial welfare

losses, regardless of freight market competition; however, losses are **worse** thanks to imperfectly-competitive freight pricing. Real welfare declines by 4.31% under the status-quo, and only 2.86% under perfect competition. The reason for this substantial amplification stems from the exercise of market power: as displayed by Column (2), the vast majority of freight volumes shift onto the roadway, where freight market power is concentrated. Freight-service providers may then take advantage of the drop in cross-modal competition and raise prices. Column (3) reports welfare losses stemming from the effective change in income as a result of removing the Railway. Note again that this income effect is concentrated in trucking. However, Panel (B) demonstrates that, absent an endogenous pricing response on behalf of freight carriers, welfare losses stemming from this income drop amount to only 2.77%. Hence, of the 4.23% drop reported in Panel A, approximately 1.46 percentage points – nearly 35% of the total change – is attributable to price increases stemming from a decline in modal competition. This income effect accounts for the majority of the aggregate changes reported in Column (4).

Tables 1.9 and 1.10 repeat this exercise for real imports and exports. These results are very similar to the patterns exhibited for domestic welfare: losses are substantial, and made worse by the exercise of freight market power. Specifically, real imports decline by about 6.03% under perfect competition, and by 8% under status-quo pricing; real exports decline by approximately 1.23% under perfect freight market competition, and by 4.17% under the status-quo. Note that the change in real export volumes is much larger than the change in real imports, a result that is emblematic of the outsized effect freight market power exerts over exports, as previously discussed. The table demonstrates that the vast majority of international freight shifts to the road for the domestic portion of its journey; however, in contrast to domestic welfare, a substantial share shifts to the Air, especially among imports. Given the centrality of Air and Water transport to international transactions, this result is not surprising.

Finally, Figure 1.7 breaks out these real welfare changes by geography; Panel A reports results under status-quo freight pricing, and Panel B reports under perfect competition. Overall, losses are concentrated in the Southeast, northern Midwest, and Great Plains. Urban areas along the coasts also report moderate losses. Notably, a handful of areas report welfare **gains** – these areas are served more readily by the road, Air, and Water networks, and thus see an increase in total trade volumes as trade shifts off the Rail network. Comparison of Panels A and B reveals that exercise of freight market power exacerbates welfare losses among rural and small urban areas throughout

the U.S.. This result is not surprising, as these areas report the highest concentrations of market power ex-ante. Geographic trends for imports and exports are similar, and reported in Figures 1.8 and 1.9.⁴⁵

In summary, shutting down the Rail system would have a substantial, negative impact on domestic welfare; these losses are made worse by the exercise of market power along competing modes. I report similar impacts for imports and exports; most strikingly, freight market power has an outsized impact on exports— real export losses nearly quadruple under status-quo freight pricing relative to perfect freight market competition. Turning to the geographic incidence, losses are concentrated in the Southeast, northern Midwest, and Great Plains. Some areas, which are more heavily served by the road, see **gains**. Exercise of freight market power exacerbates losses to rural and small urban areas throughout the country. Speaking broadly, these results emphasize that, should any single mode shut down, we should expect a meaningful pricing response along competing modes, most especially trucking; this pricing response will most-impact rural and small urban areas.

1.5.3 Simulating an International Trade Shock

My final counterfactual explores how freight transport influences a geographically-concentrated international trade shock. Specifically, I simulate the welfare consequences of a 36% increase in trade costs along international routes, meant to emulate price increases witnessed in the transport sector during the Covid-19 pandemic.⁴⁶ This shock is geographically concentrated in the sense that only international gates feel the immediate impact; inland locations are not directly affected, but as I will demonstrate, suffer substantial losses due to equilibrium effects. I again simulate this shock twice: once under status-quo freight pricing, and once under perfect freight market competition. Contrasting the changes in simulated welfare under these two pricing scenarios reveals the role of strategic freight pricing in determining domestic trade outcomes. More broadly, this counterfactual reveals how the freight industry influences the domestic welfare consequences of an international trade shock.

Table 1.11 reports real welfare changes from this simulation. Again, Panel A reports welfare impacts when the freight industry is allowed to exercise market power; Panel B reports welfare im-

⁴⁵These results make clear that inland areas in the Great Plains are by-far the worst impacted among international trade flows.

⁴⁶The magnitude of this shock comes from recent analysis by the St. Louis Federal Reserve ([Leibovici, May 11, 2022](#)).

pacts under perfect freight market competition. In this case, we see that market power **attenuates** welfare changes, but very, very slightly. This result accords with expectation: market power implies imperfect pass-through of exogenous cost shocks; however, as demonstrated previously, freight market power is concentrated away from international gates. Hence, non-competitive freight pricing can have only a limited impact on international trade shocks. As displayed by Column (2), modal substitution effects are limited in magnitude, and concentrated along road and multi-modal, while Air sees the largest (though still small) gains. Switching focus to Column (3), income effects are all negative and concentrated along the roadway. In total, domestic welfare declines by approximately 7.11% under status-quo freight pricing, and 7.22% under perfect competition.

Unsurprisingly, this shock has a much larger impact on international trade. Tables 1.12 and 1.13 report simulated changes in real imports, exports under the status-quo and perfect freight market competition. As reported in Panel B of each table, imports decline by approximately 17.97%, while exports decline by about 22.59% in the absence of freight market power. Attenuation rates due to non-competitive pricing are again minuscule, or even slightly negative: as reported in Panel A of each table, under the status-quo, imports decline by 17.84%, while exports decline by 22.67%. Focusing on Column (2), we see very little substitution across modes, implying a near-uniform shock across modes; this outcome is not surprising, as it is rare for an international gate to specialize in any, one mode. Column (3) reports substantial income effects; in-line with the uniform effect across modes, the relative distribution of these effects roughly corresponds to each mode's baseline trade share: Road sees the biggest declines, followed by multi-modal, Air, Rail, and finally, Water.

The geographic distribution of the welfare impacts stemming from this shock are presented in Figure 1.10. Panel A reports real welfare changes under the status-quo, while Panel B reports welfare changes under perfect competition. Unsurprisingly, the two panels are nearly identical: rural Maine, Georgia, and Alabama, as well as East St. Louis, IL and Omaha, NE, report the only observable attenuation of welfare losses. Moreover, the figure reveals that Washington, Wyoming, Wisconsin, and West Virginia are the worst-impacted states in either pricing scenario: welfare losses in each of these states amount to at least 15%, and can climb as high as 20%. This geographic concentration is telling, as – with the exception of Washington – none of these states contain major international gates. Indeed, most international gates report small to moderate impacts. This finding suggests that rural, inland areas are worst impacted by an international trade shock. One explanation for this result is that major gates lie centrally in the domestic transit network, and are

thus able to easily pick among cheaper suppliers/customers in response to more expensive foreign imports/exports. However, these increased costs are detrimental to rural areas along sparse portions of the network, who cannot easily adjust to consumption. Figures 1.11 and 1.12 breakout these effects for imports and exports and reveal largely the same pattern – the one, notable exception being for exports, where Florida reports the largest declines.

In summary, a sharp rise in international transport prices, similar to what the U.S. witnessed during the Covid-19 pandemic, creates substantial domestic welfare losses. These losses equal approximately 7% of baseline welfare, and are even more pronounced among imports and exports. Due to the concentration of freight market power away from international gates, this shock reports near-perfect pass through. Moreover, losses are generally concentrated within inland areas along relatively sparse portions of the transit network; those locations along relatively dense portions of network more easily adjust production or consumption in response to the shock.

1.6 Conclusion

This paper quantifies the impact of the transport sector in setting domestic trade outcomes. I modify a standard Ricardian trade model to account for route-choice, mode-choice, port-choice, correlations across these disparate nests, and finally, imperfect competition for freight services in geographically distinct markets. The result of these extensions is a highly plausible model of the transportation industry, as well as its effect on domestic trade. The trade costs implied by my model reflect imperfect competition for freight services in distinct locations; imperfect substitution across origins, modes, and even parallel trade routes; and finally, available infrastructure. This framework allows me to evaluate the domestic welfare and trade incidence of a number of transportation shocks: i) removal of freight market power; ii) the complete removal of Rail and (consequently) multi-modal transport; and iii) a sharp spike in international freight costs, similar to those witnessed during the Covid-19 pandemic. The model thus offers a comprehensive view of how freight markets influence domestic trade outcomes.

I estimate fundamentals and calibrate the model to domestic trade flows in 2017. The estimation yields the following insights: i) an estimate of per-mile trade costs along each mode; ii) the degree of correlation in prices across modes, origins; and iii) location-specific conduct parameters, which, in-turn, influence route-level markups throughout the domestic U.S.. The latter calibration yields 5 key insights: i) current losses due to non-competitive pricing are substantial, amounting

to roughly 5% of baseline welfare; ii) the exercise of freight market power has an outsized impact on exports— elimination of freight market power could increase national exports by nearly 20%; iii) these impacts are concentrated in rural areas throughout the Southeast and Mountain West, as well as small urban areas in the Midwest and Gulf states; iv) exercise of freight market power exacerbates the impact of mode-specific shocks; and v) non-competitive freight pricing does little to attenuate international trade shocks, due to the concentration of freight market power away from international gates.

These results yield a number of insights relevant to policy-makers. First, losses due to non-competitive freight pricing are substantial, and perhaps surprisingly, concentrated in the trucking industry. Anecdotal evidence suggests that trucking in particular suffers from a shortage of qualified drivers, granting market power to existing operators. With the exception of multi-modal, competition from other modes is insufficient to solve this problem, as trucking offers the unique ability to fulfill the first- and final-mile. Hence, addressing the driver shortage is an obvious and immediate policy intervention, which should counter the majority of welfare losses due to non-competitive freight rates; further expansion of multi-modal terminals will also deflate freight market power. Additionally, given the concentration of freight market power in rural and remote urban areas, such an intervention should help reduce economic inequality across the U.S.. Hence, action to reduce barriers to entry in trucking should achieve large impacts on domestic welfare.

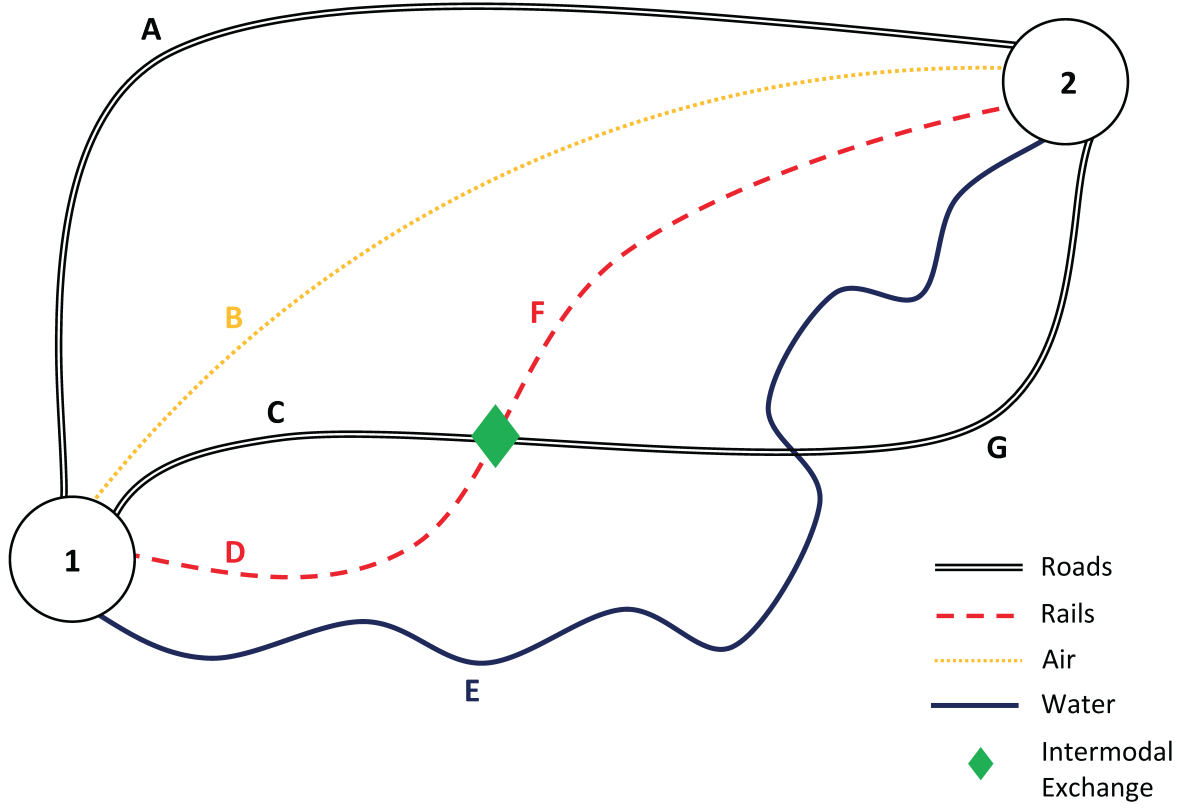
Any policy intervention designed to deflate freight market power has important ramifications for the national trade deficit, which is of key interest to many politicians and policy makers. Because non-competitive freight pricing exerts an outsized influence on exports, it offers a heretofore unexplored lever to manage international trade flows. Importantly, it is a purely domestic policy, and does not require multilateral negotiation and enforcement.

Finally, the results bulwark arguments in favor of aggressive policy interventions in response to transport shocks. Explicitly, the closure of the Railway would lead to sizeable welfare losses, made worse by the exercise of market power from competing modes; an international trade shock is born almost exclusively by consumers – freight market power is concentrated away from international gates, and I estimate near-perfect pass through. Hence, heavy-handed policy intervention is necessary to avoid the worst welfare impacts of transport shocks. It should also be noted that, due to its centrality, transportation carries consequences far beyond trade flows. To name a few, the composition of freight carries environmental, health and safety, and equity concerns which are

beyond the scope of this paper. A promising avenue for future research may apply the methods developed in this paper to these outcomes.

7 Tables and Figures

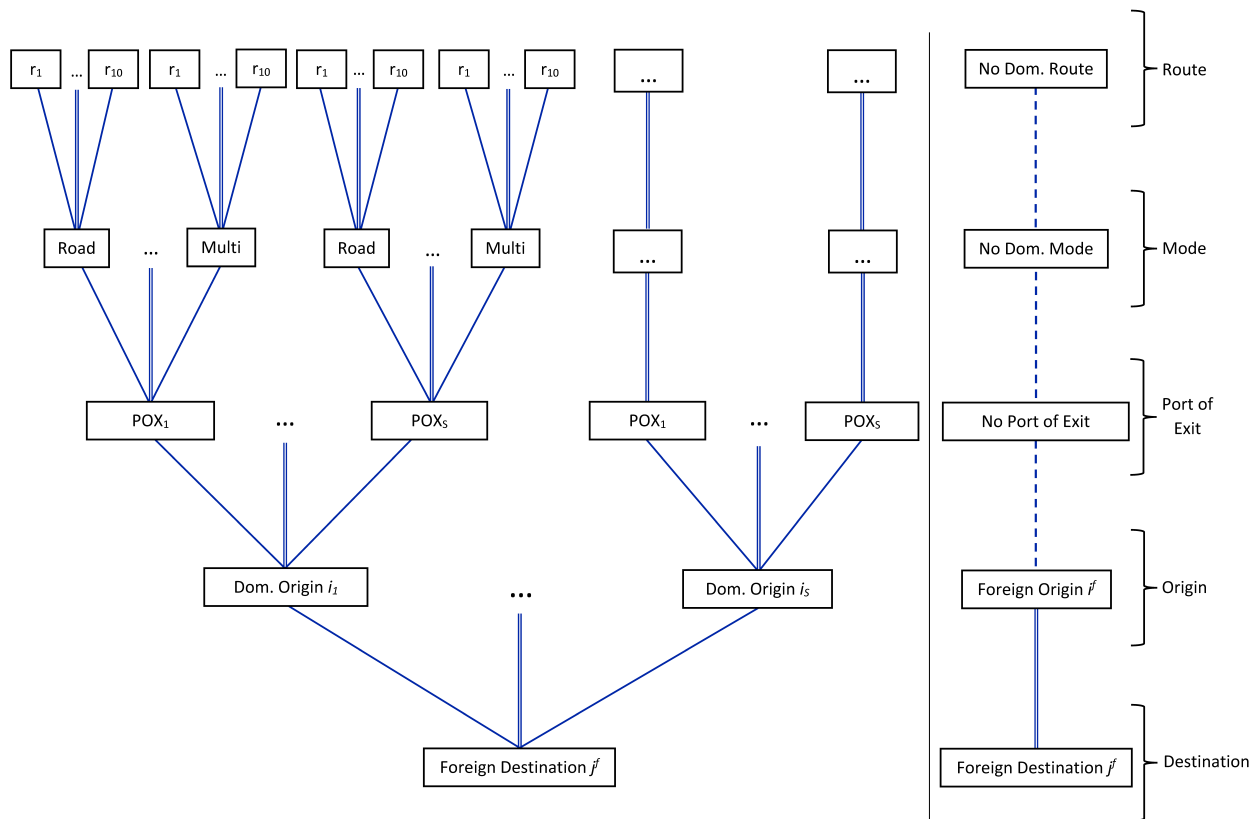
Figure 1.1: A Simple Network



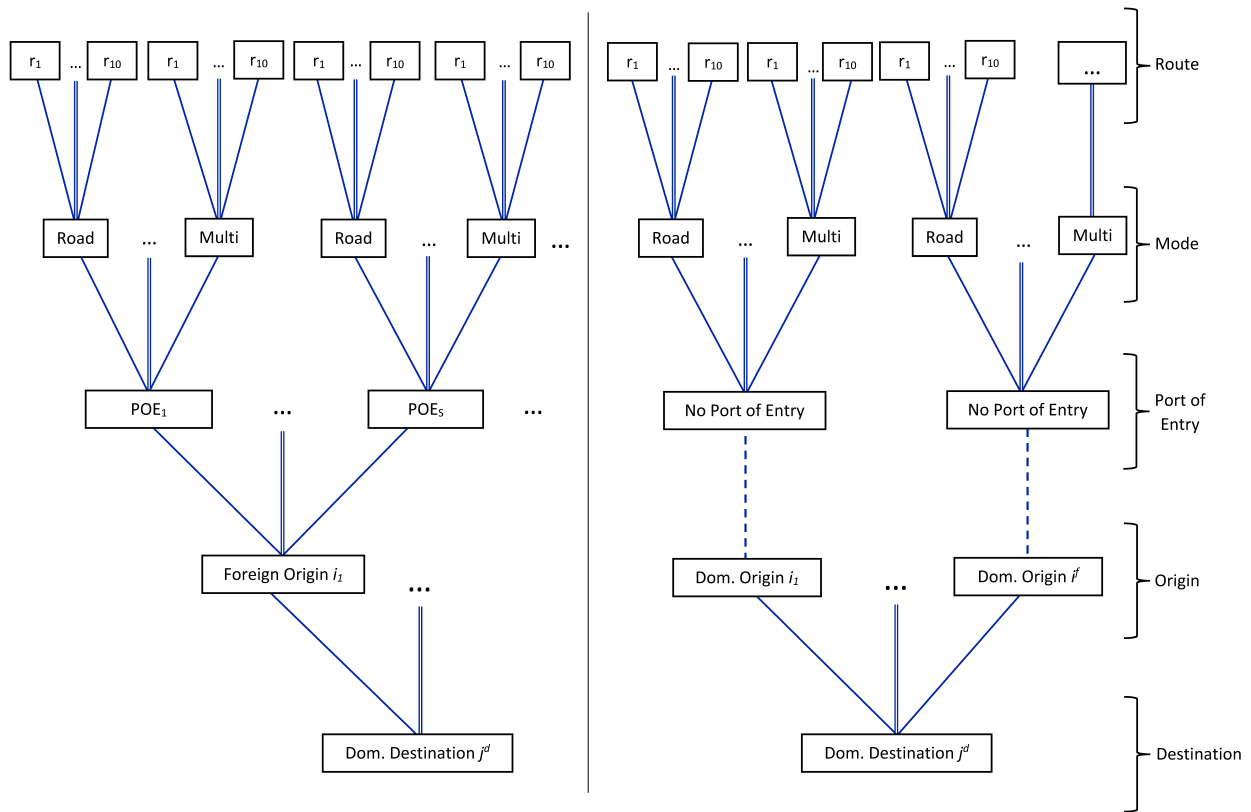
Notes: The above figure displays a simplified transport network to illustrate the basic logic of my setup. In this case, $\mathcal{S}^d = \{1, 2\}$, and the sets of simple (non-repeating) routes along each mode are given by: $\mathcal{R}_{ex}^{Road} = \{A, CG\}$, $\mathcal{R}_{ex}^{Rail} = \{DF\}$, $\mathcal{R}_{ex}^{Air} = \{B\}$, $\mathcal{R}_{ex}^{Water} = \{E\}$, and $\mathcal{R}_{ex}^{Multi-modal} = \{A, CF, CG, DF, DG\}$. 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.

Figure 1.2: Details of the Nesting Structure

(a) Foreign Destinations

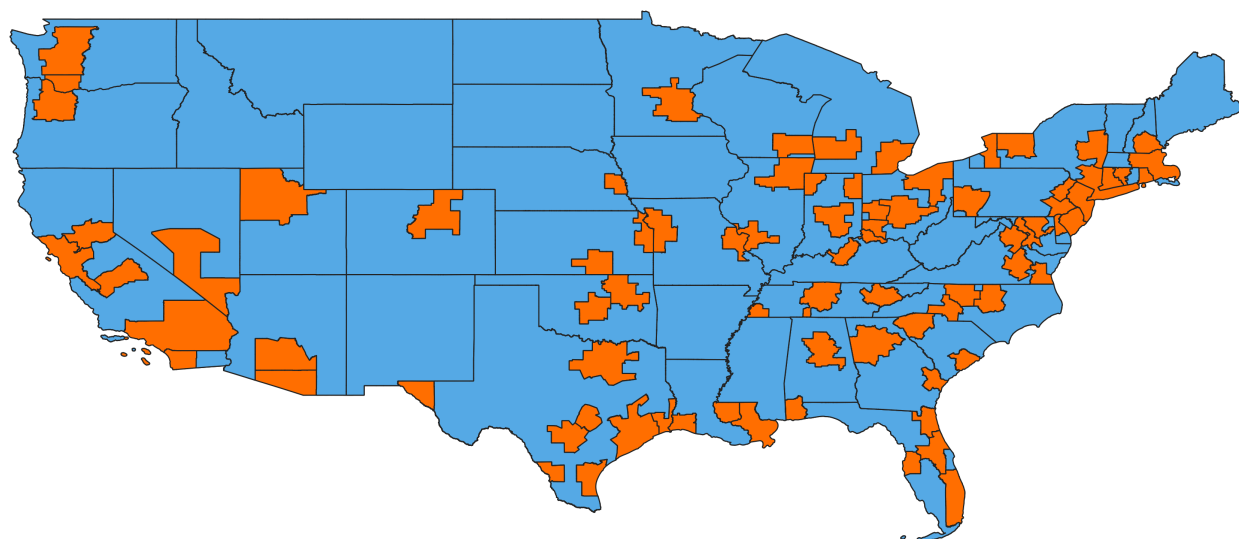
*Continued on next page...*

(b) Domestic Destinations



Notes: Panel A presents the nesting structure for foreign destinations; panel B presents the nesting structure for domestic destinations. Multiple options are presented as a compound line; degenerate branches are represented by a dashed line. Note that if a foreign destination elects a foreign origin, the tree becomes completely degenerate thereafter. Similarly, if a domestic location elects a domestic origin, the choice of port of entry/exit becomes degenerate (as there is no choice).

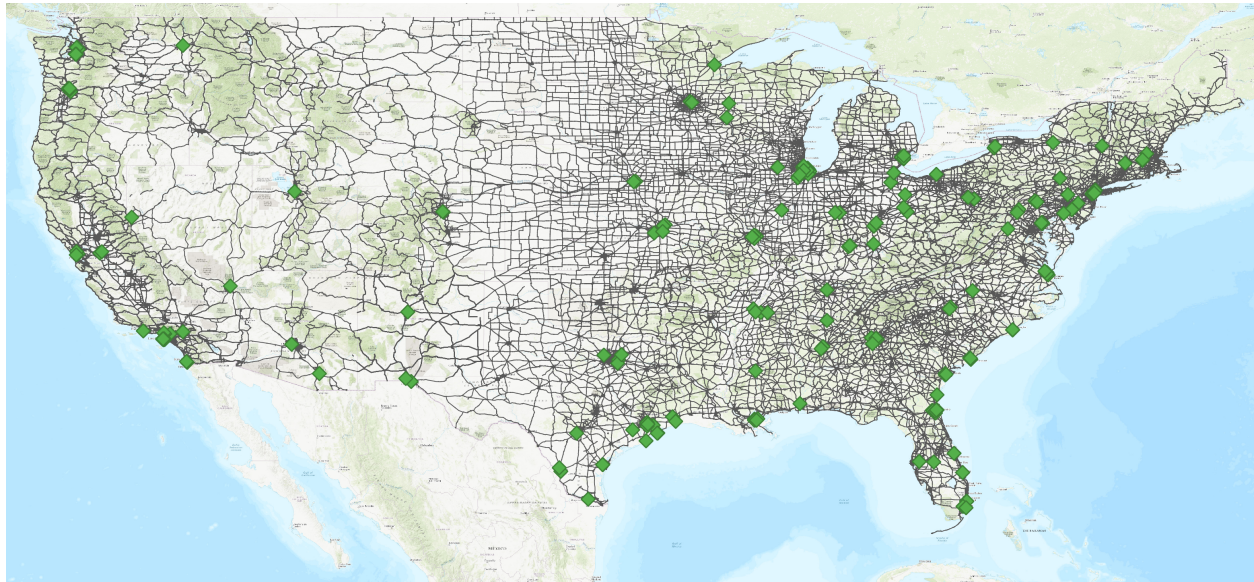
Figure 1.3: FAF Regions



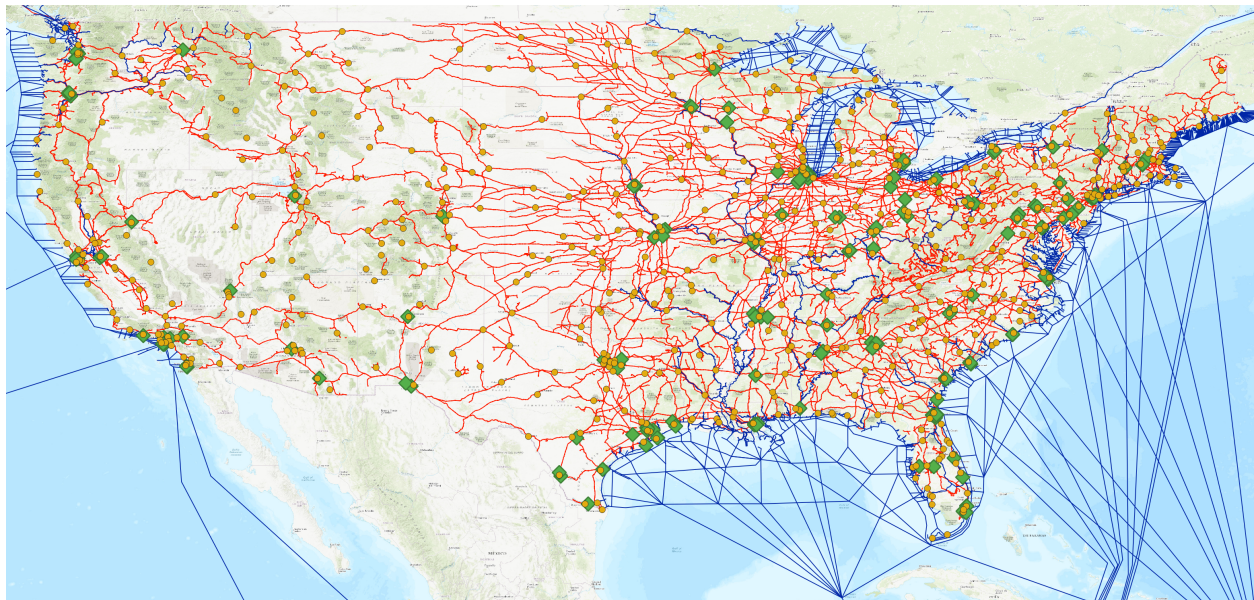
Notes: Black lines denote boundaries between regions. Bright orange areas denote major metropolitan areas. Light blue areas encompass large, rural areas. Note that there is at least one large, rural swath per state; rural areas are distinguished by their state.

Figure 1.4: 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 1.1: Evolution of Routed Mileage by Mode

Route	Road		Rail		Water		Air		Multi-modal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	1	–	1	–	1	–	1	–	1	–
2	1.044	+4.4%	1.055	+5.5%	1.042	+4.2%	1.002	+0.2%	1.043	+4.3%
3	1.074	+2.8%	1.095	+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%	1.154	+2.9%	1.153	+1.6%	1.013	+0.4%	1.114	+1.9%

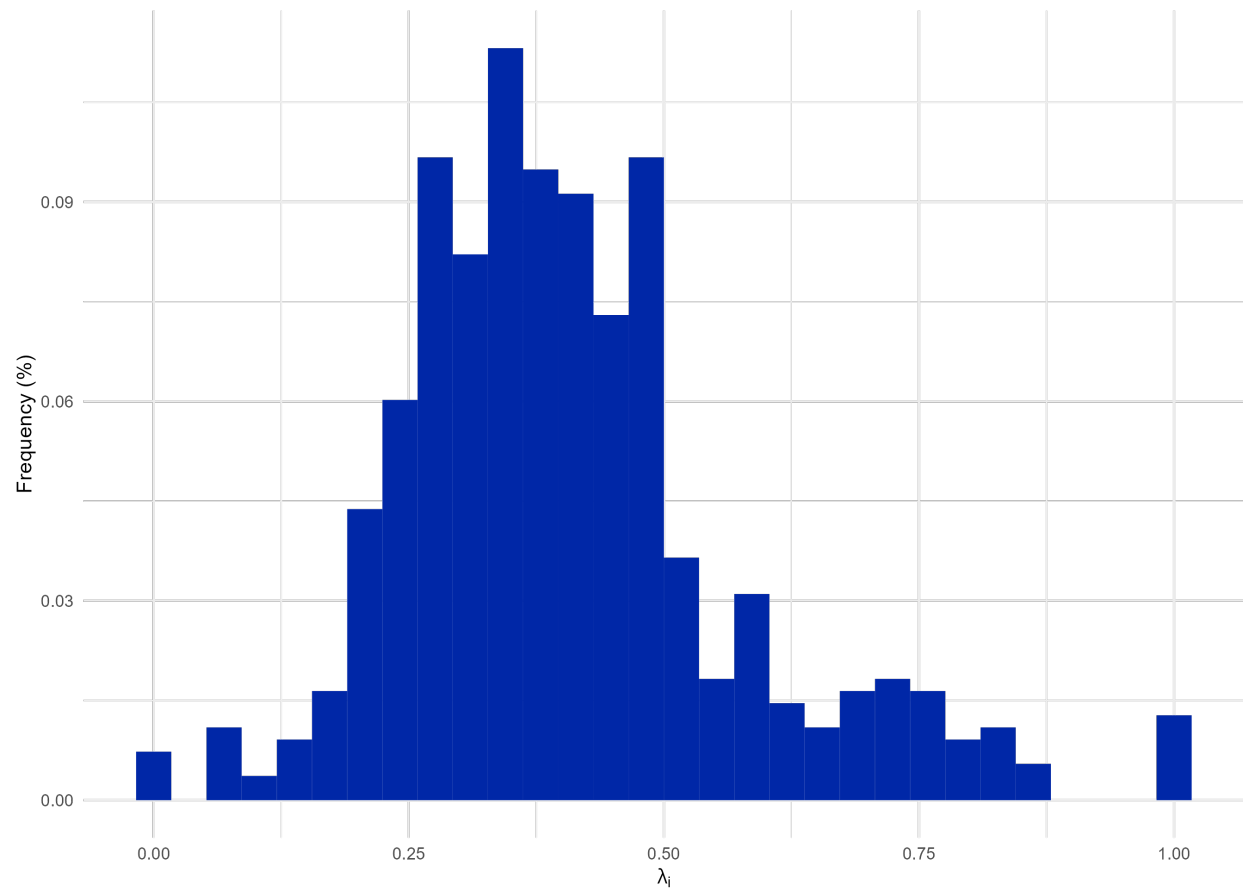
Notes: This table displays the average evolution of mileage along each route across all origin-destination pairs by mode. The odd-numbered columns display the average, scaled mileage per route; the shortest path takes a value of 1 for all origin-destination pairs. The even-numbered columns display the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

Table 1.2: Estimated Fundamentals

A. Geographic Costs $\hat{\beta}_m$						
per-Mile Costs				Multi-Modal Exchange		
Road	Rail	Water	Air			
0.200*** (0.018)	0.125*** (0.02)	0.111* (0.046)	0.085*** (0.013)	0.020*** (0.003)		
B. Inverse Correlation Coefficients						
Route Correlation φ		Mode Correlation $\hat{\rho}$		Port Correlation $\hat{\zeta}$		
1		0.543*** (0.013)		0.374*** (0.009)		
C. Markups $\hat{\mu}_{irj}$						
Min	P25	P50	P75	Max	Mean	Std. Dev.
1.000	1.022* (0.013)	1.030* (0.018)	1.043** (0.020)	1.130*** (0.033)	1.035*** (0.010)	0.021*** (0.004)
D. Model Summary						
N		Adj. R^2		First-Stage F -stat		
382,085		0.921		37.825		

Regression specification utilizes 5 routings per mode and are run with Origin $\times$ POE $\times$ Mode and Destination $\times$ POX $\times$ Mode FEs. Bootstrapped standard errors utilizing 500 iterations presented in parentheses. ***, **, and * respectively denote 0.1%, 1%, and 5% significance. Note that, in Panels B and C, I report significance tests relative to the null of 1. All parameter estimates assume a trade elasticity of 4.

Figure 1.5: Histogram of Estimated Conduct Parameters



Notes: This figure displays the distribution of my estimated conduct parameters. All estimates assume a trade elasticity of 4, and utilize my favored specification, which encompasses 5 potential routings per origin-destination-mode combination. Note that all estimates are normalized to span the $[0, 1]$ range.

Table 1.3: Parameter Estimates under Stricter Modelling Assumptions

	Main Specification	No Markups	No Correlation	Single Route
	(1)	(2)	(3)	(4)
A. Cost Coefficients				
Road	0.200	0.198	0.215	0.226
Rail	0.125	0.122	0.099	0.076
Water	0.111	0.108	0.086	0.091
Air	0.085	0.083	0.113	0.113
Multi	0.020	0.019	0.009	0.011
B. Inverse Correlation Parameters				
Route φ	1.000	1.000	1.000	1.000
Mode $\hat{\rho}$	0.543	0.542	1.000	1.000
Origin $\hat{\zeta}$	0.374	0.376	1.000	1.000
C. Distribution of Markups				
Min	1.000	—	—	—
P25	1.022	—	—	—
P50	1.030	—	—	—
P75	1.043	—	—	—
Max	1.130	—	—	—
Mean	1.035	—	—	—
s.d.	0.021	—	—	—
D. Model Summary				
Observations	382,085	382,085	382,085	76,417
Adj. R^2	0.921	0.920	0.843	0.833
1st Stage F-stat	37.823	—	—	—

Notes: This table displays my reduced-form estimates under simpler modelling specifications. Column (1) restates the results of my primary specification; Column (2) shows my cost and correlation estimates, assuming perfect freight-market competition; Column (3) further restricts the model by assuming zero correlation of prices across geographies, modes; and finally, Column (4) imposes a single route, as opposed to 5.

Table 1.4: Sensitivity to Non-Zero Route-Correlation

Main		φ		
Specification		0.75	0.5	0.25
(1)		(2)	(3)	(4)
A. Cost Coefficients				
Road	0.200	0.200	0.200	0.200
Rail	0.125	0.125	0.125	0.125
Water	0.111	0.111	0.111	0.111
Air	0.085	0.085	0.085	0.085
Multi	0.020	0.020	0.020	0.020
B. Inverse Correlation Parameters				
φ	1.000	0.750	0.500	0.250
$\hat{\rho}$	0.543	0.543	0.543	0.543
$\hat{\zeta}$	0.374	0.374	0.374	0.374
C. Distribution of Markups				
Min	1.000	1.000	1.000	1.000
P25	1.022	1.022	1.022	1.022
P50	1.030	1.030	1.030	1.030
P75	1.043	1.043	1.043	1.043
Max	1.130	1.130	1.130	1.130
Mean	1.035	1.035	1.035	1.035
s.d.	0.021	0.021	0.021	0.021
D. Model Summary				
Observations	382,085	382,085	382,085	382,085
Adj. R ²	0.921	0.921	0.921	0.921
1st Stage F-stat	37.823	37.823	37.823	37.824

Notes: This table displays my reduced-form estimates under different values of the inverse route-correlation parameter φ . Column (1) re-states my main results; Columns (2) - (4) display my results assuming a value of φ equal to 0.75, 0.5, and 0.25, respectively.

Table 1.5: Additional Robustness Checks

	Main	Restricted	Excluding	Urban Areas	Alternate Years	
	Specification	Commodities	Water & Air	Only	2012	2022
	(1)	(2)	(3)	(4)	(5)	(6)
A. Cost Coefficients						
Road	0.200	0.189	0.202	0.159	0.194	0.200
Rail	0.125	0.107	0.130	0.093	0.126	0.116
Water	0.111	0.059	–	0.079	0.114	0.092
Air	0.085	0.062	–	0.070	0.093	0.090
Multi	0.020	0.006	0.021	0.017	0.007	0.020
B. Inverse Correlation Parameters						
φ	1.000	1.000	1.000	1.000	1.000	1.000
$\hat{\rho}$	0.543	0.643	0.512	0.481	0.625	0.500
$\hat{\zeta}$	0.374	0.399	0.410	0.348	0.393	0.378
C. Distribution of Markups						
Min	1.000	1.000	1.000	1.000	1.000	1.000
P25	1.022	1.033	1.022	1.015	1.026	1.015
P50	1.030	1.047	1.035	1.024	1.035	1.024
P75	1.043	1.067	1.053	1.036	1.049	1.038
Max	1.130	1.165	1.164	1.125	1.123	1.121
Mean	1.035	1.053	1.042	1.029	1.040	1.030
s.d.	0.021	0.031	0.030	0.021	0.022	0.023
D. Model Summary						
Observations	382,085	277,6100	301,520	200,665	359,275	400,140
Adj. R ²	0.921	0.915	0.904	0.935	0.818	0.855
1st Stage F-stat	37.823	22.355	32.167	34.664	19.365	35.512

Notes: This table displays the robustness of my estimates to alternate specifications. Column (1) re-states my main results; Column (2) restricts the set of commodities to those that are frequently carried by all modes; Column (3) excludes Water and Air routes; Column (4) omits rural areas; Columns (5) and (6) re-estimate my primary specification using trade data from 2012 and 2022, respectively.

Table 1.6: Robustness to Alternate Starting Values

	Main	Mode Receiving Weight				
	Specification	Road	Rail	Water	Air	Multi
	(1)	(2)	(3)	(4)	(5)	(6)
A. Cost Coefficients						
Road	0.200	0.200	0.200	0.200	0.200	0.200
Rail	0.125	0.125	0.125	0.125	0.125	0.125
Water	0.111	0.111	0.111	0.111	0.111	0.111
Air	0.085	0.085	0.085	0.085	0.085	0.085
Multi	0.020	0.020	0.020	0.020	0.020	0.020
B. Inverse Correlation Parameters						
φ	1.000	1.000	1.000	1.000	1.000	1.000
$\hat{\rho}$	0.543	0.543	0.543	0.543	0.543	0.543
$\hat{\zeta}$	0.374	0.374	0.374	0.374	0.374	0.374
C. Distribution of Markups						
Min	1.000	1.000	1.000	1.000	1.000	1.000
P25	1.022	1.022	1.022	1.022	1.022	1.022
P50	1.030	1.030	1.030	1.030	1.030	1.030
P75	1.043	1.043	1.043	1.043	1.043	1.043
Max	1.130	1.130	1.130	1.130	1.130	1.130
Mean	1.035	1.035	1.035	1.035	1.035	1.035
s.d.	0.021	0.021	0.021	0.021	0.021	0.021
D. Model Summary						
Observations	382,085	382,085	382,085	382,085	382,085	382,085
Adj. R ²	0.921	0.921	0.921	0.921	0.921	0.921
1st Stage F-stat	37.823	37.824	37.824	37.823	37.823	37.824

Notes: This table displays the robustness of my estimates to alternate starting values. Explicitly, I parameterize the starting values to take a value of 1 for a specific mode and zero for the remaining. The mode receiving all the weight (initially) is specified in each column.

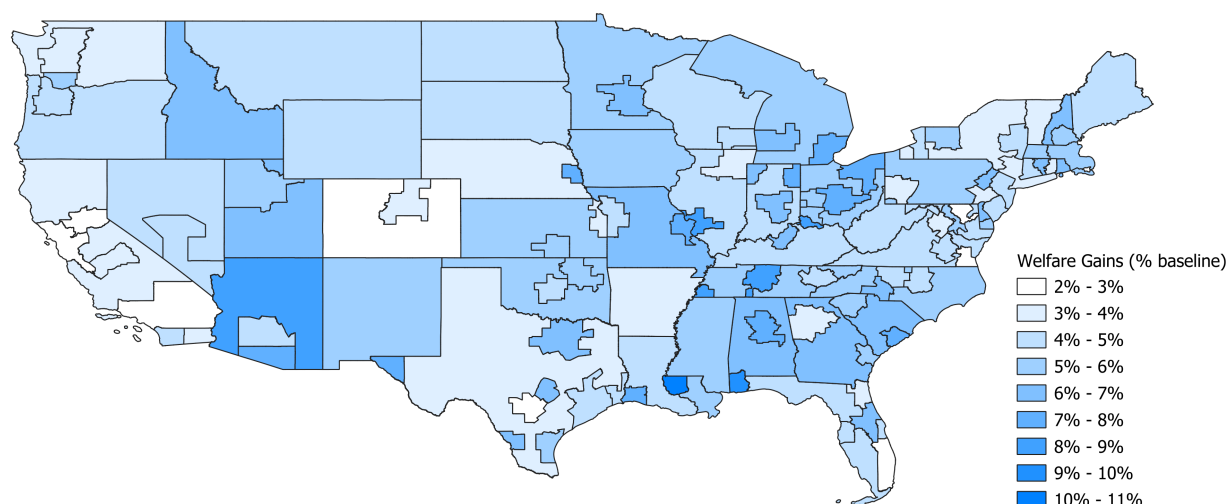
Table 1.7: Change in Real Welfare, Imports, and Exports under Perfect Freight Competition

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. National Welfare				
Road	78.84	1.85	4.14	5.99
Rail	3.79	-0.17	0.12	-0.04
Water	1.61	0.16	0.13	0.28
Air	1.95	-0.18	0.14	-0.05
Multi	13.82	-1.65	0.52	-1.13
Total	100.00	0.00	5.04	5.04
B. Real Imports				
Road	60.72	3.37	5.22	8.59
Rail	9.53	-0.88	0.15	-0.72
Water	3.35	-0.25	0.16	-0.09
Air	10.27	-0.78	0.81	0.03
Multi	16.13	-1.46	1.18	-0.28
Total	100.00	0.00	7.52	7.52
C. Real Exports				
Road	67.03	1.96	13.59	15.54
Rail	11.39	-1.51	1.58	0.07
Water	8.20	0.11	2.39	2.50
Air	6.33	-0.14	0.99	0.85
Multi	7.05	-0.42	1.29	0.87
Total	100.00	0.00	19.84	19.84

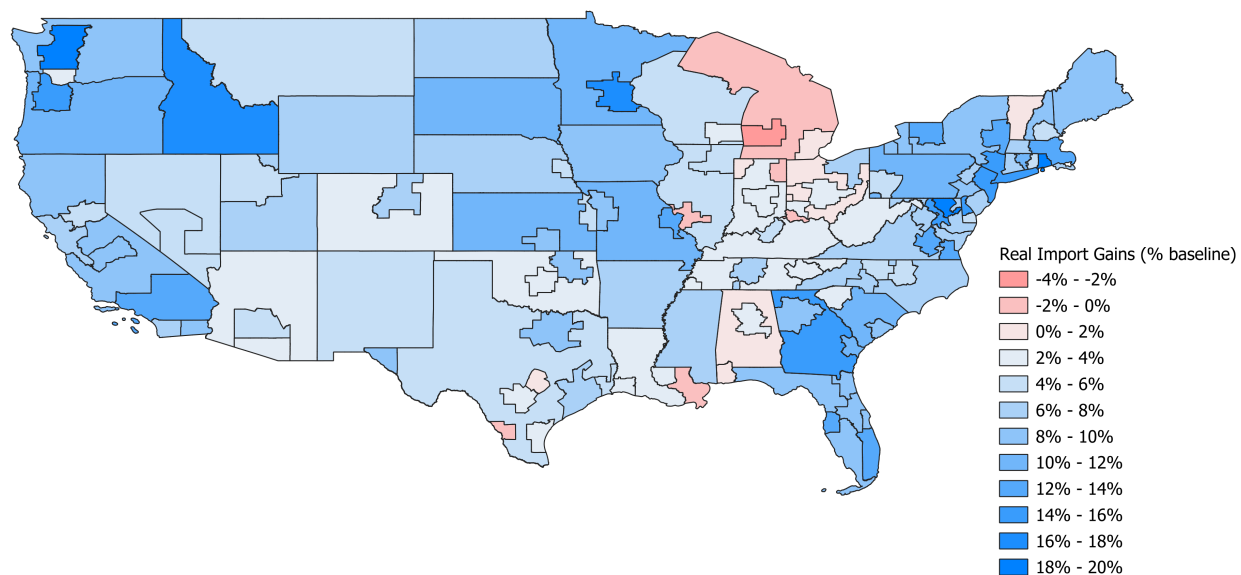
Notes: This table displays changes in real welfare accruing to each mode stemming from elimination of non-competitive pricing in the transport sector. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

Figure 1.6: Geographic Incidence from Elimination of Non-Competitive Markups

(a) Welfare

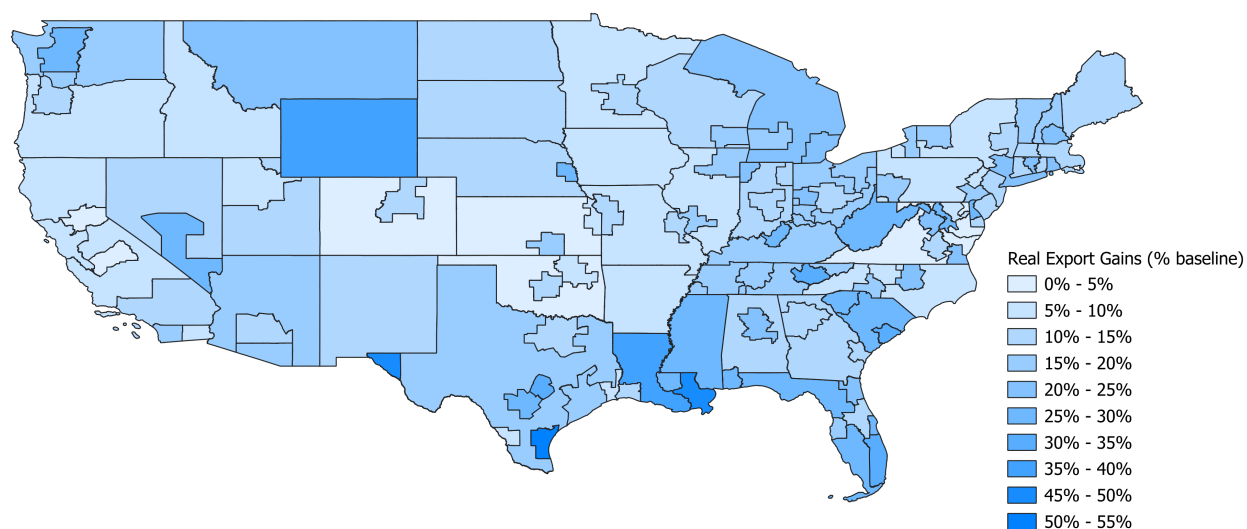


(b) Imports



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(c) Exports



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

Table 1.8: Change in Real Welfare under a Rail Strike

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. Status-Quo Freight Pricing				
Road	78.84	15.91	-3.90	12.01
Rail	3.79	-3.79	0.00	-3.79
Water	1.61	0.34	-0.02	0.32
Air	1.95	1.27	-0.30	0.97
Multi	13.82	-13.82	0.00	-13.82
Total	100.00	-0.08	-4.23	-4.31
B. Perfect Freight Market Competition				
Road	80.75	14.43	-2.50	11.93
Rail	3.57	-3.57	0.00	-3.57
Water	1.80	0.32	-0.04	0.28
Air	1.81	0.79	-0.22	0.57
Multi	12.07	-12.07	0.00	-12.07
Total	100.00	-0.09	-2.77	-2.86

Notes: This table displays national welfare changes stemming from removal of rail and multi-modal transport. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant—note that, in this case, due to imperfect modal substitution and the elimination of certain modes, Column (2) need not sum to 0; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

Table 1.9: Change in Real Imports under a Rail Strike

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. Status-Quo Freight Pricing				
Road	60.72	18.58	-6.13	12.46
Rail	9.53	-9.53	0.00	-9.53
Water	3.35	1.51	-0.43	1.08
Air	10.27	5.57	-1.44	4.13
Multi	16.13	-16.13	0.00	-16.13
Total	100.00	-0.01	-7.99	-8.00
B. Perfect Freight Market Competition				
Road	64.46	17.52	-4.25	13.28
Rail	8.19	-8.19	0.00	-8.19
Water	3.02	1.30	-0.52	0.78
Air	9.57	4.11	-1.25	2.86
Multi	14.75	-14.75	0.00	-14.75
Total	100.00	-0.01	-6.02	-6.03

Notes: This table displays aggregate real import changes stemming from removal of rail and multi-modal transport. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant—note that, in this case, due to imperfect modal substitution and the elimination of certain modes, Column (2) need not sum to 0; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. Panel A lists the change under status-quo freight pricing, while Panel B lists the change under perfect freight market competition. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

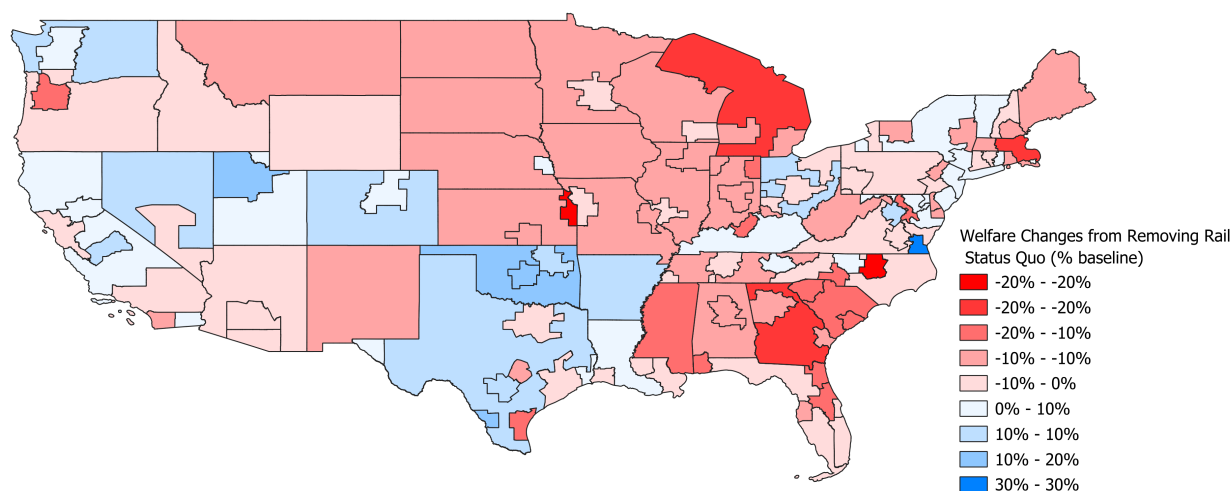
Table 1.10: Change in Real Exports under a Rail Strike

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. Status-Quo Freight Pricing				
Road	67.03	15.83	-2.97	12.87
Rail	11.39	-11.39	0.00	-11.39
Water	8.20	0.71	-0.42	0.30
Air	6.33	1.89	-0.79	1.10
Multi	7.05	-7.05	0.00	-7.05
Total	100.00	0.00	-4.17	-4.17
B. Perfect Freight Market Competition				
Road	68.90	14.21	-0.35	13.86
Rail	9.56	-9.56	0.00	-9.56
Water	8.93	0.52	-0.29	0.22
Air	5.99	1.44	-0.58	0.86
Multi	6.61	-6.61	0.00	-6.61
Total	100.00	0.00	-1.23	-1.23

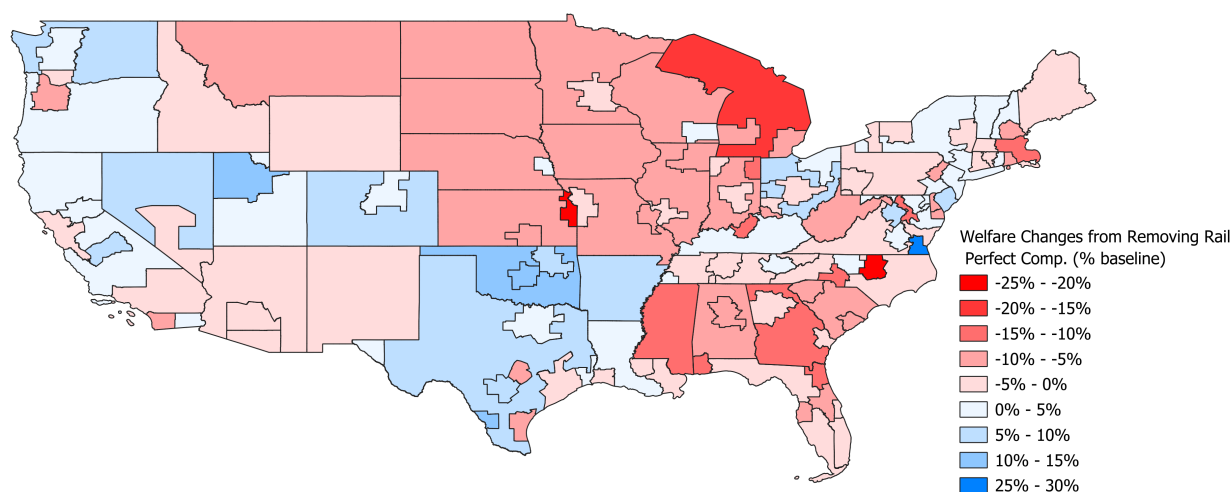
Notes: This table displays aggregate real export changes stemming from removal of rail and multi-modal transport. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant—note that, in this case, due to imperfect modal substitution and the elimination of certain modes, Column (2) need not sum to 0; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. Panel A lists the change under status-quo freight pricing, while Panel B lists the change under perfect freight market competition. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

Figure 1.7: Geographic Welfare Incidence of a Rail Strike

(a) Status-Quo Freight Pricing



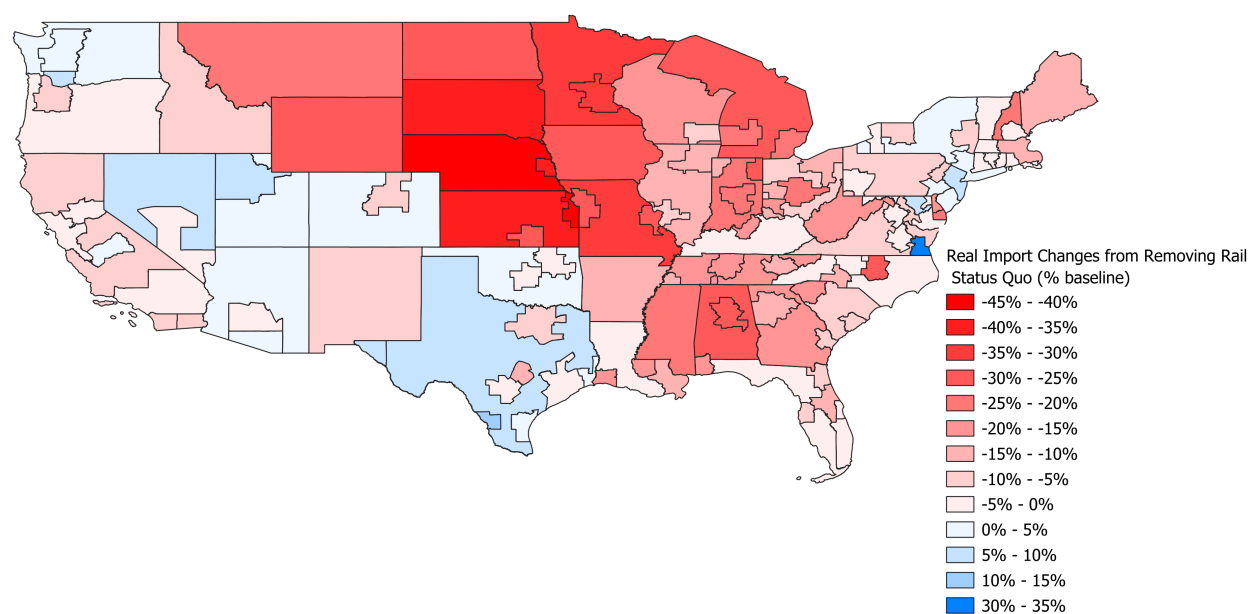
(b) Perfect Freight Market Competition



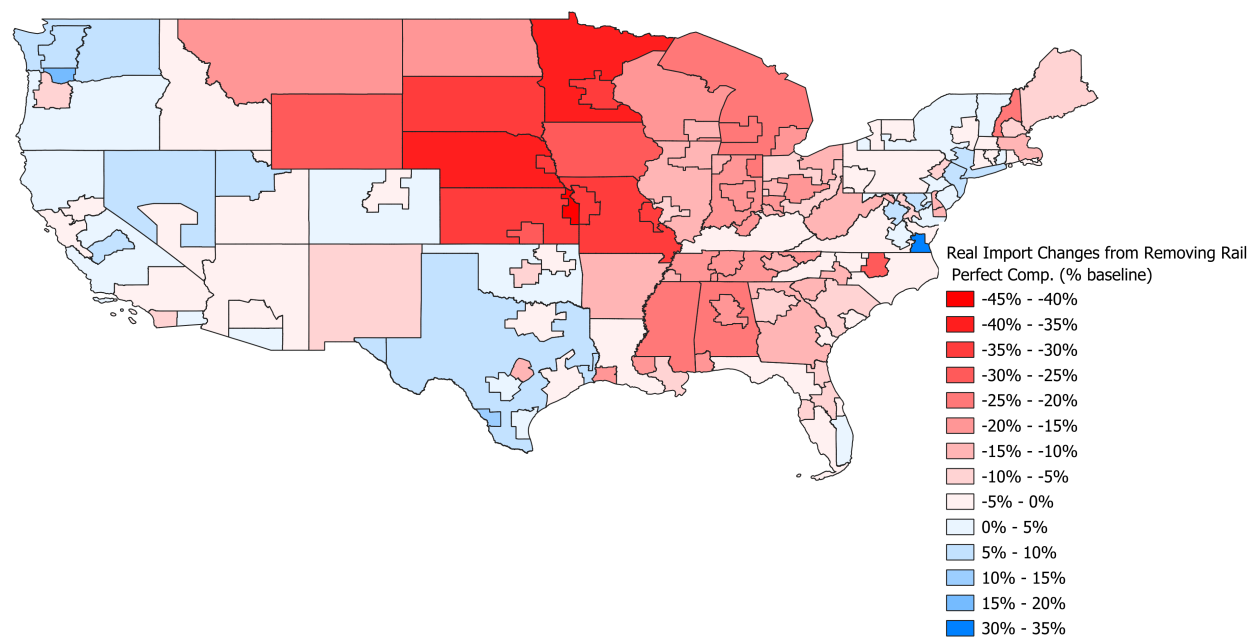
Notes: This figure presents percent changes in real welfare as a result of removing rail and multi-modal transport. Panel A reports welfare changes under the status-quo, while Panel B presents welfare changes under the perfect freight market competition. Darker colors signify greater changes— red denotes a decline in value, while blue denotes a gain.

Figure 1.8: Geographic Import Incidence of a Rail Strike

(a) Status-Quo Freight Pricing



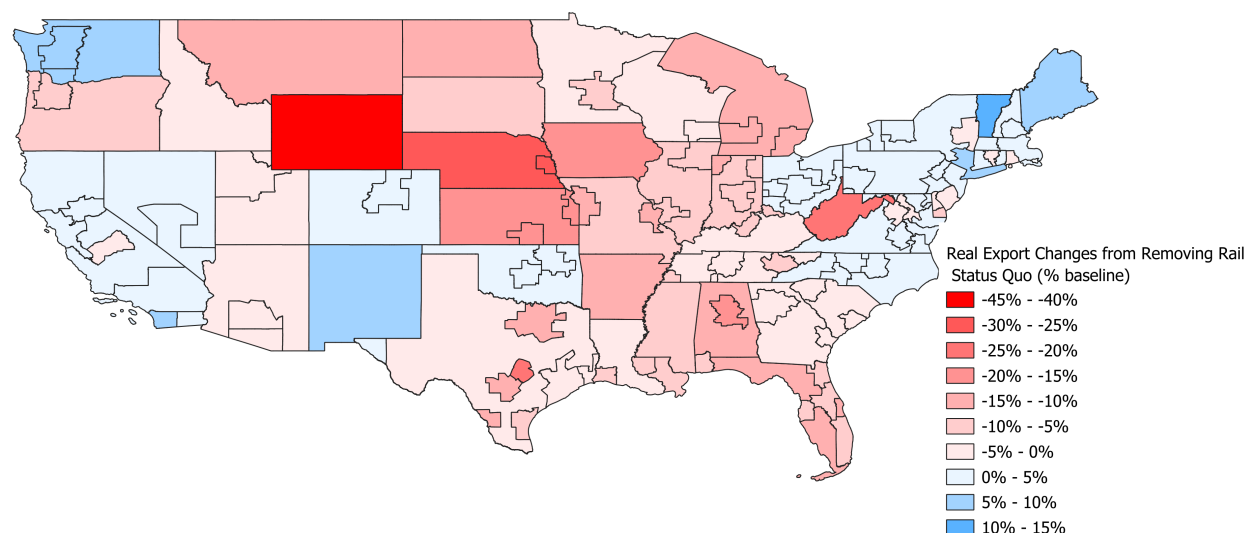
(b) Perfect Freight Market Competition



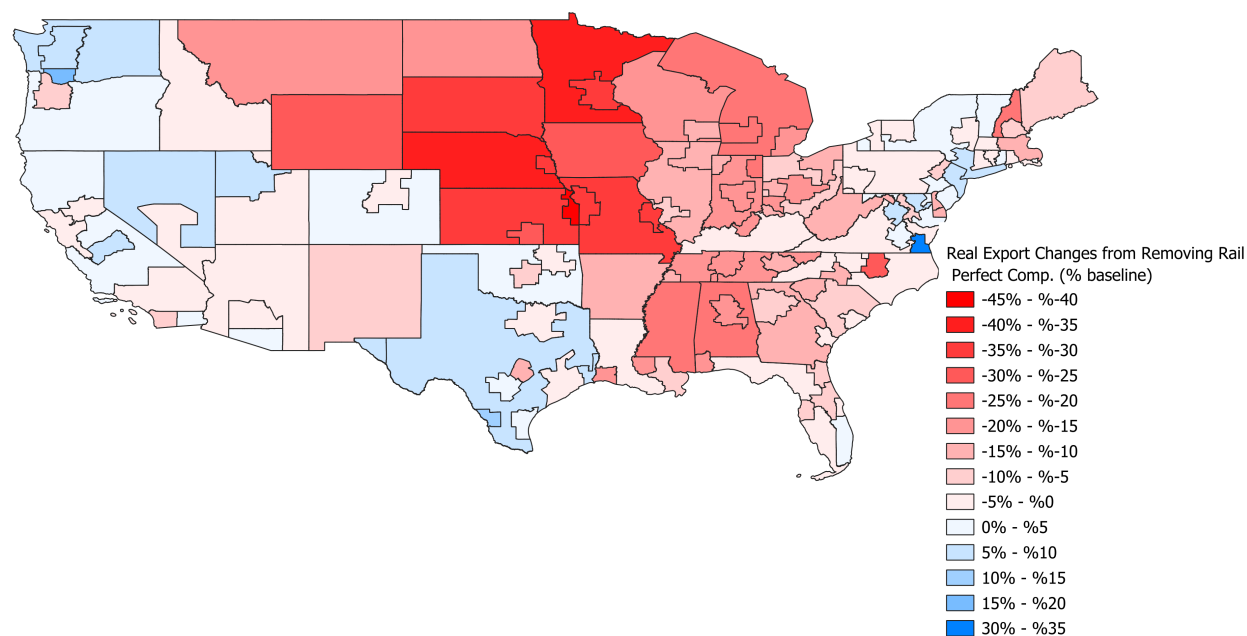
Notes: This figure presents percent changes in real imports as a result of removing rail and multi-modal transport. Panel A reports import changes under the status-quo, while Panel B presents import changes under the perfect freight market competition. Darker colors signify greater changes— red denotes a decline in value, while blue denotes a gain.

Figure 1.9: Geographic Export Incidence of a Rail Strike

(a) Status-Quo Freight Pricing



(b) Perfect Freight Market Competition



Notes: This figure presents percent changes in real exports as a result of removing rail and multi-modal transport. Panel A reports export changes under the status-quo, while Panel B presents export changes under the perfect freight market competition. Darker colors signify greater changes— red denotes a decline in value, while blue denotes a gain.

Table 1.11: Change in Real Welfare from an International Trade Shock

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. Status-Quo Freight Pricing				
Road	78.84	-0.02	-5.33	-5.35
Rail	3.79	0.03	-0.41	-0.38
Water	1.61	0.02	-0.13	-0.10
Air	1.95	0.18	-0.28	-0.09
Multi	13.82	-0.22	-0.97	-1.19
Total	100.00	0.00	-7.11	-7.11
B. Perfect Freight Market Competition				
Road	80.75	-0.05	-5.56	-5.61
Rail	3.57	0.04	-0.39	-0.35
Water	1.80	0.02	-0.13	-0.11
Air	1.81	0.22	-0.28	-0.05
Multi	12.07	-0.24	-0.87	-1.10
Total	100.00	0.00	-7.22	-7.22

Notes: This table displays national welfare changes stemming from an international trade shock meant to emulate the jump in prices parked by the Covid-19 pandemic. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

Table 1.12: Change in Real Imports from an International Trade Shock

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. Status-Quo Freight Pricing				
Road	60.72	-0.15	-10.55	-10.70
Rail	9.53	0.27	-1.87	-1.61
Water	3.35	0.17	-0.66	-0.49
Air	10.27	1.50	-2.04	-0.54
Multi	16.13	-1.79	-2.72	-4.51
Total	100.00	0.00	-17.84	-17.84
B. Perfect Freight Market Competition				
Road	64.46	-0.42	-11.08	-11.50
Rail	8.19	0.32	-1.63	-1.31
Water	3.02	0.19	-0.63	-0.44
Air	9.57	1.80	-2.02	-0.22
Multi	14.75	-1.89	-2.56	-4.46
Total	100.00	0.00	-17.92	-17.92

Notes: This table displays aggregate real import changes stemming from an international trade shock meant to emulate the jump in prices parked by the Covid-19 pandemic. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

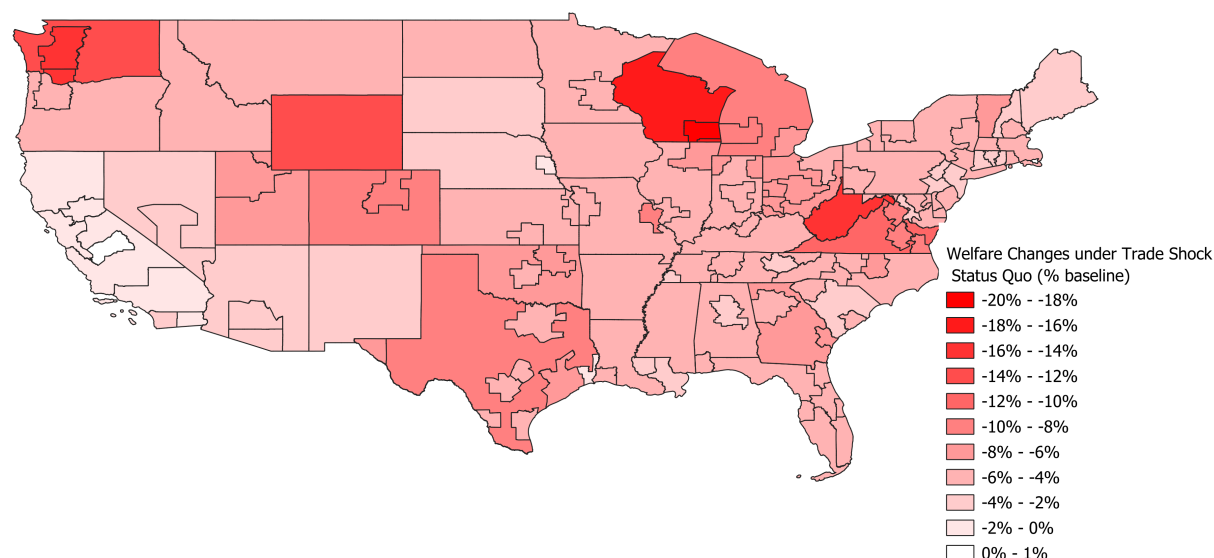
Table 1.13: Change in Real Exports from an International Trade Shock

	Baseline Trade Share (%)	Subs. Effect (ppt)	Income Effect (ppt)	Total Change (ppt)
	(1)	(2)	(3)	(4)
A. Status-Quo Freight Pricing				
Road	67.03	-0.73	-14.78	-15.52
Rail	11.39	0.00	-2.61	-2.61
Water	8.20	0.36	-2.04	-1.68
Air	6.33	-0.19	-1.50	-1.69
Multi	7.05	0.57	-1.74	-1.16
Total	100.00	0.00	-22.67	-22.67
B. Perfect Freight Market Competition				
Road	68.90	-0.87	-15.12	-15.99
Rail	9.56	0.17	-2.23	-2.06
Water	8.93	0.32	-2.19	-1.87
Air	5.99	-0.22	-1.42	-1.63
Multi	6.61	0.60	-1.64	-1.04
Total	100.00	0.00	-22.59	-22.59

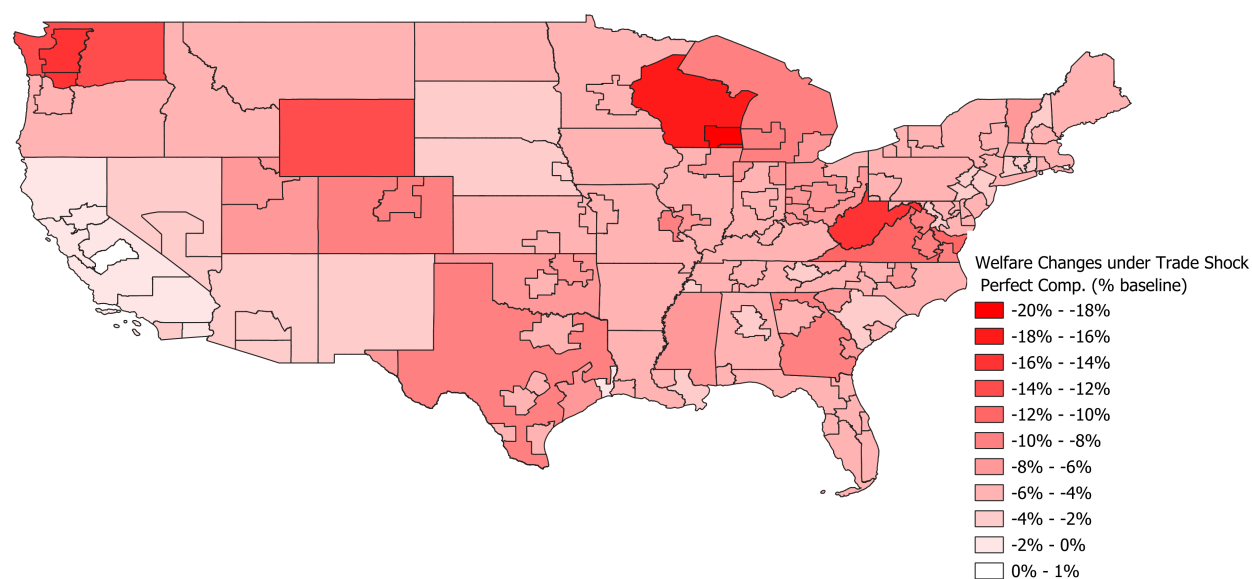
Notes: This table displays aggregate real export changes stemming from an international trade shock meant to emulate the jump in prices parked by the Covid-19 pandemic. Column (1) displays each mode's share of national trade in baseline, and is included for reference; Column (2) lists the change in trade volumes across modes, holding incomes constant; Column (3) lists the change in trade volumes resulting from a change in income, holding mode, route, and port choices constant; Column (4) = Column (2) + Column (3) lists the total change in transport volume (as a percent of national welfare) along each mode. The simulated changes are calculated using 5 potential routings for each mode-origin-destination combination.

Figure 1.10: Geographic Welfare Incidence of an International Trade Shock

(a) Status-Quo Freight Pricing



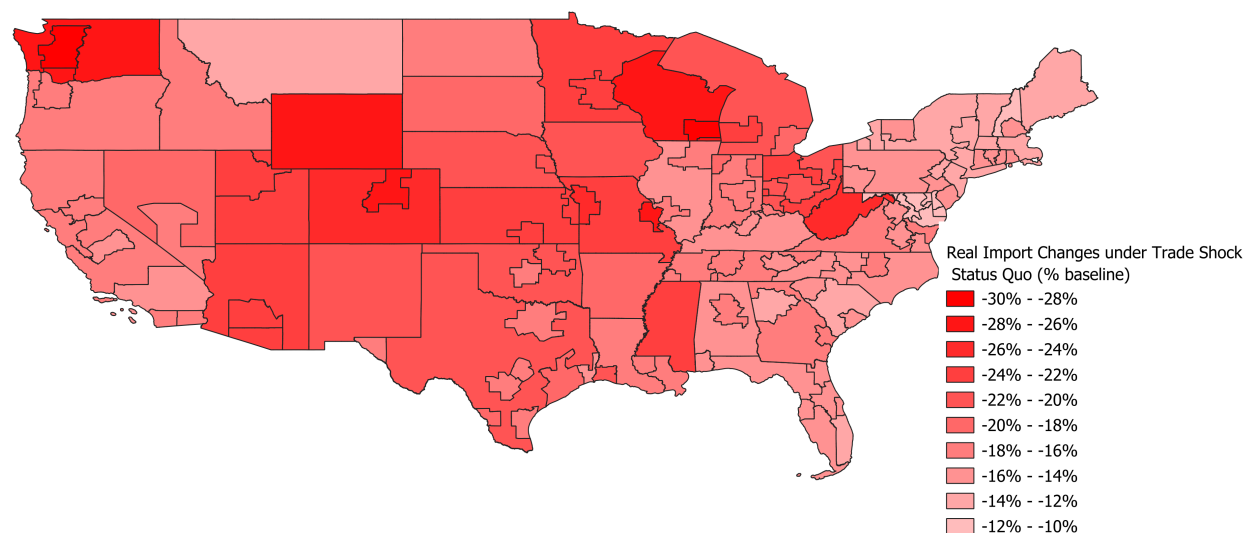
(b) Perfect Freight Market Competition



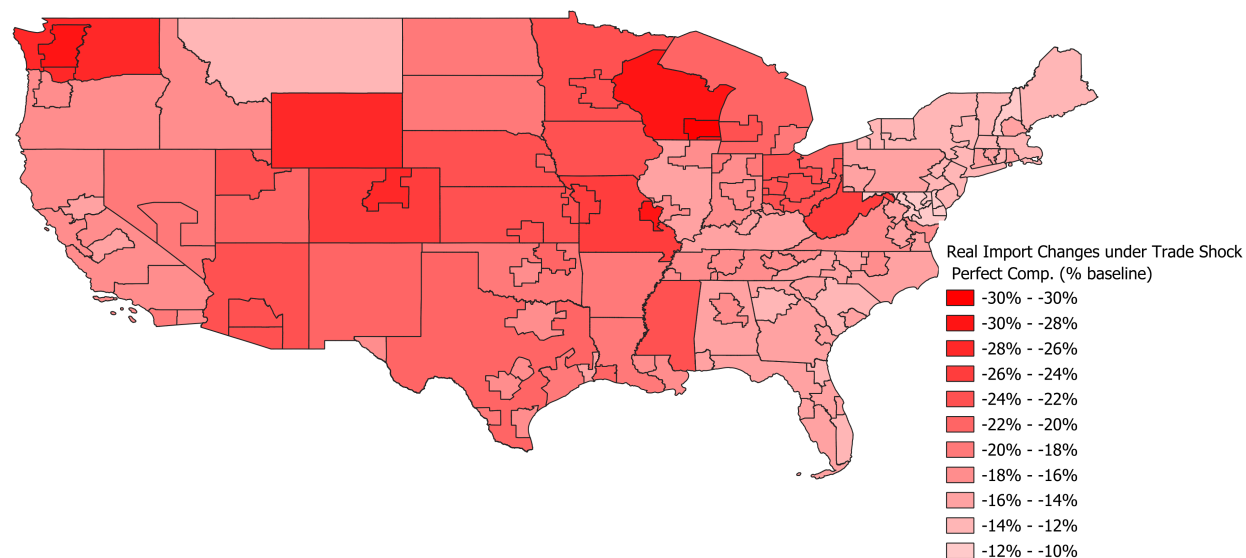
Notes: This figure presents percent changes in real welfare as a result of an international trade shock meant to emulate the spike in shipping prices witnessed during the Covid-19 pandemic. Panel A reports welfare changes under the status-quo, while Panel B presents welfare changes under the perfect freight market competition. Darker colors signify greater changes— red denotes a decline in value, while blue denotes a gain.

Figure 1.11: Geographic Import Incidence of an International Trade Shock

(a) Status-Quo Freight Pricing



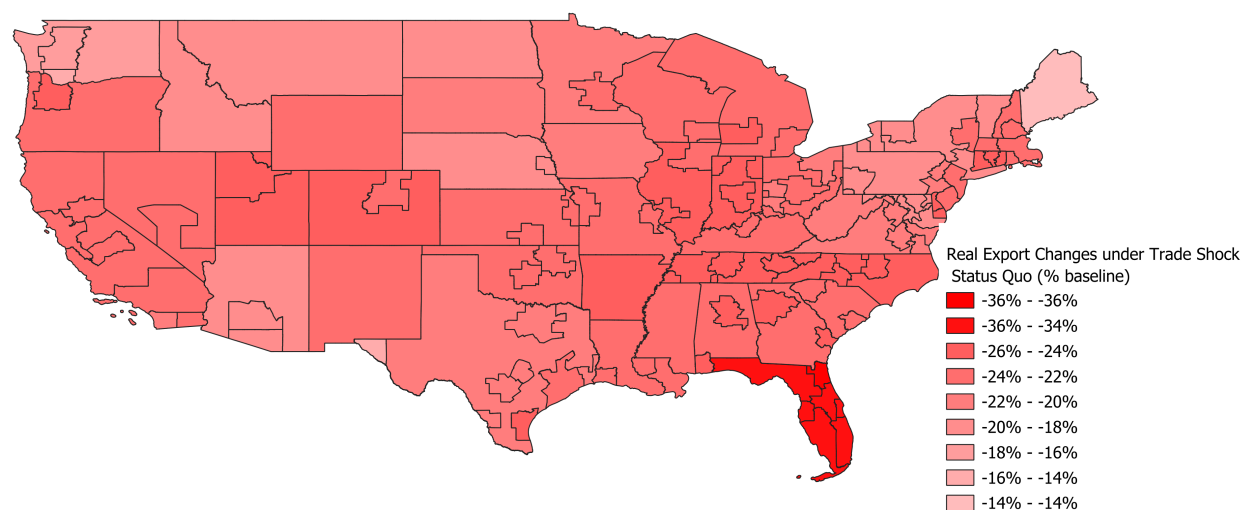
(b) Perfect Freight Market Competition



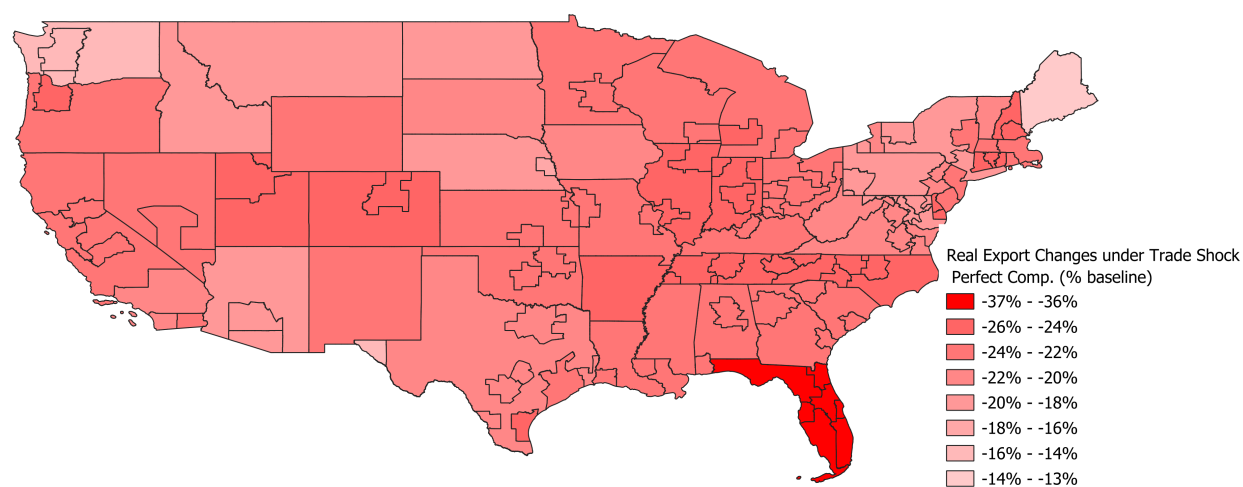
Notes: This figure presents percent changes in real imports as a result of an international trade shock meant to emulate the spike in shipping prices witnessed during the Covid-19 pandemic. Panel A reports import changes under the status-quo, while Panel B presents import changes under the perfect freight market competition. Darker colors signify greater changes— red denotes a decline in value, while blue denotes a gain.

Figure 1.12: Geographic Export Incidence of an International Trade Shock

(a) Status-Quo Freight Pricing



(b) Perfect Freight Market Competition



Notes: This figure presents percent changes in real exports as a result of an international trade shock meant to emulate the spike in shipping prices witnessed during the Covid-19 pandemic. Panel A reports export changes under the status-quo, while Panel B presents export changes under the perfect freight market competition. Darker colors signify greater changes— red denotes a decline in value, while blue denotes a gain.

Chapter 2

Between-Establishment Mobility within Firms by U.S. Workers: Scope, Prevalence, and Effects on Worker Earnings

Several recent papers have documented the concentration of U.S. employment and revenue among a small set of large “superstar” firms (Song et al., 2019; Autor et al., 2020; De Loecker et al., 2020). These large firms tend to divide their employment across several establishments: at least 25% of U.S. workers are at firms operating more than 100 establishments and overall at least 60% of workers are at multi-establishment firms, with both of these values increasing over time. Thus, most workers could switch establishments without switching firms, and many workers have a large set of possible establishment options. This paper uses matched employer-employee data to study the prevalence and importance of opportunities for between-establishment job mobility within firms (denoted BEM below) in the United States.

We make two primary contributions. First, we estimate the annual within-firm mobility rate between establishments in the United States. Standard measures of employer-to-employer (E-to-E) mobility conflate firm-to-firm transitions with between-establishment transitions within the same firm.¹ Thus, our estimate allows us to isolate the firm-to-firm mobility rate. This is important in part because the E-to-E rate is often used to gauge the labor market’s “dynamism”, its ability to reallocate workers to more productive firms and facilitate efficient worker-firm matching (Fujita et al., 2024). It is also used as a key moment in job search models to calibrate search frictions (e.g. Berger et al. (2024)), which are likely to be far greater for between-firm than within-firm moves. Furthermore, characterizing BEM access and transition rates is important in its own right

¹For example, two commonly used sources for job-to-job mobility rates are at odds on how to handle establishment mobility. The Quarterly Workforce Indicators (QWI) measure SEIN transition rates in LEHD data, which reflect within-firm and between-firm mobility (Abowd et al., 2009); in contrast, the Current Population Survey (CPS) asks respondents whether they still work at the same company as the previous wave, which mostly measures between-firm mobility (Fallick and Fleischman, 2004) and struggles to capture between-state transitions involving a change of residence.

to evaluate the importance of internal labor markets as a driver of residential mobility and worker career progression, particularly given the rising employment concentration among firms with many establishments. To assess which kinds of workers and firms rely most on BEM, we also examine heterogeneity in BEM prevalence and access. In addition, our descriptive analysis explores how geographic distance to other establishments within the same firm mediates BEM transitions.

Second, we assess the importance of BEM in shaping workers’ career paths by estimating the causal effect of greater access to BEM opportunities on workers’ short and medium-run earnings growth. We measure BEM access based on geographic proximity to jobs at the firm’s other establishments, exploiting variation in the locations of workers’ establishments within the firms’ establishment network, and show that our measure strongly predicts workers’ BEM use.

Research on BEM in the United States is complicated by two key features of the U.S. matched employer-employee data, the Longitudinal Employer Household Dynamics (LEHD) database.² First, while each firm’s full employee roster is faithfully reported in each state, each worker’s establishment must be imputed in nearly all states for firms who group multiple establishments within the same State Employer Identification Number (hereafter SEIN).³ Second, the imputation procedure used by the Census Bureau intentionally eschews allowing between-establishment job transitions within an employment spell at a SEIN in order to avoid creating spurious job transitions (Vilhuber and McKinney, 2014). We show that these aspects of the data are less limiting than they appear, and highlight two other data features that permit a fruitful analysis of BEM.

First, between-establishment job transitions are observed when a worker changes SEIN within a firm. Thus, we observe all between-state transitions within the same firm among the 25 states in our sample.⁴ Additionally, we document that large firms generally create many SEINs within the same state. Overall, we find that 90% of employment at multi-establishment firms is contained within the subset of firms featuring multiple SEINs (56.9% of all U.S. workers).

This insight motivates our analysis of between-SEIN transitions within a firm. We find that between-SEIN mobility is quite common: among our 25-state sample, about 1.4% of workers at multi-SEIN firms change SEINs within the same firm each year, with 6.6% changing SEINs at least once within 7 years. Adding in our estimates of within-SEIN mobility and SEIN mobility to

²Note that the other potential data source, CPS, use addresses as sampling unit, hence it is not able to capture BEM that may also require residential changes.

³SEINs are a state-specific accounting identity used by firms primarily to manage taxes, unemployment insurance, and legal liability. SEINs are used as employer identifiers in labor market statistics such as the LEHD-based QWI.

⁴Each state must provide separate approval of LEHD data access for each project.

out-of-sample states brings the total BEM rate to 2.2% for workers at multi-SEIN firms and 1.4% among all workers. Since 16.7% of workers change firms each year on average, this implies that 7.8% of all E-to-E transitions and 26.9% of between-state E-to-E transitions are within firms ($\sim 500,000$ and $\sim 250,000$ transitions per year, respectively). The latter statistic suggests that internal labor markets may help workers and firms overcome frictions associated with long-distance moves.

These aggregate numbers mask substantial heterogeneity in the prevalence of establishment mobility by both firm and worker characteristics. Particularly striking are differences by firm size, where annual rates of observed SEIN mobility are 1.8% (18.2% of all job transitions) for the 27.5% of workers at firms with more than 5,000 employees vs. 0.1% (0.4% of job transitions) for the 37.5% of workers at firms with fewer than 100 workers.

The second valuable LEHD feature is that all establishments' locations and sizes are fully observed, so that access to BEM opportunities can be correctly measured and analyzed even though actual within-firm establishment transitions are not fully observed. Our earnings growth estimates exploit the fact that assignment to establishments with differential opportunities for moves to nearby establishments may contain an exogenous component.

Specifically, we measure a worker's access to BEM opportunities by constructing the shares of within-firm employment that lie in discrete distance bands relative to the worker's establishment. Regressing average percentage changes in annual earnings over a time window (3, 5 or 7 years) on this vector of distance shares estimates the degree to which a more geographically proximate employment distribution within the firm contributes to workers' earnings growth.

A crucial element of our identification strategy is the use of both firm-by-year and county-by-year fixed effects in all of our regressions. This allows us to leverage the fact that locations that are central to one firm's establishment network may be quite remote in another's. For example, CVS and Rite Aid pharmacies may both hire pairs of workers in Philadelphia and Boston who all have nearly identical jobs, but Rite Aid's Philadelphia worker will be near a much larger share of other Rite Aid jobs than its Boston worker, and the opposite will be true for the CVS workers.

This approach removes two potential biases that would otherwise obscure the causal relationship of interest: (1) more productive firms may generate faster growth in revenue and earnings while also expanding outward geographically, so that higher worker earnings growth would be correlated with smaller shares of nearby BEM opportunities, and (2) workers with greater earnings prospects regardless of firm may sort into larger firms with more geographic breadth.

The position of a worker’s establishment within the firm’s network is also likely to contain an endogenous component. The sorting of workers with greater growth potential to particular establishments within firms may be non-random and correlated with the geographic centrality of the establishment (e.g., workers being groomed for management getting assigned to the headquarters). Also, some establishments may enjoy higher revenue and award greater raises than others independently of worker composition or BEM opportunities. Furthermore, establishments in rural locations will tend to have a smaller share of nearby jobs at the firm, and may experience different earnings growth trends. We address these sources of bias by including a variety of worker, establishment, and location controls, and then assess the potential for remaining bias by examining patterns of selection on observable characteristics and constructing placebo tests.

The findings from our baseline specification suggest that a greater share of employment at more proximate establishments leads to meaningfully faster earnings growth for workers at multi-establishment firms. Specifically, shifting just 10% of the firm’s employment from establishments more than 500 miles away to those within 10 miles increases average annual earnings over the following 5 years by 0.27% relative to baseline year earnings. Predicted earnings gains fall monotonically as one considers alternative 10% shifts to less proximate jobs: 0.17%, 0.15%, 0.10%, and 0.06% for 10-25, 25-50, 50-100, and 100-500 miles, respectively. Our distance profile estimates are quite robust to alternative ways of measuring the geographic distribution of BEM opportunities.

Since there is substantial variation in the distance distribution of other-establishment employment within and particularly across firms, these estimated distance profiles can potentially account for a non-trivial amount of variation in earnings growth among workers at multi-establishment firms: a worker at the 90th percentile of earnings gains from more proximate within-firm job opportunities can expect to enjoy 2% higher average real earnings growth over the following five years than a worker at the 10th percentile with the same baseline earnings.

Consistent with the idea that greater BEM opportunity is the mechanism driving these earnings gains, we also find a strong monotonic relationship between greater employment shares at closer establishments and within-firm SEIN transition rates: 10% employment shifts from very distant establishments to those 0-10, 10-25, 25-50, 50-100, and 100-500 miles away predict increases in the worker share making a SEIN transition within 5 years of 1.0%, 0.9%, 0.7%, 0.4%, and 0.2%

We also find substantial heterogeneity across different types of workers and firms in the sensitivity of workers’ earnings growth and SEIN mobility rates to the distance distribution of jobs at

their firms' other establishments. For example, for workers at the largest firms (> 5000 workers), the same 10% shift in employment share from establishments over 500 miles away to those within 10 miles predicts a 0.35% increase in per-year earnings over 5 years and a 0.5% increase in annual SEIN mobility. More generally, we see that elevated baseline SEIN mobility rates and elevated earnings and SEIN mobility sensitivity to the distance distribution of BEM opportunities all tend to occur in concert, with greater levels of all three occurring at higher paying firms, at firms in the information, finance/real estate, and trade/transportation/utilities supersectors, as well as among younger workers and workers with higher baseline earnings.

We construct placebo tests that (1) replace future earnings growth with past earnings growth for new hires and (2) replace workers' BEM access measures with those of workers from other firms in the same census tract. We find no evidence of selection into more central establishments of workers with higher persistent ability to raise their earnings nor evidence of systematically lower earnings growth among workers in tracts that tend to be less central to their firms' networks, conditional on other location controls. Examination of the sensitivity of our results to the exclusion of various establishment and worker controls does not reveal evidence of bias from unobserved establishment-level factors correlated with BEM access (Altonji et al. (2005)), but does indicate some selection of workers with favorable characteristics for growth into establishments with a greater share of more distant job opportunities. This suggests that our substantial estimates may actually understate the earnings growth impact of greater BEM access.

Our paper builds upon and bridges a number of existing strands of research. Most directly, there are studies from Norway (Huttunen et al., 2011), Portugal (Tavares et al., 2018), and France (Cestone et al., 2023) that examine aspects of the use of BEM in those countries. We are the first to document the prevalence of and scope for BEM in the United States. Huttunen et al. (2011) show that engaging in BEM reduces the earnings losses from plant closings, while Tavares et al. (2018) observes that BEM yields greater earnings premia than switching firms. Although Cestone et al. (2023) focus on firm outcomes, they show that worker flows between firms within broader business groups facilitate these conglomerates' expansions in industries where a major competitor has exited. Rather than focus on BEM responses to particular exogenous shocks, which cannot be perfectly foreseen when a worker decides to join a firm, we contribute by estimating the importance of **access** to potential BEM opportunities on a key worker decision factor, their expected short- and medium-run earnings growth. We also provide a more thorough account of the variation across

demographic groups in access to, take up of, and earnings sensitivity to BEM opportunities.

Because the first two papers focus on quite small countries, they are not well-positioned to assess how the proximity of other establishments affects their value to workers. Consistent with our findings, [Cestone et al. \(2023\)](#) show that increases in within-conglomerate flows are largest for business groups with many workers at other firms in the same labor market. We expand on this result by using several distance bins to explore sensitivity of BEM flows to spatial frictions within and across local labor markets and by using a more comprehensive measure of BEM flows.

A second literature focuses on measuring levels of and trends in worker residential and employer mobility ([Molloy et al., 2011](#); [Hyatt et al., 2018](#); [Fujita et al., 2024](#)), with the goal of understanding the role of moving and search frictions in equilibrating markets and shaping the evolution of the business cycle ([Moretti, 2011](#); [Moscarini and Postel-Vinay, 2016](#); [Cadena and Kovak, 2016](#)). A sub-literature on the scale of local labor markets documents how job and residential mobility rates decay with distance to destinations ([Tolbert and Sizer, 1996](#); [Manning and Petrongolo, 2017](#); [Mansfield, 2018](#)). Here we contribute by highlighting the importance of distinguishing within-firm from between-firm transitions when measuring worker E-to-E rates, particularly for long-distance moves that govern rates of regional wage convergence ([Blanchard and Katz, 1992](#)).

A third, long-standing literature uses detailed data from single firms to document the important role of well-defined within-firm job ladders in earnings dynamics, particularly for workers at large firms ([Baker et al., 1994](#); [DeVaro and Waldman, 2012](#)). This literature has struggled to determine the scope of an internal labor market: a single large establishment, a set of establishments in a local area, an entire multi-establishment firm, etc. ([Althauser, 1989](#)). We show that internal labor markets can and do operate at a national scale. That said, greater distance between establishments still dramatically reduces within-firm flows, so that multi-establishment internal labor markets are likely to be more effective when establishments are closer together.

A related literature uses national matched employer-employee data, often from Europe, to jointly characterize worker mobility within and across firms, and quantify the relative contributions of internal and external job transitions to worker earnings growth ([Van der Klaauw and Dias da Silva, 2011](#); [DeVaro et al., 2019](#); [Kramarz et al., 2014](#); [Papageorgiou, 2018](#)). By leveraging workers' relative positions in their firms' establishment networks, we provide causal estimates of obtaining greater access to an internal labor market, rather than simply observing the distribution of outcomes within one firm's internal labor market or comparing earnings changes of those changing jobs and/or

occupations internally vs. externally.

A fourth literature shows that workers at large firms enjoy higher earnings and faster earnings growth (Brown and Medoff, 1989; Arellano-Boyer, 2024). We find greater mobility and earnings gains among large firms, suggesting that greater access to BEM opportunities within larger firms may be one mechanism or mediating force through which superior earnings growth is realized.

A related literature measures the extent and recent rise of monopsony power within U.S. labor markets (Berger et al., 2022; Yeh et al., 2022; Azar et al., 2022; Jarosch et al., 2024). These papers generally argue that concentrating employment within fewer firms reduces worker earnings by limiting outside offers. Our paper suggests that large firms with many establishments may have the offsetting benefit to workers of increasing access to jobs at distant locations. Such access is valuable if workers need insurance against negative local shocks (consistent with Huttunen et al. (2011)’s plant closings evidence) or if their optimal residential locations evolve with age.

Several papers provide theoretical mechanisms and/or empirical evidence to explain why establishment transitions happen within firms. A primary reason for a firm to initiate such transitions is that relative product demand across its establishment network shifts, changing its optimal allocation of labor. Giroud and Mueller (2019) formalize this mechanism and show that shocks to one establishment’s location affect employment at other distant establishments. Cestone et al. (2023) find that firms with a larger pool of nearby workers within their business conglomerate disproportionately rely on reallocating the conglomerate’s workers following positive shocks and enjoy larger increases in market share and sales.⁵ We show that there is sufficient long-distance BEM to suggest that even firms with geographically dispersed establishments prefer to use BEM rather than a combination of layoffs and hires to facilitate establishment-level employment shifts.

A firm may prefer employee transitions to reward its best performing workers as part of a promotion tournament used to incentivize worker effort (Lazear and Rosen, 1981). Or the firm may wish to retain or better exploit substantial firm-specific or even task-specific human capital accumulated by the worker (Becker, 1962; Carmichael, 1983; Lazear, 2009; Gibbons and Waldman, 2004). Or search costs associated with hiring a new worker of similar quality may exceed the moving costs from transferring a worker (Schmutz and Sidibé, 2019). The models in Papageorgiou (2018) and Lazear (2009) make clear that the latter two explanations are possibly mutually reinforcing, and that search frictions can raise the payoff to retaining a worker whose skills are scarce or partly

⁵Retirements, quits, and skill development also alter the optimal allocation even without product demand changes.

portable to other firms. These explanations are all consistent with our findings that establishment transitions are more common among higher-paid, moderately-tenured employees.

If employee establishment transitions were desired exclusively by the firm, then the firm might need to offer higher salaries or promotions to induce workers to incur the moving or commuting costs required by the transition. [Mulalic et al. \(2014\)](#) show that firms do pay such compensating differentials when moving entire establishments to new locations. This scenario helps explain the link we report between greater BEM access and earnings growth, and also suggests that the earnings growth impacts we find could overstate worker utility gains.

Alternatively, some BEM may be initiated by workers rather than (or in conjunction with) firms, so that our earnings growth estimates might understate utility gains from greater BEM access. For example, workers' location preferences may change due to spousal job opportunities or family care responsibilities ([McKinnish, 2008](#); [Compton and Pollak, 2014](#)), or they may request promotions or even lateral transfers to jobs or occupations at other establishments that they have learned they would enjoy, be productive at, or that would provide opportunities to develop skills or signal ability ([Jovanovic, 1979](#); [Waldman, 1984](#); [Papageorgiou, 2014](#); [Pastorino, 2015](#)).⁶

Finally, models of statistical discrimination ([Miller and Schmutte, 2021](#); [Altonji, 2005](#)) also suggest that talented workers from subpopulations who are generally assumed to have low levels of accumulated skill may benefit from seeking jobs within the same firm, since their true productivity has already been revealed. We do not find evidence for this mechanism, as groups thought to suffer from statistical discrimination do not exhibit greater earnings sensitivity to BEM access.

The paper is organized as follows. Section 2.1 describes the LEHD data, with a focus on which kinds of establishment mobility can and cannot be observed. Section 2.2 provides a descriptive analysis of U.S. workers' access to and use of BEM. Section 2.3 describes how we estimate the impact of greater spatial proximity to jobs at other establishments on worker earnings and SEIN mobility. Section 2.4 presents the main earnings growth and SEIN mobility results, assesses threats from omitted variable and sorting bias, demonstrates robustness to alternative measures of BEM access, and analyzes worker and firm heterogeneity in sensitivity to BEM access. Section 2.5 provides a rough estimate of the frequency of unobserved establishment transitions. Section 2.6 concludes.

⁶Both firm-specific human capital and search frictions might also increase the worker surplus from establishment transitions. After all, workers with substantial firm-specific human capital may struggle to find similar promotion opportunities at other firms, and firms may be able to more efficiently inform existing employees about its other job opportunities that require particular skills or experience ([Papageorgiou, 2018](#)).

2.1 Data

Our analysis relies on matched employer-employee data from a sample of 25 U.S. states representing around 60% of U.S. population within the 2014 snapshot of the Census Bureau’s Longitudinal Employer Household Dynamics database (LEHD).⁷ We focus on the years 2003-2014, for which we have a balanced panel of contributing states. The core of the LEHD consists of quarterly state-level job records reporting the earnings and identification number of each employee as well as the state-specific employer identification number (SEIN). The LEHD augments these job-level records with four additional sources of information: 1) employee demographic information from social security registers; 2) a firm identification number derived from federal tax records that links SEINs sharing the same ownership; 3) the industry, geographic location (census block), and quarterly employment and payroll of each of the SEIN’s establishments (called SEINUNITs) from an employer survey (ES202); and 4) a unit-to-worker file that imputes each worker’s establishment based on residential information from tax records and establishment employee counts.⁸

A few key aspects of the data are worth emphasizing. First, the combination of features 2), 3) and 4) above allows the construction of the full distribution of existing (filled) jobs across establishments within each worker’s firm, which we use to characterize workers’ potential future opportunities for between-establishment mobility within firms.⁹

Second, the algorithm used by the Census Bureau to impute workers’ current establishments within a SEIN generally assigns each worker to only one establishment throughout a SEIN employment spell to avoid creating spurious job transitions (Vilhuber et al., 2018). This choice essentially suppresses any information about worker transitions across establishments within SEINs. However, all worker transitions within our sample that are between establishments with the same firm ID but different SEINs are observed. In particular, we observe all across-state establishment transitions within our 25 state sample (but not outside of it), and we also observe transitions between

⁷States that approved data access for our sample cover all major U.S. regions and most U.S. coastline. The national LEHD covers 96% of U.S. employment, with exclusions for federal, farm, and self-employment, among others (Abowd et al., 2009).

⁸We use the terms “establishment” and “unit” synonymously throughout the paper.

⁹Due to the establishment assignment algorithm’s reliance on a worker’s initial residential location within a SEIN employment spell, most errors in assignment will occur when two candidate establishments are both near a worker’s residence. But then these two establishments will generally feature similar spatial distributions of other-establishment employment within the firm, so that the measures of access to alternative employment opportunities within the firm introduced below should be negligibly affected. Also, remote work was considerably less common during the period we consider, further mitigating the frequency of imputation errors. The conclusion discusses how the rise of remote work might affect the value of and measurement of BEM.

establishments in different SEINs within the same (in-sample) state.¹⁰ Firms in general and large firms in particular often create many SEINs within the same state, particularly when there is a natural way to group establishments into subsidiaries of the broader business, often for the purpose of limiting their liability. In Appendix Table F, we analyze the determinants of firms’ SEIN counts, conditional on establishment counts. We find that multiple SEINs are commonly used across all U.S. supersectors, and that a 10% increase in establishment counts predicts a 5% increase in SEIN count, suggesting that SEINs proliferate quickly as firms expand in size and scope. In Section 2.5, we generate an estimate of the frequency of within-SEIN transitions based on the geographic distribution of establishment locations and the distribution of distances among observed SEIN transitions. These results suggest that as much as 61% of between-establishment transitions within the same state are between SEINs, though this may be somewhat overstated if establishments in different SEINs differ more in job composition than establishments in the same SEIN.

Third, because a firm’s federal EIN can change over time, we use a longitudinally consistent firm ID designed by the Census Bureau that reflects mergers, spinoffs, and other reorganizations (Chow et al., 2021). Thus, we expect to miss very few worker establishment changes due to contemporaneous changes in firm ID by the parent firm. We also remove small shares of within-firm SEIN transitions in which (1) a worker’s new and old SEIN are in the same census block, since these are likely to reflect cases in which the worker’s work location did not change, or (2) the new and old SEINs are linked by the Census Bureau’s success-predecessor file, since these generally reflect cases in which the firm moved the physical location of the establishment for all workers rather than changing the transitioning worker’s tasks and co-workers.

Fourth, while the LEHD records all of a worker’s jobs with nonzero pay, we select a primary SEIN (and accompanying firm ID and SEINUNIT assignment) for each worker in each year, defined as the SEIN responsible for the largest share of total worker earnings. This procedure avoids excessive focus on secondary jobs that account for little worker pay, but may cause us to miss changes in SEIN within a firm that are either temporary or quickly superseded by a firm separation. To capture a worker’s annual salary rather than the share of the year he/she worked, we construct “annualized” earnings for each worker by prorating earnings from full quarters only. All earnings are adjusted for inflation using the CPI series and expressed in 2017 dollars.

¹⁰Note that initial establishments need not be imputed and between-establishment mobility among our sample states is perfectly observed for the 24.6% of workers and 38.7% of workers at multi-establishment firms that have only a single establishment in their SEIN.

2.2 Descriptive Analysis of SEIN Mobility

Figure 2.1 shows the pooled distribution of employment among all worker-years in our 2003-2014 sample across bins defined by the firm's number of establishments and number of distinct SEINs. We see that 59.3% of workers' primary firms operate multiple establishments among our sample of states. About 90.5% of these firms group their establishments into multiple SEINs, accounting for 53.7% of all worker-years. Moreover, 23.4% and 11.0% of all employment is concentrated at firms with at least 100 and 500 establishments, respectively, while 9.5% is concentrated at firms with at least 100 SEINs. Thus, a sizable minority of U.S. workers have many potential destination establishments within their firms.¹¹

Furthermore, Figure 2.2 shows that there is a consistent upward trend in BEM opportunities. Specifically, the overall multi-establishment and multi-SEIN shares of employment increased from 57.3% and 52.8% in 2003 to 62.1% and 57.6% in 2013, and the shares of workers at multi-establishment (multi-SEIN) firms with more than 100 establishments (SEINs) increased from 22.4% to 24.8% (8.6% to 10.8%). Given that the share of firms with multiple establishments barely changed over this time span, these shifts seems to be primarily driven by increased concentration of employment among already large firms.

The first row of Table 2.1 reports statistics for the subsample of worker-years in which the worker was employed within our sample states both in the chosen and subsequent year, so that movers' destination establishments can be observed. Imposing this condition slightly increases the multi-establishment and multi-SEIN shares to 63.5% and 56.8%, respectively. About 43% of workers at multi-SEIN firms work in a single-establishment SEIN (24.6% of the sample workforce), so that their subsequent between-establishment mobility is perfectly observed within our sample states.

The next five rows of column 2 display the share of the firm's employment outside the worker's own establishment that is located in establishments within 10 miles, 10-25 miles, 25-50 miles, 50-100 miles, 100-500 miles, and over 500 miles, respectively. These will be used as measures of BEM access in our causal analysis below. Because many multi-unit firms are national in scope, the average worker at such firms is more than 500 miles away from 46.7% of the jobs at their firm's other establishments and 100-500 miles away from another 22.6%. Nonetheless, on average about 12.7%

¹¹Because many of these firms presumably have additional establishments in the remaining 25 states outside of our sample, each of these shares should be treated as a lower bound estimate of the true share.

of jobs at other establishments are within 10 miles and 19.5% are within 25 miles. These shares vary widely among workers, however, reflecting the mix of local, regional, and national companies in the data. For example, the share of other-establishment employment within 10 miles has a standard deviation of 0.265, while the share over 500 miles has a standard deviation of 0.361. The distribution of shares of employment across distance bins is considerably more locally concentrated for the subset of multi-unit firms that only operate one SEIN, with about 24.1% (30.4%) of jobs at other establishments located with 10 miles (25 miles).

The yellow curve in Figure 2.3 displays the CDF of the distribution across workers at multi-establishment firms of the distance to the nearest other establishment within the firm. Over 40% work within 4 miles of another establishment and over 50% work within 10 miles, confirming that most of these workers could potentially switch establishments without making a residential move. The blue curve displays the analogous CDF for the distance to the nearest establishment in a different SEIN within the same firm among workers at multi-SEIN firms. About 25% and 35% of workers at multi-SEIN firms are within 4 and 10 miles of an establishment. This suggests that other establishments within the same SEIN are generally closer on average than those in other SEINs. However, the distribution of potential establishment transition distances that would be observable in our data is fairly similar to the true distribution among all establishments, and contains substantial support at short distances. We exploit these distributions when generating an estimate of the frequency of unobserved within-SEIN establishment transitions in Section 2.5.

The first row in the third panel of Table 2.1 shows that 1.4% of workers at multi-SEIN firms make transitions to one of their firms' establishments in other SEINs within our sample in the typical year. Since multi-SEIN firms account for nearly 90% of employment at multi-unit firms, this also implies a lower bound between-establishment mobility rate for workers at multi-unit firms of 1.2%. The rates of SEIN mobility are similar for workers with and without other establishments within their own SEIN (columns labeled "MUMS" and "SUMS"), suggesting that availability of within-SEIN establishment "substitutes" is not unduly suppressing between-SEIN mobility.

The next six rows of column 3 of the third panel provide the shares of observed SEIN transitions whose distance between origin and destination establishment falls into each of six distance bins. Frictions that deter long-distance transitions clearly exist: even though only 12.4% of jobs at other same-firm establishments are within 10 miles, 26.5% of SEIN transitions involve establishments less than 10 miles away. By contrast, only 20.6% of between-SEIN transitions involve establishments

over 500 miles away even though 47.3% percent of other-establishment employment at the firm is at least 500 miles away. We exploit this differential propensity to make short- and long-distance moves in Section 2.4 to estimate the earnings effects of better spatial access to BEM options.

The first row of the last panel of Table 2.1 reveals that 12.5% of all workers and 12.8% of workers at multi-SEIN firms who remain employed in our sample states switch firms in a typical year, so that firm-to-firm transitions are about 10 times as common as SEIN-to-SEIN transitions within firms. However, firm transitions feature a much more locally concentrated mix of destinations than SEIN transitions within a firm. Distances of over 500 miles and over 100 miles account for only 5.5% and 23.6% of firm transitions but account for 20.6% and 41.9% of SEIN transitions, respectively. This is despite the fact that a much larger share of other-firm jobs are over 500 miles away than other-SEIN jobs within the same firm. Thus, there must be some additional value or source of surplus to either workers or firms that causes a worker to be willing to make long-distance job transitions within a firm that they would not be willing to make for a job at a different firm.

If this surplus stems primarily from workers preferring to live or work in alternative locations, worker pay need not rise when their requests for transfers are granted. However, if the surplus stems primarily from lower firm recruiting costs or greater firm productivity from better allocation of talent or experience, one would expect workers to be paid a premium to facilitate the transfer.

Table 2.7 characterizes SEIN mobility rates for a variety of subpopulations defined by categories of various worker and firm characteristics. Specifically, for each subpopulation we display its share of all sample workers, the share of the subpopulation that is in a multi-SEIN firm, the (conditional) annual SEIN mobility rate among those at risk in the subpopulation, and the subpopulation's unconditional SEIN mobility rate.

Starting with firm employment size categories, we see that SEIN mobility rates are much higher at the largest firms. The annual share of workers who change SEINs within a firm are 1.7% at firms with over 5,000 workers compared with 0.1%, 0.3%, 0.5%, and 0.9% among those at firms with < 100, 101-500, 500-1,000, and 1,000-5,000 workers, respectively. 68% of all SEIN transitions are concentrated among the 27.5% of workers at firms with more than 5,000 workers. These vast differences are primarily driven by differences across firm size categories in whether workers are at risk of changing SEINs. Only 10.5% and 43.9% of workers are in multi-SEIN firms among those in firms with 1-100 workers or 101-500 workers, versus 84.1% and 94.6% among those at firms with between 1,000 and 5,000 workers and over 5,000 workers, respectively. However, rates of SEIN

mobility conditional on working at a multi-SEIN firm are also higher at large employers, despite greater shares of more distant positions (Table 2.7): among multi-SEIN workers, 1.8% of those at firms with over 5 thousand workers change SEINs each year relative to between 0.7% and 1.1% of those in smaller firm size categories. This partly reflects the fact that there are simply more alternative jobs within such firms at other establishments, but may also suggest that large firms have more developed establishment transfer procedures or firm-wide promotion ladders, consistent with [Gumpert et al. \(2021\)](#)'s finding that firms with many, geographically dispersed establishments create more layers of management.

SEIN mobility is also more common (1.4%) among workers at the highest paying (worker-weighted) quintile of firms relative to lower-paying quintiles (between 0.6% and 0.8%). Again, these differences are primarily driven by differences in the probability of working in a multi-SEIN firm, which increases from 38.6% for the lowest paying quintile to 78.3% for the highest paying quintile. Conditional SEIN mobility rates are meaningfully higher, however, for workers at the highest-paying quintile of firms (1.8%) than at other quintiles (1.2-1.5%). This is consistent with the idea that retaining and properly allocating talented workers might be particularly valuable for such firms. Wide variation in the share of workers at risk of making a SEIN transition also drives the large differences in SEIN mobility rates across industry supersectors, with the share of workers in multi-SEIN firms varying from 26% in construction and other-services to around 71% in manufacturing and finance and 85% in information. Finance and information also have high rates of SEIN mobility conditional on their multi-SEIN share, in keeping with their reputations as industries that prize individual productivity and reward it via strong corporate ladders. Information's high rate occurs despite having the largest mean share of other-establishment jobs over 500 miles away (64.4%), reflecting the national scope of many of its largest firms.

Moving to worker characteristics, we find monotonic increases with worker's initial earnings for both multi-SEIN shares (44.2% to 69.7%, reflecting assortative matching to larger and higher-paying firms) and conditional SEIN mobility rates (1.0% to 1.9%), despite monotonically increasing shares of other-establishment jobs over 500 miles away (43.1% to 52.3%). The higher conditional rates in particular suggest that the surplus from retaining worker-firm matches is most valuable among the most skilled workers, perhaps because of greater firm-specific human capital and/or larger search costs of finding appropriate matches for workers offering or firms seeking specialized skill sets. Putting the two together, unconditional SEIN mobility rates are over three times as high

for the highest earnings quintile (1.3%) relative to the lowest (0.4%), and the 20% of workers in the top earnings quintile account for 36% of all SEIN transitions. We also see that conditional and unconditional SEIN mobility are common at all ages, but peak for the 30-39 year old age group at 1.6% and 0.9% before declining to 1.1% and 0.6%, respectively, for workers over 55 years old. Note that this mid-career peak contrasts with the generally monotonically decreasing age profile of firm mobility rates (Bosler and Petrosky-Nadeau, 2016; Gittleman, 2019), again consistent with an important role for firm-specific human capital. We observe limited heterogeneity in SEIN mobility rates by gender, race/ethnicity, or firm tenure, though the panel is not long enough to evaluate mobility rates for workers with more than 10 years of firm tenure.

Taken together, our descriptive statistics suggest that mobility between establishments within firms is fairly common across all types of workers and firms. They also suggest that such mobility is sensitive to the distance between worker's own and other establishments, though less so than for transitions between firms. We now seek to leverage variation across workers in the spatial distribution of other establishments at their firm to better understand how superior access to BEM opportunities affects their earnings paths.

2.3 Regression Methodology

Our baseline specification relates the average percent change in earnings relative to base year t over the following p years for worker i at establishment $e(i, t)$, denoted $\% \Delta Earnings_{it}^p$, to the worker's year t access to opportunities to change establishments within their current firm $f(i, t)$ ¹²:

$$\% \Delta Earnings_{it}^p = \sum_{d \in bins} BEM\ Access_{et}^d \beta_d + X_{it} \delta + X_{et} \lambda + \gamma_{ft}^F + \gamma_{ct}^C + \gamma_{nst}^N + \varepsilon_{it} \quad (2.1)$$

where we have dropped the dependence of e , f , c , n , and s on (i, t) to simplify notation. We choose as our outcome the average percent change in earnings relative to a single base year rather than an average of year-to-year annual growth because low earnings in a single year makes annual growth extremely volatile, such that the same cumulative income can be associated with very different average year-to-year growth. Since most workers' annual earnings grows over time, the outcome mean grows with the length of the window p .

¹²For example, a worker who earns \$20,000 in the base year and \$25,000, \$30,000, and \$35,000 in each of the next three years would have an average percent change in earnings over the three-year window of $\% \Delta Earnings_{it}^3 = \frac{25,000+30,000+35,000}{3 \times 20,000} - 1 = .5$, or 50% growth.

Our regression sample for this earnings outcome consists of all worker-years in which the worker is initially employed and whose subsequent annual earnings we observe at least twice for a 3-year window, three times for a 5-year window, and five times for a 7-year window. The latter restrictions are intended to ensure sufficiently large samples and reasonably precise measurement of the individual's outcome while limiting the selection problem created by dropping those that experience years of nonemployment.

Our preferred set of measures of access to BEM opportunities, $BEM\ Access_{et}^d$, consists of the employment shares in other establishments of the same firm that fall into distance bin d for each of the following distance bins: 0-10, 10-25, 25-50, 50-100, 100-500, and 500+ miles. As discussed, the second panel of Table 2.1 provides means of these measures for various worker subsamples. Since a worker's origin location is based on an assigned establishment rather than his/her residence, our measure varies at the establishment-year level. Because the employment shares across distance bins, $BEM\ Access_{et}^d$, sum to one for each worker, we normalize to zero the coefficient for the share of other-establishment employment that is more than 500 miles away.

By relying on shares of workers in each distance bin, we focus on how mobility costs that may be non-linear in distance mediate opportunities for establishment mobility. However, this access measure imposes that the same distance share distribution will predict the same rate of mobility and the same earnings growth impacts regardless of the overall employment count of the firm. If every job opportunity at the firm within a given distance bin were equally likely to spawn an establishment transition, one should use the position count rather than the share of positions in each bin. However, firms with many large establishments may also have a wider array of occupations, perhaps because they are more vertically integrated. And larger firms also offer more within-firm competitors for available vacancies. Thus, the number of relevant and obtainable job opportunities need not grow linearly with overall firm size. We investigate alternative measures of access that incorporate the scale of employment in each bin in Section 2.4.

One reason for our focus on spatial distributions rather than scale is that we wish to isolate variation in exposure among workers from different establishments within the same firm-year, so as to remove any endogeneity bias stemming from more or less geographically concentrated firms tending to either share faster revenue growth with workers or hire workers with greater earnings growth potential. We do this by including a full set of firm-year fixed effects, represented by γ_{ft}^F . But this choice naturally eliminates differential earnings gains from BEM options that operate

purely through variation in the firm-wide scale of employment opportunities.

Note that we isolate for identification exclusively within-firm variation in access only to minimize scope for omitted variable bias; we expect the coefficients β capturing the importance of better BEM access to be relevant for analyzing differences in BEM opportunities between firms as well, and we exploit between-firm variation in predicted values when seeking to quantify the overall importance of superior geographic access to opportunities for worker earnings growth below. That said, our proximity-based access measures only permits us to place a lower bound on the importance of access to a multi-establishment internal labor market, since they do not allow us to capture the difference in value between having all other same-firm establishments be over 500 miles away and having no other same-firm establishments to which to move. This difference in value is likely to be substantial given that we estimate that the origin-destination distance is greater than 500 miles for at least 15% of establishment transitions within multi-SEIN firms.

X_{it} is a vector of individual controls consisting of categorical indicators for sex, race, ethnicity, age, highest level of education (including a flag for imputed education status), bins of tenure at firm f , and earnings decile in (initial) year t . These controls mitigate selection bias from non-random selection into centrally located establishments within firms of individuals likely to experience inferior or superior earnings growth regardless of their establishment's geographic centrality.

X_{et} is a vector of establishment-level controls associated with worker i 's establishment in year t . It consists of annual growth rates of employment, payroll and average pay, as well as indicators for bins of the levels of these variables. These establishment controls address selection bias from the possibility that more geographically central establishments may tend to be higher-performing and thus cause their workers to experience higher earnings growth for reasons unrelated to the quality of these workers or their BEM opportunities. This might occur if the firm tries to create new establishments in the same area as its most successful branch.

Finally, γ_{ct}^C and γ_{nst}^N denote county-by-year and 4-digit industry-by-state-by-year fixed effects that absorb the impact of labor market trends or shocks that are specific to particular geographic areas and/or industries that may both drive differential earnings growth and be correlated with the employment distance distributions of establishments.

Our goal is to isolate random variation in which workers sort to establishments that are near versus far from other establishments within the same firm. As discussed in the introduction, such random variation might be created by naturally occurring turnover that leads different establish-

ments within a firm to hire at different times, and thus match with particular workers among the qualified pool who happen to be searching at the same time. The inclusion of county-by-year and industry-by-state-by-year fixed effects exploits the fact that different firms have concentrations of employment in different regions and different counties within regions.

To see this, suppose that Wells Fargo (highly concentrated within San Francisco) and Citizen’s Bank (highly concentrated in Boston) each post vacancies in March and in April, but Wells Fargo’s March and April vacancies are in San Francisco and Boston, respectively, while Citizen’s Bank’s are in Boston and San Francisco. Suppose further that two pairs of similar job applicants from Boston and from San Francisco sort into the particular positions within their cities based on their slightly different job search timings. Then the share of Wells Fargo employment that is within 10 miles will be high for its Boston worker relative to its San Francisco worker, and the opposite will be true for the Citizen’s Bank pair, thus providing exogenous identifying variation in the impact of greater BEM access conditional on both firm-by-year and location-by-year fixed effects.

Note that we are explicitly trying to capture the causal effect of expanding potential opportunities to switch establishments rather than the causal effect of actually making such a transition. There are three reasons for this. First, we do not fully observe the correct (endogenous) treatment variable, an indicator for making an establishment switch, because we only observe changes in establishments if they also involve a SEIN change. This precludes a standard instrumental variable approach, since greater geographic proximity to potential job opportunities could also affect earnings via establishment switches within a SEIN.

Second, even if we observed all establishment mobility within firms, the IV exclusion restriction would be invalid if within-firm opportunities affected earnings growth through altered bargaining power with outside firms even in the absence of actual between-establishment transitions.

Finally, the “reduced form” effect of greater access to opportunities that we do estimate is arguably at least as practically relevant as the effect of transitions themselves. Many policy levers might affect which workers sort to initial jobs with greater BEM access, such as requiring or facilitating better dissemination of information about vacancies at firms with a national reach. And early-career workers may benefit from learning that a multi-establishment firm might provide a more streamlined promotion path or better insurance against adverse local demand shocks.

Even though we do not seek to recover an estimate of the causal effect of between-SEIN mobility on earnings, we do wish to demonstrate that the earnings effects we find could plausibly be generated

via better access to BEM opportunities. Thus, we also investigate the “first stage” impact of our measure of geographic access to BEM opportunities on SEIN mobility.

A few adjustments to the estimating equation are necessary when the outcome is an indicator for making a between-SEIN transition within a firm:

$$SEIN\ Transition_{it}^p = \sum_{d \in bins} BEM\ Access_{SEINt}^{d,X-SN} \theta_d + \sum_{d \in bins} BEM\ Access_{SEINt}^{d,W/in-SN} \zeta_d \quad (2.2) \\ + X_{it}\mu + X_{et}\nu + \pi_{ft}^F + \pi_{ct}^C + \pi_{nst}^N + \omega_{it}$$

First, our regression sample only includes workers at multi-SEIN firms, since only these workers are at risk for making a between-SEIN transition. Second, to properly capture options for SEIN transitions, we only include between-SEIN employment when constructing shares of employment at various distance bins in our SEIN-level access measures, $BEM\ Access_{SEINt}^{d,X-SN}$. Third, we replace indicators for bins of total employment at other establishments within the firm (an element of X_{et}) with bins of employment at other SEINs. Fourth, we add an additional vector of controls for the shares of within-SEIN positions at other establishments that are in each of our distance bins, which we denote $BEM\ Access_{SEINt}^{d,W/in-SN}$. These additional controls address the possibility that a high share of jobs within one’s SEIN that are nearby indicates a more appealing set of outside options that reduce the impact of between-SEIN opportunities on SEIN mobility.

We cluster standard errors at the worker and firm levels to capture likely dependence across observations due to persistent shocks to workers and firms.

2.4 Main Results

2.4.1 Earnings Effects

The first three columns of Table 2.2 display the results of our baseline specification for earnings windows of 3, 5 and 7 years. We find very strong evidence that greater geographic concentration of within-firm employment increases workers’ future earnings. For all three windows, expected earnings gains increase monotonically as employment at other establishments within the worker’s firm shifts to closer and closer distance bins relative to the worker’s current establishment. The average annual effects increase in magnitude with the length of the window considered. This is consistent with the arrival of better earnings opportunities from within-firm job transitions accumulating over time. Focusing on the 5-year window, we find that a worker with 100% of

out-of-establishment employment within 10 miles can expect to earn an average of 2.7% more per year for the next 5 years than a comparable worker at an otherwise comparable establishment that is more than 500 miles away from all other establishments at the firm. Relative to this same hypothetical worker in the most remote establishment, a worker with 100% of other-establishment employment 10-25, 25-50, 50-100, and 100-500 miles away can expect to enjoy 1.7%, 1.5%, 1.0%, and 0.6% higher per year earnings.

Of course, very few workers have 100% of other-establishment employment in one particular distance bin, so we use three other approaches to gauge the economic importance of these findings. First, we evaluate the earnings impact of a one standard deviation increase in the share of employment at a given distance bin (at the expense of the 500+ category). For the 5 year window, a one SD shift for 0-10 miles increases average per-year earnings by 0.7%, with corresponding values of 0.5%, 0.2%, 0.2%, and 0.2% for the 10-25, 25-50, 50-100, and 100-500 mile bins.

Second, we evaluate the predicted contribution of BEM access to earnings growth for a worker with the sample mean employment share for each distance bin compared to a worker with all BEM opportunities over 500 miles away. These values are 0.4%, 0.7%, and 0.9% for 3-year, 5-year, and 7-year windows, respectively, which would represent 17%, 19%, and 21% of the median earnings growth in the sample for these windows.

Such comparisons with workers facing exclusively long-distance options represent the tightest lower bounds one can recover with a distance-based identification approach for the effects of typical BEM access at multi-establishment firms relative to workers at single-establishment firms who have no option for switching establishments within the same firm.

However, we also wish to characterize the importance of heterogeneity in proximity to other establishments among workers at multi-establishment firms. Thus, our third approach examines the person-level distribution of predicted BEM access contributions to earnings among such workers. Column 1 of Table 2.3 reports selected vingtile cutoffs of this distribution for the 5-year window. While BEM access generates less than 0.1% additional growth for about 20% of workers at multi-establishment firms, 45% of workers gain more than 0.5% in earnings, 25% of workers gain more than 1%, and there is a tail of 10% of workers who gain more than 2%.

These predicted values combine the within-firm and between-firm variation in distance bin shares, which assumes that the coefficients identified from within-firm variation are externally valid for variation across firms. If we instead remove the firm-specific mean from each earnings prediction,

we can consider the contribution of greater proximity to other jobs at the firm relative to other workers at the same firm. This distribution is far more concentrated, with a 90-to-10 percentile difference among employees from the same firm only accounting for a 0.4% per-year difference in earnings over 5 years. Thus, the bulk of the variation in value of BEM access comes from comparisons between firms.

2.4.2 SEIN Mobility Effects

Columns 4-7 of Table 2.2 report the results of our “first stage” regression specification (2.2) that relates employment shares by distance bin among jobs in other SEINs to indicators for making at least one SEIN transition within 1, 3, 5, or 7 years, respectively, for the sample of workers at multi-SEIN firms. As with the earnings outcome, we find very strong evidence of sensitivity of SEIN mobility to the distance distribution of employment at other SEINs. For each time window, expected SEIN mobility rates also increase monotonically as other-SEIN employment within the worker’s firm shifts to closer and closer distance bins. This again is suggestive evidence in favor of potential opportunities for establishment mobility serving as the causal mechanism producing the reduced-form earnings gains described above.

Specifically, a worker with 100% of other-SEIN employment within 10 miles has a 0.039 higher probability of making a SEIN transition within the year than a comparable worker at an otherwise comparable establishment that is more than 500 miles away from all of the firm’s establishments in other SEINs. The corresponding increases for the 10-25, 25-50, 50-100, and 100-500 mile categories are 0.036, 0.029, 0.019, and 0.010, respectively. These probability increases naturally become larger as the time window expands, since more workers have had sufficient time to find a suitable opportunity at another establishment. For example, a worker whose SEIN transition opportunities are all within 10 miles is a full 10 percentage points more likely to switch SEINs at least once within 5 years than one whose SEIN transition opportunities are all over 500 miles away.

As with our earnings results, we gauge the economic importance of these distance profiles by evaluating the predicted contribution of access to other-SEIN BEM opportunities to the probability of making a SEIN transition for a worker with the sample mean employment share for each distance bin compared to one of the $\sim 10\%$ workers with all of their out-of-SEIN opportunities over 500 miles away. These predicted contributions at the mean are 0.8% for annual transition rates and 1.6%, 1.9%, and 1.9% for rates of making at least one SEIN transition within 3, 5, and 7 years,

respectively. The 90th-to-10th percentile difference in predicted contributions of access to annual SEIN transition rates is 4.5 percentage points. Note that these values understate the degree to which differences in proximity to other establishments drive establishment mobility, since we do not include within-SEIN establishments when computing our distance bin shares (because we cannot observe those transitions), and such establishments tend to be closer to the worker’s own establishment. Thus, there is a sizable population of workers for whom a large share of employment at nearby establishments within the same firm is substantially increasing their job mobility.

2.4.3 Evaluating the Magnitude of Sorting and Selection Biases

The validity of our estimates of earnings sensitivity to more proximate BEM access requires that, conditional on controls, other determinants of worker earnings growth are orthogonal to the vector of other-establishment employment shares in each distance bin. In this subsection, we investigate several sources of potential bias.

As discussed earlier, we include a full set of firm-year fixed effects in all our estimating equations to eliminate any bias from unobservably greater earnings contributions at firms with more or less geographically concentrated employment distributions, either because they are attracting unobservably superior workers or because they are sharing some of the rents from faster productivity growth that is causing both geographic expansion and earnings growth. Because the lion’s share of variation in employment shares by distance bin is between firms or (to a lesser extent) between years within firm, the firm-year fixed effects remove considerable identifying variation.

Thus, column 1 of Table 2.7 uses firm rather than firm-year fixed effects, so that identifying variation in average earnings gains across years within firm is included. The *BEM Access* coefficients continue to monotonically increase as one considers closer distance bins, but are now generally about 25% smaller than before, suggesting that firms that are geographically expanding within the sample are delivering faster earnings growth in later sample years. Column 2 removes the firm fixed effects and replaces them with controls for observed firm characteristics (bins of total employment and interactions between average pay bins and firm’s international trade engagement status).¹³ The coefficients on all of the employment shares by distance bin become small and statistically insignificant, suggesting that other sources of greater earnings growth that are correlated with firms’ geographic scope would hide any effects of differential access to BEM opportunities in

¹³International trade engagement status has 6 categories that reflect whether the firms export, import, and their relationship with their trade partners.

the absence of firm-year and particularly firm fixed effects.

The potential sources of bias that remain relate to non-random sorting of workers to current establishments within their firms and differential establishment-specific and location-specific components of earnings growth that are correlated with the position of workers' establishments in their firms' establishment networks.

We already include a set of controls that effectively exhaust the information contained in the few worker and establishment characteristics available in the LEHD: categories of worker pay, age, SEIN tenure, race, gender, education (with a flag for imputed education status), establishment employment and average pay bins and past midpoint growth rates for payroll, employment, and average pay. However, we can explore the degree of selection on these observable characteristics as a rough guide to the possible correlation between earnings-relevant unobserved establishment and worker characteristics and distance bin employment shares (Altonji et al., 2005; Oster, 2019).

Column 3 of Table 2.7 displays coefficients from a simplified version of our baseline earnings specification that omits observed establishment and worker characteristics, but retains firm-year fixed effects, state-year-industry effects and county-year fixed effects. Coefficients on all distance bins are statistically significantly different from 0 (relative to the employment share at establishments more than 500 miles away), but the effects are much smaller and not perfectly monotonically increasing as one considers closer bins. Adding the establishment controls (column 4) barely changes the estimates, even though the past employment and average pay growth rate controls in particular are strong predictors of earnings growth. This insensitivity is consistent with the idea that unobserved establishment level factors are not major drivers of endogeneity bias. In column 5, we further add indicators for individual initial earnings deciles. Since greater baseline earnings strongly negatively predicts earnings growth (there is less scope for large growth rates from a higher base), selection of higher earnings workers into more centrally located establishments has the greatest potential to dampen the distance profile of coefficients. Sure enough, controlling for initial earnings decile restores monotonicity in coefficients with the proximity of the distance bin. Finally, comparing column 5 to our baseline specification from Table 2.2 isolates the impact of controlling for our other demographic characteristics. All *BEM Access* coefficient magnitudes increase by about 50%, creating a much steeper profile in distance.

On one hand, these results suggest that selection into centrally located establishments is related to worker characteristics that predict future earnings gains, so that distance shares of employment

at other establishments may not be fully exogenous, even conditional on firm-year and county-year fixed effects and the other controls. On the other hand, suppose the signs of the correlations are the same between shares in closer distance bins and regression indices of observed and unobserved worker characteristics, respectively, as one might expect if firms make establishment allocation decisions based on worker evaluations that reflect a mix of characteristics from both sets. Then the true profile of coefficients would feature even greater sensitivity of earnings to closer proximity of BEM opportunities than we have estimated. This suggests that our estimates may even understate true contribution to earnings differences of differential BEM access.

As an additional assessment of the scope for further selection bias from worker sorting conditional on our controls, we run a placebo test for whether the current set of distance shares of other-establishment employment predicts the average percent change in earnings over the previous 5 years (relative to a baseline from 6 years earlier) for newly hired workers. The idea beyond the test is that current firm-specific BEM options should not predict earnings growth prior to the worker's arrival at the firm unless workers with a persistent unobserved ability to be promoted faster are systematically being assigned to more or less central establishments within their new firm. To implement this placebo test, we include the full sample of workers with sufficiently long prior earnings histories in order to estimate reasonable firm-year fixed effect values, but we interact the coefficients on distance bin shares with an indicator for whether the worker is a new hire to isolate the relevant subpopulation for the test. The results of this exercise are displayed in column 6 of Table 2.7. The coefficients are generally small, inconsistent in sign, and statistically insignificant at the 5% level except for the 0-10 distance bin. This coefficient is negative, which suggests that, if anything, the strength of our distance profile is understated, since past earnings growth is a positive predictor of future growth conditional on our other controls. Thus, we do not find evidence of selection of workers with persistent ability to garner larger raises into establishments with more proximate BEM opportunities. Note that the absence of a pattern here is not driven by focusing on new firm-switchers (i.e. zero-tenure workers). Running our baseline specification with our original earnings outcome on the same sample with the same interaction with a firm-switcher indicator (column 7) produces nearly the same pattern as our original results.

Finally, we examine whether our estimates suffer from bias due to omitted location-specific trends or shocks to earnings that are common to all workers and establishments in the area. For example, a firm's remote establishments may be more likely to be in rural areas or isolated cities

that have different average earnings growth trajectories. Our baseline specification already includes county-by-year fixed effects, so any remaining concerns stem from systematic relationships between within-county establishment location, distance bin shares, and earnings growth.

We address this possibility by constructing a second placebo in which we replace the worker’s own distribution of employment shares by distance bin with the distribution of another, randomly chosen worker at a different multi-establishment firm within the same census tract. Any correlation between a different firm’s distance distribution and the worker’s own earnings growth would be driven by a common geographic component of both distance shares and earnings growth. Column 8 of Table 2.7 shows that all of the *BEM Access* coefficients are tiny in magnitude, providing reassurance that common location shocks are not a meaningful source of bias.¹⁴

2.4.3.1 Assessing Robustness to Alternative Exposure Measures

The distance bin employment shares that we use as measures of access to BEM opportunities impose that the creation of a large nearby establishment at a large firm is equivalent to the creation of a small nearby establishment at a small firm. However, one might imagine that a worker might benefit more from the creation of a greater number of local jobs for the worker to apply to even if it represents the same shift in the local share of firm-wide employment.

Thus, in column 1 of Table 2.7 we report results from a specification featuring logs of within-firm job counts at other establishments within each distance bin rather than employment shares.¹⁵ While there is a bit of evidence that a greater number of local jobs increases expected growth, the distance profile is much weaker and less consistent in pattern than for the baseline specification. Column 2 presents results from a “horse-race” specification in which both log counts and firm-wide employment shares are included for each distance bin. The log counts have almost no predictive power conditional on the shares, while the shares still show a strong pattern of greater earnings growth for higher shares of geographically proximate jobs. Columns 3 and 4 consider the same two specifications with the SEIN transition indicator as the outcome. Here we do see some evidence that the distribution of log job counts predicts SEIN mobility, but again the relationship gets

¹⁴Note that the standard errors on these coefficients are an order of magnitude smaller, so that the coefficients are often statistically significantly different from zero despite their economic unimportance. This is because there is far more residual variation in distance bins with which to identify these coefficients due to the weak correlation between the firm-year fixed effect of the worker’s actual firm and the geographic employment distribution within their tract neighbor’s firm.

¹⁵Using levels of job counts rather than logs causes the vast majority of variation to come from a few extremely large firms. Even when these firms are removed, the leverage of the largest remaining firms in the regression is substantial.

weaker once we control for shares, which retain nearly the same coefficient pattern as our baseline SEIN mobility specification. One possible explanation for the weak predictive power of the distance distribution of job counts is that as firms grow and establishments get bigger, they become more occupationally differentiated, so that a smaller share of jobs at each establishment is relevant for any given worker.

Thus, in an effort to better capture access to relevant jobs at other firms, in column 5 we consider a specification in which we construct the shares of other-establishment employment in each distance bin only among jobs that pay at least as much as the worker's current job (i.e. the same earnings decile or higher). The coefficients on each distance bin are quite similar to our baseline coefficients. The main reason for the similarity is that the share of higher-paying jobs in each distance bin is very highly correlated with the share of all jobs in each distance bin, since different establishments often have very similar earnings distributions to each other. This collinearity undermines our ability to assess which job opportunities are the relevant ones.

We also consider a specification that uses the share of establishments rather than the share of employment in each distance bin. This specification shows remarkably similar patterns of coefficients by distance bin to the employment share specification for both the earnings and SEIN mobility outcomes (columns 6 and 7). Again, the fact that different establishments of the same firm tend to have similar sizes prevents us from distinguishing between these two access measures.

2.4.4 Heterogeneous Effects

Rather than treating job counts and job shares at different distance bins as competing access measures, another approach is to examine whether the sensitivity of earnings gains and SEIN mobility to the shares of other-establishment workers at different distance bins varies with the overall size of the firm. To this end, the blue bars in the top panel of Figure 2.4 display coefficients from a specification that interacts the distance bin shares with a vector of indicators for five firm size categories: 0-100, 101-500, 501-1,000, 1,001-5,000, and over 5,000 workers. The two smallest categories do not exhibit a consistent pattern of statistically significant, monotonically increasing coefficients. This partly reflects the fact that the smallest firms naturally do not have many establishments distributed widely across space, which leads to larger standard errors. However, the pattern of increasing coefficients with closer distance bins emerges for 501-1,000 employee firms and becomes stronger and stronger as one considers 1,001-5,000 employee firms and firms with over

5,000 employees. This is consistent with the idea that a greater and more diverse set of options increases a worker's probability of finding a sufficiently good job match at another establishment. [Hazell et al. \(2022\)](#) show that large firms tend to exhibit very similar pay distributions across establishments, suggesting that the greater earnings growth from workers at more centrally located establishments is likely driven primarily by greater ability to find promotions to higher management tiers or avoid job loss from establishment shocks rather than greater opportunity to move to higher paying establishments.

Interestingly, despite the steeper distance profile for the largest firms, the predicted earnings growth gain at the mean firm-size specific employment distribution across distance bins for a 5000+ employee firm relative to all BEM opportunities being 500+ miles away is 0.7%, while the same predicted gain for a typical worker at a 501-100 employee firm is 0.8%. This is because the largest firms tend to be national in scope, and thus have substantially larger mean shares of positions over 500 miles away (Table 2.7), so that the large coefficients associated with nearby distance bins are given little weight when generating mean predicted values. As discussed earlier, this finding reflects the fact that the need to normalize to zero the coefficient on the 500+ mile employment share precludes the ability to value access to very distant BEM opportunities, which are particularly plentiful and frequently exploited at the largest firms.

The same basic pattern of increasing distance sensitivity with greater firm size emerges when we use a SEIN transition indicator as the outcome variable in Figure 2.4 (yellow bars), albeit with a more consistent profile among smaller firms and a particularly pronounced profile among the largest firms. This may indicate that larger firms are more likely to have well-established procedures for advertising vacancies internally and facilitating establishment transfers.

More generally, the various panels of Figure 2.4 and the various columns of Tables 2.7-2.7 explore how the sensitivity of earnings gains and SEIN mobility to more proximate BEM access varies across categories of several other firm and worker characteristics.

The second panel shows that the steepness of the distance profile increases as one moves from the lowest to the second-highest paying quintile of firms, consistent with the idea that higher productivity firms may place greater value on optimal assignment of workers and limiting vacancy duration in high-value positions. There is a slight reversal for the highest paying firms, perhaps because firms employing almost exclusively high-paid workers tend to be smaller. SEIN mobility rates are sensitive to distance bins' employment shares across all average pay categories.

Industry-specific distance profiles (bottom panels of Tables 2.7 and 2.7) are a bit noisy, particularly for supersectors with small shares of at-risk multi-establishment workers. However, the manufacturing, trade/transportation/utilities, information, and finance & real estate sectors all exhibit clear profiles of increasing coefficients with closer distance bins, both for earnings and for SEIN mobility. The predicted earnings contributions at the mean distance bin shares for these industries (relative to full employment concentration at 500+ miles) are 0.7%, 0.5%, 0.8%, and 1.1% versus only 0.3% for leisure and hospitality. Despite having a fairly shallow profile of rising coefficients with closer distance bins, the predicted earnings contribution at its mean shares is among the highest for the education & health supersector (0.8%). This is due to its extraordinarily high share of other-establishment employment within 10 miles among its multi-establishment employers (34.6%), perhaps reflecting school districts operating several schools or medical practices operating several clinics within the same local area.

Moving to worker characteristics (Tables 2.7 and 2.7), we find that sensitivity of earnings changes to the distance distribution of BEM opportunities is concentrated among the three highest quintiles of worker baseline earnings. These quintiles also exhibit strong relationships between SEIN mobility and the distance distribution of BEM opportunities. The predicted mean 5-year earnings growth contribution (relative to having only distant BEM opportunities) for the top two quintiles is 1.0% versus only 0.1% for the second lowest quintile. This reinforces the idea that firms particularly prize the ability to reallocate their most skilled workers to the highest value location. The presence of a strong distance profile for SEIN transitions but not for earnings growth for initially low-paid workers suggests that these workers may be more likely than their firms to value and initiate establishment transitions, so that no increase in pay is necessary to induce the transition.

Among age groups, the distance profile of earnings coefficients is strongest for 30-39 year old workers, with distance share coefficients generally shrinking by 10% or so for workers under 30, 25% for workers between 40 and 54, and by 50% or more for workers over 55. The age pattern of coefficients for SEIN mobility is quite similar. Smaller earnings effects for older workers are consistent with their lower SEIN mobility rates, so that potential opportunities are less likely to translate into realized transitions or earnings gains. Indeed, workers under 40 reap an expected 0.9% higher per-year earnings from the average distance distribution of other-establishment employment relative to exclusively long-distance jobs, compared to just 0.2% for workers over 55. However, since older workers are less likely to generate earnings growth through firm switching, BEM access

constitutes a larger share of median (or average) earnings growth at later ages.

The earnings and SEIN mobility distance profiles are fairly similar for men versus women. However, a closer look suggests somewhat greater sensitivity among women for both outcomes to BEM opportunities at the closest distance bins, 0-10 miles, 10-25 miles, and 25-50 miles. This is consistent with existing work ([Abraham et al., 2019](#)) showing that couples less frequently make long-distance moves to pursue opportunities for the wife than the husband, so that opportunities within current commuting range are particularly valuable for women. Because women also tend to be closer to BEM opportunities at their firms, the predicted earnings growth contribution for them at their average distance bin shares is meaningfully higher (0.9%) than for men (0.6%).

We see relatively similar distance profiles of SEIN mobility coefficients across race/ethnicity categories, but the earnings gains from greater shares of nearby within-firm jobs accrue primarily to non-Hispanic white workers and Asian workers, with a less pronounced profile for black workers and no discernible pattern at all for Hispanic white workers. Thus, we do not find evidence that historically underprivileged workers disproportionately rely on within-firm promotion opportunities due to statistical discrimination in the broader labor market. Instead, smaller gains from nearby jobs may partly reflect the fact that black and Hispanic white workers are underrepresented in the baseline earnings and industry categories where within-firm promotion ladders are most prominent and lucrative.

Finally, we see limited heterogeneity by categories of tenure at the firm, with slightly larger earnings and SEIN mobility payoffs to greater shares of nearby jobs for workers with 3-5 years of tenure relative to those with less or more tenure, consistent with the idea that one needs some degree firm-specific human capital and a sufficient remaining length of career to generate sufficient value from switching establishments.

More broadly, a glance from afar at Figure 2.4 reveals that larger shares of jobs at closer establishments within the firm predict both larger earnings increases and greater probabilities of switching SEINs for the vast majority of worker and firm subpopulations we consider. This demonstrates that responses to greater access to BEM opportunities are widespread throughout the economy and that our baseline results are not driven by unrealistically steep distance profiles for one small group. Furthermore, although not perfectly aligned, subpopulations that exhibit greater earnings sensitivity to the proximity of BEM opportunities also tend to show greater sensitivity for SEIN mobility. This provides further evidence, albeit suggestive, that the mechanism generating the

earnings gains is in fact establishment transitions rather than other earnings-relevant unobserved worker, establishment, or location attributes correlated with distance bin shares of employment at other establishments. It also suggests that BEM is generating considerable value for firms, since they seem to be willing to pay more to facilitate these transfers.

2.5 Estimating National Between-Establishment Mobility Rates

In this section, we summarize how we construct a conservative estimate of the overall share of U.S. workers who make between-establishment moves within the same firm each year. A complete description of our procedure is provided in Appendix E.

Our goal is to estimate the frequency of two kinds of unobserved job transitions: 1) transitions between establishments within the same SEIN, and 2) SEIN transitions from states within our sample to states outside our sample. Table 2.7 presents a decomposition of the contributions to our final establishment mobility estimate of each of the steps taken to generate these predictions.

Starting with 1), we exploit the fact that we observe the universe of establishment locations and sizes in our sample states, regardless of SEIN, and we have estimates capturing how changes in the scale and geographic distribution of within-firm employment drive within-firm job mobility. Because we find marked heterogeneity in SEIN mobility rates by firm size category, we use as our starting point predicted values from the version of our SEIN mobility regression reported in Table 2.7 that features separate distance bin profiles for each out-of-SEIN employment bin.

These naive predicted values contain four sources of mismeasurement when used to capture predicted rates of all between-establishment mobility (not just between-SEIN mobility). First, our access measures for the SEIN mobility outcome consist of the shares of the firm’s employment in other SEINs besides the worker’s own that fell into each distance bin. Since we now wish to measure all BEM opportunities, not just between-SEIN opportunities, we include employment at other within-SEIN establishments when constructing these shares. This requires assuming that the parameters relating SEIN mobility rates to out-of-SEIN employment shares by distance bin also correctly capture the corresponding relationship between establishment mobility rates and firm-wide employment shares by distance bin. This is arguably a conservative assumption, since the distance profile may be steeper for within-SEIN opportunities if jobs are more similar to workers’ current jobs at establishments within the same SEIN than in other SEINs.

Second, to capture the scale of firmwide BEM opportunities rather than SEIN transition oppor-

tunities, we use total other-establishment employment rather than other-SEIN employment when constructing the indicators for the size category of employment that interact with the distance bin shares (with the same category cutoffs). These swaps assume that the heterogeneity in sensitivity of SEIN mobility to the distance distribution across different out-of-SEIN size classes captured in the original regression translates to the relationship between any establishment mobility and out-of-establishment size classes.

Taken together, these adjustments increase the predicted share of workers at multi-SEIN firms who remain in the sample that make within-firm establishment transitions from 1.36% to 1.64%.

Third, the component of the naive predicted values contributed by the other control variables has a mean that is scaled to fit observed SEIN rather than establishment mobility rates. To re-scale this component, we regress this component on the same controls except for the firm-year fixed effects, which we replace with indicators for categories of both within-SEIN and out-of-SEIN employment. These indicators' coefficients capture the (conditional) relationship between Efirm scale and SEIN mobility that was previously absorbed by the firm-year fixed effects.

As before, we replace the out-of-SEIN employment categories with out-of-establishment employment categories and impose that the coefficients capturing the relationship between SEIN mobility and out-of-SEIN employment bins apply also to the relationship between establishment mobility and out-of-establishment employment bins. We also zero out all of the within-SEIN employment indicators, since these captured the role of unobservable “outside options” for SEIN mobility that are now reflected in the out-of-establishment size categories. Adding the change in this auxiliary regression's predicted values created by these adjustments yields a predicted annual rate of establishment mobility for workers at multi-SEIN firms of 1.81%.

Fourth, we use the same procedure to generate predicted establishment mobility rates for workers at multi-unit, single SEIN firms that were previously excluded from the regression sample, since we observe all the variables necessary to form their predicted values: distance bin employment shares, out-of-establishment size bins, and other worker, establishment, and location controls. This produces an annual establishment transition rate for such workers of 1.58%.

For workers at multi-SEIN firms, we must add to the predicted values an estimate of the rate of between SEIN transitions to out-of-sample states. Here, we use the fact that the LEHD reports an indicator for whether a worker is employed in some U.S. state even if that state did not grant us data access. This allows us to estimate the share of all job transitions from our sample states

whose destinations are outside the sample: 9.6%. Next, we assume that the share of within-firm transitions is the same for between-state transitions to out-of-sample states as for other in-sample states: 26.8%.¹⁶ Multiply these two shares, we estimate that 2.6% of all job transitions involve within-firm transitions to an out-of-sample state. Multiplying this by the job transition rate (17.7%) and adding to our previous totals suggests that 2.24% of multi-SEIN workers switch establishments within their firms each year. Since the multi-SEIN and multi-unit-single-SEIN populations account for 56.8% and 6.6% of U.S. workers, respectively, this implies an annual within-firm transition rate of 1.4% among all U.S. workers in our sample states, and that 7.8% of all establishment transitions occur within the same firm. Since our sample states are scattered throughout the U.S., we assume that these rates would also hold among workers initially in the out-of-sample states, so that as many as 2.3 million workers switch establishments within their firm in each year.

Finally, because SEIN transition rates vary so strongly with firm size, we perform the same set of adjustments separately by firm size category. The adjustments are trivial for workers at the smallest firms, but are substantial for workers at the largest firms. We find that within-firm establishment transition rates are 2.9% among the 27.5% of workers at firms with over 5,000 employees, and are 1.5% among the 10.5% of workers at 1001-5000 employee firms. Establishment transitions within firms account for 18.2% and 7.7% of all employment location changes among these categories of workers, respectively, and 33.8% and 13.2% of employment location changes crossing state lines. Thus, this exercise reinforces the finding that internal labor markets within large firms are driving a large share of the establishment mobility observed in publicly reported statistics for nearly a third of the workforce, particularly among long distance transitions.

2.6 Conclusion

This paper analyzes an overlooked but important aspect of U.S. labor markets: changes in workers' primary establishments within firms. We provide novel measurements showing that at least 0.8% and likely around 1.4 % of U.S. workers switch establishment locations within the same firm each year, accounting for 7.8% percent of all worker changes in employment location. We show that within-firm establishment transitions are far more likely than between-firm transitions to exhibit a long distance between origin and destination establishments, suggesting that sufficient value is created by reallocating workers to overcome mobility frictions that would preclude analogous

¹⁶Note that since any within-firm transition across states requires a SEIN change, both the numerator and denominator of the latter share are fully observed

transitions for firm-switchers. Nonetheless, remaining geographic mobility frictions are substantial enough to exploit by using variation among same-firm workers in their establishments' distribution of distances to other within-firm positions to estimate the effect of greater access to potential establishment-switching opportunities on earnings growth. We find that a worker at the 90th percentile of our proximity- based measure of access can expect to earn about 2% more per-year over five years relative to a 10th percentile worker with the same base year pay.

The fact that firms are generally paying a premium to facilitate worker reallocations suggests that increased firm productivity or lower recruiting costs rather than worker preferences likely accounts for most of the underlying surplus created by such transitions. We show that establishment mobility is concentrated among early- to mid-career workers with higher initial pay and among large and higher-paying firms, and that these types of workers and firms also exhibit stronger earnings growth responses to greater access to potential establishment switching opportunities.

These findings are consistent with models suggesting that high skill workers and high productivity firms face greater returns to finding optimal matches (e.g. [Teulings and Gautier \(2004\)](#)). However, further research is necessary to determine whether the gains from establishment reallocation of such workers are driven by high payoffs to efficient allocation of firm-specific human capital or instead by high payoffs to avoiding recruiting costs for hard-to-fill positions. In particular, additional insight might be gleaned using data that reports workers' titles or tasks performed before and after establishment transitions to analyze whether workers' past experience is being better leveraged at new positions.

Finally, analysis of the interplay between establishment mobility and increased use of remote work is a particularly compelling extension of this paper's research. Remote work dramatically reduces costs of re-allocating workers when their most desired or highest productivity task changes, which may increase the value of working at a large firm that operates many teams with many projects in many markets. At the same time, such remote work makes recorded assignments to physical establishment locations less reliable (to the extent such physical locations exist at all). This may undermine researchers' ability to detect such mobility across tasks, teams, and markets in large-scale administrative data.

8 Tables and Figures

Table 2.1: SEIN and Firm Mobility Rates and Distance Distributions among Workers Clas-sified by Scope for Between Establishment Mobility

		Overall	Multi-Unit	Multi-SEIN	SUMS	MUMS
		Population				
Worker Share	Total	1	0.635	0.568	0.246	0.322
Share by Distance	0-10		12.7%	12.4%	8.2%	15.6%
	10-25		6.8%	6.6%	4.1%	8.5%
	25-50		5.2%	5.0%	3.3%	6.3%
	50-100		6.1%	6.0%	4.3%	7.3%
	100-500		22.6%	22.7%	22.9%	22.5%
	500+		46.7%	47.3%	57.2%	39.8%
		SEIN Mobility				
Rate	Total	0.008	0.012	0.014	0.013	0.014
Share by Distance	0-10			26.5%	27.3%	25.4%
	10-25			14.7%	13.3%	15.5%
	25-50			8.8%	7.0%	9.9%
	50-100			8.1%	6.3%	9.9%
	100-500			21.3%	21.9%	21.1%
	500+			20.6%	24.2%	18.3%
		Firm Mobility				
Rate	Total	0.125	0.127	0.128	0.137	0.121
Share by Distance	0-10	35.4%	32.3%	32.3%	36.0%	28.1%
	10-25	22.0%	22.0%	22.0%	21.6%	22.3%
	25-50	11.8%	11.8%	11.8%	10.1%	13.2%
	50-100	9.4%	10.2%	10.2%	7.9%	13.2%
	100-500	15.7%	18.1%	18.1%	18.0%	18.2%
	500+	5.5%	5.5%	5.5%	6.5%	5.0%

Source: LEHD 2014 snapshot.

Notes: “Worker Share”: Share of all worker-year observations in the baseline sample whose primary firm belongs to the subpopulation defined by the column-label. “SEIN Mobility Rate”: Share of worker-years in which the worker transitions to a different primary SEIN within the same firm by the following year. “Firm Mobility Rate”: Share of worker-years in which the worker transitions to a different primary firm by the following year. “Multi-Unit” and “Multi-SEIN”: Set of workers whose firms feature multiple establishments (units) and SEINs (State Employer Identification Numbers), respectively. “SUMS”: Set of workers in multi-SEIN firms who are in the sole establishment within their SEIN. “MUMS”: Set of workers in multi-SEIN firms with multiple establishments within their SEIN. “Share of Other-Establishment Employment by Distance Bin”: Average share of employment at other within-firm establishments at the same firm whose distance from the worker’s own establishment falls into the row’s distance bin within the column’s subpopulation. “Share of SEIN Transitions by Distance Bin”: Share of all within-firm SEIN transitions within the column’s subpopulation whose distance between the worker’s baseline and new establishment falls into the row’s distance bin. “Share of Firm Transitions by Distance Bin”: Share of all transitions between primary firms within the column’s subpopulation whose distance between the worker’s baseline and new establishment falls into the row’s distance bin.

Table 2.2: Heterogeneity in Scope for and Frequency of SEIN Mobility within Firms across Worker and Firm Subpopulations

	Firm Characteristics					Worker Characteristics				
	Firm Size					Earnings				
	1-100	101-500	501-1K	1K-5K	>5K	Q1	Q2	Q3	Q4	Q5
Full Sample Share	0.376	0.176	0.068	0.105	0.275	0.20	0.20	0.20	0.20	0.20
Prob(Multi-SEIN)	0.105	0.439	0.676	0.841	0.946	0.442	0.481	0.531	0.601	0.697
SEIN Mobility-Cond.	0.011	0.007	0.008	0.010	0.018	0.010	0.011	0.012	0.014	0.019
SEIN Mobility-All	0.001	0.003	0.005	0.009	0.017	0.004	0.005	0.006	0.008	0.013
	Firm Average Pay					Tenure				
	Q1	Q2	Q3	Q4	Q5	Hires	1-2 yrs	3-5 yrs	>5 yrs	
Full Sample Share	0.20	0.20	0.20	0.20	0.20	0.243	0.109	0.219	0.429	
Prob(Multi-SEIN)	0.386	0.464	0.539	0.644	0.783	0.570	0.569	0.584	0.562	
SEIN Mobility-Cond.	0.015	0.013	0.012	0.012	0.018	0.013	0.015	0.015	0.013	
SEIN Mobility-All	0.006	0.006	0.006	0.008	0.014	0.008	0.009	0.009	0.007	
	Industry					Age				Sex
	Min.	Const.	Manuf.	Trade & Trans.	Infor.	< 30	30-39	40-54	55 +	M F
Full Sample Share	0.008	0.046	0.087	0.211	0.026	0.261	0.230	0.343	0.166	0.474 0.526
Prob(Multi-SEIN)	0.573	0.260	0.709	0.648	0.846	0.569	0.588	0.575	0.504	0.563 0.577
SEIN Mobility-Cond.	0.019	0.020	0.009	0.015	0.021	0.015	0.016	0.013	0.011	0.014 0.015
SEIN Mobility-All	0.011	0.005	0.006	0.010	0.018	0.009	0.009	0.008	0.006	0.008 0.008
	Industry (Cont)					Race				
	Fin. & Real Estate	Prof. Bus. Serv.	Educ. & Health	Leis. & Hosp.	Other Serv.	White N-Hisp	Black Hisp	Black	Asian/ Pac. Is	Other
Full Sample Share	0.067	0.166	0.234	0.111	0.043	0.650	0.148	0.104	0.069	0.029
Prob(Multi-SEIN)	0.698	0.610	0.414	0.425	0.259	0.564	0.543	0.648	0.593	0.566
SEIN Mobility-Cond.	0.018	0.016	0.010	0.015	0.012	0.015	0.012	0.014	0.014	0.014
SEIN Mobility-All	0.013	0.010	0.004	0.007	0.003	0.008	0.006	0.009	0.009	0.008

Source: LEHD 2014 snapshot.

Notes: "Full Sample Share": Share of all worker-year observations from the baseline sample who falls into the category defined by the column label. "Prob(Multi-SEIN)": Worker-year-weighted share of firms in the subpopulation defined by the column label who operate multiple SEINs. "SEIN Mobility-Cond.": Annual SEIN mobility rate among workers at multi-SEIN firms within the firm category defined by the column label. "SEIN Mobility-Cond.": Annual SEIN mobility rate among workers at any firm within the firm category defined by the column label (including those in single-SEIN firms not at risk of changing SEINs). "Tenure": Years since the worker was hired by their current firm. "Q1"- "Q5" = Quintiles of the relevant worker-year-weighted distribution (Worker Earnings or Firm-Average Pay). Supersector labels: "Min."- Natural Resources and Mining; "Const."- Construction; "Manuf."- Manufacturing; "Trade & Trans"- Retail/Wholesale Trade, Transportation, and Utilities; "Infor."- Information; "Fin. & Real Estate"- Finance and Real Estate; "Prof. Bus. Serv."- Professional and Business Services; "Leis. & Hosp."- Leisure and Hospitality; "Other Serv."- Other Services. "N-Hisp"-Not Hispanic; "Hisp": Hispanic.

Table 2.3: Heterogeneity in the Distance Distribution of Employment at Other Establishments within the Firm across Worker and Firm Subpopulations

Distance Share	Firm Heterogeneity					Worker Heterogeneity				
	Firm Size					Earnings				
	1-100	101-500	501-1K	1K-5K	>5K	Q1	Q2	Q3	Q4	Q5
500+ miles	0.431	0.344	0.366	0.435	0.533	0.431	0.435	0.437	0.462	0.523
100-500 miles	0.241	0.218	0.228	0.224	0.228	0.231	0.230	0.235	0.236	0.208
50-100 miles	0.069	0.081	0.075	0.060	0.053	0.070	0.066	0.064	0.062	0.052
25-50 miles	0.062	0.076	0.069	0.056	0.039	0.065	0.059	0.054	0.050	0.043
10-25 miles	0.082	0.101	0.097	0.074	0.050	0.081	0.074	0.070	0.064	0.061
0-10 miles	0.115	0.180	0.166	0.151	0.097	0.123	0.136	0.138	0.125	0.113
	Firm Average Pay					Tenure				
	Q1	Q2	Q3	Q4	Q5	0	1-2 yrs	3-5 yrs	>5 yrs	
500+ miles	0.440	0.453	0.394	0.430	0.579	0.496	0.488	0.465	0.432	
	0.237	0.234	0.240	0.245	0.190	0.228	0.224	0.229	0.226	
100-500 miles	0.071	0.065	0.071	0.060	0.046	0.057	0.058	0.060	0.066	
50-100 miles	0.065	0.059	0.060	0.048	0.037	0.048	0.049	0.050	0.057	
25-50 miles	0.080	0.071	0.073	0.071	0.053	0.064	0.066	0.067	0.073	
10-25 miles	0.107	0.117	0.162	0.146	0.096	0.107	0.116	0.128	0.146	
0-10 miles	Industry					Age				Sex
	Min.	Const.	Manuf.	Trade & Trans.	Infor.	< 30	30-39	40-54	55 +	F M
500+ miles	0.344	0.388	0.566	0.546	0.644	0.486	0.483	0.453	0.421	0.428 0.500
100-500 miles	0.373	0.344	0.236	0.238	0.191	0.224	0.223	0.230	0.228	0.212 0.238
50-100 miles	0.084	0.087	0.049	0.059	0.037	0.059	0.058	0.063	0.066	0.063 0.059
25-50 miles	0.057	0.061	0.038	0.045	0.028	0.050	0.049	0.053	0.058	0.057 0.047
10-25 miles	0.071	0.059	0.042	0.052	0.038	0.066	0.064	0.069	0.078	0.079 0.058
0-10 miles	0.071	0.061	0.068	0.061	0.062	0.115	0.123	0.132	0.148	0.161 0.097
	Industry (Cont)					Race				
	Fin. & Real Estate	Prof. Bus. Serv.	Educ. & Health	Leis. & Hosp.	Other Serv.	White N-Hisp	White Hisp	Black	Asian/ Pac. Is	Other
500+ miles	0.516	0.589	0.159	0.404	0.452	0.458	0.499	0.446	0.524	0.486
100-500 miles	0.210	0.211	0.194	0.199	0.201	0.235	0.221	0.211	0.175	0.223
50-100 miles	0.052	0.049	0.081	0.064	0.056	0.065	0.051	0.054	0.046	0.058
25-50 miles	0.042	0.039	0.087	0.065	0.057	0.053	0.048	0.052	0.044	0.049
10-25 miles	0.064	0.051	0.133	0.086	0.089	0.066	0.066	0.082	0.070	0.064
0-10 miles	0.114	0.061	0.346	0.183	0.146	0.123	0.115	0.155	0.141	0.120

Source: LEHD 2014 snapshot.

Notes: Each entry in the table provides the mean share of employment at the worker's firm (excluding employment at the worker's own establishment) that is concentrated at establishments whose distance from the worker's establishment falls within the distance bin defined by the row label among all worker-year observations in the subpopulation defined by the category of the worker or firm characteristic in the column label. See Table 2.2 for full names of the abbreviated column labels for characteristic categories.

Table 2.4: Effects on Average Percent Change in Earnings and SEIN Transition Rates of Greater Distance-Based Access to Opportunities for Between-Establishment Mobility over Various Time Windows

Distance Share	Mean % Δ (Earnings)			$\mathbb{I}$ (SEIN Transition)			
	3 yrs	5 yrs	7 yrs	1 yr	3 yrs	5 yrs	7 yrs
500+ miles (s.d.= 0.381)	—	—	—	—	—	—	—
100-500 miles (s.d.= 0.270)	0.003 $\dagger$ (0.001)	0.006 $^{\circ}$ (0.002)	0.007 $^{\circ}$ (0.002)	0.010 $\dagger$ (0.001)	0.018 $\dagger$ (0.003)	0.021 $\dagger$ (0.003)	0.025 $\dagger$ (0.004)
50-100 miles (s.d.= 0.150)	0.005 $^{\circ}$ (0.002)	0.010 $\dagger$ (0.003)	0.009 $\dagger$ (0.004)	0.019 $\dagger$ (0.002)	0.038 $\dagger$ (0.004)	0.044 $\dagger$ (0.005)	0.050 $\dagger$ (0.006)
25-50 miles (s.d.= 0.142)	0.008 $\dagger$ (0.002)	0.015 $\dagger$ (0.003)	0.020 $\dagger$ (0.004)	0.029 $\dagger$ (0.002)	0.059 $\dagger$ (0.004)	0.071 $\dagger$ (0.006)	0.080 $\dagger$ (0.007)
10-25 miles (s.d.= 0.150)	0.011 $\dagger$ (0.002)	0.017 $\dagger$ (0.003)	0.026 $\dagger$ (0.004)	0.036 $\dagger$ (0.002)	0.077 $\dagger$ (0.005)	0.091 $\dagger$ (0.006)	0.100 $\dagger$ (0.007)
0-10 miles (s.d.= 0.265)	0.017 $\dagger$ (0.002)	0.027 $\dagger$ (0.003)	0.036 $\dagger$ (0.004)	0.039 $\dagger$ (0.002)	0.083 $\dagger$ (0.005)	0.100 $\dagger$ (0.006)	0.109 $\dagger$ (0.007)
Controls							
Demographics	X	X	X	X	X	X	X
Establish. Charact.	X	X	X	X	X	X	X
Firm-Year FE	X	X	X	X	X	X	X
Sector-State-Year FE	X	X	X	X	X	X	X
County-Year FE	X	X	X	X	X	X	X
Predicted Effects							
Pred. Eff. at $\bar{X}$	0.004	0.007	0.009	0.008	0.016	0.019	0.019
Pred. Eff. at $\bar{X}/\text{med}(Y)$	0.166	0.192	0.205				
Median Outcome	0.025	0.038	0.046	—	—	—	—
Mean Outcome	0.078	0.102	0.125	0.014	0.035	0.053	0.066
Obs.	43.1M	34.4M	26.6M	27.4M	24.8M	19.6M	15.0M
R-squared	0.3825	0.4108	0.4206	0.1148	0.1282	0.1303	0.1267

Source: LEHD 2014 snapshot.

Notes: The sample in a given column consists of all worker-years in which the worker is employed in a sample state in the base year and is observed with positive earnings at a firm in a sufficient share of the subsequent years within the outcome window given by the column label (next year for the 1 year outcome window, 2 of 3 years for the 3 year window, 3 of 5 years for the 5 year window, 5 of 7 years for the 7 year window. “Mean % Δ (Earnings)”: Mean percent change in the worker’s earnings across the years in the outcome window given by the column label relative to the baseline year. “ $\mathbb{I}$ (SEIN Transition)”: An indicator for whether the worker changed primary SEIN affiliation within the same firm between the observation year and the subsequent year. Control categories: “Demographics”—Indicators for categories of race (5), ethnicity (2), gender (2), firm tenure (4), age (4), and worker baseline earnings (9); “Establish. Charact.”: Indicators for establishment size (5) and average pay categories (5), midpoint growth rates over prior 3 years of establishment employment and average pay. “Firm-Year FE”: indicator variables for each firm $\times$ year combination. “Sector-State-Year FE”: Indicators for each combination of 4-digit NAICS code, U.S. State, and year. “County-Year FE”: Indicators for each combination of county and year. The share of workers in establishments over 500 miles is the reference category. Clustered two-way standard errors by firm and work in parenthesis.

$\dagger$, $\dagger$, and $^{\circ}$ denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.5: Percentiles of the Worker-Level Distributions of Pre-dicted Contributions to 5-Year Earnings Growth and Annual SEIN Transition Rates of Access to Between-Establishment Mobility Opportunities

Percentile	Mean % Δ (Earnings)		$\mathbb{I}$ (SEIN Transition)	
	Overall	Within-Firm	Overall	Within-Firm
0.10	0.000	-0.002	0.000	-0.007
0.20	0.001	-0.001	0.001	0.000
0.30	0.002	0.000	0.001	0.005
0.40	0.003	0.000	0.002	0.008
0.50	0.004	0.000	0.004	0.012
0.60	0.006	0.000	0.005	0.016
0.70	0.009	0.001	0.009	0.020
0.75	0.010	0.001	0.010	0.023
0.80	0.014	0.001	0.012	0.027
0.85	0.017	0.002	0.018	0.032
0.90	0.021	0.002	0.027	0.039
0.95	0.026	0.003	0.036	0.052

Source: LEHD 2014 snapshot.

Notes: Each entry in the column entitled “Mean % Δ (Earnings) - Overall” provides the percentile associated with the row label from the worker-level distribution of predicted contributions ($BEM\ Access_{it}\hat{\beta}$) to average 5-year earnings as a share of baseline-year earnings from the worker’s access to between-establishment mobility (BEM) opportunities (as measured by distance bin shares of other-establishment employment within the firm), relative to a worker whose establishment is more than 500 miles away from all others in the same firm (whose contribution has been normalized to 0). The column “Mean % Δ (Earnings) - Within-firm” reports percentiles from an analogous distribution of predicted contributions from workers’ BEM access relative to the mean BEM access contribution at the worker’s firm. “ $\mathbb{I}$ (SEIN Transition) - Overall” and “ $\mathbb{I}$ (SEIN Transition) - Within-firm” report the analogous percentiles of the distributions of predicted contributions of BEM access to annual SEIN transition rates ($BEM\ Access_{it}^{X-SN}\hat{\beta}$).

Table 2.6: Assessing Endogeneity Threats to the Validity of Causal Effect Estimates of Distance-Based Access to Opportunities for Between Establishment Mobility on the Average Percent Change in Worker's Earnings Across the Following 5 Years

Distance Share	Alternative FEs		Alternative Controls			Placebos		
	Firm	Firm	Min.	Min. +	Min.+ Inc.	Firm Switchers		Tract
	FE	Charact.		Estab	+ Estab	Placebo	Baseline	Placebo
500+ miles	—	—	—	—	—			
100-500 miles	0.004 [°] (0.002)	0.000 (0.001)	0.008‡ (0.002)	0.007‡ (0.002)	0.004 (0.002)	0.000 (0.003)	0.002 (0.003)	-0.001† (0.001)
50-100 miles	0.007† (0.002)	0.001 (0.002)	0.012‡ (0.003)	0.011‡ (0.003)	0.006 [°] (0.003)	0.001 (0.004)	0.000 (0.004)	-0.002‡ (0.001)
25-50 miles	0.013‡ (0.002)	-0.002 (0.002)	0.013‡ (0.003)	0.013‡ (0.003)	0.010† (0.003)	-0.008 (0.004)	0.007 (0.004)	0.000 (0.001)
10-25 miles	0.015‡ (0.002)	-0.003 (0.002)	0.007 [°] (0.003)	0.007 [°] (0.003)	0.010‡ (0.003)	-0.002 (0.004)	0.014‡ (0.004)	-0.002† (0.001)
0-10 miles	0.023‡ (0.002)	0.001 (0.002)	0.013‡ (0.003)	0.015‡ (0.003)	0.019‡ (0.003)	-0.011† (0.004)	0.025‡ (0.004)	0.000 (0.001)
Controls								
Demographics	X	X				X	X	X
Income	X	X			X	X	X	X
Establish. Charact.	X	X		X	X	X	X	X
Firm Charact.		X						
Firm FE	X							
Firm-Year FE			X	X	X	X	X	X
Sector-State-Year FE	X	X	X	X	X	X	X	X
County-Year FE	X	X	X	X	X	X	X	X
Obs.	34.4M	34.4M	34.4M	34.4M	34.4M	21.6M	34.4M	20.1M
R-squared	0.322	0.191	0.300	0.300	0.388	0.340	0.411	0.258

Source: LEHD 2014 snapshot.

Notes: Specification Labels: "Firm FE"- Replaces firm×year fixed effects with firm fixed effects; "Firm Charact."- Replaces firm×year fixed effects with indicators for firm size categories and for combinations of firm average pay category and firm trade status category (non-trader, arms-length importer only, arms-length exporter only, arms-length importer and exporter, related-party importer or exporter, related-party importer and exporter); "Min."- Minimal controls consisting of fixed effects as noted. "Min + Estab"- Minimal controls plus indicators for establishment size and average pay categories and midpoint growth rate over prior 3 years of establishment size and average pay. "Min + Inc. + Estab"- Minimal controls, establishment controls, and indicators for a worker's initial earnings decile. "Tract Placebo": a worker's actual within-firm employment shares by distance bin are replaced with those of another randomly chosen worker from a different multi-unit firm within the same census tract. "Firm Switchers Placebo": the outcome is the worker's average percent change in earnings over the previous 5 years relative to a baseline from 6 years ago, the worker's within-firm employment shares by distance bin are interacted with an indicator for whether the worker is a new hire at the firm, and the sample consists of workers who worked in both the current year and 6 years earlier and 3 of the 5 intervening years. "Firm Switchers Baseline": Same sample years and interactions with employment distance shares as the "Firm Switchers Placebo", but using the worker's forward-looking earnings as the outcome rather than their earnings growth at the previous firm. The share of workers in establishments over 500 miles away is the reference category. Clustered two-way standard errors by firm and work in parenthesis.

‡, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.7: Exploring Alternative Measures of Distance-Based Access to Opportunities for Between Establishment Mobility

Distance	Mean % Δ (Earnings)		$\mathbb{I}$ (SEIN Transition)		Mean % Δ (Earnings)		$\mathbb{I}$ (SEIN Transition)
	Log-Level	Both	Log-Level	Both	Worker Exposure	Establish. Exposure	Establish. Exposure
Log(Count)							
500+ miles	7.66e-5 (0.0002)	-0.0002 (0.0003)	0.0005‡ (0.0002)	0.0004° (0.0002)			
100-500 miles	0.0002 (0.0002)	0.0002 (0.0002)	0.0003† (0.0001)	0.0003 (0.0001)			
50-100 miles	0.0002 (0.0001)	5.15e-5 (0.0001)	0.0006‡ (0.0001)	0.0005‡ (0.0001)			
25-50 miles	0.0003† (0.0001)	0.0003 (0.0001)	0.0011‡ (0.0001)	0.0009‡ (0.0001)			
10-25 miles	0.0010‡ (0.0001)	0.0007‡ (0.0001)	0.0014‡ (0.0001)	0.00012‡ (0.0001)			
0-10 miles	-0.0006 (0.0004)	8.18e-5 (0.0003)	7.88e-5 (0.0004)	0.0008 (0.0008)			
Shares							
500+ miles		—		—	—	—	—
100-500 miles		0.006° (0.003)		0.005° (0.003)	0.006‡ (0.002)	0.003 (0.002)	0.011‡ (0.003)
50-100 miles		0.006 (0.003)		0.011‡ (0.003)	0.007† (0.002)	0.007° (0.003)	0.020‡ (0.003)
25-50 miles		0.012† (0.004)		0.015‡ (0.003)	0.013‡ (0.002)	0.015‡ (0.004)	0.030‡ (0.003)
10-25 miles		0.011† (0.004)		0.018‡ (0.003)	0.015‡ (0.002)	0.016‡ (0.003)	0.038‡ (0.004)
0-10 miles		0.017‡ (0.004)		0.019‡ (0.003)	0.020‡ (0.003)	0.028‡ (0.004)	0.038‡ (0.003)
Controls							
Baseline Controls	X	X	X	X	X	X	X
Baseline FEs	X	X	X	X	X	X	X
Obs.	34.4M	34.4M	27.4M	27.4M	34.4M	34.4M	27.4M
R-squared	0.411	0.411	0.115	0.115	0.411	0.411	0.114

Source: LEHD 2014 snapshot.

Notes: See Table 2.1 notes for outcome definitions. Column Specifications: “Log-Level”- Measures access to between-establishment mobility (BEM) opportunities via the logarithm of the count of employees at other establishments (in any of the firm’s SEIN for the earnings outcome, in other SEINs within the firm for the SEIN mobility outcome) within each of the distance bins defined by row labels (relative to the worker’s own establishment); “Both”- Includes both the share of workers and the log count of workers at other establishments within each distance bin as measures of access to BEM opportunities. “Worker Exposure”- Restricts the shares of other-establishment workers in each distance bin to be calculated only among workers in an earnings decile at least as high as the worker’s own. “Establish. Exposure”-Replace the share of other-establishment employment in each distance bin with the share of other establishments within each distance bin. “Baseline Controls” and “Baseline FEs”: See Table 1 notes. Clustered two-way standard errors by firm and work in parenthesis.

‡, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.8: Heterogeneity across Firm Subpopulations in the Effects of Distance-Based Access to Opportunities for Between Establishment Mobility on Workers' Earnings over the Following 5 Years

Mean %Δ(Earnings)										
Distance (mi.)	Firm Size					Firm Average Pay				
	1-100	101-500	501-1K	1K-5K	>5K	Q1	Q2	Q3	Q4	Q5
100-500	-0.004 (0.0060)	0.000 (0.0030)	0.007 (0.0036)	0.007† (0.0026)	0.007° (0.0033)	0.000 (0.0042)	0.001 (0.0036)	0.004 (0.0033)	0.010‡ (0.0029)	0.010° (0.0038)
50-100	-0.001 (0.0091)	-0.001 (0.0042)	0.010 (0.0052)	0.010° (0.0041)	0.012° (0.0049)	-0.001 (0.0063)	-0.003 (0.0057)	0.010° (0.0042)	0.020‡ (0.0045)	0.015° (0.0065)
25-50	0.016 (0.0097)	0.001 (0.0043)	0.014° (0.0054)	0.016‡ (0.0042)	0.018† (0.0057)	0.007 (0.0064)	0.012° (0.0052)	0.011° (0.0048)	0.025‡ (0.0055)	0.018° (0.0071)
10-25	0.012 (0.0094)	0.001 (0.0041)	0.016† (0.0051)	0.021‡ (0.0040)	0.019‡ (0.0051)	0.012 (0.0063)	0.022‡ (0.0050)	0.015‡ (0.0046)	0.023‡ (0.0046)	0.011 (0.0057)
0-10	0.022° (0.0093)	0.005 (0.0039)	0.022‡ (0.0048)	0.027‡ (0.0041)	0.035‡ (0.0056)	0.008 (0.0060)	0.027‡ (0.0061)	0.031‡ (0.0050)	0.034‡ (0.0044)	0.027‡ (0.0067)
Predicted Effects										
Pred. Eff. at $\bar{X}$	0.003	0.001	0.008	0.009	0.007	0.002	0.006	0.008	0.011	0.006
Mean	0.106	0.090	0.093	0.092	0.109	0.167	0.103	0.079	0.077	0.096
Median	0.029	0.034	0.037	0.038	0.047	0.058	0.033	0.027	0.033	0.048
Distance (mi.)	Industry									
	Min.	Const.	Manuf.	Trade & Trans.	Infor.	Fin. & Real Estate	Prof. Bus. Serv.	Educ. & Health	Leis. & Hosp.	Other Serv.
100-500	-0.025° (0.0122)	0.006 (0.0065)	0.006 (0.0043)	0.003 (0.0033)	0.016 (0.0089)	0.015° (0.0061)	0.009° (0.0037)	0.000 (0.0065)	-0.003 (0.0072)	0.033‡ (0.0090)
50-100	-0.023 (0.0251)	0.036‡ (0.0105)	0.011 (0.0070)	0.014° (0.0054)	0.014 (0.0117)	0.007 (0.0092)	0.004 (0.0059)	0.007 (0.0070)	-0.017 (0.0122)	0.045† (0.0155)
25-50	-0.016 (0.0189)	0.021 (0.0122)	0.026‡ (0.0062)	0.014° (0.0055)	0.018 (0.0242)	0.027† (0.0097)	0.011 (0.0063)	0.006 (0.0071)	0.006 (0.0105)	0.045† (0.0167)
10-25	-0.056° (0.0234)	-0.002 (0.0142)	0.032‡ (0.0065)	0.022‡ (0.0053)	0.022 (0.0126)	0.030‡ (0.0087)	0.010 (0.0065)	0.006 (0.0076)	0.007 (0.0089)	0.042° (0.0180)
0-10	-0.004 (0.0185)	0.009 (0.0108)	0.035‡ (0.0060)	0.030‡ (0.0055)	0.048‡ (0.0136)	0.035‡ (0.0106)	0.018† (0.0061)	0.019° (0.0078)	0.021 (0.0122)	0.035° (0.0156)
Predicted Effects										
Pred. Eff. at $\bar{X}$	-0.016	0.007	0.007	0.005	0.008	0.011	0.004	0.008	0.003	0.021
Mean	0.132	0.085	0.048	0.104	0.092	0.113	0.129	0.110	0.154	0.102
Median	0.067	0.018	0.017	0.033	0.037	0.052	0.057	0.044	0.048	0.032

Source: LEHD 2014 snapshot.

Notes: The coefficients reported in this table are interactions between shares of other-establishment employment within the firm that fall into the distance bin given by the row label and indicators for the firm subpopulation defined by the characteristic category in the column label. The outcome is the average percent change in a worker's earnings across the subsequent five years relative to the baseline year. Interactions featuring all the characteristic categories in a given panel are included in the same regression, but different panels featuring different characteristics represent different regressions. See the Table 2 notes for definitions of the categories defined by the column labels. Clustered two-way standard errors by firm and work in parenthesis.

‡, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.9: Heterogeneity across Firm Subpopulations in the Effects of Distance-Based Access to Opportunities for Between Establishment Mobility on Workers' Annual SEIN Transition Rates

Distance (mi.)	I(SEIN Transition)									
	Firm Size					Firm Average Pay				
	1-100	101-500	501-1K	1K-5K	>5K	Q1	Q2	Q3	Q4	Q5
100-500	0.007† (0.0015)	0.006† (0.0009)	0.006† (0.0011)	0.007† (0.0010)	0.013† (0.0026)	0.012† (0.0021)	0.017† (0.0056)	0.006† (0.0022)	0.005° (0.0021)	0.010† (0.0019)
50-100	0.009† (0.0026)	0.010† (0.0012)	0.009† (0.0014)	0.013† (0.0015)	0.027† (0.0035)	0.018† (0.0025)	0.022† (0.0068)	0.015† (0.0032)	0.014† (0.0033)	0.024† (0.0035)
25-50	0.020† (0.0035)	0.014† (0.0015)	0.015† (0.0020)	0.022† (0.0018)	0.038† (0.0040)	0.027† (0.0031)	0.031† (0.0072)	0.021† (0.0038)	0.023† (0.0043)	0.038† (0.0039)
10-25	0.025† (0.0038)	0.020† (0.0017)	0.019† (0.0022)	0.027† (0.0018)	0.047† (0.0045)	0.033† (0.0031)	0.036† (0.0066)	0.026† (0.0042)	0.029† (0.0039)	0.049† (0.0056)
0-10	0.031† (0.0040)	0.020† (0.0017)	0.021† (0.0020)	0.029† (0.0021)	0.050† (0.0040)	0.035† (0.0031)	0.034† (0.0057)	0.029† (0.0040)	0.033† (0.0039)	0.056† (0.0047)
Predicted Effects										
Pred. Eff. at $\bar{X}$	0.009	0.009	0.008	0.010	0.013	0.012	0.014	0.010	0.010	0.012
Mean	0.001	0.003	0.005	0.009	0.017	0.006	0.006	0.006	0.008	0.014

Distance (mi.)	Industry									
	Min.	Const.	Manuf.	Trade & Trans.	Infor.	Fin. & Real Estate	Prof. Bus. Serv.	Educ. & Health	Leis. & Hosp.	Other Serv.
100-500	0.015 (0.0084)	0.002 (0.0039)	0.006† (0.0018)	0.016† (0.0032)	0.005 (0.0032)	0.011† (0.0025)	0.010† (0.0022)	-0.001 (0.0059)	0.007 (0.0033)	0.008 (0.0042)
50-100	0.006 (0.0109)	-0.003 (0.0056)	0.017† (0.0028)	0.023† (0.0037)	0.018° (0.0077)	0.027† (0.0042)	0.023† (0.0042)	0.006 (0.0076)	0.012† (0.0036)	0.011° (0.0051)
25-50	0.015 (0.0103)	0.013 (0.0076)	0.025† (0.0035)	0.031† (0.0045)	0.056† (0.0124)	0.042† (0.0065)	0.029† (0.0036)	0.011 (0.0071)	0.024† (0.0047)	0.020° (0.0086)
10-25	0.035° (0.0140)	0.033† (0.0113)	0.042† (0.0066)	0.036† (0.0047)	0.080† (0.0223)	0.042† (0.0058)	0.038† (0.0044)	0.019† (0.0071)	0.025† (0.0038)	0.024+ (0.0074)
0-10	0.040° (0.0157)	0.015° (0.0075)	0.048† (0.0061)	0.042† (0.0044)	0.065† (0.0108)	0.046† (0.0055)	0.044† (0.0050)	0.022† (0.0065)	0.022† (0.0040)	0.017+ (0.0062)
Predicted Effects										
Pred. Eff. at $\bar{X}$	0.012	0.004	0.008	0.011	0.010	0.013	0.009	0.011	0.010	0.008
Mean	0.011	0.005	0.006	0.010	0.018	0.013	0.010	0.004	0.007	0.003

Source: LEHD 2014 snapshot.

Notes: The coefficients reported in this table are interactions between shares of other-establishment employment within the firm that fall into the distance bin given by the row label and indicators for the firm subpopulation defined by the characteristic category in the column label. The outcome is an indicator for whether the worker changed its primary SEIN within the same firm between the baseline and subsequent year. Interactions featuring all the characteristic categories in a given panel are included in the same regression, but different panels featuring different characteristics represent different regressions. See the Table 2.2 notes for definitions of the categories defined by the column labels. Clustered two-way standard errors by firm and work in parenthesis.

†, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.10: Heterogeneity across Worker Subpopulations in the Effects of Distance-Based Access to Opportunities for Between Establishment Mobility on the Average Percent Change in Workers' Earnings Across the Following 5 Years

Distance (mi.)	Mean %Δ(Earnings)									
	Earnings					Race				
	Q1	Q2	Q3	Q4	Q5	White N-Hisp	Hispanic	Black	Asian/ Pac. Is	Other
100-500	-0.026† (0.0087)	-0.004 (0.0038)	0.008† (0.0027)	0.009† (0.0028)	0.012‡ (0.0034)	0.007‡ (0.0020)	-0.002 (0.0038)	0.008 (0.0043)	0.003 (0.0069)	0.009 (0.0051)
50-100	-0.041‡ (0.0117)	-0.011° (0.0053)	0.016‡ (0.0035)	0.016‡ (0.0040)	0.021‡ (0.0054)	0.012‡ (0.0029)	-0.001 (0.0061)	0.012 (0.0063)	0.007 (0.0108)	0.009 (0.0098)
25-50	-0.037† (0.0118)	0.001 (0.0053)	0.017‡ (0.0038)	0.020‡ (0.0044)	0.028‡ (0.0069)	0.017‡ (0.0032)	-0.001 (0.0058)	0.023‡ (0.0070)	0.019 (0.0108)	0.018 (0.0111)
10-25	-0.031° (0.0122)	0.005 (0.0053)	0.021‡ (0.0036)	0.019‡ (0.0043)	0.026‡ (0.0052)	0.020‡ (0.0031)	0.004 (0.0050)	0.016° (0.0063)	0.018° (0.0092)	0.007 (0.0102)
0-10	-0.035† (0.0135)	0.015° (0.0060)	0.024‡ (0.0035)	0.039‡ (0.0047)	0.037‡ (0.0061)	0.033‡ (0.0033)	0.013° (0.0056)	0.011 (0.0064)	0.030‡ (0.0085)	0.027† (0.0094)
Predicted Effects										
Pred. Eff. at $\bar{X}$	-0.018	0.001	0.008	0.010	0.010	0.009	0.001	0.006	0.007	0.007
Mean	0.446	0.155	0.062	0.041	0.037	0.100	0.099	0.091	0.138	0.114
Median	0.268	0.069	0.025	0.017	0.019	0.037	0.037	0.034	0.055	0.044
Distance (mi.)	Age				Sex		Tenure			
	< 30	30-39	40-54	55 +	M	F	0	1-2 yrs	3-5 yrs	>5 yrs
100-500	0.010† (0.0034)	0.008† (0.0026)	0.005° (0.0023)	-0.007 (0.0038)	0.005° (0.0025)	0.007† (0.0022)	0.005 (0.0030)	0.007† (0.0025)	0.007† (0.0027)	0.005 (0.0033)
50-100	0.013† (0.0052)	0.012† (0.0040)	0.007° (0.0033)	0.003 (0.0057)	0.011† (0.0033)	0.009† (0.0034)	0.003 (0.0045)	0.009° (0.0039)	0.010† (0.0039)	0.014‡ (0.0044)
25-50	0.019‡ (0.0052)	0.021‡ (0.0041)	0.013‡ (0.0037)	-0.005 (0.0060)	0.019‡ (0.0035)	0.012† (0.0037)	0.011° (0.0049)	0.014‡ (0.0041)	0.020‡ (0.0045)	0.016‡ (0.0049)
10-25	0.014† (0.0050)	0.020‡ (0.0040)	0.018‡ (0.0034)	0.011° (0.0052)	0.022‡ (0.0033)	0.012‡ (0.0034)	0.012† (0.0044)	0.015‡ (0.0039)	0.022‡ (0.0041)	0.019‡ (0.0043)
0-10	0.032‡ (0.0058)	0.032‡ (0.0041)	0.023‡ (0.0034)	0.017† (0.0056)	0.028‡ (0.0033)	0.028‡ (0.0039)	0.021‡ (0.0046)	0.029‡ (0.0045)	0.031‡ (0.0043)	0.027‡ (0.0043)
Predicted Effects										
Pred. Eff. at $\bar{X}$	0.009	0.009	0.006	0.002	0.006	0.009	0.005	0.007	0.009	0.008
Mean	0.224	0.099	0.047	-0.006	0.100	0.104	0.161	0.151	0.087	0.032
Median	0.124	0.046	0.015	-0.016	0.041	0.035	0.071	0.070	0.036	0.010

Source: LEHD 2014 snapshot.

Notes: The coefficients reported in this table are interactions between shares of other-establishment employment within the firm that fall into the distance bin given by the row label and indicators for the worker subpopulation defined by the characteristic category in the column label. The outcome is the average percent change in a worker's earnings across the subsequent five years relative to the baseline year. Interactions featuring all the characteristic categories in a given panel are included in the same regression, but different panels featuring different characteristics represent different regressions. See the Table 2.2 notes for definitions of the categories defined by the column labels. Clustered two-way standard errors by firm and work in parenthesis.

‡, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

Table 2.11: Heterogeneity across Worker Subpopulations in the Effects of Distance-Based Access to Opportunities for Between Establishment Mobility on Workers' Annual SEIN Transition Rates

Distance (mi.)	I(SEIN Transition)									
	Earnings					Race				
	Q1	Q2	Q3	Q4	Q5	White N-Hisp	White Hisp	Black	Asian/ Pac. Is	Other
100-500	0.011‡ (0.0023)	0.010‡ (0.0020)	0.008‡ (0.0016)	0.009‡ (0.0014)	0.011‡ (0.0015)	0.010‡ (0.0012)	0.009‡ (0.0020)	0.010‡ (0.0021)	0.016‡ (0.0034)	0.011‡ (0.0019)
50-100	0.017‡ (0.0027)	0.017‡ (0.0023)	0.017‡ (0.0022)	0.019‡ (0.0022)	0.021‡ (0.0026)	0.020‡ (0.0016)	0.017‡ (0.0028)	0.017‡ (0.0031)	0.025‡ (0.0044)	0.014‡ (0.0027)
25-50	0.021‡ (0.0030)	0.022‡ (0.0026)	0.027‡ (0.0025)	0.028‡ (0.0026)	0.037‡ (0.0032)	0.028‡ (0.0019)	0.027‡ (0.0033)	0.034‡ (0.0034)	0.039‡ (0.0054)	0.023‡ (0.0032)
10-25	0.025‡ (0.0029)	0.028‡ (0.0026)	0.032‡ (0.0026)	0.036‡ (0.0026)	0.046‡ (0.0046)	0.035‡ (0.0022)	0.033‡ (0.0033)	0.040‡ (0.0037)	0.046‡ (0.0059)	0.029‡ (0.0035)
0-10	0.027‡ (0.0027)	0.031‡ (0.0025)	0.033‡ (0.0024)	0.040‡ (0.0026)	0.050‡ (0.0040)	0.039‡ (0.0022)	0.033‡ (0.0030)	0.040‡ (0.0034)	0.050‡ (0.0066)	0.033‡ (0.0033)
Predicted Effects										
Pred. Eff. at $\bar{X}$	0.010	0.011	0.011	0.012	0.013	0.012	0.010	0.014	0.016	0.010
Mean	0.004	0.005	0.006	0.008	0.013	0.008	0.006	0.009	0.009	0.008
	Age				Sex		Tenure			
	< 30	30-39	40-54	55 +	M	F	0	1-2 yrs	3-5 yrs	> 5 yrs
100-500	0.012‡ (0.0015)	0.010‡ (0.0014)	0.010‡ (0.0014)	0.008‡ (0.0015)	0.011‡ (0.0019)	0.010‡ (0.0011)	0.011‡ (0.0015)	0.010‡ (0.0013)	0.011‡ (0.0026)	0.008‡ (0.0018)
50-100	0.019‡ (0.0020)	0.021‡ (0.0020)	0.020‡ (0.0020)	0.016‡ (0.0020)	0.021‡ (0.0024)	0.018‡ (0.0016)	0.019‡ (0.0021)	0.018‡ (0.0020)	0.022‡ (0.0031)	0.018‡ (0.0023)
25-50	0.028‡ (0.0023)	0.034‡ (0.0024)	0.029‡ (0.0023)	0.020‡ (0.0023)	0.031‡ (0.0027)	0.027‡ (0.0019)	0.030‡ (0.0024)	0.029‡ (0.0022)	0.031‡ (0.0032)	0.026‡ (0.0029)
10-25	0.036‡ (0.0025)	0.043‡ (0.0027)	0.036‡ (0.0026)	0.024‡ (0.0023)	0.038‡ (0.0028)	0.035‡ (0.0023)	0.038‡ (0.0032)	0.039‡ (0.0027)	0.037‡ (0.0030)	0.031‡ (0.0031)
0-10	0.040‡ (0.0024)	0.045‡ (0.0026)	0.038‡ (0.0025)	0.027‡ (0.0024)	0.040‡ (0.0025)	0.038‡ (0.0024)	0.041‡ (0.0032)	0.040‡ (0.0025)	0.039‡ (0.0030)	0.036‡ (0.0035)
Predicted Effects										
Pred. Eff. at $\bar{X}$	0.012	0.013	0.012	0.010	0.010	0.015	0.012	0.012	0.013	0.012
Mean	0.009	0.009	0.008	0.006	0.008	0.008	0.008	0.009	0.009	0.007

Source: LEHD 2014 snapshot.

Notes: The coefficients reported in this table are interactions between shares of other-establishment employment within the firm that fall into the distance bin given by the row label and indicators for the worker subpopulation defined by the characteristic category in the column label. The outcome is an indicator for whether the worker changed its primary SEIN within the same firm between the baseline and subsequent year. Interactions featuring all the characteristic categories in a given panel are included in the same regression, but different panels featuring different characteristics represent different regressions. See the Table 2.2 notes for definitions of the categories defined by the column labels. Clustered two-way standard errors by firm and work in parenthesis.

‡, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

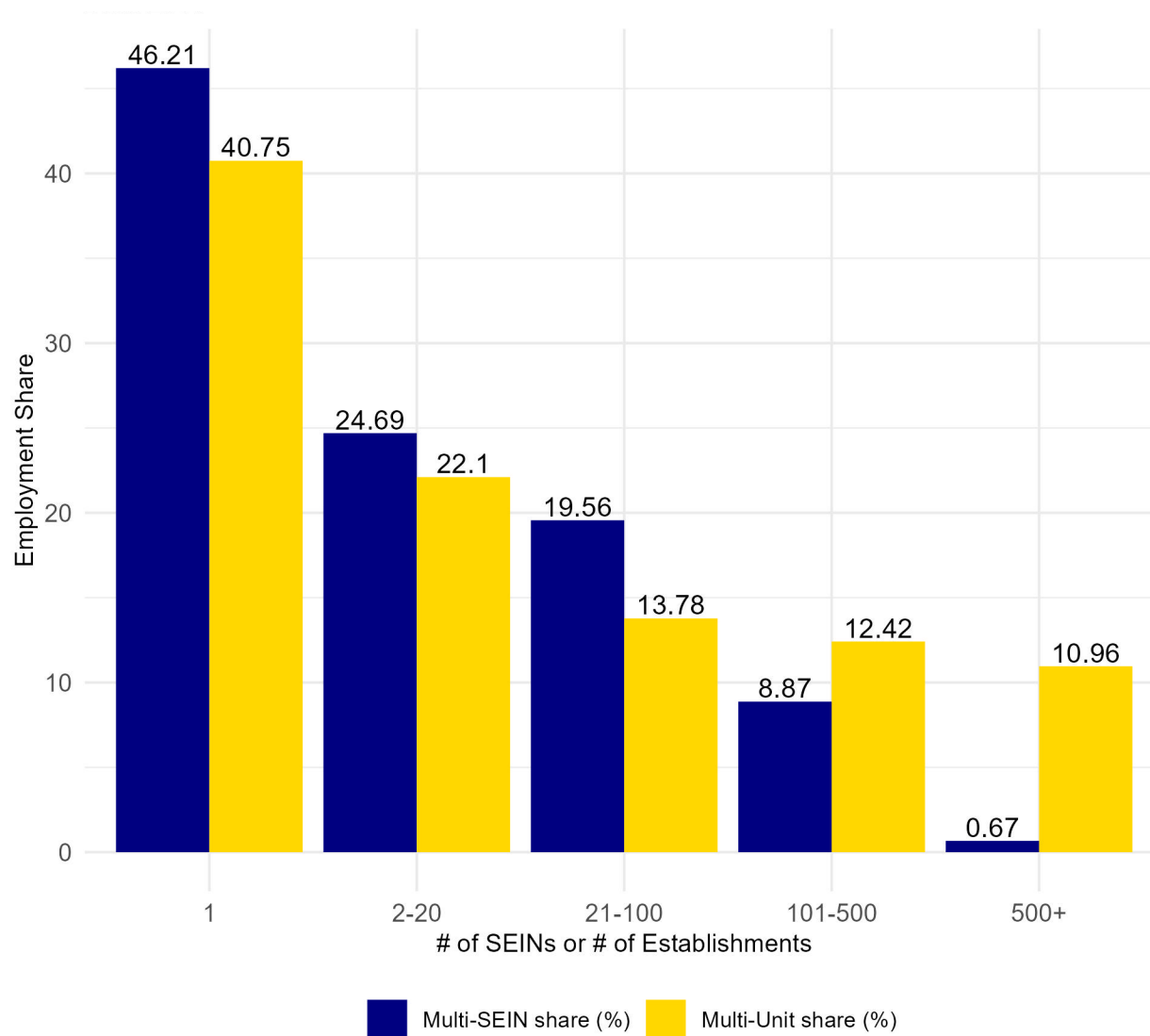
Table 2.12: Estimates of the Annual Rate of Establishment Mobility within Firms, Overall and by Initial Firm Size Category

SEIN Mobility	Overall	Firm Size				
		1-100	101-500	501-1K	1K-5K	>5K
Observed	1.362%	0.848%	0.682%	0.770%	0.994%	1.773%
Controls adjustment						
Employment distance shares	+0.165%	+0.007%	+0.052%	+0.097%	+0.152%	+0.220%
Employment size bins	+0.109%	+0.000%	+0.080%	+0.121%	+0.149%	+0.111%
Firm-Year FE adjustment						
Employment size bins	+0.035%	+0.000%	+0.004%	+0.012%	+0.029%	+0.050%
In-SEIN employment	+0.141%	+0.000%	+0.005%	+0.021%	+0.072%	+0.226%
Out-of-Sample adjustment						
State transitions	+0.426%	+0.022%	+0.090%	+0.158%	+0.253 %	+0.534%
Adjusted Estimate						
Multi-SEIN Firms	2.237%	0.876%	0.913%	1.179%	1.650%	2.913%
Multi-Unit-Single-SEIN Firms	1.591%	0.658%	1.144%	1.487%	1.894%	2.852%
All Multi-Unit Firms	2.169%	0.829%	0.976%	1.237%	1.670%	2.911%
All Firms	1.378%	0.110%	0.588%	1.031%	1.534%	2.882%
Movers	7.755%	0.436%	2.728%	5.177%	7.700%	18.184%
State Movers	26.855%	1.878%	5.617%	8.389%	13.21%	33.78%

Source: LEHD 2014 snapshot.

Notes: Each row in the top panel captures the increase in predicted within-firm establishment mobility rate from a different adjustment to the prediction methodology. See sections 6 and A.1 for details about each adjustment. “Controls adjustment - Employment distance shares”: uses employment at all other establishments rather than only at establishments in other SEINs when forming distance shares of BEM options. “Controls adjustment - Employment size bins”: uses employment at all other establishments rather than only at establishments in other SEINs when assigning workers to the employment size bins that are interacted with distance shares of BEM options. “Firm-Year FE adjustment - Employment size bins”: uses employment at all other establishments rather than only at establishments in other SEINs when assigning workers to the employment size bins used to predict firm-year fixed effect values and other firm-level components of the original predicted value. “Firm-Year FE adjustment - In-SEIN employment”: Sets to zero the indicators for categories of total within-SEIN employment when predicting firm-year fixed effect values, since within-SEIN transitions are not an outside option when predicting all establishment transitions rather than only between-SEIN transitions. “Out-of-Sample adjustment”: includes the predicted probability of making a between-SEIN transition within the firm to a destination state outside of the 25 states observed in the data. “Adjusted Estimate - Multi-SEIN Firms”: Estimated annual within-firm establishment mobility rate among workers at Multi-SEIN firms after making the adjustments in the top panel to account for unobserved within-SEIN transitions and between-SEIN transitions to out-of-sample states. “Multi-Unit-Single-SEIN firms”, “All Multi-Unit Firms”, and “All Firms” provide analogous adjusted estimates among workers in these subpopulations. “Movers” estimates the share of all establishment transitions that are within the same firm, while “State Movers” estimates the share of all between-state establishments transitions that are within the same firm.

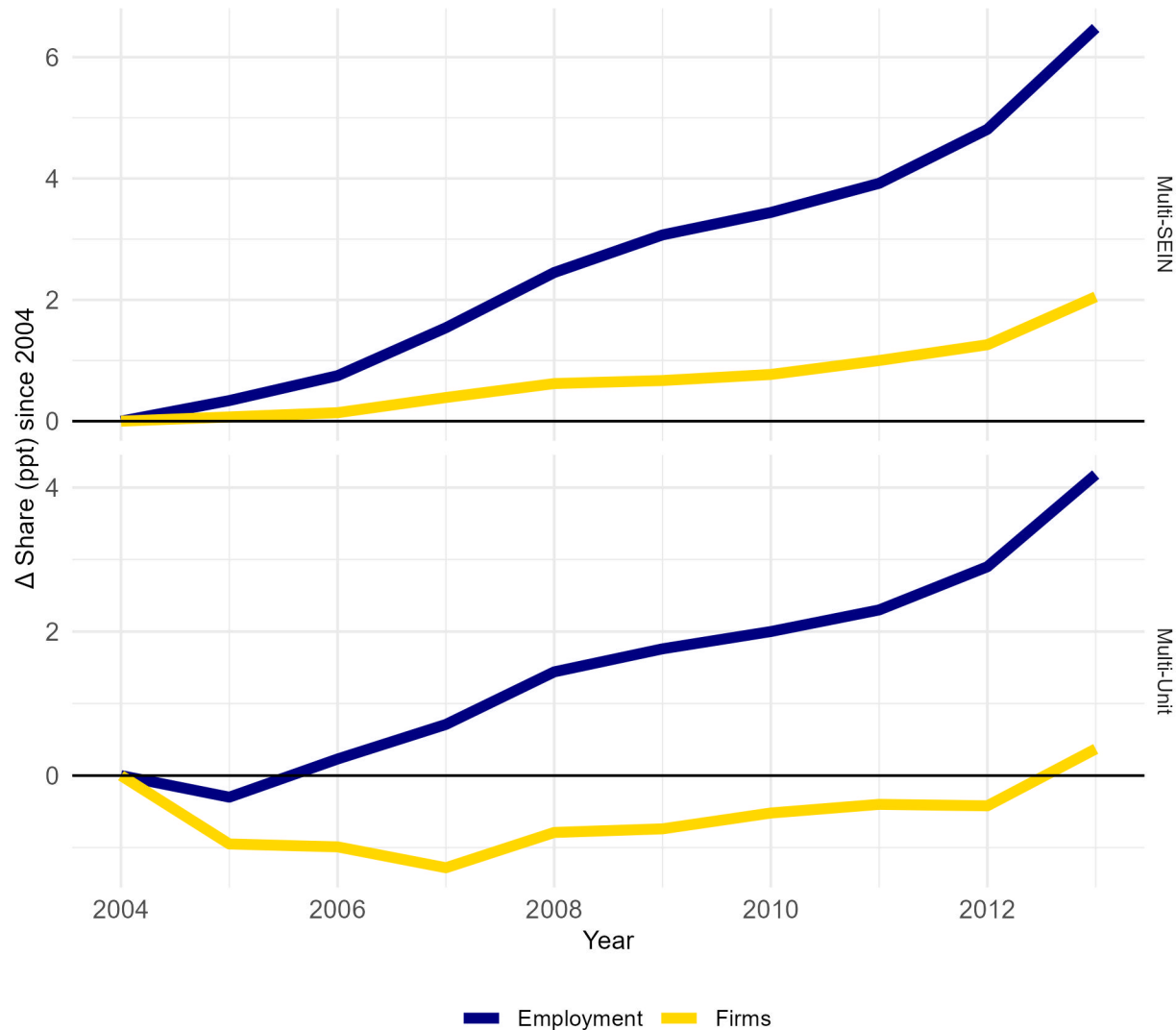
Figure 2.1: Employment Shares by Bins of Number of Establishments and Number of SEINs



Source: LEHD 2014 snapshot

Notes: Blue bar heights capture the share of all worker-years in the baseline sample whose primary employer operates a number of establishments that falls within the range given by the bar label. Yellow bar heights capture the analogous shares for bins based on number of SEINs rather than number of establishments.

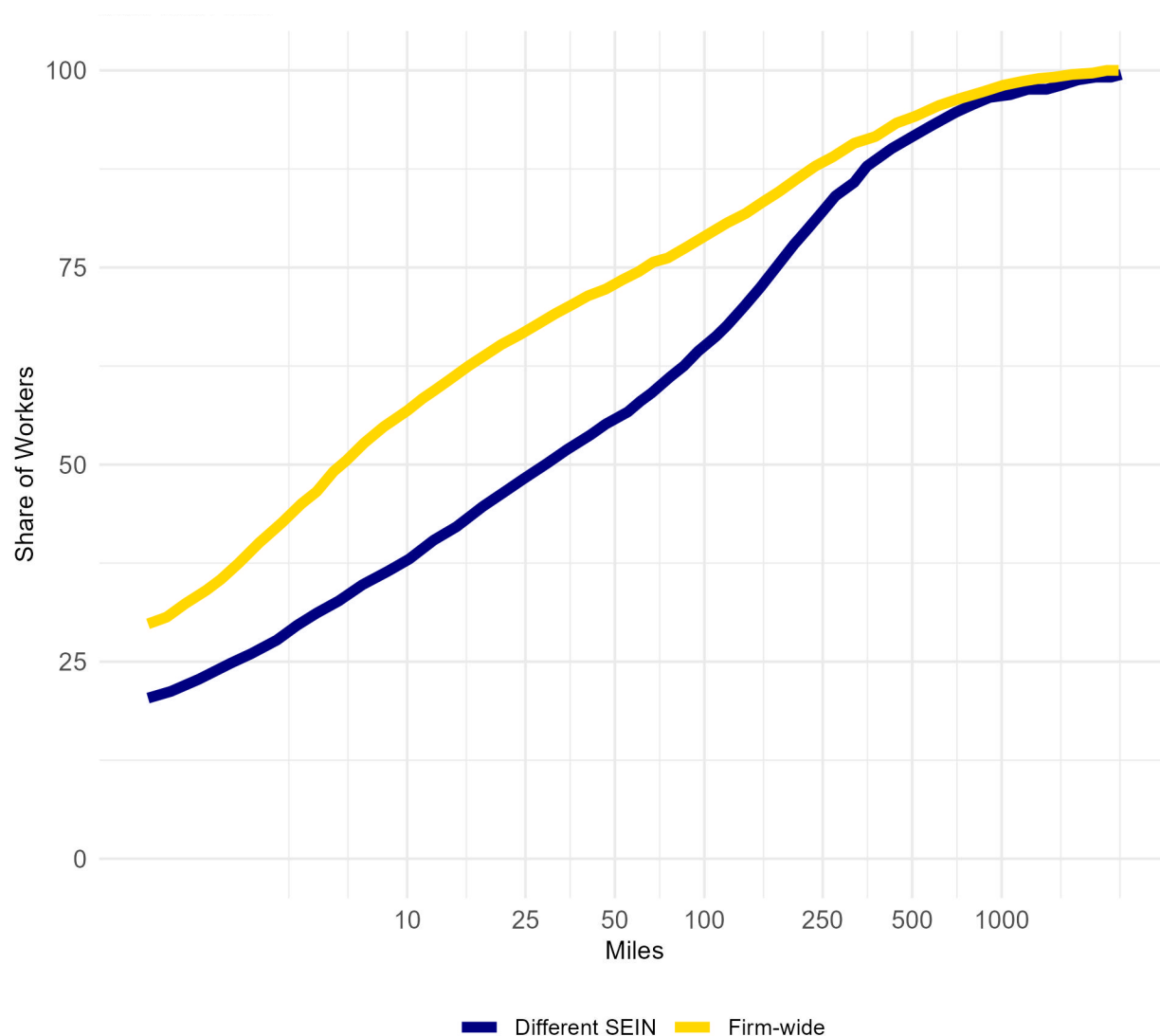
Figure 2.2: 2004-2013 Changes in the Multi-SEIN and Multi-Unit Shares of Employment and Firms



Source: LEHD 2014 snapshot

Notes: The blue line in the top (bottom) panel displays the change in the share of workers working at firms operating multiple SEINs (establishments) between 2004 and 2013. The yellow line in the top (bottom) panel displays the corresponding change in the share of firms who operate multiple SEINs (establishments).

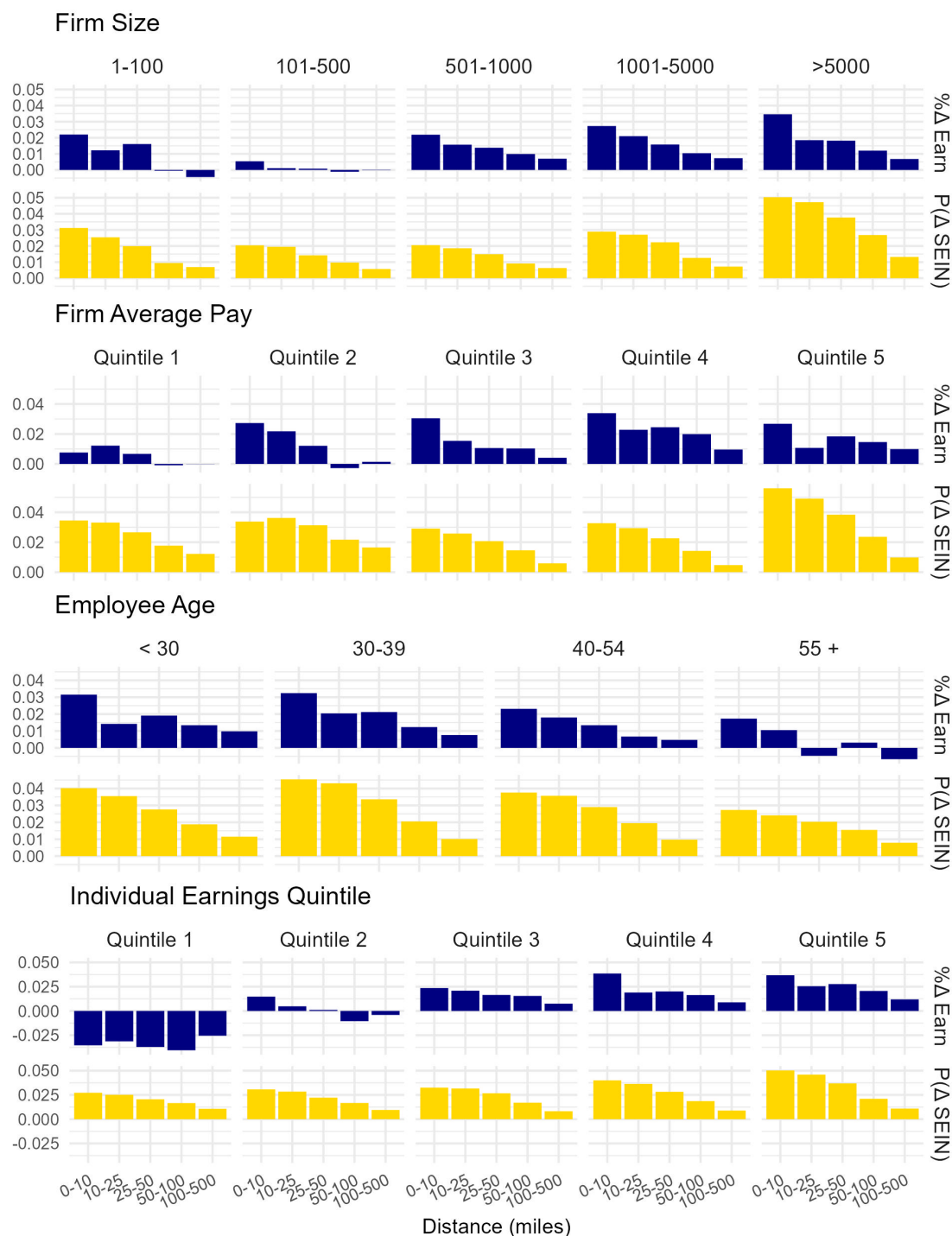
Figure 2.3: The Cumulative Distribution Functions for the Distance from a Worker's Current Establishment to the Next Closest Establishments among All the Firm's Establishments and among Establishments in the Firm's other SEINs



Source: LEHD 2014 snapshot

Notes: The sample consists of all worker-years in which the worker works in a multi-unit (i.e. multi-establishment) firm. The X-axis measures miles of distance between establishments on a log (base 10) scale. The blue curve displays the CDF across worker-years of the distance from the worker's current establishment to the next closest establishment within the same firm. The yellow curve displays the CDF across worker-years of the distance from the worker's current establishment to the next closest establishment within other SEINs at the same firm.

Figure 2.4: Heterogeneity Across Worker and Firm Subpopulations in the Profile of Effects of Shares of Other-Establishment Employment in Various Distance Bins on SEIN Transition Rates and Average Percent Gains in Earnings over 5 years



Notes: Each group of bars displays coefficients on interactions between the share of other-establishment workers in a given distance bin (relative to the worker's own establishment) and an indicator for belonging to the category of the firm characteristic given by the group label. The share of workers in establishments over 500 miles away is treated as the reference category, so its coefficient normalized to 0. Yellow bars correspond to the SEIN mobility outcome and blue bars correspond to the 5-year earnings growth outcome.

Chapter 3

Railroad Barons and American Economic Growth: A Modified Market Access Approach

3.1 Introduction

Throughout the late 19th Century, as the United States undergoes rapid economic growth and transformation, railroads web their way through the North American continent, becoming the dominant form of transport and uniting previously disparate locations with a newfound global marketplace. These railroads – along with the less cutting-edge wagon trains and inland canal network – are the gatekeepers to the international economy; however, anecdotal evidence from this time period suggests that freight markets are far from competitive. To what extent is U.S. economic growth hampered by a concentrated domestic freight market during this time period? This paper provides upper-bound estimates of total agricultural production losses and price increases stemming from the concentration of freight market power in the late-19th and early-20th Century.

I analyse county-level agricultural production in the United States from 1850 to 1910; this span is notable for – among other reasons – the rapid proliferation of railroads. Prior to the advent of the railroad, U.S. freight transportation relies primarily on wagons, which are relatively unreliable, slow, and costly; a limited Canal network is built in the early 19th Century to ease freight movement along major arteries, but these are geographically confined by proximity to water sources. The first commercial railroad opens in the U.S. in 1826; as of 1830, the national railroad network comprises only 61 miles of operable track ([Atack, 2016](#)). By 1850 – the start of my analysis – the rail network grows to a sparse patchwork totalling approximately 8,500 miles throughout the East coast and Midwest; by 1870, the rail network comprises about 35,000 miles, unites most major urban centers in the Northeast, Midwest, and upper South, and extends as far West as the Rocky Mountains. The total length of the rail network roughly doubles over each of the subsequent two decades, reaching approximately 152,000 miles by 1890, and includes multiple trans-continental routes uniting the

East and West coasts. By the end of my analysis in 1910, the total length of the rail network is just shy of 200,000 miles ([Atack, 2016](#)).

Concurrent with this railroad boom comes rapid economic development. Figure 3.1 documents the growth of nominal per-capita U.S. manufacturing and agricultural output from 1850 to 1910, as well as the expansion of the transit network. Importantly, as of 1850 when the railroad is still in its infancy, manufacturing output is roughly level with agricultural production; though both sectors grow substantially over the subsequent decades, manufacturing significantly outpaces agriculture, such that the manufacturing output is roughly 3.5 times larger than agricultural output by 1910 ([Michael R. Haines and ICPSR, 2010](#)). The rail network follows a similar, rapid expansion, though the canal network stagnates. Previous analyses of this era have addressed to what extent the railroad boom enabled this rapid industrial expansion ([Fogel, 1964](#); [Donaldson and Hornbeck, 2016](#); [Hornbeck and Rotemberg, 2024](#)). I contribute to this literature by focusing on freight market power: I evaluate the extent to which horizontal concentration in the market for freight transportation shaped America’s economic expansion.

My focus on freight market power is vital to my historical setting. In addition to rapid economic and infrastructure development, this period of history is also notable for the inception of U.S. antitrust policy: the landmark U.S. antitrust law, the Sherman Antitrust Act, passes Congress in 1890. One of the first cases brought under the Act, [United States v. Trans-Missouri Freight Association, 166 U.S. 290 \(1897\)](#), alleges that three railroad operators had entered into a price-fixing agreement for freight running West of the Mississippi and Missouri Rivers; the U.S. Supreme Court agrees and orders the dissolution of the cartel. Just one year later, the the Supreme Court disbands a similar price-fixing scheme among 31 carriers transporting freight between Chicago and the East Coast ([United States v. Joint Traffic Association, 171 U.S. 505, 18 98](#)). These two legal cases underscore a lack of effective competition in freight markets during this time period, especially amongst the railroad; however, the economic literature has not yet explored the long-run consequences of this freight market concentration.

To evaluate the impact of non-competitive freight pricing, I modify a multi-sector Ricardian trade model to include endogenous transport costs. Specifically, I assume that a representative freight-service provider sets prices to maximize profit, subject to exogenous bilateral frictions (i.e., the distance between locations), as well as demand for transport services (i.e., trade flows). Trade flows, in turn, are a function of these freight prices. This endogenous freight-pricing framework

contrasts with the approach typically taken in the trade literature, which assumes purely exogenous bilateral costs. My theoretical approach is attractive for two, key reasons: i) it permits a wide array of solution concepts, including the extremes of perfect competition and perfect oligopoly (monopoly) in the freight market; and ii) it is a generalization of a wide range of canonical trade models (Eaton and Kortum, 2002; Costinot et al., 2011), and perhaps most importantly, the models used in Donaldson and Hornbeck (2016) and Chan (2022) to analyse the historical impact of the railroads; hence, my estimates are immediately comparable to previous estimates in the literature.

I utilize my theoretical framework to develop a modified “market access” term. This term summarizes the demand for goods out of any one county, as determined by exogenous productivities and bilateral frictions. My formulation of market access not only reflects exogenous distances between locations, but also the endogenous markup set by a monopolistic transporter. This market access framework is used widely in the literature to understand the influence of trade frictions on local production (Donaldson and Hornbeck, 2016; Chan, 2022; Hornbeck and Rotemberg, 2024); however, these analyses omit endogenous freight pricing. I estimate that the effect of market access expansion is nearly double when accounting for freight market power. Hence, existing estimates in the literature constitute the lower-bound. Additionally, I confirm that market access expansions lead to substantial increases in the total volume of agricultural production; I further disentangle this estimate into a price and quantity effect, which have distinct welfare considerations. I also find substantial convexity in this treatment effect by initial output size; the smallest producers stood the most to gain from the expansion of market access in the 19th Century. However, this finding also means that these smaller producers are the most vulnerable to the exercise freight market power. I show that the distribution of losses from freight market concentration is highly skew right – those counties that are worst affected tend to be along the American Frontier.

This paper contributes to a long-standing literature estimating the contribution of railroads to American economic growth. First amongst this strand of literature is Fogel (1964), who utilizes a “social saving methodology” to argue that the impact of the railroads is actually quite limited; in the absence of railroad expansion, Fogel contends that the canal network would have provided comparable transport services at only slightly elevated prices. Responding to this conclusion some years later, Donaldson and Hornbeck (2016) utilize a “market access” approach – a reduced-form expression derived from equilibrium trade theory – to argue that railroads contributed significantly to U.S. agricultural output in the late 19th Century; these losses could not be overcome by other

modes. Importantly, this market access methodology captures the effect of railroad development nationwide on any one county, even if it is not directly connected to the network; moreover, the estimates from this method are well-identified. I build upon this framework to estimate the causal impact of freight market concentrations on domestic agricultural production.

This notion of market access is key to my analysis and thus merits some exposition. In short, it is the weighted-sum of total expenditure across all available markets; the weights are inversely proportional to bilateral trade costs. Hence, market access reflects the global (or in my case, national) demand for goods from any one county. Importantly, this term captures both the direct and indirect effect of changes to trade frictions: a new rail line built between, e.g., Denver and Los Angeles will undoubtedly increase trade between these two cities; this trade will, in turn, make these two cities wealthier, and thus increase market access for all cities nationwide, even if they are not connected to this new rail line. This latter effect is critical to identifying the causal impact of changes to market access on agricultural output: changes to transit costs throughout the nation (due to, e.g., expansion of the railroad network or changes to the competitive landscape for freight services) will affect market access, meaning changes to market access are largely exogenous to local economic conditions. Thus, the railroad boom of the 19th century offers a natural experiment to evaluate how changes in market access affect county-level agricultural production. In Section 3.4.2, I detail this identification argument more completely.

A number of papers utilize similar measures of market access to evaluate the economic impacts of rapid expansion of the railroad. [Chan \(2022\)](#) utilizes a market access framework to assess how the 19th Century railroad boom influenced U.S. agricultural production; they find that railroads sparked greater total agricultural output via increased agricultural land use and population growth, but had limited to null effects on productivity and the variety of crop output. [Hornbeck and Rotemberg \(2024\)](#) utilize a similar empirical approach to analyse how the railroad affected county-level manufacturing productivity; they find that the railroads greatly increased allocative efficiency, but found limited effects on total factor productivity. Hence, one of the primary mechanisms, through which the railroad increased economic output was by lessening input-output distortions.

I contribute to this literature by focusing on the role non-competitive freight pricing. I utilize a market access framework, but allow for transport costs to be set endogenously under familiar structural assumptions. This theoretical approach generates upper-bound estimates of how U.S. agricultural production was hampered by non-competitive freight pricing; no paper to-date exam-

ines the influence of freight market concentration on a national scale, nor in this historical context. Additionally, I build upon this market access methodology to separately identify the effects of changes in market access – brought about by either the expansion of the railroad or, as I focus on, counterfactual changes to the competitive landscape for freight services – on both agricultural prices and the quantity of agricultural output. Previous estimates in the literature focus on the total value of production ([Chan, 2022](#); [Hornbeck and Rotemberg, 2024](#)), or on the value of agricultural land ([Donaldson and Hornbeck, 2016](#)). This paper is the first to separately identify these price and quantity effects, which have distinct implications for consumer welfare.

A number of other papers have explored the historical significance of transport and infrastructure. Among this literature, [Jaworski et al. \(2023b\)](#) develop a Ricardian trade model with endogenous congestion and varying port efficiency to quantify the economic impacts of the U.S. interstate highway system. Taking a more reduced-form approach, [Donaldson \(2018\)](#) explore the economic impact of the British railway system in colonial India. Both of these papers highlight the importance of these national and international transport systems for economic integration and development, especially in rural areas. However, these papers do not consider the role of imperfect competition in the freight services sector, for which there is strong anecdotal evidence during this period. The welfare impacts of these large infrastructure projects may be muted by non-competitive freight rates; this paper seeks to set an upper bound on these losses in the case of North America.

More broadly, the theoretical model posited in this paper contributes to an expanding literature that embed endogenous trade costs into canonical trade models. Recent examples of this literature include [Allen and Arkolakis \(2022\)](#), who embed a model of trade costs with endogenous congestion externalities into a neoclassical trade model, and [Fuchs and Wong \(2023\)](#), who then adapt this model to span multiple modes, and explore how congestion at ports spreads throughout the domestic transit network. I contribute to this strand of literature in two distinct ways: i) I focus on the role of horizontal concentration in the market for freight services, emphasizing the role that non-competitive freight rates play in determining domestic trade flows, and ii) I analyse production in the late 19th Century, a time of rapid economic transformation, as well as noted freight market concentration. This paper is also closely related [Brancaccio et al. \(2020\)](#), who examine the market for international sea shipping, and are the first to allow market power on behalf of freight carriers. In contrast to this model, I focus on the market for domestic freight spanning multiple modes, moreover I focus on this historical consequences of this freight market concentration, during a time

when freight markets were far from competitive.

The rest of the paper proceeds as follows. Section 3.2 develops my theoretical model, which will inform a method to identify markups absent data on trade flows or freight prices. Section 3.3 outlines my data sources and develops a strategy to simulate bilateral trade flows and freight rates absent available data exploiting my theoretical structure. Section 3.4 evaluates my strategy to identify the effect of changes in market access on output and prices; it also describes how counterfactual shifts in domestic production. Section 3.5 concludes.

3.2 Theoretical Framework

In this section, I construct a theoretical framework to analyse the influence of freight market power on domestic production. First, I adapt a well-known multi-sector Ricardian trade model ([Costinot et al., 2011](#)) to allow endogenous freight pricing subject to exogenous bilateral frictions – namely, distance. Second, I model the transporter’s pricing decision; utilizing long-standing insights from the empirical Industrial Organization literature, I develop a pricing rule that permits a continuum of solution concepts, including the extremes of perfect oligopoly (monopoly) and perfect competition.¹ This theoretical approach contrasts with standard practice in the trade literature, which typically assumes purely-exogenous bilateral frictions. I now delve into the details of the model.

3.2.1 Transport Demand: Equilibrium Trade Flows

The demand for freight transport between an origin and destination is given by the flow of goods. To analyse these trade flows, I utilize a multi-sector Ricardian trade model with no input-output linkages, as in [Costinot et al. \(2011\)](#).² This trade setting is critical to my analysis for two reasons: i) the model yields a log-linear expression for trade flows, which I will later exploit to derive an estimable equation; and ii) it provides a tractable structure to evaluate the impact of non-competitive freight pricing on total output, welfare, and population in each location (in my context, counties). Finally, let t index the year (decade) of observation. It is worth highlighting

¹I utilize much the same framework as [Pfander \(2024\)](#); however, I make the following modifications to make the model more appropriate to my empirical setting: i) I utilize a multi-sector trade model to capture the production and trade of distinct agricultural goods; ii) I simplify the routing structure such that I consider only the least-cost path between two locations along any one mode; and iii) I simplify the correlation structure between competing trade routes. These latter two simplifications are necessary due to a lack of bilateral trade data. See Section 3.3.1 for further detail.

²While the assumption of zero input-output linkages is strict, I contend that it is appropriate for my empirical setting. Specifically, I analyse the production of a distinct set of agricultural commodities, which do not generally exhibit any input-output structure. See Table 3.2 for detail.

that, though my data span multiple time periods, I do not model savings or investment; each time period is thus completely independent.

I first establish some preliminaries. Let $\mathcal{K}$ denote a discrete, finite set of commodities (sectors), which will be indexed by $k \in \mathcal{K}$. Trade in these commodities occurs amongst a discrete, finite set of locations, $\mathcal{S}$; let $i, j \in \mathcal{S}$ index origins, destinations. Within each commodity, agents consume a continuum of varieties Ω^k ; for each variety $\omega^k \in \Omega^k$, agents consume a quantity $q(\omega^k)$ to maximize utility given by

$$U_{jt} = \sum_{k \in \mathcal{K}} \left(\left(\int_{\omega^k \in \Omega^k} q(\omega^k)^{\frac{\sigma^k - 1}{\sigma^k}} d\omega \right)^{\frac{\sigma^k}{\sigma^k - 1}} \right)^{\zeta^k} \quad (3.1)$$

where $\sum_{k \in \mathcal{K}} \zeta^k = 1 \forall j$.

Locations vary in their productivity, creating incentive to trade. Let the marginal cost of producing variety $\omega^k \in \Omega^k$ in location i be given by

$$c_{it}(\omega^k) = \frac{c_{it}}{z_{it}^k(\omega^k)} \quad (3.2)$$

where c_i is a uniform input cost and $z_i(\omega^k)$ is a Hicks-neutral productivity shifter. I assume that $z_{it}^k(\omega^k) \sim \text{Fréchet}$ with location parameter A_{it}^k and shape parameter θ .³ The former parameter represents location i 's productivity and governs absolute advantage; the latter parameter dictates the dispersion of these productivities across locations, and it governs comparative advantage (Costinot et al., 2011). I further impose perfect competition in the goods market such that the price paid for ω^k in market j is equal to its marginal cost:

$$p_{jt}(\omega^k) = \min_{i \in \mathcal{S}} \left\{ c_{it}(\omega^k) \bar{\tau}_{ijt} \mu_{ijt}^k \right\} \quad (3.3)$$

where $\bar{\tau}_{ijt}$ denotes the expected, exogenous, ad-valorem cost of travelling from i to j , and μ_{ijt}^k is an endogenous markup set by a representative transporter. In Section 3.2.2, I further elaborate this markup term; for the purpose of deriving equilibrium transport demand (i.e., trade flows), I treat it as fixed. It follows that the share of commodity k travelling to j from i is given by

$$\pi_{ijt}^k = A_{it}^k (c_{it} \bar{\tau}_{ijt} \mu_{ijt}^k)^{-\theta} (\phi_{jt}^k)^{-1} \quad (3.4)$$

³As in Costinot et al. (2011), I require $\theta > \sigma^k - 1 \forall k$.

where $\phi_{jt}^k = \sum_{i' \in \mathcal{S}} A_{i't}^k (c_{i't} \bar{\tau}_{i'jt} \mu_{i'jt}^k)^{-\theta}$ governs the price index in location j .⁴ Equation 3.4 constitutes the well-known gravity expression for trade flows between i and j (Costinot et al., 2011).

Exogenous bilateral trade costs, $\bar{\tau}_{ijt}$, are incurred while traversing the transit network. I follow what has become standard practice in the literature and assume a logit model of mode-choice (Allen and Arkolakis, 2014; Donaldson and Hornbeck, 2016; Donaldson, 2018); agents choose the cheapest alternative among a set modes, whose cost is determined by the available infrastructure. A logit formulation for modal shares is attractive because it yields a reduced-form expression for expected trade costs that nests neatly into Equation 3.4. However, this model does impose some strict restrictions on demand for freight services – most notably the “independence of irrelevant alternatives” assumption, which requires that, upon the introduction of a new mode like the railroad, trade shares among existing modes remain proportional. This assumption likely fails, as railroads are more closely substitutable with canals than with roadways, as highlighted by (Fogel, 1964). I now expound the structure of this logit formulation.

Let $\mathcal{M}_{ijt}$ denote the set of modes serving a particular origin-destination pairing.⁵ Let the cost of travelling between i and j via m be given by $\tau_{ijt}^m = \exp(Miles_{ijt}^m \beta^m + f^m + \epsilon_{ij}^m)$, where β^m denotes the cost per-mile, and f^m is a route-invariant, mode-specific cost. Intuitively, β^m captures the cost incurred en-route (e.g., fuel, labor, and time), while f^m captures “fixed” costs (e.g., loading, unloading, and maintenance).⁶ The variable $Miles_{ijt}^m$ denotes the distance of the least-cost path between i and j via m .⁷ Further assume that $\epsilon_{ij}^m \sim \text{Gumbel (Type-1 EV)}$ with shape parameter ρ . From this setup, expected trade costs are

$$\bar{\tau}_{ijt} = \frac{1}{\rho} \Gamma\left(\frac{1}{\rho}\right) V_{ijt}^{-\frac{1}{\rho}}, \quad \text{where} \quad (3.5)$$

$$V_{ijt} = \sum_{m \in \mathcal{M}_{ijt}} \exp(-\rho(\beta^m Miles_{ijt}^m + f^m)) \quad (3.6)$$

⁴Explicitly, the price index for a given commodity in market j is given by $P_{jt}^k = \Gamma\left(\frac{\theta+1-\sigma^k}{\theta}\right)^{\frac{1}{1-\sigma^k}} (\phi_{jt}^k)^{-1/\theta}$. This formulation follows immediately from the utility assumption in Equation 3.1.

⁵Recall that not all locations are served by every mode; the canal network is geographically confined by the availability of major water sources; the rail network is only a loose patchwork at the start of my analysis (1850). See Figure 3.2 for further detail.

⁶A well-known feature of logit models is that they are only identified up to scale. I thus follow Donaldson and Hornbeck (2016) and Donaldson (2018) and normalize $f^{Road} = 0$; this normalization has intuitive appeal, as it is easy to imagine that road transport requires minimal loading, unloading, and maintenance relative to barges and/or rail.

⁷Details of generating these least-cost paths are reported in Section 3.3.2.

and Γ denotes the gamma function.⁸ Combining Equations 3.4 and 3.5 yields:

$$\pi_{ijt}^k = \kappa_1 A_{it}^k (c_{it} \mu_{ijt}^k)^{-\theta} V_{ijt}^{\theta/\rho} (\phi_{jt}^k)^{-1} \quad (3.7)$$

where $\kappa_1 = (\rho^{-1} \Gamma(\rho^{-1}))^{-\theta}$. Thus, Equation 3.7 reformulates the gravity equation described in Equation 3.4 to be a function of available infrastructure at time t .

3.2.2 Freight Prices: Transport Supply

In this section, I elaborate the endogenous, bilateral markup, μ_{ijt}^k . A representative transporter provides all freight transport services to a destination j .⁹ This transporter's total profit is given by $\Pi_{jt} = \sum_{i \neq j} \sum_k \zeta^k B_{jt} \pi_{ijt}^k (\mu_{ijt}^k - 1) \bar{\tau}_{ijt}$, where B_{jt} is the total expenditure of market j , which the transporter treats as exogenous. It is evident from this formulation that the transporter makes zero profit on domestic trade; this normalization pins-down the scale of total freight profits. Maximizing profit with respect to μ_{ijt}^k yields the following pricing rule:

$$\mu_{ijt}^k = \frac{(1 - \pi_{ijt}^k) \bar{\tau}_{ijt} + \sum_{i' \neq i, j} (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \pi_{i'jt}^k}{(1 - \pi_{ijt}^k) \bar{\tau}_{ijt} - (\lambda/\theta) \bar{\tau}_{ijt}} \quad (3.8)$$

where $\lambda \in [0, 1]$ dictates the state of competition for freight services nationally. A detailed derivation of this pricing rule is presented in Appendix G. This formulation is based on long-standing insights from the empirical Industrial Organization literature ([Bresnahan, 1982](#)); it is attractive because it does not assume a particular solution to the transporter's pricing game, but permits a continuum of equilibria, as determined by λ . This parameter is immediately interpretable at the extremes — as displayed by Equation 3.8, setting $\lambda = 1$ yields the monopoly pricing rule, while $\lambda = 0$ corresponds to perfect competition; intermediate values of λ correspond to intermediate solution concepts. Hence, I develop flexible pricing rule that permits a continuum of potential pricing regimes.

While this formulation is mathematically appealing, it is worth discussing its limitations. For one, it is agnostic about the source of market power — it cannot distinguish illegal price collusion from a natural monopoly. As stated in the Introduction, there is substantial anecdotal evidence

⁸Note that this formulation is identical to the expected trade costs posited in [Allen and Arkolakis \(2014\)](#).

⁹This setup is a minor departure from the markup model used in [Pfander \(2024\)](#); in that paper, I assume that the representative transporter is mode-specific. However, in this historical context, I cannot estimate the state of freight market competition due to a lack of bilateral flow data (see Section 3.3.1 for detail). I thus fix markups to their theoretical maximum to derive theoretically tractable upper-bound estimates.

of freight cartels during this time period; however, transport is also a high fixed-cost industry, naturally yielding some pricing power to existing carriers. The model is thus somewhat limited in terms of policy prescriptions.¹⁰ Relatedly, I do not model long-term investments; the transporter’s profit is completely static. However, infrastructure investments constitute a significant share of a transporter’s total costs. Modelling network creation is a non-trivial exercise that is beyond the scope of this paper.¹¹ Expanding the model to include network creation is a promising avenue for future research; for now, I treat the network as exogenously given. Finally, the model assumes that prices are the only avenue of competition among freight service providers. In reality, transporters may compete along numerous dimensions – e.g., safety, reliability, speed, and/or volume, among numerous other potential dimensions. While these alternate forms of service are not explicitly modeled in my framework, they are captured to the extent that they are capitalized into aggregate trade costs.

3.3 From Theory to Empirics

A non-trivial challenge of my historical analysis is that I do not observe bilateral trade flows, which would otherwise enable estimation of the gravity equation (Equation 3.7). Importantly, absent this flow data, or any other data on freight prices, I do not observe freight markups. I do, however, observe county-level production of distinct commodities, as well as total farm output, manufacturing production, population, and the farm value (land plus equipment and buildings). I thus exploit the structure of the equilibrium trade model developed in Section 3.2.1 to derive an equation, which permits estimation of my model fundamentals. With these fundamentals, I may simulate trade flows, and in turn, markups subject to an assumption of freight market conduct. In this section, I discuss my data sources, elaborate my procedure to estimate model fundamentals, and finally, elaborate a procedure to simulate endogenous bilateral frictions in the absence of trade or freight price data.

¹⁰While the model is agnostic about the source of market power in its current formulation, it could easily be adapted to distinguish between illegal collusion and natural barriers; this more flexible formulation would require additional data on fixed costs and/or firm entry and exit to be of empirical value.

¹¹Fajgelbaum and Schaal (2020) tackle optimal network formation in the context of a neoclassical trade model; however, their notion of “optimal” focuses on consumer welfare. In reality, transport firms build networks in response to a profit motive, with likely limited attention paid to consumer welfare.

3.3.1 Data

I utilize county-level agricultural production data from the U.S. Census of Agriculture from 1850 through 1910 ([Michael R. Haines and ICPSR, 2010](#)). These data provide snapshots of agricultural production in distinct commodities across every U.S. county at the start of each decade. The set of commodities included in the Census expands over time; I clean and harmonize production data for 15 of them, listed in Table 3.2. It is also important to note that U.S. counties are not static throughout my analysis: counties shift their borders, and the total number of counties grows as more counties and states incorporate. I follow [Donaldson and Hornbeck \(2016\)](#) to hold county borders static to their 1880 limits; I adjust the population and acreage measurements accordingly.¹² Finally, in addition to these commodity-specific production series, I utilize three aggregate variables per county, which will be used to estimate production productivities and input costs: the total number of improved acres in farmland, the total (nominal) value of farm equipment, and the total value of farmland (inclusive of land, capital, and buildings).

In addition to this agricultural data, I incorporate population and output data for each county from the decennial Censuses. Specifically, I observe total population, urban population (defined as cities with greater than 25,000 citizens), the total (nominal) value of manufacturing output, and the total (nominal) value of farm output. These aggregate data will again inform county-level estimates of productivity and input costs in each time period.

My other main data source is historical records on the expansion of the rail and waterway networks in the mainland U.S. through the latter half of the 20th Century. Specifically, I utilize historical rail and inland waterway (canals and navigable rivers) shapefiles from [Atack \(2015, 2016, 2017\)](#). Importantly, these data record not only the location of rail lines and waterways, but also report their first year of operation, as well as their year of closing where relevant. From this data, I create a snapshot of the national transportation network for each decade reported in the Census of Agriculture. Historical records dating back to 1850 do not exist for the road network, so I connect all county centroids within a 300km radius with a straight line; these roads are assumed available every decade. Finally, I augment this inland transport network with Sea and Lake routes from [Donaldson and Hornbeck \(2016\)](#); as with the road network, I assume that these lines are available throughout my analysis period. Full detail of the transport network from 1850 through 1910 is provided in Figure 3.2.

¹²Specifically, I assume that improved farm acres and rural population are uniformly distributed across the county; the total adjustment to acres and population equals the total change in size of the county.

3.3.2 Generating Distances in the Transport Network

As highlighted by Equation 3.6, a key input into the model is the distance along the least-cost path between two counties i and j via a given mode m . To generate these distances, I first calculate the (exogenous) cost of traversing the network. I follow [Donaldson and Hornbeck \(2016\)](#) and assume the relative cost structure displayed in Table 3.1. Note that the “fixed” cost of roadway travel is normalized to zero, so all f^m parameters are in reference to the roadway.¹³ Moreover, the per-mile cost of traversing the road is normalized to 1, so all cost parameters (both β^m and f^m) are in road-mile equivalents. Note that, absent bilateral trade data, I cannot estimate these cost parameters, and so hold them fixed. This parameterization further imposes that exogenous costs are symmetric.¹⁴ I apply this cost structure to my historical snapshots of the transport network at the start of each decade; I thus observe the exogenous portion of trade costs.

Given this detailed topography of transit costs throughout the U.S., I calculate the least-cost distance between counties along each mode using Dijkstra’s algorithm. Because I do not observe the distribution of economic activity within counties, I calculate the distance between county centroids.¹⁵ All centroids are connected to the road network by construction (see Section 3.3.1 for detail); freight originating at any centroid within 50 kilometers (approximately 31 miles) of a rail or water line may immediately travel via these networks. Freight coming from farther afield must first travel via the road network to reach one of these more proximate counties. Fixed costs are incurred at the start and end of journey, and when switching between modal networks.¹⁶ I thus generate ad-valorem, exogenous transit costs along every mode between every county pair at the start of each decade.

¹³While likely greater than zero, it seems reasonable to assume that roadway travel incurs the lowest “fixed” cost per mode: unlike rail, ships, or barges, which require travel to stations/ports and must be loaded completely before getting underway, wagons can be loaded at the factory gates relatively quickly.

¹⁴This assumption, while standard in the trade literature, is likely inaccurate when considering, e.g., asymmetric congestion ([Allen and Arkolakis, 2022](#); [Fuchs and Wong, 2023](#)) or elevation ([Sun, 2024](#)). However, my model allows for asymmetric trade costs due to bilateral markups set by the transport sector; see Section 3.2.2 for detail.

¹⁵This methodology contrasts with the routing logic utilized [Donaldson and Hornbeck \(2016\)](#), who calculate routes from multiple uniformly-distributed points within each county to generate a mean routed distance for each origin-destination pairing. This approach is undoubtedly more accurate but significantly more cumbersome; my approach is appealing for both its simplicity and its computational feasibility.

¹⁶The only trans-shipment I allow is for freight to switch between the road and either the rail or water networks. I do not allow multi-modal movements that incorporate both rail and water.

3.3.3 Transforming the Gravity Equation

I now develop a framework to simulate bilateral trade flows, and consequently, freight markups. The overall goal is to isolate an expression for trade flows, as well as aggregate production of a commodity k , in quantities as opposed to value; the necessity of this theoretical exposition stems from not observing commodity-specific prices or values in my data. Importantly, the structure elaborated here follows immediately from the trade model developed in Section 3.2.1; I do not impose any further assumptions.

From Equation 3.1, it follows that demand for variety ω^k in location j is given by

$$q_{jt}(\omega^k) = \zeta^k B_{jt} P_{jt}^k (\sigma^k - 1) p_{jt}(\omega^k)^{-\sigma^k} \quad (3.9)$$

where P_{jt}^k is the CES price index. Aggregating demand across varieties yields the following expression for the total quantity of k consumed in j :

$$\begin{aligned} Q_{jt}^k &= \int_{\Omega^k} q_{jt}(\omega^k) d\omega^k \\ &= \kappa_2^k B_{jt} \phi_{jt}^k (1/\theta) \end{aligned} \quad (3.10)$$

where $\kappa_2^k = \zeta^k \Gamma\left(\frac{\theta - \sigma^k}{\theta}\right) / \Gamma\left(\frac{\theta - \sigma^k + 1}{\theta}\right)$. It follows that the total quantity of k travelling from i to j is given by

$$\begin{aligned} Q_{ijt}^k &= Q_{jt}^k \pi_{ijt}^k \\ &= \kappa_3^k A_{it}^k (c_{it} \mu_{ijt}^k)^{-\theta} V_{ijt}^{\theta/\rho} (\phi_{jt}^k)^{\frac{1-\theta}{\theta}} B_{jt} \end{aligned} \quad (3.11)$$

Total production in i is thus

$$\begin{aligned} Q_{it}^k &= \sum_j Q_{ijt}^k \\ &= \kappa_3^k A_{it}^k c_{it}^{-\theta} \underbrace{\sum_j \left(\mu_{ijt}^k V_{ijt}^{-1/\rho} \right)^{-\theta} (\phi_{jt}^k)^{\frac{1-\theta}{\theta}} B_{jt}}_{\text{"Market Access"}} \end{aligned} \quad (3.12)$$

where $\kappa_3^k = \kappa_1 \kappa_2^k$. Note that the summation in Equation 3.12 constitutes a modified market access term; it captures the global (or in my case, national) demand for good k out of i . In contrast to

other formulations of market access in the literature (Donaldson and Hornbeck, 2016; Chan, 2022; Hornbeck and Rotemberg, 2024), I measure demand in terms of quantity, not value. To understand market access intuitively, it is helpful to re-write Equation 3.12 as

$$Q_{it}^k = \kappa_4^k A_{it}^k c_{it}^{-\theta} \sum_j \left(\frac{\mu_{ijt}^k \bar{r}_{ijt}}{P_{jt}^k} \right)^{-\theta} \left(\frac{B_{jt}}{P_{jt}^k} \right) \quad (3.13)$$

where $\kappa_4^k = \zeta^k \Gamma\left(\frac{\theta - \sigma^k}{\theta}\right) \Gamma\left(\frac{\theta - \sigma^k + 1}{\theta}\right)^{\frac{1}{\theta}}$. It is evident from this equation that market access is a weighted sum of real expenditure across all available destinations; the weights are inversely related to bilateral trade costs (exogenous transit costs and markups), discounted by the price level in the destination county j .

Finally, it will prove expedient to define the share of exports from i travelling to j , which may be found by combining Equations 3.11 and 3.12:

$$\begin{aligned} \tilde{\pi}_{ijt}^k &= \frac{Q_{ijt}^k}{Q_{it}^k} \\ &= \frac{\left(\mu_{ijt}^k V_{ijt}^{-1/\rho}\right)^{-\theta} (\phi_{jt}^k)^{\frac{1-\theta}{\theta}} B_{jt}}{\sum_{j' \in \mathcal{S}} \left(\mu_{ij't}^k V_{ij't}^{-1/\rho}\right)^{-\theta} (\phi_{j't}^k)^{\frac{1-\theta}{\theta}} B_{j't}} \end{aligned} \quad (3.14)$$

Note that this trade share formulation differs from Equation 3.7, as this expresses the share of **exports** (in quantities) out of i that travel to j ; in contrast, Equation 3.7 describes the share of **imports** (in value) into j that originate in i . I utilize the equations elaborated here to develop my estimation framework.

3.3.4 Simulating Trade Flows, Markups

The final task is to convert the structure expounded in Section 3.3.3 into an estimable equation. Recall that I observe aggregate production of commodity k in each county i , but do not observe bilateral frictions, trade flows, or commodity-specific prices. Thus, the market-access term in Equation 3.12 remains unobserved. It is particularly challenging to estimate bilateral markups μ_{ijt}^k absent data on freight prices or trade flows. I thus rely on a simulated method of moments strategy to estimate these fundamental parameters. In short, I simulate bilateral trade flows π_{ijt}^k to facilitate estimation of Equation 3.11, which is log-linear and thus provides a convenient framework to estimate my model fundamentals. The goal is to generate estimates of input costs c_{it} and

productivities A_{it}^k that are consistent with the model structure derived in Section 3.2.

I emphasize that, absent bilateral data, I cannot estimate all model parameters via this strategy. Explicitly, all parameters that govern bilateral frictions – the modal elasticity parameter ρ and the conduct parameter λ – are not identified by my production data. In the case of the former, I rely on estimates of ρ from [Donaldson and Hornbeck \(2016\)](#), who – broadly speaking – examine the same time period, utilize similar data sources, and also employ a Ricardian trade model to identify the influence of the transportation sector on the domestic economy. The similarity of our approaches suggests that this estimate of the modal elasticity is appropriate. Regarding λ : due to the absence of comprehensive, national price data from the 19th Century, no comparable estimates of freight market conduct exist. Rather than calibrate this parameter from the literature, I simply set it to 1 at the outset. I thus present the upper-bound of markups assuming that freight markups were perfectly concentrated.

My estimation technique utilizes an Expectation-Maximization (EM) algorithm.¹⁷ I utilize this framework to estimate the production parameters A_{it}^k and c_{it} , as well as bi-lateral markups. The process proceeds as follows.

- (1) From Equation 3.6, calculate $V_{ijt} = \sum_{m \in \mathcal{M}_{ijt}} \exp(-\rho(\beta^m \text{Miles}_{ijt}^m + f^m))$.
- (2) Take an initial guess at the production parameters, $\{A_{it}^{k(0)}, c_{it}^{(0)}\}$. Recall that, throughout this analysis, I hold fixed the exogenous cost parameters β^m, f^m , the trade elasticity θ , as well as the modal elasticity parameter ρ and the conduct parameter λ .
- (3) Utilize a contraction mapping to calibrate trade shares, markups based on the current set of parameter estimates:
 - (a) From Equation 3.7: $\pi_{ijt}^{k(0)} = A_{it}^{k(0)} \left(c_{it}^{(0)} \mu_{ijt}^{k(0)} \right)^{-\theta} V_{ijt}^{(\theta/\rho)} \left(\phi_{jt}^{k(0)} \right)^{-1}$, where the price parameter $\phi_{jt}^{k(0)} = \sum_{i'} A_{i't}^{k(0)} \left(c_{i't}^{(0)} \mu_{i'jt}^{k(0)} \right)^{-\theta} V_{i'jt}^{(\theta/\rho)}$.
 - (b) From Equation 3.8: $\mu_{ijt}^{k(0)} = \frac{(1 - \pi_{ijt}^{k(0)}) \bar{\tau}_{ijt} + \sum_{i' \neq i, j} (\mu_{i'jt}^{k(0)} - 1) \bar{\tau}_{i'jt} \pi_{i'jt}^{k(0)}}{(1 - \pi_{ijt}^{k(0)}) \bar{\tau}_{ijt} - (\lambda/\theta) \bar{\tau}_{ijt}}$.
- (4) Calculate the total quantity travelling between i and j utilizing Equation 3.14:

$$Q_{ijt}^{k(0)} = Q_{it}^k \tilde{\pi}_{ijt}^{k(0)}$$

¹⁷An EM process has been used to some extent in the economics literature – see, e.g., [Bonadio \(2021\)](#), as well as the parallel paper [Pfander \(2024\)](#)

$$= Q_{it}^k \left(\frac{(\mu_{ijt}^{k(0)})^{-\theta} V_{ijt}^{(\theta/\rho)} (\phi_{jt}^{k(0)})^{\frac{1-\theta}{\theta}} B_{jt}}{\sum_{j' \in \mathcal{S}} (\mu_{ij't}^{k(0)})^{-\theta} V_{ij't}^{(\theta/\rho)} (\phi_{j't}^{k(0)})^{\frac{1-\theta}{\theta}} B_{j't}} \right)$$

noting that Q_{it}^k and B_{jt} is observed.¹⁸

(5) Utilize Equation 3.11 to inform a log-linear estimating equation:

$$\left(Q_{ijt}^{k(0)} + \theta \mu_{ijt}^{k(0)} - (\theta/\rho) V_{ijt} \right) = \underbrace{\gamma_{s(i)t}^k + f(x_i, y_i) \gamma_t + X_{it} \alpha_t}_{\kappa_3^k + \ln A_{it}^k - \theta \ln c_{it}} + \underbrace{\gamma_{jt}^k}_{\frac{1-\theta}{\theta} \ln \phi_{jt}^k + \ln B_j} + \varepsilon_{ijt}^k \quad (3.15)$$

where $\sinh$ denotes the inverse hyperbolic sine transformation,¹⁹ γ denotes the corresponding fixed-effects, $s(i)$ denotes the U.S. state of the originating county, $f(x_i, y_i) \gamma_t$ is a cubic polynomial of the centroid's longitude and latitude interacted with a time fixed-effect, X_{it} is a vector of time-varying county characteristics, and finally, ε_{ijt}^k is a structural error term. I will provide further detail on this specification shortly.

Denote the estimated production parameters from this equation $\{A_{it}^{k(1)}, c_{it}^{(1)}\}$.

(6) Return to step 3 with the new parameter estimates and repeat.

Under assumptions normally required for linear regression model, the parameter estimates from this process converge to the maximum-likelihood estimates, which I will denote $\hat{\pi}_{ijt}^k$, $\hat{\phi}_{ijt}^k$, and $\hat{\mu}_{ijt}^k$.²⁰

The regression specification presented in Equation 3.15 merits some discussion. First, the variation that identifies productivities and input costs stems from differences in aggregate production across commodities, counties, and time. The bilateral variation (i.e., the flow of goods between i and j) is simulated for the sake of making OLS estimation feasible; it adheres strictly to the constructs of the model.²¹ To isolate the non-simulated variation, I include destination-by-commodity-by-year fixed effects, γ_{jt}^k , which control for a wide array of demand determinants like preferences for a particular commodity in a particular location, as well as budget constraints and local price levels. I also normalize the quantity by two variables that capture bilateral frictions, $\ln V_{ijt}$ and $\ln \mu_{ijt}^{k(0)}$.

¹⁸While I do not directly observe a county's total expenditure, I assume that B_{jt} is proportional to the sum of its manufacturing and agricultural output.

¹⁹This function, defined as $(x) = \ln(x + \sqrt{x^2 + 1})$ for some real-valued variable x , approximates the natural logarithm but has the advantage of being defined at zero.

²⁰Pfander (2024) provides a detailed proof of convergence.

²¹A consequence of this simulated variation is that, were I to estimate a version of Equation 3.15 including an origin-by-commodity-by-year fixed effect, my regression would perfectly predict quantity flows; the estimated fixed-effect would not only capture productivity and input costs for a given county, but also market access, which is exactly what I aim to isolate via this EM procedure.

These variables control for the remaining, simulated bilateral variation. The residual variation I attribute to the productivity and cost parameters A_{it}^k and c_{it} .

The portion of the fixed effects that vary by commodity and year are crucial to identifying the productivity parameters. These fixed-effects remove variation in aggregate production across commodities due to commodity- and year-specific idiosyncrasies, for example, differences in units of measurement²² or for broad climate conditions that may affect the national production of a particular commodity. They also control for potential differences in bilateral trade costs across commodities. Though not explicitly modeled in the structure developed in Section 3.2, it is easy to imagine that different commodities incur different transit costs due to, e.g., weight, bulk, or spoilage rates. To the extent that these commodity-specific frictions are multiplicative of mean trade costs, they are captured by these fixed effects. Hence, my fixed-effects control for a wide array of measurement and/or structural errors.

The parameters A_{it}^k and c_{it} , which collectively govern productivity and input costs in a given location, are jointly estimated by a bevy of time-varying county characteristics X_{it} , as well as time-specific cubic polynomials of the county centroid's longitude and latitude $f_t(x_i, y_i)$ and state-by-commodity-by-year fixed-effects $\gamma_{s(i)t}^k$. Explicitly, X_{it} includes the inverse hyperbolic sine transform of the county's total population, rural population (defined as all those living in areas with fewer than 25,000 residents), nominal dollar-value of farm equipment, total improved farm acreage, and nominal dollar-value of all farm output. Because these productivities and input costs are not directly observed, there is some concern regarding mis-specification of these production parameters. Explicitly, failure to accurately estimate these production parameters will result in error in my calibrated trade shares $\hat{\pi}_{ijt}$, which in turn will bias my estimates of bilateral markups $\hat{\mu}_{ijt}^k$. Absent additional, time-varying data on agricultural productivity or worker's wages, it is difficult to evaluate how well this parameterization fits the data. However, it is worth noting that a similar formulation is used by [Chan \(2022\)](#) to estimate agricultural productivity.

Recall that the goal of this section is to develop a methodology to estimate the fundamental parameters of my equilibrium trade model; with these fundamentals, I may simulate otherwise unobserved bilateral trade flows and the resultant markups. The EM process described above results in well-identified, robust estimates of A_{it}^k and c_{it} ; subject to a calibrated modal elasticity and an

²²To elaborate, production of livestock (cattle and sheep) are measured in individual animals; production of corn is measured in tons; and production of wine is measured in gallons. The commodity fixed-effects control for these differences in units.

assumed value of the conduct parameter, I simulate trade flows and freight markups according to the structure laid out in Section 3.2. I thus arrive at theoretically tractable estimates of freight markups, specified to distinct origin-destination pairs, throughout the latter-half of the 19th Century. Because I set the conduct parameter to 1, my estimates of markups represent the upper-bound. In the next section, I use these upper-bound estimates to assess the maximum impact of freight market concentration on domestic output during this time period.

3.4 Evaluating the Impact of Transport Pricing on Output

I adopt a relatively simple, reduced-form framework to evaluate the impact of freight market concentration on domestic output. The purpose of this analysis is to estimate how changes to market access affect agricultural production. Recall that, in this context, market access is a weighted-sum of real expenditure across every U.S. county; the weights are inversely proportional to transit costs, inclusive of freight markups. As a first step, I exploit plausibly-exogenous variation in market access across time to identify how changes in market access affect domestic production. With these causal estimate in hand, I estimate how increases in market access brought about by counterfactual reductions in freight market power cause corresponding shifts in production and price levels in each U.S. county throughout the mid 19th and early 20th Century.

3.4.1 Estimating the Effects of Market Access on the Level of Production

I first isolate the effect of market access on agricultural production. My estimating equation is:

$$Q_{it}^k = \gamma_{s(i)t}^k + \gamma_i^k + f(x_i, y_i)\gamma_t + \xi \underbrace{\text{MA}_{it}^k}_{\sum_{j \neq i} \left(\hat{\mu}_{ijt}^k V_{ijt}^{-1/\rho} \right)^{-\theta} \left(\hat{\phi}_{jt}^k \right)^{\frac{1-\theta}{\theta}} B_{jt}} + u_{it}^k \quad (3.16)$$

where γ , as before, denotes the corresponding fixed effects, and $f(x_i, y_i)\gamma_t$ is a cubic polynomial of the county's latitude and longitude interacted with a time fixed-effect. A nearly-identical specification is used by both [Donaldson and Hornbeck \(2016\)](#) and [Chan \(2022\)](#) to evaluate the effect of market access on agricultural land values and the total value of agricultural production, respectively. The parameter ξ is the effect that I want to estimate: the causal impact of changes in market access on domestic quantity of production. I now describe why this relationship is causal.

The fixed-effects are crucial to my identification strategy. As in Equation 3.15, the parameter

$\gamma_{s(i)t}^k$ controls for unobservable variation due to commodity, time, and state-specific idiosyncrasies like differences in units or measurement or statewide climate shocks; it also controls for state-specific policies that may influence agricultural output – for instance, settlement incentives. The parameter γ_i^k removes variation unique to the origin county and commodity; it controls for a county’s overall suitability at growing k . Similarly, the polynomial of the county’s latitude and longitude control for overall growing conditions. The residual variation that identifies ξ is thus the differential change in market access to specific counties over time within the state. This variation stems development of the transit network, the economic growth of destination markets (i.e., all other U.S. counties), and the resultant change in the bilateral markup.

An immediate concern is that these bilateral markups are endogenous to the total quantity produced. Counties that become relatively more productive over time will garner larger trade shares than their less-productive neighbors, thus earning higher bilateral markups and lower market access. Co-movement of total agricultural production and market access is thus at least partially determined by the endogenous pricing response of imperfectly competitive transporter.²³ To address this threat to identification, I utilize the perfectly-competitive version of market access as an instrument. Explicitly, my first-stage estimating equation is

$$\text{MA}_{it}^k = \delta_{s(i)t}^k + \delta_i^k + f(x_i, y_i)\delta_t + \vartheta \underbrace{\widetilde{\text{MA}}_{it}^k}_{\sum_{j \neq i} V_{ijt}^{\theta/\rho} (\hat{\phi}_{jt}^k)^{\frac{1-\theta}{\theta}} B_{jt}} + v_{it}^k \quad (3.17)$$

where δ now denotes fixed-effects. As emphasized by [Donaldson and Hornbeck \(2016\)](#), [Chan \(2022\)](#), and [Hornbeck and Rotemberg \(2024\)](#), the variation of this perfectly-competitive market access term over time within a particular county is plausibly exogenous to that county’s agricultural production. The national scale is so large that local conditions (that is, economic and transit network development in your own and neighboring counties) matter relatively little in the calculation of the instrument. To further alleviate potential endogeneity of market access to agricultural output, I omit a county’s own expenditure from the market access calculation. The variation in perfectly-competitive market access over time thus stems from expansion of the transit network nationally.

²³It should be noted that my formulation does **not** suffer from endogeneity due to market entry. Counties that become more productive over time will garner higher trade volumes, thus attracting more freight service providers and, ideally, lowering freight rates. However, I observe neither trade flows nor freight prices – as explained in Section 3.3.4, the markups entering into equation 3.16 are simulated from the estimated productivity parameters and assume a perfect monopoly in the market for freight services. There is thus no scope for endogenous changes to the transporter’s pricing conduct; rather, the estimates displayed here impose that freight markups are at the upper-bound.

Finally, there is the risk that growth in the destination's expenditure, B_{jt} , is endogenous to growth in agricultural output due to unobserved, bilateral factors. While this risk is perhaps greatest for own-county expenditure, which is removed from my calculation of market access, I further alleviate this concern by re-calculating both the endogenous market access term and the perfectly-competitive market access used as an instrument with alternate measures of market size. Specifically, I utilize: i) population, which is correlated with total expenditure but less obviously related to agricultural output;²⁴ ii) expenditure in 1850, which removes any variation in market size over time, such that all changes in market access are attributable solely to the development of the transit network and the consequent changes in markups;²⁵ and iii) population in 1850, which combines the previous two methods and presents the least endogeneity concerns, at the cost of potentially mis-measuring market access.²⁶

My estimation sample comprises 1,572 counties and 15 commodities that are observed in all years of data. Utilizing the balanced panel mitigates concerns regarding endogenous county creation: new population centers are likely to develop in areas that stand to gain the most from the new transit network; I thus limit my primary specification to counties that exist throughout my analysis period.²⁷ Even amongst this balanced panel, small, remote counties will likely see bigger percentage gains relative to larger, established counties. To mitigate the effect of these small counties, I follow [Donaldson and Hornbeck \(2016\)](#) and [Chan \(2022\)](#), and weight my regressions by the value of agricultural output in 1850. Results of my primary specification, as well as those using alternative market access measures and an unweighted version are displayed in Panel A of Table 3.4. Reassuringly, my estimates are highly similar across all specifications, assuaging concerns of endogeneity.

²⁴Explicitly, $MA_{it}^{kPop} = \sum_{j \neq i} \left(\hat{\mu}_{ijt}^k V_{ijt}^{-1/\rho} \right)^{-\theta} N_{jt}$, where N_{jt} denotes the population of market j at time t . The perfectly-competitive versions of this formulation (where bilateral markups mu_{ijt}^k are set to 1) is used by both [Donaldson and Hornbeck \(2016\)](#) and [Chan \(2022\)](#) as a primary measure of market access.

²⁵Explicitly, $MA_{it}^{k1850} = \sum_{j \neq i} \left(\hat{\mu}_{ijt}^k V_{ijt}^{-1/\rho} \right)^{-\theta} (\hat{\phi}_{jt}^k)^{\frac{1-\theta}{\theta}} B_{j1850}$.

²⁶In this case, $MA_{it}^{kPop1850} = \sum_{j \neq i} \left(\hat{\mu}_{ijt}^k V_{ijt}^{-1/\rho} \right)^{-\theta} N_{j1850}$

²⁷As a robustness check, I re-run my analysis utilizing my full sample of 2,725 counties. Results from this unbalanced panel are presented in Table 3.6, and are generally larger than my primary specification.

3.4.2 Estimating the Effects of Market Access on Total Value

I also evaluate the effect of market access on the nominal value of total agricultural production. My estimating equation is as follows:

$$Y_{it} = \gamma_i + \gamma_{s(i)t} + f(x_i, y_i)\gamma_t + \underbrace{\eta \text{MMA}_{it}}_{\mathbf{E}_k[\text{MA}_{it}^k]} + u_{it} \quad (3.18)$$

where Y_{it} denotes the sum-total value of all agricultural production in i and MMA denotes “mean market access”, the simple average of market access across commodities in i . The parameter η captures the effect of changes in market access on the total value of agricultural production. In contrast to ξ , which identified the effect of market access on the quantity of production, this identifies the effect of market access on the **value** of production. This distinction is important, as granular price data are scarcely available for this period – however, using my estimates of η and ξ , I may approximate the effect of market access on local agricultural prices, which I will elaborate shortly.

As before, there is concern of endogeneity of mean market access due to bilateral markups. I utilize a similar IV strategy where my instrument is the simple average of perfectly-competitive market access across commodities. Explicitly, my first-stage estimating equation is given by:

$$\text{MMA}_{it} = \delta_i + \delta_{s(i)t} + f(x_i, y_i)\delta_t + \underbrace{\eta \widetilde{\text{MMA}}_{it}}_{\mathbf{E}_k[\widetilde{\text{MA}}_{it}^k]} + v_{it} \quad (3.19)$$

The identification argument for Equation 3.18 is very similar to the argument just laid out for Equation 3.16; I thus speak briefly to why my estimates of η are causal. Origin and time fixed effects respectively control for unobservable county-specific productivity – like the overall quality of farmland in the county – as well as national macroeconomic trends like inflation or technology growth. The state-by-time fixed effects controls for unobserved trends that would affect agricultural productivity statewide; similarly, the time-varying polynomial of a county’s latitude and longitude control for the overall agricultural productivity of a particular county. As in Equation 3.16, the residual variation that identifies η is the change in market access within county over time, which is driven by the expansion of the transit network, the economic development of every other U.S. county, and the resultant change in freight markups. The IV strategy removes identification concerns stemming from the potential endogeneity of these bilateral markups to aggregate agricultural

production.

I reiterate that, because perfectly-competitive market access reflects the national distribution of economic activity, variation in the instrument is almost purely exogenous to local economic conditions – namely, agricultural output; this exogeneity is reinforced by the fact that I omit local expenditure from the calculation of market access. To evaluate the potential for endogeneity of expenditure nationwide to the total value of production in county i , I again re-calculate market access using a variety of measures for market size: contemporaneous population, expenditure in 1850, and population in 1850. These alternate measures reduce endogeneity problems, but potentially mis-measure market access.

My estimating sample consists of a balanced panel of 1,572 counties. I again omit counties that incorporate during my sample period to address concerns of endogenous entry. I further weight my regressions by the value of farm output in 1850, thus limiting the impact of small, isolated counties that would see large percentage gains from market access. As a robustness check, I again run an unweighted version. Results of this analysis are reported in Panel B of Table 3.4; the stability of my estimates across specifications again suggest that endogeneity is of relatively minor concern.

As stated previously, the combination of η and ξ allow me to estimate the effect of market access on local price levels. Explicitly, from the fact that $\ln Y_{it} = \ln Q_{it} + \ln P_{it}$, it follows that $\eta = \xi + \kappa$, where κ is the effect of increased market access on local agricultural prices. Hence, with estimates of η and ξ from estimating Equations 3.16 and 3.18, I also estimate the price effect κ . Results of this exercise are reported in Panel C of Table 3.4.

3.4.3 Results

Table 3.3 presents summary statistics on the key variables in my regression analysis for my primary estimation sample. These include the total quantity of each commodity produced, the total nominal value of farm output, as well as market access and its perfectly-competitive analogue in each decade. In addition to providing context to the forthcoming regression analysis, these summary measures also reveal that bilateral markups at the upper-bound are non-trivial. Existing measures of market access in the literature, which exclude endogenous freight pricing, may thus drastically over-state the change in market access caused by the 19th-Century railroad boom. In this section, I utilize the reduced-form methodology expounded in Sections 3.4.1 and 3.4.2 to evaluate how my measure of market access – which includes upper-bound estimates of bilateral freight markups – affect U.S.

agricultural production. Importantly, I utilize this same regression framework to quantify the extent of bias introduced by excluding endogenous freight pricing from my measures of market access.

I focus first on the causal impact of market access changes on agricultural production. Results of this analysis are displayed in Table 3.4; Panel A displays the effects of increased market access on the level of output; Panel B describes the effect of market access on the total value of production; Panel C isolates the effect on local agricultural prices, and is calculated by subtracting the estimated coefficient in Panel B from the estimate in Panel A.²⁸ Columns (2) through (4) utilize alternative formulations of market access to address potential sources of endogeneity, as discussed previously. Column (5) presents an unweighted version of my regression results.

The Table reveals substantial impacts of increased market access on agricultural output. Focusing first on Column (1), the estimate reported in Panel A reveals that a 1% increase in market access leads to an estimated 0.974% increase in the total level of production within a given county. Switching focus to Panel B, a 1% increase in market access leads to a 1.87% increase in the total value of agricultural production. In tandem, these two estimates imply that a 1% increase in market access leads to a 0.896% increase in mean agricultural prices, as displayed by Panel C. These effects are all statistically different from zero at the 1% level of confidence, if not greater.

Columns (2) through (4) report highly similar coefficients. The measures of market access using population tend to find slightly lower impacts on output, but highly stable price effects. The stability of my estimates across alternate measures of market access suggest that endogeneity of my instrument presents relatively little concern. Column (5) reports estimates from an unweighted regression analysis and finds much larger effects. This noted difference from my primary specification in Column (1) suggests that, as expected, the smallest counties see the biggest percentage increases. In other words, the treatment effect is likely convex by initial market size, biasing up the average treatment effect reported in Column (5); the weighting utilized in Columns (1) through (4) offsets this bias. However there remains concern that the weighting does not completely address this bias. To evaluate this further, I estimate heterogeneous effects by market size in Section 3.4.4.

A notable finding is that, across the weighted specifications, the price and quantity effects are roughly equivalent in magnitude and of the same sign. This finding is important for consumer welfare considerations: although the total quantity of production increases, the accompanying and equivalently-sized price effects offset potential welfare gains. This finding also suggests that, if

²⁸Standard errors in Panel C are pooled from the standard errors reported in Panels A and B.

the change to market access is purely a demand shock,²⁹ then the agricultural supply curve is approximately unit-elastic. The magnitude of welfare consequences of this change to market access thus depend entirely on the elasticity of demand for agricultural goods.

How does incorporating freight market power into the calculation of market access shape our understanding U.S. production growth? This question is central to the contribution of this paper; to address it directly, I re-estimate Equation 3.16 using perfectly-competitive market access (my instrument from the previous regression).³⁰ This version of market access more closely mirrors existing measures in the literature (Donaldson and Hornbeck, 2016; Chan, 2022); however, it imposes perfect competition in the freight-services sector, an assumption that likely fails during this historical period, which saw the rise and subsequent dissolution of numerous freight cartels. As displayed by Table 3.3, excluding endogenous freight pricing leads to drastic changes in the measure of market access. How does this mis-measurement impact estimates of the causal effect of market access changes on U.S. output?

Results of the analysis using the perfectly-competitive market access are displayed in Table 3.5.³¹ Notably, the same patterns hold as in my primary specification: i) the price and quantity effects are roughly similar in magnitude and of the same sign; ii) the findings are robust to alternate measures of market access that address potential endogeneity; and iii) the unweighted versions create much larger estimates, suggesting some convexity of the treatment effects by initial market size. However, the coefficients from this analysis are generally just over half the size of the coefficients reported in Table 3.4. This noted change in magnitude accords with expectation: the perfectly-competitive measure of market access omits potentially large bilateral frictions, generating positive bias.³² This upward bias in the independent variable biases downward the estimated coefficient. Hence, existing estimates in the literature likely understate the true effect of market access improvements by omitting endogenous freight pricing; the extent of the bias can be substantial, nearly double the reported coefficient at the upper-bound.³³

²⁹This view is reinforced by findings in the literature that market access changes scale up the level of production but have limited effect on agricultural factor productivity (Chan, 2022).

³⁰Explicitly, my regression specification is $Q_{it}^k = \gamma_{s(i)t}^k + \gamma_i^k + f(x_i, y_i)\gamma_t + \xi \widetilde{\text{MA}}_{it}^k + u_{it}^k$.

³¹Note that this versions does not require an instrumental variables strategy, as the endogenous portion of trade costs is omitted.

³²Table 3.3 summarizes the extent of this bias.

³³Recall that I assume that freight markets are perfectly concentrated throughout this analysis. Hence, I present the upper-bound on bias stemming from this mis-measurement of market access.

3.4.4 Heterogeneous Effects

The un-weighted regressions suggest convexity of the treatment effects by initial level of farm output. To evaluate this heterogeneity directly, I repeat my regression analysis allowing for heterogeneous effects of market access expansion by deciles of initial farm output. My regression specifications are as follows:

$$Q_{it}^k = \gamma_{s(i)t}^k + \gamma_i^k + f(x_i, y_i)\gamma_t + \xi^d \left(D_{i1850} \times MA_{it}^k = D_{i1850} \times \widetilde{MA}_{it}^k \right) + u_{it}^k \quad (3.20)$$

$$Y_{it} = \gamma_{s(i)t} + \gamma_i + f(x_i, y_i)\gamma_t + \eta^d \left(D_{i1850} \times MMA_{it} = D_{i1850} \times \widetilde{MMA}_{it} \right) + u_{it} \quad (3.21)$$

where D_{i1850} is a vector of indicators denoting a county's decile of total farm output in 1850. As before, the endogenous market access term is instrumented by the perfectly-competitive market access formulation more common in the literature. I again back-out the price effects $\kappa^d = \eta^d - \xi^d$. Results of this analysis are presented in Figure 3.2; Panel A reports the effects on quantity, Panel B reports the effects on the total value, and Panel C reports effects on price.

As displayed by the Figure, the estimated effects on the quantity and the total value of farm output decrease monotonically in the county's initial size; the effects on local agricultural prices are flat. As expected, the smallest counties see the largest gains: counties in the first decile of farm production in 1850 see an approximately 0.994% increase in the total quantity of production for every 1% increase in market access; this effect falls to 0.829% in the second decile and 0.710% in the third. The highest-producing counties in 1850 see an effect of 0.472%, just over half the size of the effects for the smallest counties. The patterns for total value are similar: the counties in the first decile of production see the total value of agricultural production increase 1.36% for every 1% increase in market access, while the highest-producing counties see an effect 0.853%. All of these effects are statistically significant at the 0.1% level; the difference in coefficients between the first and tenth decile are statistically significant for the quantity and value regressions at the 5% level of confidence. Finally, the average effects reported in Figure 3.2 are smaller than the average treatment effect reported in my main specification, suggesting that the weighting in my primary specification does not completely resolve bias due to the convexity of the treatment effect by market size.

This pattern of heterogeneity aligns with expectation. As stated previously, the literature has established that market access improvements have limited impacts on factor productivity (Chen, 2022; Hornbeck and Rotemberg, 2024). Larger, more initially-productive counties have less scope

to scale-up production via increased land use, equipment, or population. Less-productive counties, in contrast, may simply have more (or at least, more easily-accessible) untapped resources to devote to agricultural production in response to market access shifts. Notably, no decile reports a null or negative effect, meaning market access improvements have non-trivial, positive effects on the level of agricultural production across the distribution of farm output.

Given this marked heterogeneity in the effects on quantity, it is notable that my estimated price effects are uniform. There are two potential explanations for this result. First, market access improvements – which may be thought of as an upward shift in the local demand curve – spark an equivalent, downward shift in the local agricultural supply curve; the uniform, $\sim 0.4\%$ effect that I find reflects the difference in elasticity across these two curves. This explanation seems unlikely, as [Chan \(2022\)](#) find that market access has relatively little impact on agricultural factor productivity; rather, the new output is almost entirely explained by an increase in inputs (namely, land, rural laborers, and equipment value) – hence, increases in quantity seem to stem from movement along, not a shift in, the supply curve. A second potential explanation is that agricultural prices are set on large, regional markets.³⁴ Because my specification includes state-by-commodity-by time fixed effects, the residual variation that I capture is the national change in agricultural prices generally, which affects all counties equally.³⁵ However, absent disaggregate, historical price data, it is difficult to confirm this hypothesis empirically.

3.4.5 Estimating the Effects of Freight Market Concentration

The final stage of my analysis is to understand which particular regions are affected by the exercise of freight market power. Towards this end, I conduct a simple exercise: utilizing the heterogeneous estimates from Section 3.4.4, I estimate how agricultural production would have shifted in response to the total elimination of freight market power. Explicitly, for every county in every decade, and for each commodity, I calculate the difference between my favored measure of market access and its perfectly-competitive counterpart:

$$\widehat{\text{MA}}_{it}^k = \underbrace{\widehat{\text{MA}}_{it}^k}_{\sum_{j \neq i} (\bar{\tau}_{ijt}/P_{jt}^k)^{-\theta} (B_{jt}/P_{jt}^k)} - \underbrace{\text{MA}_{it}^k}_{\sum_{j \neq i} (\mu_{ijt}^k \bar{\tau}_{ijt}/P_{jt}^k)^{-\theta} (B_{jt}/P_{jt}^k)} \quad (3.22)$$

³⁴[Craig \(1993\)](#) emphasizes that agricultural prices are set in large, geographic regions.

³⁵An implication of this theory is that local producers treat the demand curve as perfectly inelastic.

I then utilize my causal estimates of the impact of market access changes to assess how this counterfactual elimination of freight market power would have affected agricultural production:

$$\hat{Y}_{it}^k = \eta^d \left(D_{i1850} \times \widehat{MA}_{it}^k \right) \quad (3.23)$$

I then convert these counterfactual changes into percent changes from the observed production. The counties that see the largest gains from this counterfactual exercise are most vulnerable to the broad exercise of freight market power.³⁶

I present the results of this analysis in two forms. Table 3.7 presents summary statistics on the distribution of these production changes each decade. This table reveals that these distributions are extremely skew right in every period. In 1910, 50% of observable counties³⁷ see production gains of approximately 0.20% or less as a result of the complete elimination of freight market power. The county at the 75th percentile see gains of just over 1%, while the most-affected county see gains of nearly 357%.³⁸ This same pattern holds for the preceding decades, with the period from 1860 through 1890 reporting the most extreme effects.

It is evident from these distributions that freight market power affects relatively few counties extremely. Where are these impacted counties? Figure 3.3 presents a heat map of counterfactual production changes each decade from 1950 through 1910. Dark red denotes more extreme reactions; lighter colors represent a more mild response. Generally, the worst-affected areas are newer, re-mote counties located along the American frontier, as well more-established counties in the Pacific Northwest, Appalachian mountain range, and along the Gulf of Mexico. Over time, these losses move west with American expansion into the Great Plains and Rocky Mountains; frontier counties along the plains generally exhibit more extreme losses than established population centers in the Midwest and along the East Coast.

This geographic pattern is at least partially explained by my earlier result that smaller, initially less-productive counties see the greatest impacts of market access; these coefficients input directly into this calculation of potential gains. However, the level of heterogeneity exhibited in this geographic distribution is not completely explained by differences in my estimated causal effects —

³⁶What this analysis misses are the consequences of geographically heterogeneous exercise of freight market power. Throughout this paper, I assume that freight markets nationally are perfectly concentrated; absent data on bilateral trade and/or freight prices, I cannot identify the geographic distribution of freight market power.

³⁷Note that not every county is included in this analysis. Rather, it is confined to those counties that appear in the Census of Agriculture in the given decade.

³⁸This distribution omits the top 0.1% of affected counties each year to remove extreme outliers.

rather, the residual difference is attributable to higher impacts of market power in these remote areas due to higher markups. By the end of my analysis period, the most extreme geographic heterogeneity subsides and losses become more uniformly distributed; a pattern which may be attributable to the proliferation of the railroad and the death of the American Frontier.

3.5 Conclusion

This paper modifies the well-known market access framework to generate upper-bound estimates of agricultural production losses due to the concentration of freight market power from 1850 to 1910. Utilizing long-standing insights from the empirical industrial organization literature, I modify a multi-sector Ricardian trade model to permit endogenous freight pricing; these bilateral freight markups respond to the demand for transport services along a given route, as well as the state of competition along that route. I employ this theoretical framework to simulate bilateral trade flows and freight prices across a panel of U.S. counties each decade from 1850 to 1910. My analysis assumes that freight markets are perfectly concentrated. I thus provide theoretically tractable, upper-bound estimates of bilateral freight markups across the U.S. throughout the latter-half of the 19th and early 20th century.

This theoretical model also generates a modified market access term – a reduced-form expression that summarizes the demand for goods out of a particular location – that accounts for these endogenous markups. My formulation of market access contrasts with existing measures in the literature, which typically assume purely exogenous bilateral trade frictions. This modification has important implications for my reduced-form analysis, which estimates the causal effect of market access expansion brought about by the 19th Century railroad boom on local agricultural production and prices. I show that omitting endogenous freight pricing leads to drastically over-stated market access, and thus, under-estimated effect sizes. Specifically, my estimated effects nearly double when accounting for endogenous freight pricing in the calculation of market access. Hence, existing estimates in the literature represent a lower-bound.

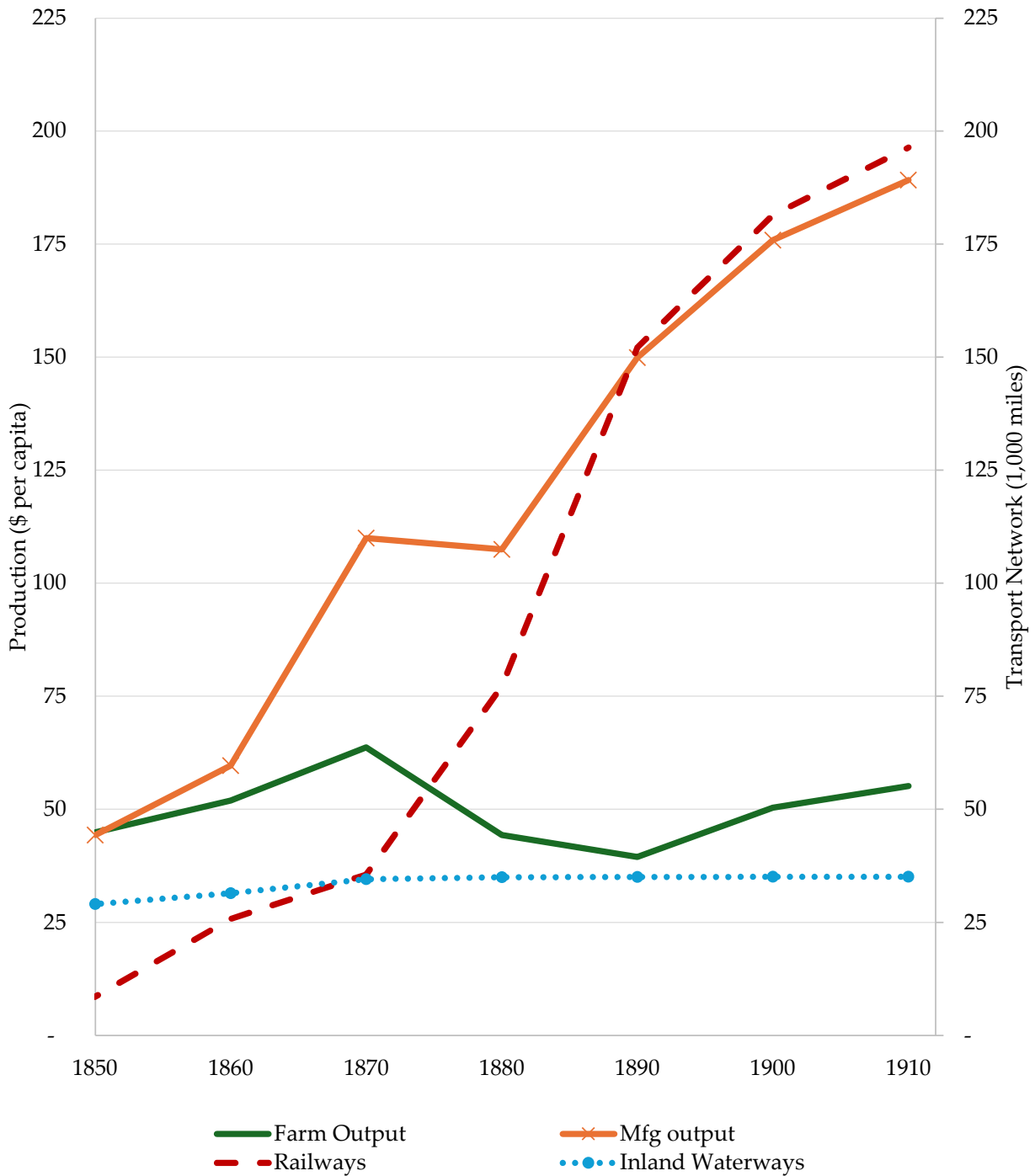
My reduced-form analysis yields a number of conclusions. First, I show that market access has substantial effects on the total value of agricultural production, which aligns with similar estimates in the literature ([Donaldson and Hornbeck, 2016](#); [Chan, 2022](#)). Second, I decompose this value effect into a quantity and price effect, which are roughly equivalent in size across my favored specifications. Third, I estimate noted convexity of this treatment effect by initial level

of output – counties in the first decile of farm output at the start of my analysis see quantity effects that are nearly double the size for the tenth decile. A similar pattern holds for effects on the quantity of production, but price effects are stable. Finally, I utilize these causal effects to estimate the geographic distribution of production losses due to the concentration of freight market power. I show that the national distribution of these losses is highly skew right, with the most-affected counties located along the American Frontier. Over time, these larger losses move West with American expansion into the Plains and Rocky Mountains. By the end of my analysis period just after the turn of the Century, agricultural losses stemming from freight market power are much more uniform, due to the saturation of the American landscape with railroads.

The primary contribution of this paper is to highlight the role of non-competitive freight pricing to our understanding of market access. While the railroad boom of the 19th Century saw significant gains to market access nationally, these increases were offset by the concentration of freight market power. I present upper-bound estimates of these losses to agricultural production; in reality, freight markets at this time are likely less-than-perfectly concentrated. However, historical records and a number of U.S. Supreme Court cases indicate that, by 1890 at latest, freight traffic was dogged by a number of railroad cartels with explicit price-fixing arrangements. Hence, it is also unrealistic to assume that transport costs are perfectly exogenous, as is standard in the literature. I provide a tractable theoretical and reduced-form framework to evaluate the impact of this endogenous freight pricing. A laudable goal of future research would be to estimate the geographic concentration of freight market power nationally; absent additional data on bilateral trade flows or freight prices, this would be a difficult exercise.

3.6 Tables and Figures

Figure 3.1: Miles vs. Output



Notes: This figure displays the growth of nominal U.S. agricultural and manufacturing output per capita from 1850 through 1910. Also pictured is a growth in the total length of the rail and inland water networks.

Figure 3.2A: Transport Network - 1850

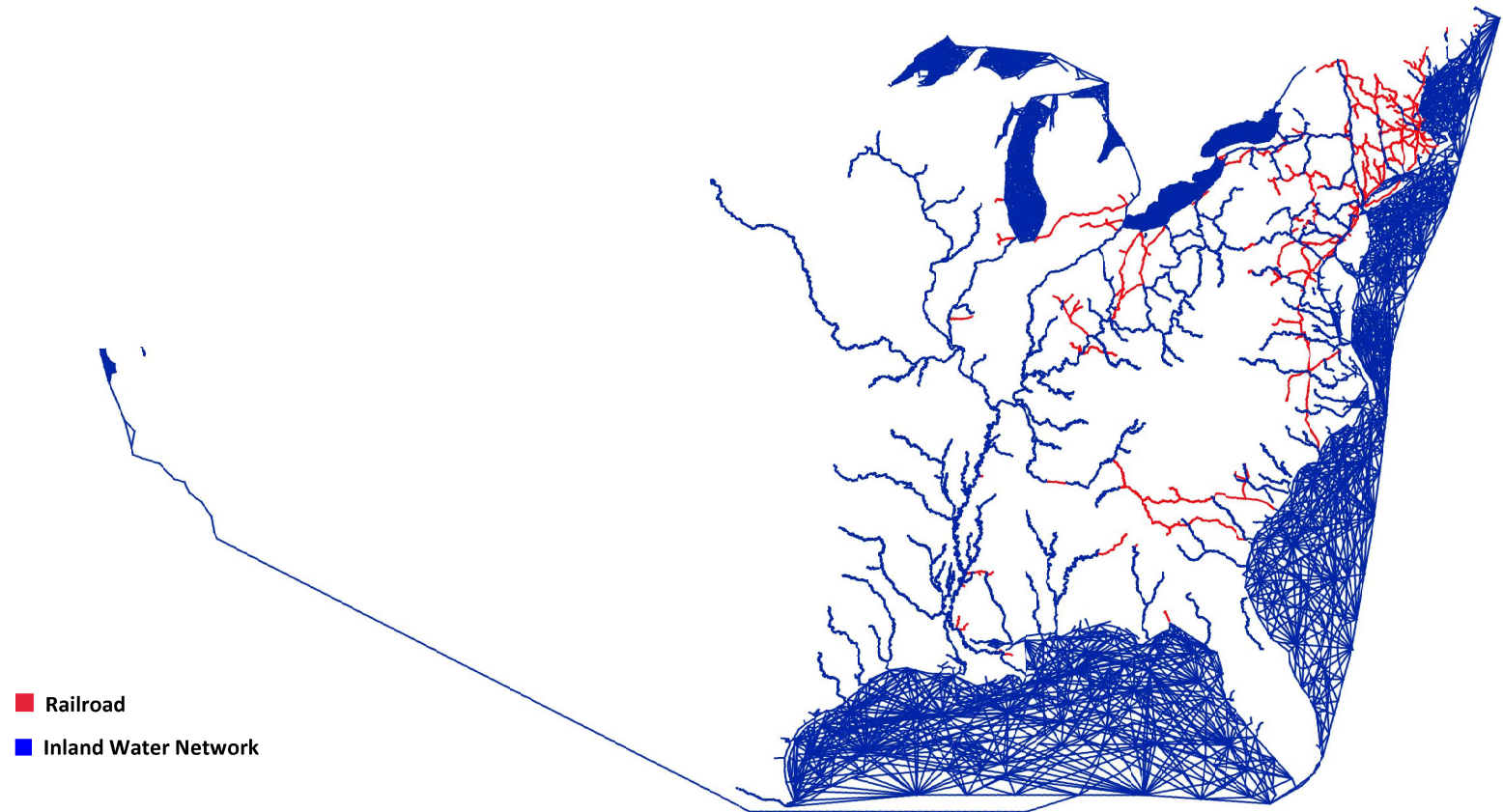


Figure 3.2B: Transport Network - 1860

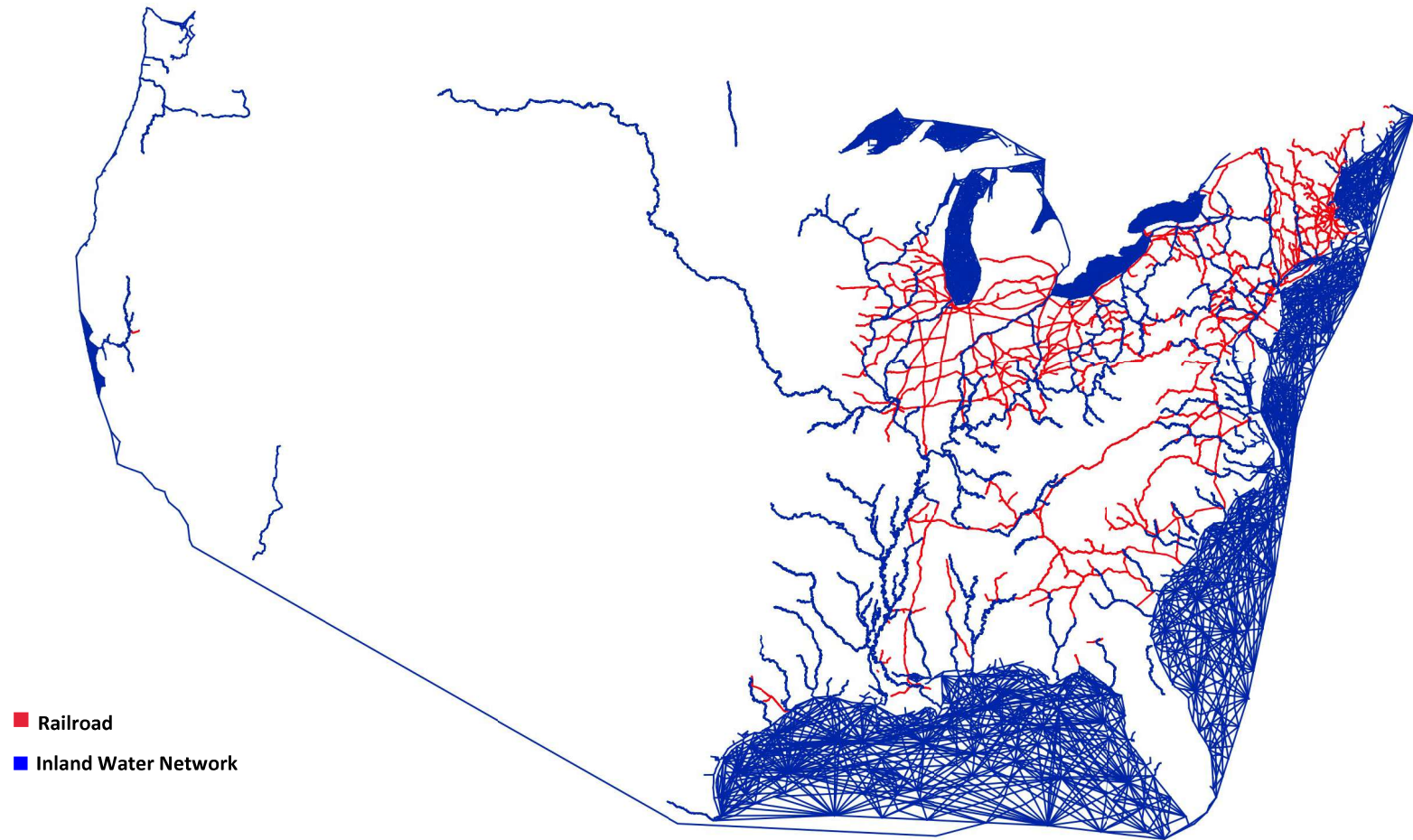


Figure 3.2C: Transport Network - 1870

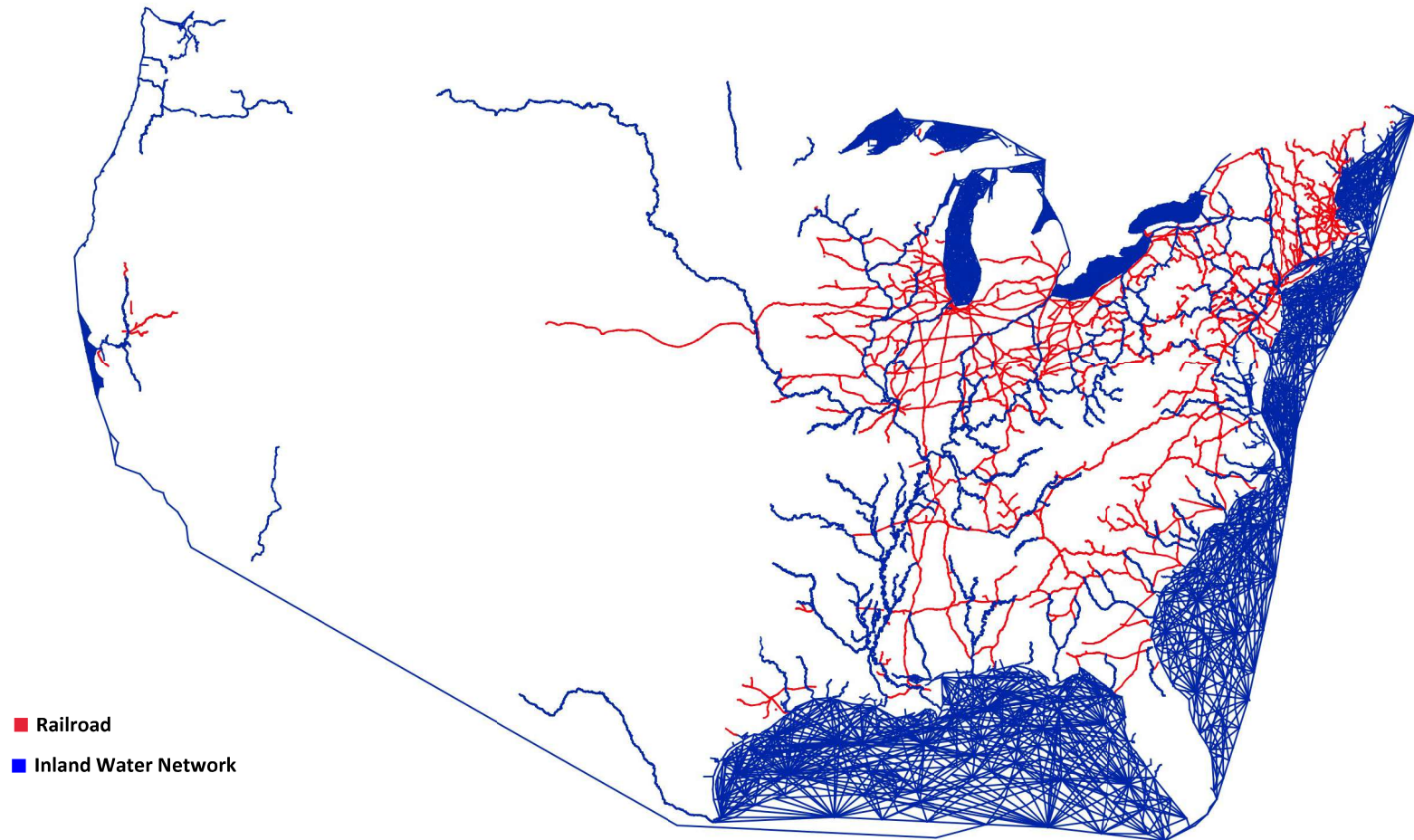


Figure 3.2D: Transport Network - 1880

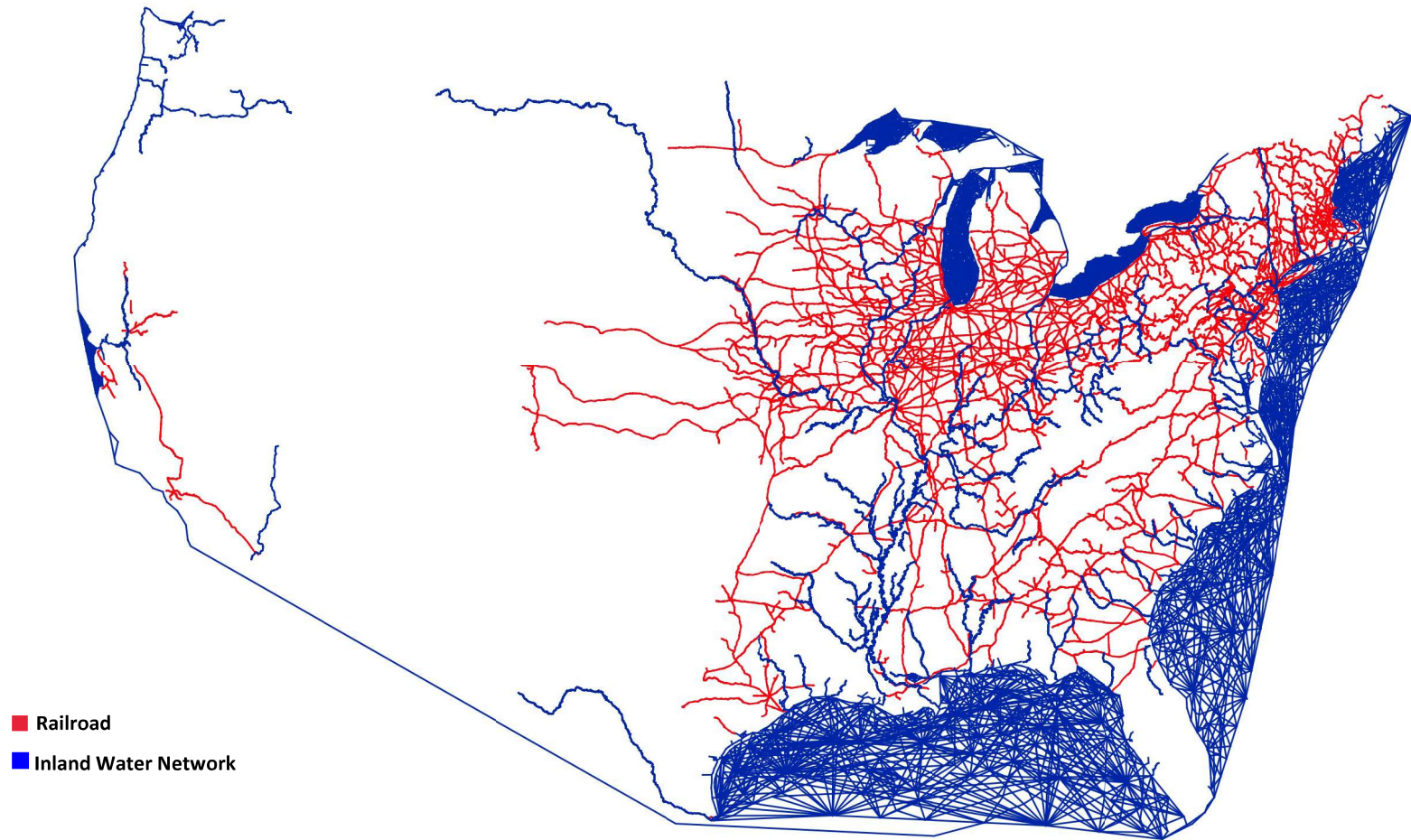


Figure 3.2E: Transport Network - 1890

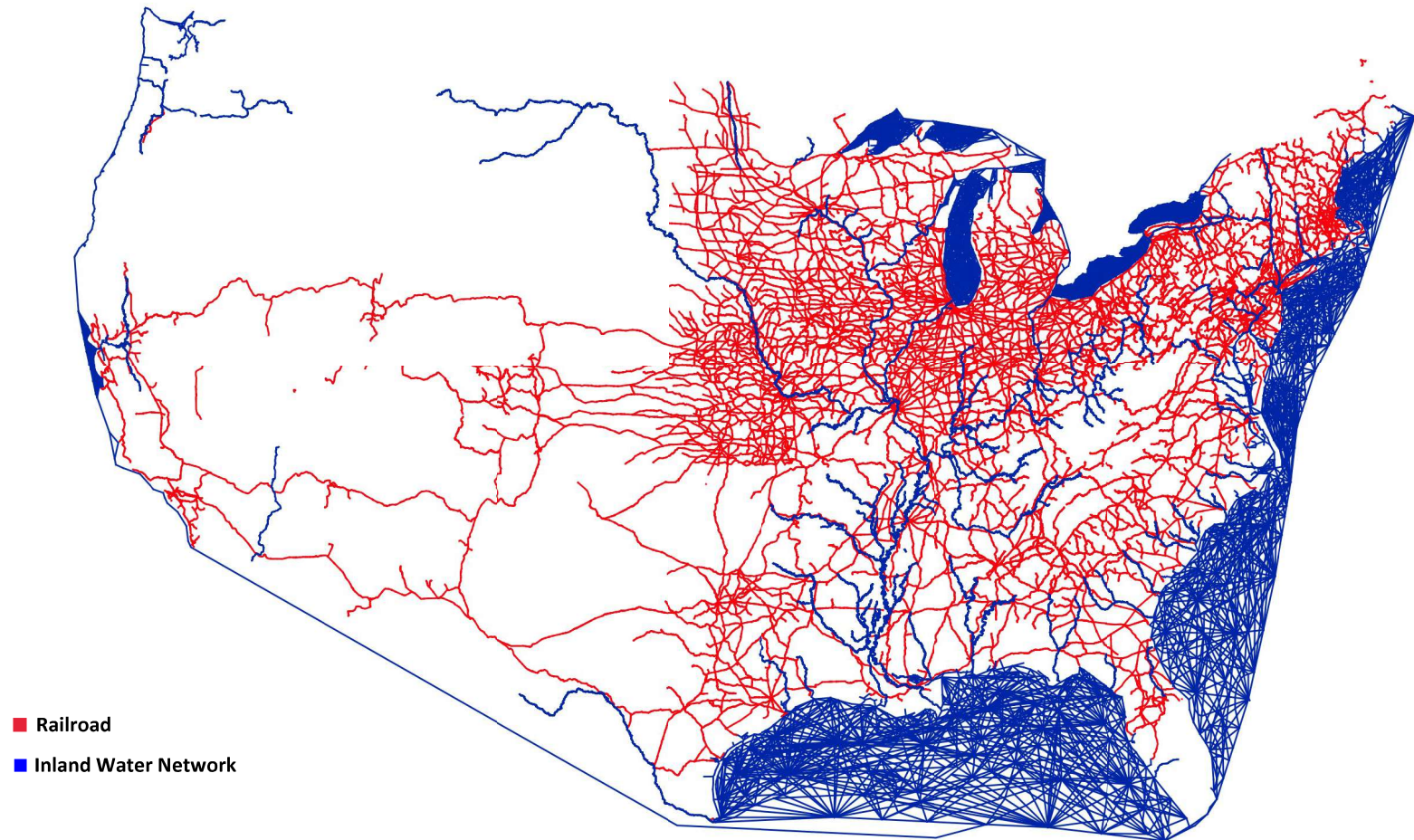


Figure 3.2F: Transport Network - 1900

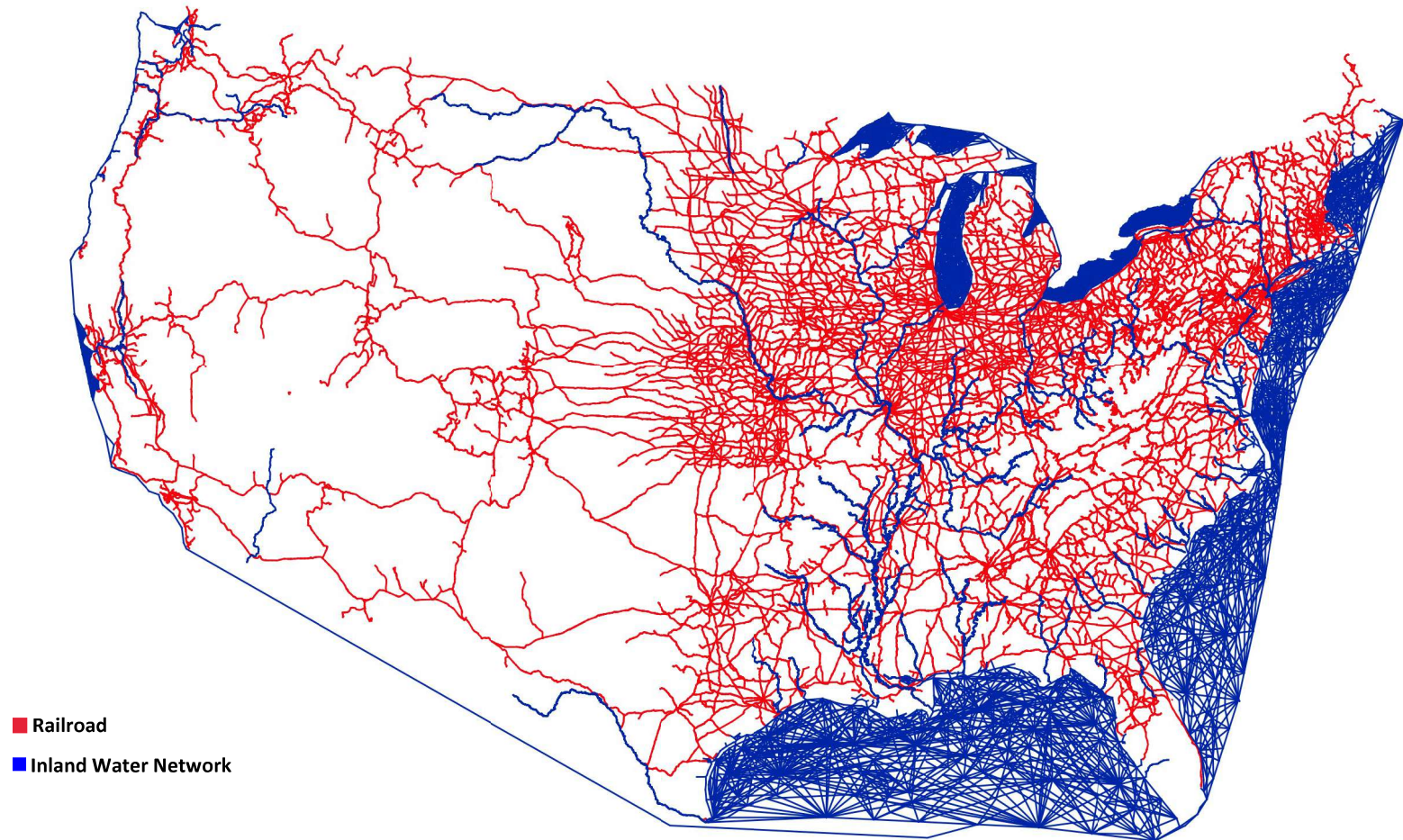


Figure 3.2G: Transport Network - 1910

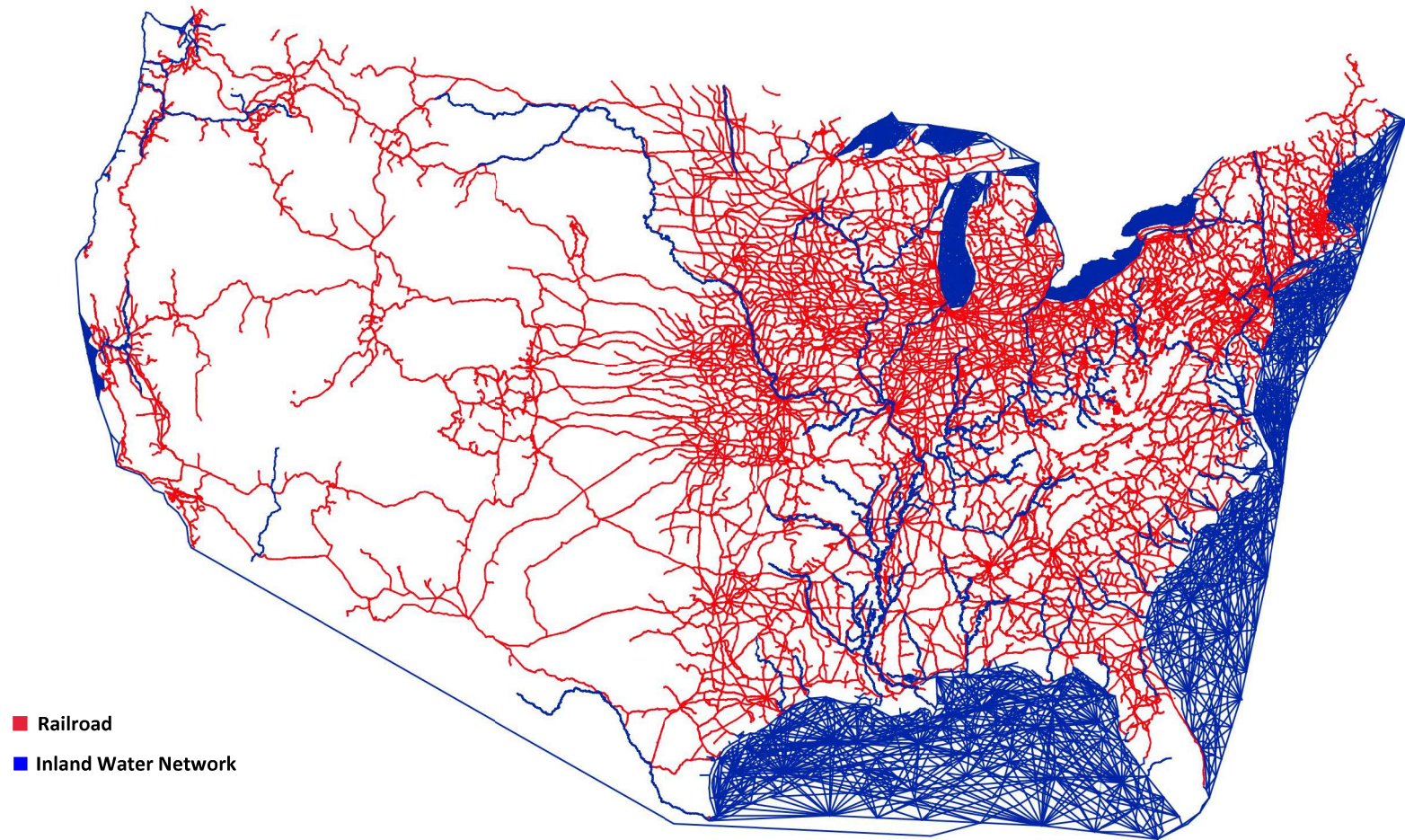


Table 3.1: Relative Modal Costs

β^m Coefficients (1000 miles)	
Road	1.0000
Rail	0.0272
Inland Water	0.0212
Sea/Lake Routes	0.0212
f^m Coefficients (fixed)	
Road	0.0000
Rail	0.0022
Inland Water	0.0022
Sea/Lake Routes	0.0022
Coast-to-Coast	0.3463

Notes: This table displays the mode-specific cost structure that I utilize to generate least-cost paths and to estimate expected, exogenous transit costs. All cost parameters come from Donaldson and Hornbeck (2016); specifically, I take their dollar-value coefficients and divide them by the dollar-cost of road travel; this exercise yields the above relative cost structure.

Table 3.2: Commodities Included

Barley (bushels)	Cotton (400lb Bales)	Swine (#)
Buckwheat (bushels)	Cows (#)	Tobacco (lbs)
Butter (lbs)	Hops (lbs)	Wheat (bushles)
Cheese (lbs)	Rice (lbs)	Wine (gal)
Corn (bushels)	Rye (lbs)	Wool (lbs)

Notes: This table presents the list of commodities included in my analysis.

Table 3.3: Summary Statistics

	Mean	Std. Dev.	Min	25 th Pctile.	Median	75 th Pctile.	Max
<i>Farm output</i> (<i>\$000, Nominal</i>)	1,271.75	1,159.20	0.73	459.23	937.32	1,746.13	12,019.82
<i>Quantity produced (000s)</i>							
Barley (bushels)	15.81	99.89	0.00	0.00	0.06	1.37	3,439.30
Buckwheat (bushels)	7.31	29.38	0.00	0.00	0.06	1.60	667.36
Butter (lbs)	367.32	513.61	0.00	69.04	198.05	475.90	9,590.35
Cheese (lbs)	28.17	248.78	0.00	0.00	0.29	3.10	10,901.52
Corn (bushels)	736.01	1,079.88	0.00	195.29	402.37	804.30	16,001.36
Cotton (400lb Bales)	3.22	8.04	0.00	0.00	0.00	1.27	141.49
Cows (#)	12.72	12.43	0.00	5.14	9.05	15.71	198.79
Hops (lbs)	14.56	189.16	0.00	0.00	0.00	0.02	6,119.74
Rice (lbs)	77.88	1,212.87	0.00	0.00	0.00	0.00	55,805.39
Rye (lbs)	10.95	32.27	0.00	0.13	1.09	6.35	547.90
Swine (#)	21.52	20.66	0.00	8.55	15.96	27.08	247.76
Tobacco (lbs)	325.88	1,406.98	0.00	0.01	1.51	16.71	36,892.87
Wheat (bushels)	143.49	251.99	0.00	4.06	40.30	160.44	2,959.44
Wine (gal)	4.87	269.57	0.00	0.01	0.13	0.52	27,921.18
Wool (lbs)	53.02	116.14	0.00	6.74	17.09	48.01	2,635.95
<i>log(Market Access)</i>							
1850	7.37	0.73	2.96	6.80	7.48	7.91	8.64
1860	7.26	0.68	3.18	6.69	7.34	7.80	8.39
1870	9.16	0.59	5.76	8.85	9.25	9.55	10.19
1880	9.37	0.59	6.63	8.78	9.52	9.72	10.43
1890	9.83	0.59	7.96	9.35	9.97	10.27	10.95
1900	9.97	0.70	8.04	9.45	10.19	10.49	11.18
1910	10.03	0.84	7.67	9.64	10.32	10.62	11.47
<i>log(Perfectly-Competitive Market Access)</i>							
1850	14.69	0.90	9.17	14.09	14.58	15.29	16.87
1860	14.86	0.81	9.39	14.37	14.74	15.39	16.76
1870	16.76	0.69	12.09	16.40	16.68	17.21	18.23
1880	17.25	0.64	13.31	16.91	17.14	17.60	18.78
1890	17.92	0.61	15.69	17.55	17.77	18.22	19.73
1900	18.19	0.61	15.95	17.81	18.01	18.41	19.97
1910	18.37	0.60	16.07	18.00	18.27	18.58	20.24

Notes: This table presents summary statistics on the total value of farm output, the total quantity produced, the inverse hyperbolic sine transform of market access, as well as the inverse hyperbolic sine transform of perfectly-competitive market access. The summary statistics are calculated over the estimation sample – a balanced panel of 1,572 counties and 15 commodities from 1850-1910.

Table 3.4: Estimates of Market Access on Output, Prices

	Model-Derived Market Access	MA Calculated using Current Population	MA Calculated using 1850 Expenditure	MA Calculated using 1850 Population	Model-Derived Market Access (Unweighted)
	(1)	(2)	(3)	(4)	(5)
A. Effects on Quantity Produced					
log(MA)	0.942***	0.890***	0.849***	0.886***	1.95***
	(0.207)	(0.183)	(0.205)	(0.182)	(0.143)
Fixed-Effects					
Origin × Comm.	X	X	X	X	X
State × Comm. × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	123,071	123,071	123,071	123,071	123,071
# of Counties	1,572	1,572	1,572	1,572	1,572
# of Commodities	15	15	15	15	15
First-Stage F stat	1,287,786	1,894,713	1,368,351	2,025,965	1,678,901
Adj. R ²	0.921	0.921	0.921	0.921	0.916
B. Effects on Agricultural Value					
log(MA)	1.87***	1.68***	1.83***	1.67***	2.50***
	(0.184)	(0.166)	(0.186)	(0.167)	(0.227)
Fixed-Effects					
Origin	X	X	X	X	X
State × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	11,004	11,004	11,004	11,004	11,004
# of Counties	1,572	1,572	1,572	1,572	1,572
First-Stage F stat	254,976	814,570	295,874	905,445	226,999
Adj. R ²	0.933	0.933	0.933	0.933	0.919
C. Effects on Average Agricultural Prices					
log(MA)	0.928***	0.790***	0.981***	0.784***	0.550***
	(0.205)	(0.182)	(0.204)	(0.181)	(0.152)

Notes: This table presents impacts of the effect of increases in market access on agricultural output, value, and prices. Panel A reports the results on quantity produced. Panel B reports the results on the total value of agricultural output. Panel C is simply the coefficient reported in B minus the coefficient reported in A. Columns (1) - (4) utilize different versions of market access to address potential endogeneity concerns. Following Donaldson and Hornbeck (2016), the regressions in Columns (1) - (4) are weighted by a county's initial value of all farm output to minimize the influence of outliers. Column (5) utilizes the same market-access measure as in Column (1) but does not utilize any weighting. Standard errors in Panel A are clustered by origin-commodity pairing; standard errors in Panel B are clustered by origin county; standard errors in Panel C are pooled from the errors reported in Panels A and B. ***, **, and * denote significance at the 0.1%, 1% and 5% levels, respectively. The estimation sample is restricted to county-commodity combinations that are present in all years.

Table 3.5: Estimates of Perfectly-Competitive Market Access on Output, Prices

	Model-Derived Market Access	MA Calculated using Current Population	MA Calculated using 1850 Expenditure	MA Calculated using 1850 Population	Model-Derived Market Access (Unweighted)
	(1)	(2)	(3)	(4)	(5)
A. Effects on Quantity Produced					
log(MA)	0.497*** (0.109)	0.536*** (0.110)	0.447*** (0.108)	0.532*** (0.109)	1.08*** (0.079)
Fixed-Effects					
Origin × Comm.	X	X	X	X	X
State × Comm. × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	123,071	123,071	123,071	123,071	123,071
# of Counties	1,572	1,572	1,572	1,572	1,572
# of Commodities	15	15	15	15	15
Adj. R ²	0.921	0.921	0.921	0.921	0.916
B. Effects on Agricultural Value					
log(MA)	0.999*** (0.098)	1.02*** (0.100)	0.975*** (0.099)	1.01*** (0.100)	1.40*** (0.124)
Fixed-Effects					
Origin	X	X	X	X	X
State × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	11,004	11,004	11,004	11,004	11,004
# of Counties	1,572	1,572	1,572	1,572	1,572
Adj. R ²	0.933	0.933	0.933	0.933	0.920
C. Effects on Average Agricultural Prices					
log(MA)	0.502*** (0.108)	0.484*** (0.109)	0.528*** (0.107)	0.478*** (0.108)	0.320*** (0.084)

Notes: This table presents impacts of the effect of increases in perfectly-competitive market access on agricultural output, value, and prices. In contrast to Table 4, bilateral freight markups are excluded from the calculation of market access. Panel A reports the results on quantity produced. Panel B reports the results on the total value of agricultural output. Panel C is simply the coefficient reported in B minus the coefficient reported in A. Columns (1) - (4) utilize different versions of market access to address potential endogeneity concerns. Following Donaldson and Hornbeck (2016), the regressions in Columns (1) - (4) are weighted by a county's initial value of all farm output to minimize the influence of outliers. Column (5) utilizes the same market-access measure as in Column (1) but does not utilize any weighting. Standard errors in Panel A are clustered by origin-commodity pairing; standard errors in Panel B are clustered by origin county; standard errors in Panel C are pooled from the errors reported in Panels A and B. ***, **, and * denote significance at the 0.1%, 1% and 5% levels, respectively. The estimation sample is restricted to county-commodity combinations that are present in all years.

Table 3.6: Estimates of Market Access on Output, Prices using Unbalanced Panel

	Model-Derived Market Access	MA Calculated using Current Population	MA Calculated using 1850 Expenditure	MA Calculated using 1850 Population	Model-Derived Market Access (Unweighted)
	(1)	(2)	(3)	(4)	(5)
A. Effects on Quantity Produced					
log(MA)	1.24*** (0.135)	1.08*** (0.118)	0.926*** (0.135)	1.02*** (0.117)	1.69*** (0.118)
Fixed-Effects					
Origin × Comm.	X	X	X	X	X
State × Comm. × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	174,057	174,057	174,057	174,057	174,057
# of Counties	2,725	2,725	2,725	2,725	2,725
# of Commodities	15	15	15	15	15
First-Stage F stat	2,202,168	3,768,813	1,267,868	2,034,850	3,338,671
Adj. R ²	0.919	0.919	0.919	0.919	0.906
B. Effects on Agricultural Value					
log(MA)	1.65*** (0.175)	1.40*** (0.151)	1.40*** (0.166)	1.33*** (0.150)	1.96*** (0.324)
Fixed-Effects					
Origin	X	X	X	X	X
State × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	16,266	16,266	16,266	16,266	16,266
# of Counties	2,725	2,725	2,725	2,725	2,725
First-Stage F stat	406,928	1,407,765	336,863	1,034,066	527,427
Adj. R ²	0.926	0.926	0.925	0.926	0.879
C. Effects on Agricultural Prices					
log(MA)	0.410** (0.139)	0.320** (0.121)	0.474*** (0.138)	0.310** (0.120)	0.270 (0.147)

Notes: This table presents impacts of the effect of increases in market access on agricultural output, value, and prices. Panel A reports the results on quantity produced. Panel B reports the results on the total value of agricultural output. Panel C is simply the coefficient reported in B minus the coefficient reported in A. Columns (1) - (4) utilize different versions of market access to address potential endogeneity concerns. Following Donaldson and Hornbeck (2016), the regressions in Columns (1) - (4) are weighted by a county's initial value of all farm output to minimize the influence of outliers. Column (5) utilizes the same market-access measure as in Column (1) but does not utilize any weighting. Standard errors in Panel A are clustered by origin-commodity pairing; standard errors in Panel B are clustered by origin county; standard errors in Panel C are pooled from the errors reported in Panels A and B. ***, **, and * denote significance at the 0.1%, 1% and 5% levels, respectively. Unlike Table 4, there are no restrictions placed on the sample.

Table 3.7: Estimates of Market Access on Extensive Margin

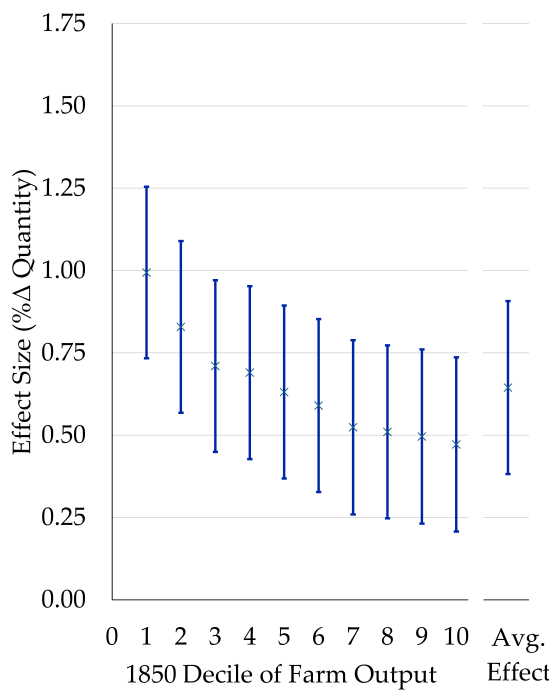
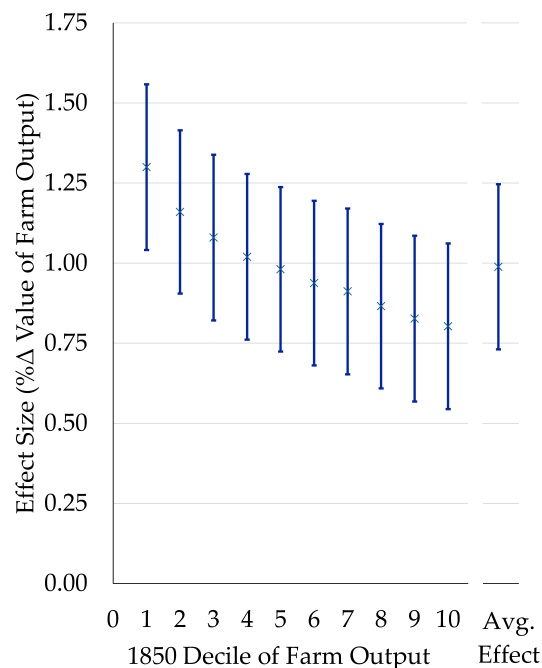
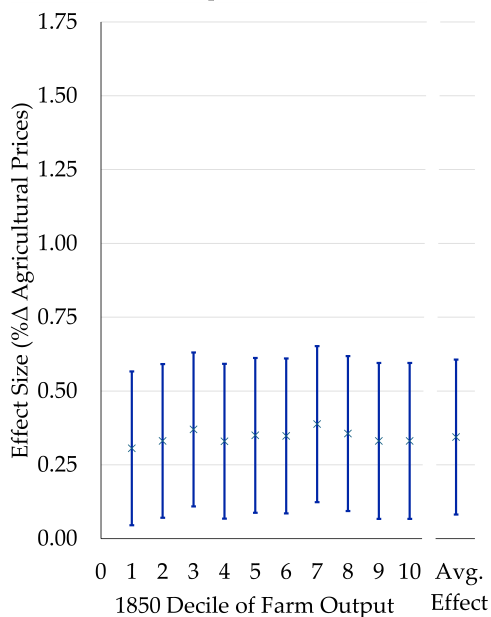
	Model-Derived Market Access	MA Calculated using Current Population	MA Calculated using 1850 Expenditure	MA Calculated using 1850 Population	Model-Derived Market Access (Unweighted)
	(1)	(2)	(3)	(4)	(5)
A. Average Effect					
log(MA)	0.107**	0.069*	0.097*	0.068	0.240***
	(0.039)	(0.035)	(0.039)	(0.035)	(0.025)
Fixed-Effects					
Origin × Comm.	X	X	X	X	X
State × Comm. × Yr.	X	X	X	X	X
Lat, Lon polynomial	X	X	X	X	X
# of Obs	165,060	165,060	165,060	165,060	165,900
# of Counties	1,572	1,572	1,572	1,572	1,572
# of Commodities	15	15	15	15	15
First-Stage F stat	1,857,837	2,367,536	1,938,924	2,511,375	2,309,744
Adj. R ²	0.760	0.760	0.760	0.760	0.725

Notes: This table presents impacts of the effect of increases in market access on the extensive margin of agricultural production. Panel A reports average effects. Columns (1) - (4) utilize different versions of market access to address potential endogeneity concerns. Following Donaldson and Hornbeck (2016), the regressions in Columns (1) - (4) are weighted by a county's initial value of all farm output to minimize the influence of outliers. Column (5) utilizes the same market-access measure as in Column (1) but does not utilize any weighting. Standard errors are clustered by origin-commodity pairing. ***, **, and * denote significance at the 0.1%, 1% and 5% levels, respectively. The estimation sample is restricted to county-commodity combinations that are present in all years.

Table 3.8: Percentage Gains from the Elimination of Freight Market Power

	Mean	Std. Dev.	Min	25 th Pctile.	Median	75 th Pctile.	Max
1850	6.35	27.94	0.01	0.08	0.31	1.44	318.40
1860	12.84	46.59	0.01	0.09	0.39	2.52	318.40
1870	10.82	44.07	0.00	0.07	0.33	2.10	318.40
1880	15.59	53.30	0.01	0.13	0.57	3.90	318.40
1890	14.13	48.87	0.01	0.17	0.73	4.40	318.40
1900	5.08	20.82	0.01	0.13	0.51	2.51	318.40
1910	3.44	14.41	0.01	0.10	0.39	2.05	318.40

Notes: This table presents the distribution of counterfactual agricultural output gains stemming from the elimination of freight market power. All units are in percent-gains from baseline.

Figure 3.3: Heterogeneous Effects**A. Effect on Agricultural Quantity by Initial Decile of Farm Output****B. Effect on Total Value of Farm Output by Initial Decile of Farm Output****C. Effect on Agricultural Prices by Initial Decile of Farm Output**

Notes: This figure displays heterogeneous effects by decile of total farm output in 1850. Panel A displays the effects on the quantity of production; Panel B displays the effects on the total value of production; Panel C displays the effect on local agricultural prices. The point estimates are plotted along with a 95% confident interval. Additionally, I display an average effect, calculated as the simple mean of each plotted coefficient, on the far right of each figure. Controls in each regression are identical to those listed in Table 4. The sample comprises a balanced panel of 1,572 counties from 1850 to 1910.

Figure 3.3A: Geographic Gains from Elimination of Freight Market Power - 1850

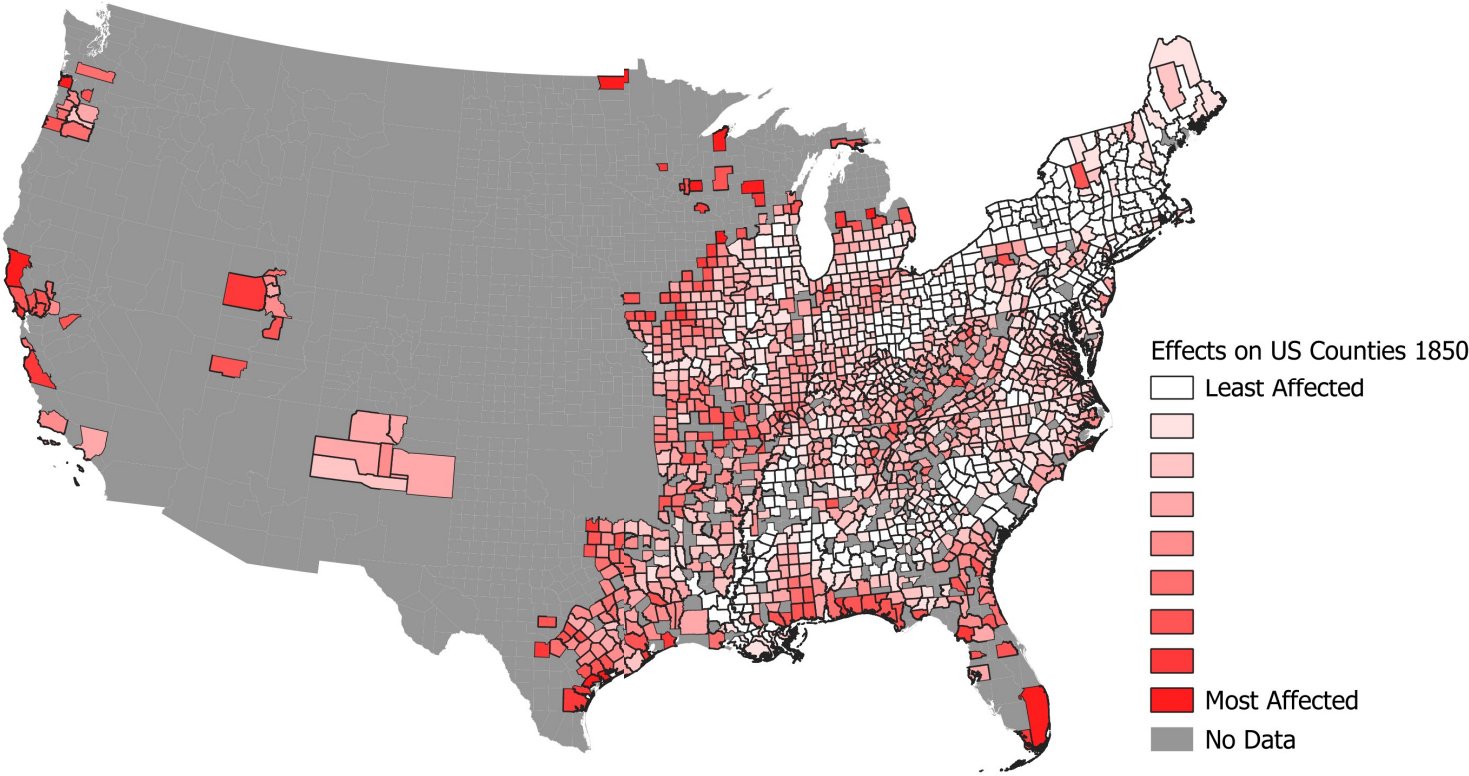


Figure 3.3B: Geographic Gains from Elimination of Freight Market Power - 1860

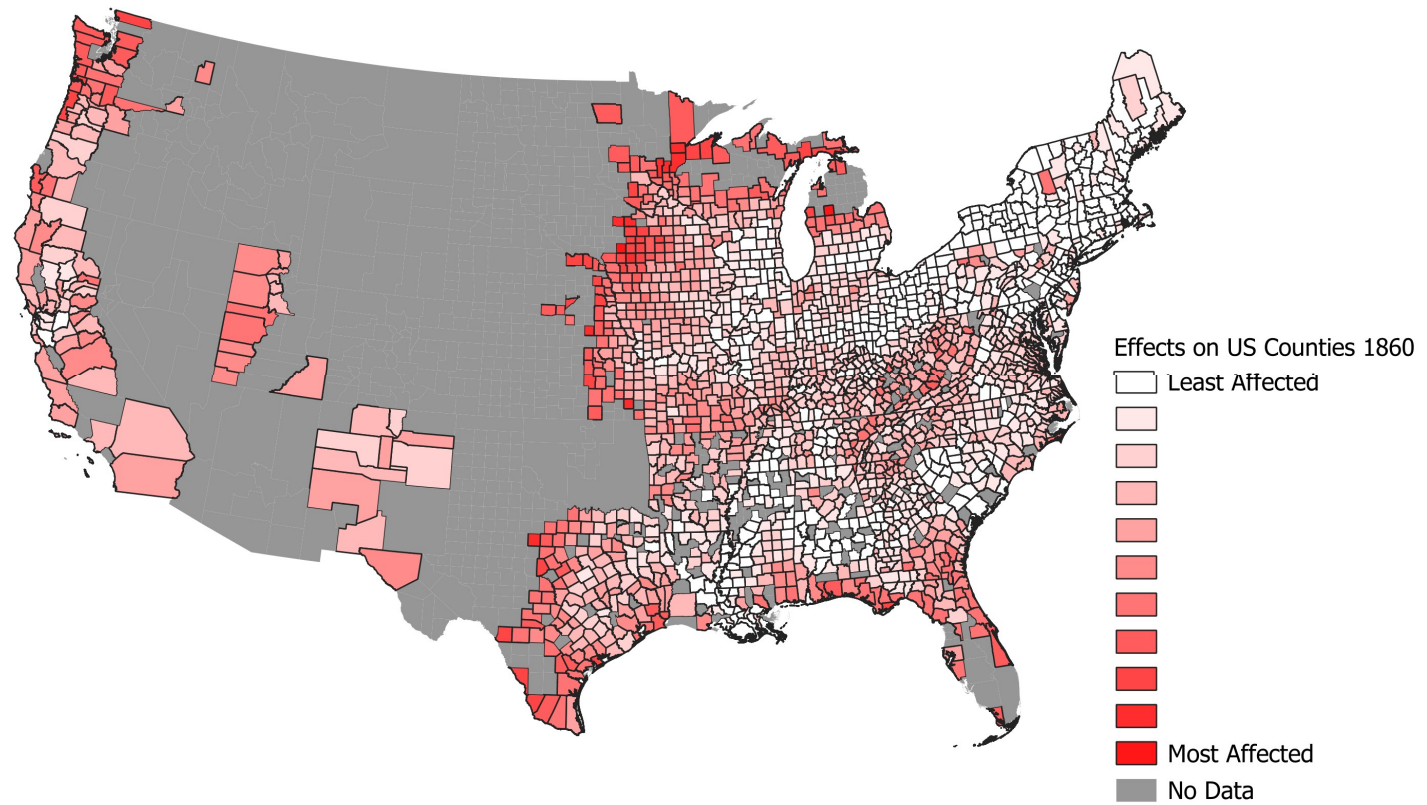


Figure 3.3C: Geographic Gains from Elimination of Freight Market Power - 1870

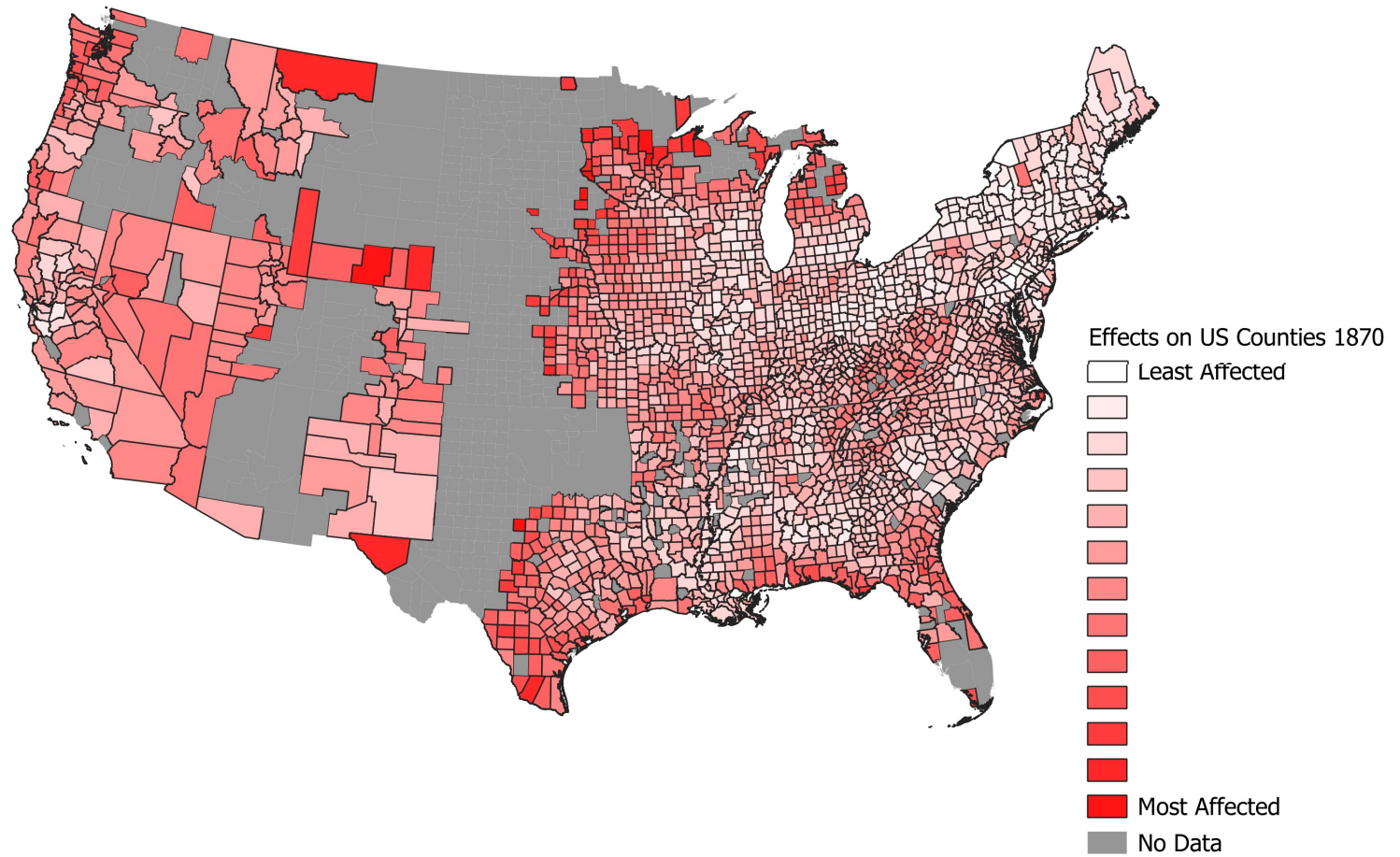


Figure 3.3D: Geographic Gains from Elimination of Freight Market Power - 1880

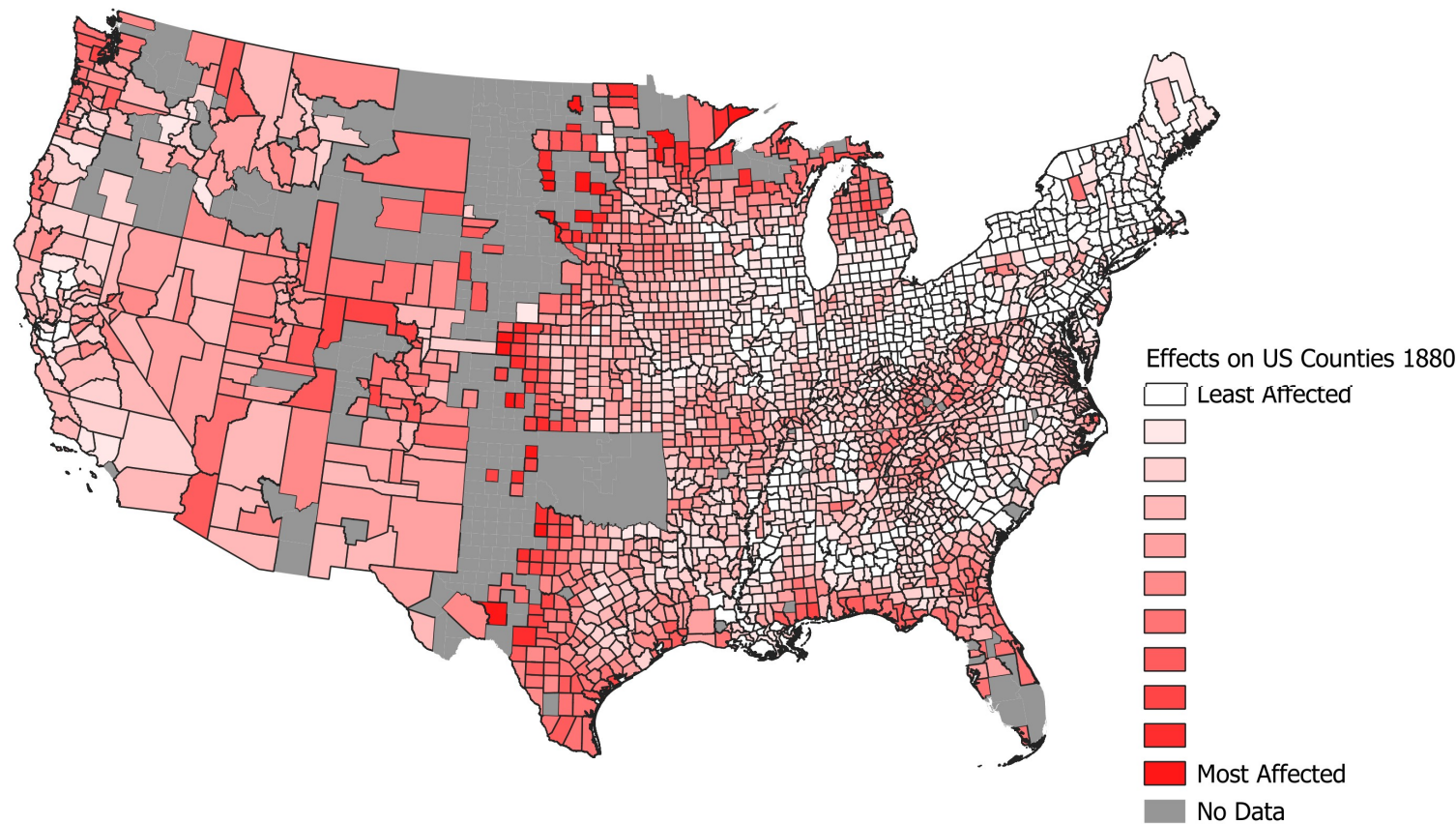


Figure 3.3E: Geographic Gains from Elimination of Freight Market Power - 1890

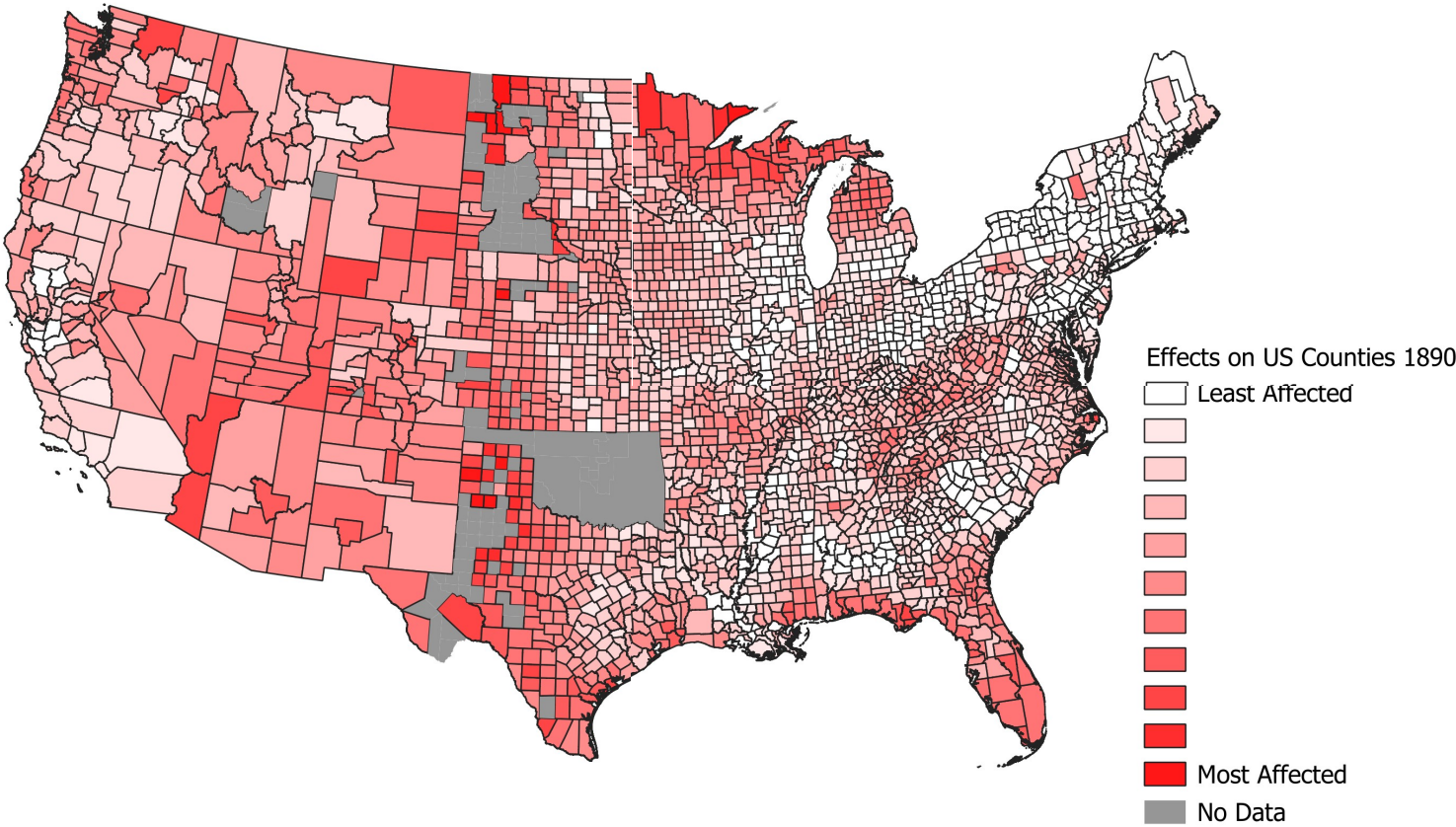
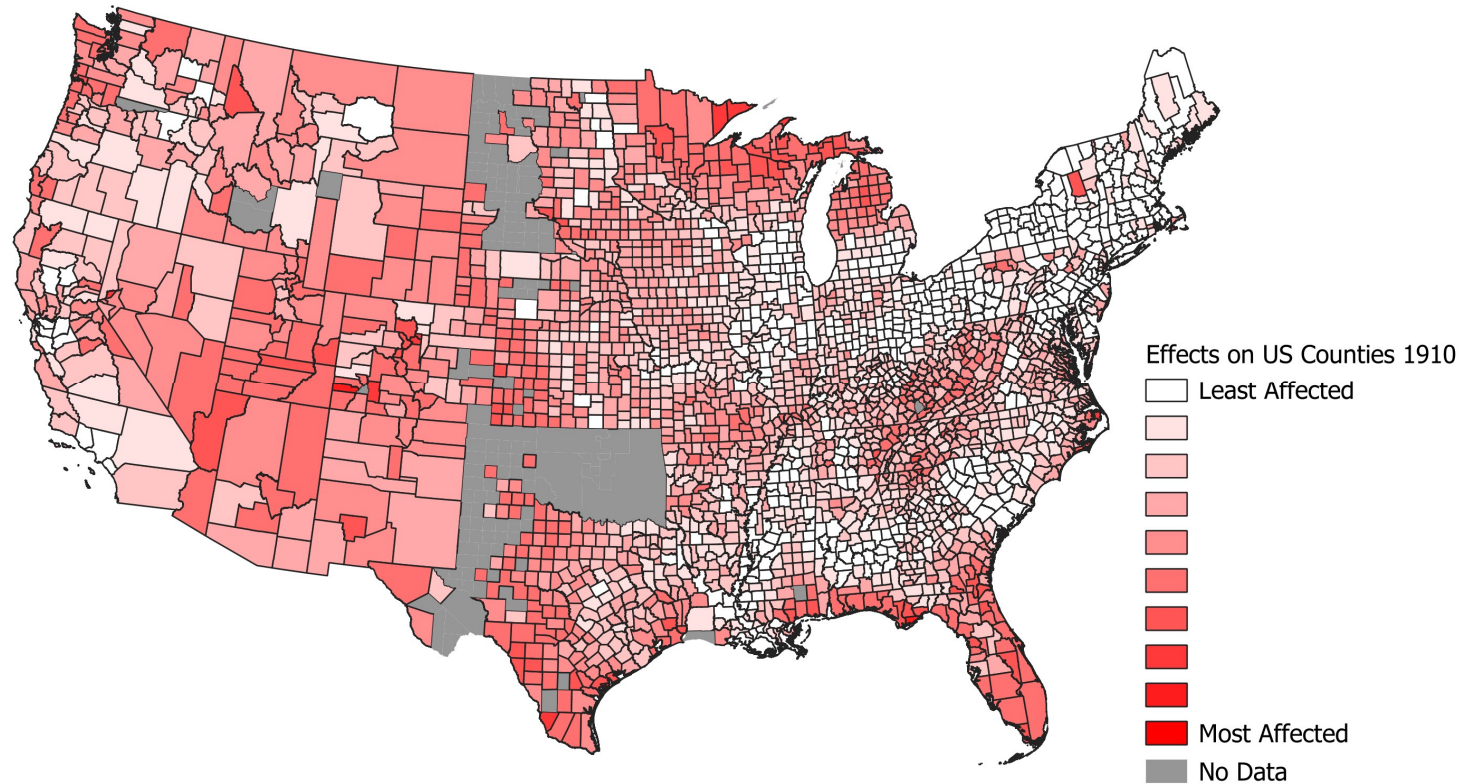


Figure 3.3G: Geographic Gains from Elimination of Freight Market Power - 1910



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Appendix A

Chapter 1: Simplifying Trade Shares

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

$$\begin{aligned}\pi_{ir(e,x,m)|j} &= \pi_{r|iexmj} \pi_{m|iexmj} \pi_{ex|ij} \pi_i|j \\ &= \exp \left(-\ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj})/(\varphi\rho\zeta) + (\alpha_{iem} + \gamma_{xmj})/(\rho\zeta) + (\eta_{ie} + \nu_{xj})/\zeta \right] \right. \\ &\quad \left. - (1 - \varphi)J_{iexmj} - (1 - \rho)V_{ieexj} - (1 - \zeta)I_{ij} - Q_j \right).\end{aligned}$$

Unfortunately, this formulation is not a tenable regression specification. The inclusive values used to identify the correlation coefficients – J_{iexmj} , V_{ieexj} , 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_{iexmj} would absorb all of the non-simulated variation present in the data. However, some simple manipulation yields a much more tractable specification:

$$\begin{aligned}\ln \pi_{ir(e,x,m)|j} &= -\ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj})/(\varphi\rho\zeta) + (\alpha_{iem} + \gamma_{xmj})/(\rho\zeta) + (\eta_{ie} + \nu_{xj})/\zeta \right] \\ &\quad + \theta [\eta_{ie} + \nu_{xj}] - \theta [\eta_{ie} + \nu_{xj}] + \rho\zeta V_{ieexj} - \rho\zeta V_{ieexj} \\ &\quad - (1 - \varphi)J_{iexmj} - (1 - \rho)V_{ieexj} - (1 - \zeta)I_{ij} - Q_j \\ &= -\ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj})/(\varphi\rho\zeta) + (\alpha_{iem} + \gamma_{xmj})/(\rho\zeta) + \eta_{ie} + \nu_{xj} \right] \\ &\quad + (1 - \zeta) \left[-\theta(\eta_{ie} + \nu_{xj})/\zeta + \rho V_{ieexj} - I_{ij} \right] - (1 - \varphi)J_{iexmj} - (1 - \rho\zeta)V_{ieexj} - Q_j \\ &= -\ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj})/(\varphi\rho\zeta) + (\alpha_{iem} + \gamma_{xmj})/(\rho\zeta) + \eta_{ie} + \nu_{xj} \right] \\ &\quad + (1 - \zeta) \ln \pi_{ex|ij} - (1 - \varphi)J_{iexmj} - (1 - \rho\zeta)V_{ieexj} - Q_j \\ &= -\ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj})/(\varphi\rho\zeta) + (\alpha_{iem} + \gamma_{xmj})/(\rho\zeta) + \eta_{ie} + \nu_{xj} \right] \\ &\quad + \theta [\alpha_{iem} + \gamma_{xmj}] - \theta [\alpha_{iem} + \gamma_{xmj}] + \varphi\rho\zeta J_{iexmj} - \varphi\rho\zeta J_{iexmj}\end{aligned}$$

$$\begin{aligned}
& + (1 - \zeta) \ln \pi_{ex|ij} - (1 - \varphi) J_{iexmj} - (1 - \rho\zeta) V_{ie xj} - Q_j \\
= & - \ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj}) / (\varphi \rho \zeta) + \alpha_{iem} + \gamma_{xmj} + \eta_{ie} + \nu_{xj} \right] \\
& + (1 - \rho\zeta) \left[-\theta(\alpha_{iem} + \gamma_{xmj}) / (\rho\zeta) + \varphi J_{iexmj} - V_{ie xj} \right] \\
& + (1 - \zeta) \ln \pi_{ex|ij} - (1 - \varphi \rho \zeta) J_{iexmj} - Q_j \\
= & - \ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj}) / (\varphi \rho \zeta) + \alpha_{iem} + \gamma_{xmj} + \eta_{ie} + \nu_{xj} \right] \\
& + (1 - \rho\zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - (1 - \varphi \rho \zeta) J_{iexmj} - Q_j \\
= & - \ln A_i - \theta \left[\ln c_i + (\mu_{irj} + \kappa_r + u_{irj}) / (\varphi \rho \zeta) + \alpha_{iem} + \gamma_{xmj} + \eta_{ie} + \nu_{xj} \right] \\
& + \theta \left[\mu_{irj} + \kappa_r + u_{irj} \right] - \theta \left[\mu_{irj} + \kappa_r + u_{irj} \right] \\
& + (1 - \rho\zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - (1 - \varphi \rho \zeta) J_{iexmj} - Q_j \\
= & - \ln A_i - \theta \left[\ln c_i + \mu_{irj} + \kappa_r + u_{irj} + \alpha_{iem} + \gamma_{xmj} + \eta_{ie} + \nu_{xj} \right] \\
& + (1 - \varphi \rho \zeta) \left[-\theta(\mu_{irj} + \kappa_r + u_{irj}) / (\varphi \rho \zeta) - J_{iexmj} \right] \\
& + (1 - \rho\zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - Q_j \\
= & - \ln A_i - \theta \left[\ln c_i + \mu_{irj} + \kappa_r + u_{irj} + \alpha_{iem} + \gamma_{xmj} + \eta_{ie} + \nu_{xj} \right] \\
& + (1 - \varphi \rho \zeta) \ln \pi_{r|ie xmj} + (1 - \rho\zeta) \ln \pi_{m|ie xj} + (1 - \zeta) \ln \pi_{ex|ij} - Q_j.
\end{aligned}$$

Appendix B

Chapter 1: Price Index

I now provide a detailed derivation of Equation (3.3). Let $\mathbf{p}_j(\omega)^\top = [p_{irj_1}(\omega) \ p_{irj_2}(\omega) \ \dots]$ be the vector of prices for good ω in market j . Define similarly the vectors $\boldsymbol{\mu}_j$, $\boldsymbol{\tau}_j$, $\boldsymbol{\epsilon}_j(\omega)$, and $\mathbf{c}_j$. Let $\mathbf{z} \in \mathbb{R}_{++}^N$, where N is the number of unique trade routes serving j . Define the function:

$$\begin{aligned}
G_j(z) &= \Pr(\mathbf{p}_j(\omega) \leq \mathbf{z}) \\
&= \Pr\left(\frac{\mathbf{c}_j \circ \boldsymbol{\tau}_j \circ \boldsymbol{\mu}_j}{\boldsymbol{\epsilon}_j(\omega)} \leq \mathbf{z}\right) \\
&= \Pr\left(\frac{\mathbf{c}_j \circ \boldsymbol{\tau}_j \circ \boldsymbol{\mu}_j}{\mathbf{z}} \leq \boldsymbol{\epsilon}_j(\omega)\right) \\
&= \Pr(\ln \mathbf{c}_j + \ln \boldsymbol{\tau}_j + \ln \boldsymbol{\mu}_j - \ln \mathbf{z} \leq \ln \boldsymbol{\epsilon}_j(\omega)) \\
&= 1 - \Pr(\ln \mathbf{c}_j + \ln \boldsymbol{\tau}_j + \ln \boldsymbol{\mu}_j - \ln \mathbf{z} \geq \ln \boldsymbol{\epsilon}_j(\omega)) \\
&= 1 - F_j(\ln \mathbf{c}_j + \ln \boldsymbol{\tau}_j + \ln \boldsymbol{\mu}_j - \ln \mathbf{z}) \\
&= 1 - \exp\left(-\sum_{i \in \mathcal{S}} \left(\sum_{e, x \in \mathcal{S}^d} \left(\sum_{m \in \mathcal{M}} \left(\sum_{r \in \mathcal{R}_{ex}^m} \exp\left(\frac{-\ln A_i - \theta(\ln c_i + \ln \tau_{irj} + \ln \mu_{irj} - \ln z)}{\varphi \rho \zeta}\right)\right)\right)^\rho\right)^\zeta\right) \\
&= 1 - \exp\left(-z^\theta \sum_{i \in \mathcal{S}} \left(\sum_{e, x \in \mathcal{S}^d} \left(\sum_{m \in \mathcal{M}} \left(\sum_{r \in \mathcal{R}_{ex}^m} \exp\left(\frac{-\ln A_i - \theta(\ln c_i + \ln \tau_{irj} + \ln \mu_{irj})}{\varphi \rho \zeta}\right)\right)\right)^\rho\right)^\zeta\right) \\
&= 1 - \exp(-z^\theta Q_j).
\end{aligned}$$

From the CES utility assumption, it follows,

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

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

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

Appendix C

Chapter 1: Derivatives of trade shares

I begin with the derivative of the trade share along a route r with respect to its own markup:

$$\frac{\partial \pi_{ir|j}}{\partial \mu_{irj}} = - \left(\frac{\theta}{\varphi \rho \zeta} \right) \pi_{ir|j} \left(1 - (1 - \varphi) \pi_{r|iexmj} - \varphi(1 - \rho) \pi_{rm|ie xj} - \varphi \rho(1 - \zeta) \pi_{re xm|ij} - \varphi \rho \zeta \pi_{ir|j} \right).$$

Now, I consider the derivatives of trade shares with respect to markups along competing routes. Let $m(r), x(r)$ denote the mode, port of entry/exit for a particular route r . If $r \neq r'$ but $m(r) = m(r')$ and $x(r) = x(r')$, then

$$\frac{\partial \pi_{ir|j}}{\partial \mu_{ir'j}} = \left(\frac{\theta}{\varphi \rho \zeta} \right) \pi_{ir|j} \left((1 - \varphi) \pi_{r'|ie xmj} + \varphi(1 - \rho) \pi_{r'm|ie xj} + \varphi \rho(1 - \zeta) \pi_{r' exm|ij} + \varphi \rho \zeta \pi_{ir'|j} \right).$$

If $r \neq r'$ and $m(r) \neq m(r')$ but $x(r) = x(r')$, then

$$\frac{\partial \pi_{ir|j}}{\partial \mu_{ir'j}} = \left(\frac{\theta}{\varphi \rho \zeta} \right) \pi_{ir|j} \left(\varphi(1 - \rho) \pi_{r'm|ie xj} + \varphi \rho(1 - \zeta) \pi_{r' exm|ij} + \varphi \rho \zeta \pi_{ir'|j} \right).$$

If $r \neq r'$ and $m(r) \neq m(r')$ and $x(r) \neq x(r')$, then

$$\frac{\partial \pi_{ir|j}}{\partial \mu_{ir'j}} = \left(\frac{\theta}{\varphi \rho \zeta} \right) \pi_{ir|j} \left(\varphi \rho(1 - \zeta) \pi_{r' exm|ij} + \varphi \rho \zeta \pi_{ir'|j} \right).$$

If $i \neq i'$, then

$$\frac{\partial \pi_{ir|j}}{\partial \mu_{i'r'|j}} = \theta \pi_{ir|j} \pi_{i'r'|j}.$$

Finally, it should be noted that I assume all destinations enjoy completely independent freight markets, such that, for all $j \neq j'$

$$\frac{\partial \pi_{ir|j}}{\partial \mu_{i'r'|j'}} = 0.$$

Appendix D

Chapter 1: Proof of Convergence of the EM Algorithm

It will prove convenient to define the following matrices:

$$\begin{aligned}\phi^\top &= [\lambda_i \quad \beta_m \quad 1 - \zeta \quad 1 - \rho\zeta \quad 1 - \varphi\rho\zeta] \\ X_{irj} &= [\delta_{irj} \quad Miles_{irj} \times \mathbb{1}(m) \quad \ln \pi_{ex|ij} \quad \ln \pi_{m|iej} \quad \ln \pi_{r|iexmj}]\end{aligned}$$

where $\mathbb{1}$ denotes the indicator function. With these matrices, I re-define my primary estimating equation:

$$\ln \boldsymbol{\pi} = \mathbf{X}\boldsymbol{\phi} + \mathbf{u}. \quad (\text{D.1})$$

where $\boldsymbol{\pi}^\top = [\pi_{ir1|j} \quad \pi_{ir2|j} \quad \dots]$, $\mathbf{X}^\top = [X_{ir1j} \quad X_{ir2j} \quad \dots]$, and $\mathbf{u}^\top = [u_{ir1j} \quad u_{ir2j} \quad \dots]$ denote the matrix representation of each variable. Obviously, Equation (D.1) presents the complete-information estimating equation. Unfortunately, elements of both $\mathbf{X}$ and $\ln \boldsymbol{\pi}$ are unobserved.¹ I therefore rely on the incomplete-information formulation:

$$\ln \boldsymbol{\pi}^{(p)} = \mathbf{X}^{(p)}\boldsymbol{\phi} + \mathbf{u}, \quad (\text{D.2})$$

where $\ln \boldsymbol{\pi}^{(p)} = \mathbb{E}(\ln \boldsymbol{\pi} | \phi^{(p)})$ and $\mathbf{X}^{(p)} = \mathbb{E}(\mathbf{X} | \phi^{(p)})$ denote the expected values of $\ln \boldsymbol{\pi}$ and $\mathbf{X}$ for some, fixed value of $\phi^{(p)}$. Estimating Equation (D.2) via OLS² yields the next entry in the EM sequence, $\phi^{(p+1)}$; denote the residuals from this estimation $\mathbf{u}^{(p+1)} = \ln \boldsymbol{\pi}^{(p)} - \mathbf{X}^{(p)}\phi^{(p+1)}$. From

¹Specifically, δ_{irj} and $\pi_{r|iexmj}$ are unobserved in my data.

²Note that OLS estimation satisfies the criteria of the EM process, as OLS estimates are also maximum-likelihood estimates.

here, define the likelihood function:

$$Q\left(\phi^{(p+1)}|\phi^{(p)}\right)=\mathbb{E}\left[\ln f\left(\mathbf{X}|\phi^{(p+1)}\right)\middle|\phi^{(p)}\right]$$

where f is the probability of $\mathbf{X}$ 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

$$Q\left(\phi^{(p+1)}|\phi^{(p)}\right)-Q\left(\phi^{(p)}|\phi^{(p)}\right) \geq c\left\|\phi^{(p+1)}-\phi^{(p)}\right\| \quad \forall p. \quad (\text{D.3})$$

Note that this inequality holds trivially when $\phi^{(p+1)} = \phi^{(p)}$. I now focus on the case $\phi^{(p+1)} \neq \phi^{(p)}$. Given the assumption that $u_{irj} \sim N(0, v)$, it follows that

$$Q\left(\phi^{(p+1)}|\phi^{(p)}\right)=-\left(n / 2\right) \ln (2 \pi)-\left(n / 2\right) \ln v-\left(1 /\left(2 v\right)\right) \mathbf{u}^{(p+1) \top} \mathbf{u}^{(p+1)}, \quad (\text{D.4})$$

where n is the number of rows in $\mathbf{X}$. Note also that, thanks to the OLS estimation,

$$\phi^{(p+1)}=\left(\mathbf{X}^{(p) \top} \mathbf{X}^{(p)}\right)^{-1}\left(\mathbf{X}^{(p) \top} \ln \boldsymbol{\pi}^{(p)}\right) . \quad (\text{D.5})$$

Combining equations (D.3) - (D.5) yields a characterization for c that satisfies Wu's criterion:

$$\frac{\left(\mathbf{u}^{(p+1) \top} \mathbf{u}^{(p+1)}-\mathbf{u}^{(p) \top} \mathbf{u}^{(p)}\right)}{2 v\left\|\left(\mathbf{X}^{(p) \top} \mathbf{X}^{(p)}\right)^{-1}\left(\mathbf{X}^{(p) \top} \ln \boldsymbol{\pi}^{(p)}\right)-\phi^{(p)}\right\|} \geq c > 0. \quad (\text{D.6})$$

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

Appendix E

Chapter 2: Methodology for Estimating the National Rate of Establishment Mobility within Firms

In this appendix, we provide a more complete description of how we construct our estimate of the overall share of U.S. workers who switch establishments within the same firm each year.

Because we find marked heterogeneity in SEIN mobility rates by firm size category, we use as our starting point the predicted values from the version of our SEIN mobility regression reported in Table 2.7 that features separate distance bin profiles by out-of-SEIN employment bin:

$$\begin{aligned}
 SEIN\ Transition_{it}^p = & \sum_{s \in size\ bins} \sum_{d \in bins} SizeCat_{SEINt}^{s,SN} \times BEM\ Access_{SEINt}^{d,X-SN} \times \kappa_{sd} \\
 & + \sum_{s \in size\ bins} \sum_{d \in bins} Size\ Cat_{SEINt}^{s,SN} \times BEM\ Access_{SEINt}^{d,In-SN} \times \psi_{sd} \\
 & + X_{it}\chi + X_{et}\eta + \rho_{ft}^F + \rho_{ct}^C + \rho_{nst}^N + \varsigma_{it}
 \end{aligned} \tag{E.1}$$

These naive predicted values contain four sources of mismeasurement when used to capture predicted rates of all between-establishment mobility (not just between-SEIN mobility). First, we adjust our exposure measures for the SEIN mobility outcome, $BEM\ Access_{SEINt}^{d,X-SN}$, so that they capture shares of the firm's employment in any other establishments besides the worker's own that fell into each distance bin, including those within the worker's SEIN. This step assumes that the parameters κ that govern the relationship between SEIN mobility rates and out-of-SEIN employment shares by distance bin also correctly capture the corresponding relationship between establishment mobility rates and firm-wide employment shares by distance bin.

Second, we replace the indicators for the size category of employment at other SEINs that interact with the distance bin shares, $Size\ Cat_{SEINt}^{s,SN}$ with corresponding size category indicators for employment among all the firm's other establishments (with the same category cutoffs), so as

to capture the relevant measure of the scale of establishment transition opportunities within the firm. These swaps assume that the heterogeneity in sensitivity of SEIN mobility to the distance distribution across different out-of-SEIN size classes captured in the original regression translates to the relationship between any establishment mobility and out-of-establishment size classes.

Third, the components of the naive predicted values contributed by the other control variables also have a mean that is scaled to fit observed SEIN mobility rates rather than overall establishment mobility rates. To estimate an appropriate re-scaling of these components, we isolate this predicted value component from the component related to distance bin shares of employment:

$$\hat{Y}_{it}^{controls} = X_{it}\hat{\chi} + X'_{et}\hat{\eta} + \hat{\rho}_{ft}^F + \hat{\rho}_{ct}^C + \hat{\rho}_{nst}^N$$

We then run an auxiliary regression of $\hat{Y}_{it}^{controls}$ on the same set controls except for the firm-year fixed effects, which we replace with indicators for categories of both within-SEIN and out-of-SEIN employment, $Size\ Cat_{SEIN,t}^{X-SN}$ and $Size\ Cat_{SEIN,t}^{In-SN}$:

$$\begin{aligned} \hat{Y}_{it}^{controls} = & \sum_{s \in size\ bins} Size\ Cat_{SEIN,t}^{s,X-SN} \times \phi_d^{X-SN} + \sum_{s \in size\ bins} Size\ Cat_{SEIN,t}^{s,In-SN} \times \phi_s^{In-SN} \\ & + X'_{et}\tilde{\eta} + \tilde{\rho}_{ct}^C + \tilde{\rho}_{nst}^N + v_{it} \end{aligned} \quad (E.2)$$

These estimates capture the (conditional) relationship between firm scale and SEIN mobility that was previously absorbed by the firm-year fixed effects. As before, we replace the out-of-SEIN employment categories with out-of-establishment employment categories, and impose that the coefficients capturing the relationship between SEIN mobility and out-of-SEIN employment also apply to the relationship between establishment mobility and out-of-establishment employment. We also set to zero all of the within-SEIN employment indicators, since these captured the role of unobservable “outside options” for establishment mobility that are now reflected in the out-of-establishment size categories. We then add the change in the auxiliary regression’s predicted values created by these adjustments, $\left(Size\ Cat_{et}^{s,X-Estab} - Size\ Cat_{SEIN,t}^{s,X-SN} \right) \hat{\phi}_s^{X-SN} - Size\ Cat_{SEIN,t}^{s,In-SN} \hat{\phi}_s^{In-SN}$, to the predicted rate of establishment mobility for multi-SEIN workers.

Fourth, we use the same procedure to generate predicted establishment mobility rates for workers at multi-unit, single SEIN firms that were previously excluded from the regression sample, since we observe all variables needed to form their predicted values: distance bin employment shares,

out-of-establishment size bins, and other worker, establishment, and location controls.

Finally, we add to these values an estimate of the rate of between SEIN transitions to out-of-sample states. Our goal is compute annual rates of within-firm establishment mobility among workers initially at multi-SEIN firms, $P(\text{Estab. trans.}|\text{Multi-SEIN})$, among those at multi-establishment firms, $P(\text{Estab. trans.}|\text{Multi-unit})$, and among all initially employed workers $P(\text{Estab. trans.}|\text{Employed})$.

We start by decomposing $P(\text{Estab. trans.}|\text{Multi-SEIN})$ using the law of total probability:

$$\begin{aligned} P(\text{Estab. trans.}|\text{Multi-SEIN}) = & \\ & P(\text{Estab. trans.}|\text{In sample, Multi-SEIN}) * P(\text{In sample}|\text{Multi-SEIN}) \\ & + P(\text{Estab. trans.}|\text{Out of sample, Multi-SEIN}) * P(\text{Out of sample}|\text{Multi-SEIN}) \end{aligned} \quad (\text{E.3})$$

The four steps above generate an estimate of $P(\text{Estab. trans.}|\text{In sample, Multi-SEIN})$, the annual within-firm establishment transition rate among workers from multi-SEIN firms whose origin and destination establishments (regardless of firm) are within our sample states.

Next, we use the fact that the LEHD reports an indicator for whether a worker is employed in some U.S. state even if that state does not grant data access to our project. This allows us to estimate the share of all workers in multi-SEIN firms originating in our sample states whose destination establishment is inside (or outside) of our sample states, $P(\text{In sample}|\text{Multi-SEIN})$ and $P(\text{Out of sample}|\text{Multi-SEIN})$.

To estimate $P(\text{Estab. trans.}|\text{Out of sample, Multi-SEIN})$, we assume that the share job transitions that are within-firm is the same for transitions to out-of-sample states as for transitions to other in-sample states: $P(\text{Estab. trans.}|\text{Out of sample, Multi-SEIN}) \approx P(\text{Estab. trans.}|\text{Change state, In sample, Multi-SEIN})$. Since any within-firm transition across states requires a SEIN change, we can correctly measure the latter share. Combining the terms in equation E.3 generates our estimate of the rate of establishment transitions among multi-SEIN workers. To compute the analogous rate among workers at multi-unit firms, we replace “Multi-SEIN” with “Multi-Unit” in E.3, and use the fact that $P(\text{Estab. trans.}|\text{Out of sample, Multi-unit}) = P(\text{Estab. trans.}|\text{Out of sample, Multi-SEIN}) * P(\text{Multi-SEIN}|\text{Multi-unit})$ under the assumption that firms that operate only a single SEIN within our sample do not operate any SEINs in states outside our sample. To compute the rate of establishment mobility among all initially employed workers, we use the fact that $P(\text{Estab. trans.}|\text{Employed}) = P(\text{Estab. trans.}|\text{Multi-unit}) * P(\text{Multi-unit}|\text{Employed})$.

Finally, because within-firm establishment transition rates vary so strongly by firm size category, we perform the same set of adjustments separately by initial size category.

Appendix F

Chapter 2: Appendix Tables

Log(# of SEINs)			
Firm Size		Industry	
Log(# of Estabs)	0.505‡ (0.041)	Mining	-0.252‡ (0.04)
Employees: 1-100	–	Construction	-0.174‡ (0.024)
Employees: 101-500	-0.022 (0.024)	Manufacturing	0.230‡ (0.027)
Employees: 501-1K	0.158‡ (0.055)	Trade & Transport	-0.362‡ (0.062)
Employees: 1K-5K	0.481‡ (0.089)	Information	0.230‡ (0.083)
Employees: >5K	0.739‡ (0.118)	Prof. Business Serv.	–
Firm Average Pay		Finance and Real Estate	-0.192‡ (0.062)
Q1	–	Education and Health	-0.649‡ (0.118)
Q2	0.032 (0.034)	Leisure and Hospitality	-0.234‡ (0.046)
Q3	0.180‡ (0.026)	Other Services	-0.203‡ (0.021)
Q4	0.199° (0.079)		
Q5	0.417‡ (0.027)		
Controls			
Demographics		X	
State FE		X	
Multi-Unit		X	
Obs.		34.4M	
R-squared		0.849	

LEHD 2014 snapshot.

Notes: Each entry in this table provides the coefficient and standard error (in parenthesis) associated with the variable in the row label from a regression that predicts the logarithm of the number of SEINs operated by a worker's firm. All worker observations using our baseline sample. See Table 2.7 for a more complete description of the characteristic categories referred by by the row labels. ‡, †, and ° denote statistical significance at the 1%, 5%, and 10% levels.

Appendix G

Chapter 3: Derivation of Pricing Rule

A representative transporter provides all transport services into location j at time t . The transporters total profit is given by

$$\Pi_{jt} = \sum_{i \neq j} \sum_k \zeta^k B_{jt} \pi_{ijt}^k (\mu_{ijt}^k - 1) \bar{\tau}_{ijt}.$$

where ζ^k is the constant consumption share of commodity k , B_{jt} is the (exogenous) expenditure of the location, π_{ijt}^k is the total share of trade in k to j that comes from i , μ_{ijt}^k is the markup set by the transporter, and $\bar{\tau}_{ijt}$ denotes expected trade costs between an origin i and the destination j . Taking first-order conditions yields:

$$\begin{aligned} 0 &= (\partial \Pi_{jt} / \partial \mu_{ijt}^k) \\ 0 &= (\partial / \partial \mu_{ijt}^k) \sum_{i' \neq j} \sum_k \zeta^k B_{jt} \pi_{i'jt}^k (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \\ 0 &= \zeta^k B_{jt} \left(\lambda \pi_{ijt}^k \bar{\tau}_{ijt} + \sum_{i' \neq j} (\partial \pi_{i'jt}^k / \partial \mu_{ijt}^k) (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \right) \\ 0 &= \lambda \pi_{ijt}^k \bar{\tau}_{ijt} + \sum_{i' \neq j} (\partial \pi_{i'jt}^k / \partial \mu_{ijt}^k) (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt}. \end{aligned} \tag{G.1}$$

where $\lambda \in [0, 1]$ captures the state of freight market competition. Note that this formulation imposes independence of trade flows across commodities, which stems from the assumption of zero input-output structure as well as exogeneity of the budget.

It will prove expedient to define the following derivatives:

$$\begin{aligned}
 \text{If } i' = i, \text{ then } (\partial \pi_{i'jt}^k / \partial \mu_{ijt}^k) &= -\theta A_{it}^k (c_{it} \bar{\tau}_{ijt})^{-\theta} (\mu_{ijt}^k)^{-\theta-1} (\phi_{jt}^k)^{-1} \\
 &\quad + \theta A_{it}^k (c_{it} \bar{\tau}_{ijt} \mu_{ijt}^k)^{-\theta} (\phi_{jt}^k)^{-2} A_{it}^k (c_{it} \bar{\tau}_{ijt})^{-\theta} (\mu_{ijt}^k)^{-\theta-1} \\
 &= -\theta \pi_{ijt}^k (1 - \pi_{ijt}^k) (\mu_{ijt}^k)^{-1}.
 \end{aligned}$$

$$\begin{aligned}
 \text{If } i' \neq i, \text{ then } (\partial \pi_{i'jt}^k / \partial \mu_{ijt}^k) &= \theta A_{i't}^k (c_{i't} \bar{\tau}_{i'jt} \mu_{i'jt}^k)^{-\theta} (\phi_{jt}^k)^{-2} A_{it}^k (c_{it} \bar{\tau}_{ijt})^{-\theta} (\mu_{ijt}^k)^{-\theta-1} \\
 &= \theta \pi_{i'jt}^k \pi_{ijt}^k (\mu_{ijt}^k)^{-1}.
 \end{aligned}$$

Plugging these expressions into Equation G.1 yields:

$$\begin{aligned}
 0 &= \lambda \pi_{ijt}^k \bar{\tau}_{ijt} - \theta \pi_{ijt}^k (1 - \pi_{ijt}^k) (\mu_{ijt}^k)^{-1} (\mu_{ijt}^k - 1) \bar{\tau}_{ijt} + \sum_{i' \neq j, i} \theta \pi_{i'jt}^k \pi_{ijt}^k (\mu_{ijt}^k)^{-1} (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \\
 0 &= (\lambda/\theta) \bar{\tau}_{ijt} - (1 - \pi_{ijt}^k) (\mu_{ijt}^k)^{-1} (\mu_{ijt}^k - 1) \bar{\tau}_{ijt} + (\mu_{ijt}^k)^{-1} \sum_{i' \neq j, i} \pi_{i'jt}^k (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \\
 0 &= (\lambda/\theta) \bar{\tau}_{ijt} - (1 - \pi_{ijt}^k) \bar{\tau}_{ijt} + (1 - \pi_{ijt}^k) (\mu_{ijt}^k)^{-1} \bar{\tau}_{ijt} + (\mu_{ijt}^k)^{-1} \sum_{i' \neq j, i} \pi_{i'jt}^k (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt}.
 \end{aligned}$$

Some re-organization of this equation yields:

$$\begin{aligned}
 (1 - \pi_{ijt}^k) (\mu_{ijt}^k)^{-1} \bar{\tau}_{ijt} + (\mu_{ijt}^k)^{-1} \sum_{i' \neq j, i} \pi_{i'jt}^k (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} &= (1 - \pi_{ijt}^k) \bar{\tau}_{ijt} - (\lambda/\theta) \bar{\tau}_{ijt} \\
 (\mu_{ijt}^k)^{-1} \left((1 - \pi_{ijt}^k) \bar{\tau}_{ijt} - \sum_{i' \neq j, i} \pi_{i'jt}^k (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \right) &= (1 - \pi_{ijt}^k) \bar{\tau}_{ijt} - (\lambda/\theta) \bar{\tau}_{ijt}.
 \end{aligned}$$

Isolating the markup term yields:

$$\mu_{ijt}^k = \frac{(1 - \pi_{ijt}^k) \bar{\tau}_{ijt} + \sum_{i' \neq j, i} (\mu_{i'jt}^k - 1) \bar{\tau}_{i'jt} \pi_{i'jt}^k}{(1 - \pi_{ijt}^k) \bar{\tau}_{ijt} - (\lambda/\theta) \bar{\tau}_{ijt}}.$$