(Don't) Take Me Home: Home Bias and the Effect of Self-Driving Trucks on Interstate Trade

Ron Yang*

2021/11/3

[Link to latest version: https://bit.ly/2W4MjH4]

Abstract

How will self-driving trucks transform U.S. interstate trade? I argue that human drivers' preferences to return home generate geographic specialization in the freight market, and self-driving trucks would eliminate this "home bias." I build a model of trucking carriers who make dynamic decisions about where to work, given that they prefer to be at home. A large home bias increases the value of driving places that are likely to bring one home and increases the value of taking time off at home. Using trucking freight transactions and highway inspections data, I estimate the model parameters and find that carriers value being at home at $70 per day or about 1/3 of the daily wage. In a counterfactual where self-driving trucks lower per-mile costs, double the daily driving range, and eliminate home bias, overall freight prices fall by 25.6 percent. Without home bias, carriers shift from driver-rich states to driver-poor states and total driving increases as carriers spend less time off. Eliminating home bias explains about 20 percent of the fall in overall prices, comparable in magnitude to the effect of increased daily driving range.

*Contact: Harvard University, Department of Economics, Littauer Center, Cambridge MA 02138, USA, rnyang@g.harvard.edu. Acknowledgements: I am deeply grateful to my advisors Ariel Pakes, Edward Glaeser, Mark Egan, Myrto Kalouptsidi, and Robin Lee. I am also thankful to Oliver Hart, Gabriel Kreindler, Isaiah Andrews, Elie Tamer, Alex McKay, David Scharfstein, Erica Moszkowski, Frank Pinter, Gregor Schubert, Nicola Rosaia, Pedro Degiovanni, Hanbin Yang, and the attendees of the Harvard Industrial Organization Workshop, Harvard Finance Workshop, Harvard Contracts Workshop, Urban Economics Association Summer School, UEA North American Meeting, and HBS Rising Scholars Conference for helpful conversations and comments. This project would have been impossible without the generosity of many industry participants who provided information, ideas, and advice.

1 Introduction

Trucking freight is an exciting frontier for self-driving technology. Freight trucks are technically simpler to automate than passenger vehicles due to highways' greater predictability than city streets. High labor costs and driver turnover present an economic case that has invited significant financial investment. In 2021, four self-driving truck firms — TuSimple, Plus, Embark, and Aurora — raised \$5.7 billion in funding and were collectively valued at about \$26 billion. TuSimple and Plus plan to begin driverless testing in late 2021 and expect to begin commercial production of autonomous trucks capable of operating on highways without a human driver in 2023-2024.

Given the rapid pace of innovation, understanding the impact of self-driving trucks on freight is essential today. Industry analysts have focused on labor cost savings, longer daily driving ranges, and decreased accident risk. Meanwhile, unions and trade associations have argued that safety and disemployment concerns justify stricter regulation on self-driving trucks.

I focus on another feature of the market that self-driving trucks will disrupt: the human preference to return home. This "home bias" causes truckers to prefer destinations which are likely to bring them home. The geographic distribution of trucker homes therefore shapes interstate trade and freight costs. Self-driving trucks without home bias will shift freight away from driver-rich locations and generate distributional consequences.

In this paper, I build and estimate a model of the trucking freight market which captures home bias. I find that trucking carriers value starting a day at home at \$70 per day, or about one-third of the average daily wage. When I eliminate this home bias in a counterfactual setting with self-driving trucks, carriers reallocate from driver-rich states to driver-poor states. The supply reallocation generates dispersion such that, for example, driver-rich California sees a 1.7 percent increase in average export prices while driver-poor Massachusetts sees a 6.5 percent decrease in average export prices. Carriers also take less time off because it is no longer attractive to stay at home. The increase in aggregate supply results in a 5 percent decrease in overall freight prices. In the context of a counterfactual which also includes the effect of self-driving trucks on daily driving ranges and per-mile costs, I find that eliminating home bias is responsible for about 20 percent of the fall in overall prices.

I use several overlapping data sources to learn about this historically fragmented industry. For prices and quantities, I use transactions from DAT RateView. RateView aggregates data from shippers, carriers, and brokers to gain a comprehensive view of the trucking market.

I combine this transactions data with pre-transaction posts and searches on DAT's online electronic marketplace - the largest spot marketplace for trucking freight. I merge my DAT data with highway inspections from the Federal Motor Carrier Safety Administration which identify carriers' home locations and travel patterns. These datasets reveal how carriers' geographies - both where they are based and where they work - affect aggregate prices and quantities. I document three motivating facts: carriers are concentrated in particular states, carriers are more likely to work in surrounding states, and the mix of home locations among carriers present in a location predicts variation in prices.

I build a dynamic model of trucking carriers and shippers across the United States, where carriers are differentiated by their home location. Each day, carriers can either choose among a set of routes to work or elect to take the outside option of not working. For every day they start at home, carriers receive a flow payoff which I call "home bias." Carriers that work a given route receive a market price and pay common and idiosyncratic travel costs. After travelling, they begin again in their destination. On the other side of the market, shippers are differentiated by origin and destination and make shipping decisions based on market prices. I study a steady-state equilibrium where shippers and carriers optimize, prices clear markets, and the geographic distribution of truckers is constant.

In this model, the home bias directly increases the value of being home for a given carrier. This indirectly increases the value of being in any location which is likely to bring the carrier home. In equilibrium, home bias spills across the economy and shapes the desirability of all locations through carrier value functions. The price of shipping along a given origin-destination route therefore depends on the desirability of the destination, conditional on the mix of carriers at the origin. For example, if a large share of working carriers in Washington state are from California, then the preferences of California carriers will have a larger weight than those of carriers from other states.

The key parameters of interest are the home bias, the price sensitivity of supply, and the observable components of route costs: distance, diesel, and road quality measures. My estimation approach is a standard dynamic discrete choice problem with two differences.

First, since the transactions data do not include carrier home locations, I use highway inspections to estimate home bias. Intuitively, as home bias increases, carriers specialize more geographically. This specialization is visible in the inspection patterns of carriers from different home locations. Highway inspections are therefore informative about the level of home bias.

Second, I allow unobservable shocks to enter route costs. For example, California exports may be unobservably costly because of congestion around its major ports. To handle these shocks when estimating carrier costs, I use an approach similar to the contraction mapping of Berry, Levinsohn, and Pakes (1995) for demand estimation. For a given level of the home bias, I find route mean payoffs which fit observed choice probabilities using an analog to the BLP contraction mapping. Given a level of home bias and route mean payoffs, my model predicts the geographic distribution of carriers from each home location and implies a likelihood for any empirical pattern of highway inspections.

My supply-side estimation proceeds in two steps. In the first step, I estimate the home bias by maximizing the likelihood of observed inspections. In the second step, I estimate price and cost coefficients using linear IV and mean payoffs from in my first step. I use variation in the availability of a substitute for trucking freight (rivers and internal waterways) as a demand shifter.

I find a home bias of \$70 per day. This magnitude is sizeable compared to the average wage of \$200 per day. I also recover reasonable estimates of carrier costs. I estimate the marginal cost of distance at \$1.61 per mile, which is in line with industry cost estimates of \$1.55 per mile. Routes with higher local diesel prices and lower quality roads, as measured by cracking, faulting, and rutting, also have higher costs.

On the other side of the market, I estimate demand with linear IV using the average route snowiness as a price instrument. I find that demand is relatively price-inelastic: a one percent increase in trucking freight prices yields a 0.54 percent decrease in quantity demanded.

Using my parameter estimates, I study the effect of self-driving trucks on US interstate trade in a series of counterfactual simulations. In the first counterfactual, I consider a scenario where automation eliminates home bias. To isolate the contribution of home bias and remain agnostic about the magnitude of other automation effects, I initially hold costs and driving range fixed.

Two effects emerge. First, there is a reallocation effect as carriers shift from driver-rich states to driver-poor states. For example, we would see a 20 percent decrease in driver-rich California's working carrier population. This fall in carrier supply raises California export prices by 1.7 percent. The opposite scenario occurs in driver-poor regions such as New England. More carriers working in New England, and more carriers willing to travel to New England, leads to lower shipping costs. Quantitatively, Massachusetts sees an 8 percent increase in carrier supply and a 6.5 percent decrease in export prices. Second, there is a capital utilization effect as fewer carriers choose to take the outside option at home. More driving increases the supply of carriers across the economy. Overall, eliminating home bias lowers average prices by 5 percent and increases total shipping volume by 2.5 percent.

To put home bias' effect in context with other impacts of self-driving trucks, I conduct a second "full" counterfactual that includes changes in per-mile costs and daily driving range. Based on previous work in the transportation literature, I decrease estimated per-mile costs by 25 percent and increase the maximum daily driving time from 11 hours to 22 hours. Overall, these three changes to the economy lower average shipping prices by 25.6 percent and contribute $8.10B to annual shipper welfare. The fall in per-mile costs makes up roughly 50 percent of the effect of automation on prices and quantities. Eliminating home bias contributes 20 percent and is comparable to the effect of doubling daily driving range. Across states, the effect of eliminating home bias is negatively correlated with the effect of lower per-mile costs and longer range. Intuitively, driver-rich states such as California, Texas, and Illinois, which suffer from eliminating home bias, also tend to have a larger share of long-distance trips.

1.1 Related Literature

Recent academic work has considered the effects of trucking automation on per-mile cost savings (Huang and Kockelman (2020)), labor turnover (Burks, Monaco, and Kildegaard 2018), labor demand (Gittleman and Monaco (2020)), traffic and road utilization (Carrone et al. (2021)), emissions (Liu, Kockelman, and Nichols (2018)), the rail industry (Bao and Mundy (2018)), and interactions with electrification (Ghandriz et al. (2020)). Other papers which study the effects of self-driving vehicles more broadly include Ostrovsky and Schwarz (2018) and Clements and Kockelman (2017). Viscelli (2018) and Viscelli (2020) describe potential effects of trucking automation on the market for truck drivers.

More broadly, my paper relates to the literature on the economics of trucking. I give a brief overview of this literature and then focus on the papers closest to mine. One strand studies the consequences of 1980's deregulation on rents (Rose 1985), labor (Rose (1987), Hirsch (1993), Belman and Monaco (2001)), productivity (Ying 1990), contracting (Marcus 1987), and firm mortality (Silverman, Nickerson, and Freeman (1997), Nickerson and Silverman (1998)). Another literature studies the asset ownership decision in trucking (e.g. Hubbard (2001), Baker and Hubbard (2003), Nickerson and Silverman (2003a), Nickerson and Silverman (2003b), Baker and Hubbard (2004)). Burks and Monaco (2018) considers the labor market for truck drivers. A literature in both economics and transportation studies long-term relationships within contracts, including dynamic considerations and drivers of reciprocity, (e.g. Masten (2009), Scott, Parker, and Craighead (2016), Aemireddy and Yuan (2019), Acocella, Caplice, and Sheffi (2020), and Harris and Nguyen (2021)).

Several related papers discuss similar effects of continuation payoffs on freight prices. Ishikawa and Tarui (2015, 2016), Behrens and Picard (2011), and Wong (2020) estimate the effect of backhaul, the desire for carriers to find a job returning to home, on freight rates. Allen et al. (2020) uses very high quality data from the Colombian trucking market to study the effect of market power on remote markets. In their model, truckers choose where to live, choose a route to service (potentially traveling to the origin and back from the destination), and set markups along each route. They find that more remote areas suffer a "triple curse": they have worse truckers, higher markups, and higher marginal costs. My approach generalizes the effects found in these papers by not restricting the potential routes that carriers may travel before returning home.

My demand estimation builds on previous estimates of trucking freight demand including Oum (1979), Graham and Glaister (2004), and Litman (2021). My cost estimation builds on previous work on estimating cost functions for trucking in Spady and Friedlaender (1978), Chiang and Friedlaender (1994), Daughety and Nelson (1988), and Gagne (1990), as well as more general work studying the effect of US highways on trade including Duranton and Turner (2012), Duranton, Morrow, and Turner (2014), Fajgelbaum and Schaal (2020), and Allen and Arkolakis (2020). A much larger literature studies the effect of physical infrastructure and transportation costs on economic activity; Redding and Turner (2015) provides a recent survey.

My model builds on the literature of models of spacial competition in transportation markets. For recent contributions, see Brancaccio, Kalouptsidi, and Papageorgiou (2020) on oceanic shipping, Buchholz (2021), Fréchette Lizzeri Salz (2019), and Lagos (2003) on taxicabs, Rosaia (2021) on rideshare, and Chen (2020) on railroads. Compared to these other settings, the importance of carrier differentiation in trucking motivates differences in my model. For example, Brancaccio, Kalouptsidi, and Papageorgiou (2020) notes that home ports are unimportant for ocean shipping because crews fly home a few times per year. Bucholz (2021) finds that although taxi cabs differ by home garage, these initial conditions "wash out" and become unimportant by 7:00 a.m. every day.

2 Industry and Data

2.1 Industry Background

The trucking freight industry is a significant component of the U.S. economy. In 2019, the truck transportation industry employed over 2 million people, generated $797.7 billion in revenue, and moved 11.84 billion tons of freight - representing 80.4 percent of total freight by value and 72.5 percent of total freight by weight (see Adler (2020) and Day and Hait (2019) for more details). Compared to alternative modes, trucking freight is less cost-efficient but more flexible than rail or water and slower but cheaper than air. Trucking freight dominates most commodity classes except for very low-value density commodities such as bulk grains, very high-value density commodities such as electronics, and specific categories of hazardous materials. In 2020 and 2021, the Covid pandemic has only reiterated the importance of the trucking sector, as truckers played a major role in sustaining supply chains for vital medical supplies as well as increased e-commerce purchasing. Continuing capacity constraints in trucking, on both labor and capital, have driven freight costs up to 40 percent higher than pre-Covid levels.

As a mode of transportation, trucking has been historically resistant to substituting inputs from labor to capital. While freight trains have increased in length, and barges and ships in tonnage, trucks have maintained a high ratio of human operators to freight shipped. The necessity of a human creates an opportunity for drivers' preferences to play an important role, and for automation to disrupt the market. Ocean shipping in the 1800s may provide a historic parallel; Glaeser (2005) describes how larger ships de-emphasized sailing skills and lead to a decline in sailor-rich Boston.

In this section, I provide a brief overview of the industry structure[1]. Since deregulation under the Motor Carrier Act of 1980, the trucking freight industry has been characterized by a decentralized market structure. Of the 396,000 long-distance trucking businesses in 2016, 88 percent were self-employed truckers. The trucking market is further segmented by (1) freight type, (2) shipment size, (3) geographic scope, and (4) contracting structure. In this paper, I will focus on the general freight, over-the-road, truckload market.

Most truckers haul general freight: commodities that can be shipped in standardized van trailers. By contrast, specialized freight types require specific licenses and skills and include refrigerated trailers ("reefer"), flatbed trailers, tanker trailers for shipping oil, hazardous

[1]For additional details, I refer readers to Burks et al. (2010) which provides a detailed industry primer covering the industry, market segments, and ongoing challenges and changes.

materials shipping, and specialized trailers for large machinery and other non-standard items. Due to trailer-type-specific skills investments and certifications, carriers often specialize in one trailer type.

Shippers may choose between several shipment sizes. Truckload (TL) services, which are the focus of this paper and the majority of shipments, sell the entire trailer capacity to one client. Less than truckload (LTL) services combine items from multiple clients in one trailer, yielding potentially lower fixed costs in exchange for lower quality service. Parcel services such as UPS and FedEx handle the smallest shipment sizes. Parcel and LTL firms are more labor-intensive than T.L. firms and rely on infrastructure for packing and re-packing trailers.

Shipments can also be segmented by the distance travelled, or "length of haul." Long-haul or "over the road" carriers specialize in shipments over 150-250 miles, and on average, return home once every three weeks. Regional carriers focus on shipments within 150-250 miles, which they can deliver and return home within a 500-mile daily driving limit. Local carriers make deliveries of less than 150 miles, such as warehouse-to-final-destination trips. Finally, some consider the low end of the long-haul segment, 150-500 miles, the "tweener" category. Shipments in this region are undesirable for both carriers who want to do longer or shorter days.

The trucking market can be divided into a spot market, a contract market, and private fleets. On the spot market, shippers and carriers match either using word-of-mouth, electronic platforms such as DAT, or centralized matching algorithms. Large shippers and carriers may directly use the spot market, while smaller shippers tend to use brokers. On the contract market, shippers conduct RFP processes where carriers bid with rates. Given bids, shippers construct routing guides that establish a priority among bidding carriers for volume[2]. Finally, carriers may choose to retain drivers and truckers in private fleets.

Since carriers may serve either spot or contract markets, and shippers may flexibly adjust between TL, LTL, and private fleets, the relative market share of these markets is volatile.

[2]Shippers keep the option of going to the spot market rather than to one of their contracted carriers, and carriers keep the option of going to the spot market rather than accepting a load. When spot prices are higher than contract prices, shippers use their contracted carriers more, and carriers are less likely to accept. The reverse holds when spot prices are lesser than contract prices. Recent papers such as Scott, Parker, and Craighead (2016), Aemireddy and Yuan (2019), Acocella, Caplice, and Sheffi (2020), and Harris and Nguyen (2021) investigate the interaction between the spot and contract markets. For my paper, this interaction means that transacted spot and contract prices tend to be very similar: in 2016, average spot and contract prices at the city-city level had a correlation of 98.04 percent, and average prices at the state-state level had a correlation of 99.09 percent.

Holm (2020) estimates a 46 percent market share for full truckload, 10 percent market share for less than truckload, and 45 percent for private fleets. Within full truckload, up to 80 percent of quantity moves through the contract market. Williams and Murray (2020) reports that in 2019 surveys, 26 percent of trips were less than 100 miles, 39 percent of trips were between 100 and 500 miles, 22 percent of trips were between 500 and 1,000 miles, and 13 percent of trips were over 1,000 miles.

Automation has generated significant industry and policy interest in recent years. Many firms have entered the self-driving truck space, from entrants like TuSimple, Waymo, Embark, and Otto, to incumbents like UPS. Plus, Aurora, Torc, and TuSimple began on-road testing of Level 4 autonomous trucks in 2021[3]. Plus and TuSimple expect to start mass production of Level 4 trucks in 2024. While passenger vehicles must achieve Level 5 automation to cover most use cases, freight trucks could run long-haul and regional routes under Level 4 autonomy alone. On the other hand, tasks like loading/unloading at the warehouse and last-mile delivery are likely to remain human-operated.

In early 2021, the U.S. Department of Transportation released its Automated Vehicles Comprehensive Plan, detailing how it plans to support the integration of automated vehicles into the surface transportation system. The three key goals of this plan include promoting collaboration and transparency, modernizing the regulatory environment, and preparing the transportation system. The U.S. DOT and FMCSA have begun preparing the regulatory system for automation, e.g., eliminating legal assumptions that humans are always present in commercial motor vehicles. Policy discussions have centered on the safety of self-driving trucks and the potential disemployment effects; the International Brotherhood of Teamsters union has lobbied lawmakers to create stricter regulations over driverless vehicles. Meanwhile, enthusiasts point to the potential for heightened efficiency and safer roads without driver fatigue. In this context, my paper points in a different direction: the potential for self-driving trucks to integrate previously geographically segmented markets and shift carriers away from their home locations.

2.2 Data

I combine several datasets to capture the spot trucking market.

First, I use a dataset of spot market transactions from DAT RateView. DAT Freight &

[3]SAE defines Level 4 autonomy as "features that can drive the vehicle under limited conditions," where "limited conditions" could include the National Highway System but not local city streets. The U.S. Department of Transportation describes Level 4 systems as having "an [operational design domain] of limited-access highways" and "capable of operating within their ODD with no human operator in the vehicle."

Analytics operates the dominant trucking freight marketplace platform in the U.S. DAT also combines in-house data generated by this platform with external data to produce data analytics products. DAT collects transactions from shippers, carriers, and third-party brokers to construct the RateView dataset. In my version of the dataset, for each origin-destination-week from 2016 to 2020, I observe the number of trips and moments of transaction prices (mean, standard deviation, etc.) for spot and contract transactions. In total, I see 669 million trips over these four years and 107 million trips for 2019 alone. Origins and destinations are observed at the Key Market Area (KMA) level. A KMA is a collection of 3-digit zip code areas roughly comparable in size to an MSA.

Next, I use DAT Trucks in Market data to measure the distribution of active carriers in the spot market. On DAT's trucking freight marketplace platform, shippers (loads) and carriers (equipment) can search for counterparties, make posts or offers, and match with each other. In the Trucks in Market dataset, for each origin-day from 2016 to 2020, I observe the number of load and equipment searches and posts on the platform. In total, I see 458 million carrier searches over the four years and 50 million carrier searches for 2019 alone.

Thus far, the DAT datasets aggregate across carriers from different home locations. To study carrier heterogeneity, I turn to motor carrier highway inspections. Under the Federal Motor Carrier Safety Administration's (FMCSA) Motor Carrier Safety Assistance Program, inspectors conduct roadside inspections of motor carriers. These inspections ensure that drivers and vehicles are safely operating in compliance with FMCSA regulations and vary in intensity from driver-only inspections to the most thorough inspections which evaluate brake systems, suspensions, etc. For each inspection, I observe the date, the state of inspection, the DOT number of the inspected vehicle, and registration state of the tractor and trailer (if present). I use the tractor's registration state as the home location as, unlike trailers, it is difficult to register a tractor outside one's home state[4]. The inspections dataset spans 3.2 million inspections and 1.8 million unique tractors over 2019[5].

To measure the total size of potential trucking freight demand, I use 2017 Census Bureau's Commodity Flow Survey (CFS). The Commodity Flow Survey samples shippers to estimate state-state shipping for each major freight modes: truck, rail, water, air, pipeline, etc. I also

[4] Alternatively, I could link each inspection report with the inspected carrier's registration data in the FMCSA's Census of Motor Carriers. However, the FMCSA Census has known data challenges, and multiple drivers/tractors may work for a given firm. For more details, see Appendix B of Burks et al. (2010).

[5] For more details on this dataset, see Liang (2021). She finds that states vary systematically in how intensely and frequently they inspect - I will incorporate this explictly in my estimation section. She also argues that, conditional on truck characteristics, there are no pre-trends between trucks which are inspected and trucks which are not.

use the FMCSA's Census of Motor Carriers to measure the total population of potential carriers.

I use several data sources to construct route characteristics within the United States. I begin by using Open Street Maps to compute the fastest driving route between any two locations. Next, I use the Highway Performance Monitoring System, an annual census of US highways, to measure physical road characteristics at the road segment level, and I use state average diesel prices from AAA. I take a weighted average of these characteristics over the fastest Open Street Maps route to construct route characteristics, where the weights are the mileage share elapsed in a given state. This construction represents the average road conditions experienced by drivers between origin and destination. For example, a carrier driving from Texas to Florida will spend a small share of the journey in Alabama. My method assigns a correspondingly small weight to Alabama diesel prices when constructing route-average diesel prices.

To construct cost shocks, I construct the percentage of days in a year that a state experiences snow. I use a weather dataset constructed by Moosavi et al. (2019) which collects reports from airport weather stations. This paper shows that airport reports of snow positively predicts deterioration in traffic, which would raise the cost for a tracker to travel along a route. For each state, I compute the average share of days in the year that snow is reported, and for each route, I weight the average state snowiness by the mileage share to construct the route-level cost shock.

To construct demand shocks, I construct the availability of river or water shipping from origin to destination using the Army Corps of Engineers' Fuel-Taxed Inland Waterway system[6]. For an origin-destination pair, I define an indicator variable which is 1 if a river flows from the origin to destination, or if an intracoastal waterway connects the origin and destination, and 0 otherwise.

2.3 Descriptive Statistics

I begin by documenting three empirical facts about the trucking freight industry: carrier home locations are unevenly distributed across states, carriers are more likely to work close to home, and the composition of carriers in a state predicts differences in prices. The combination of these three patterns motivate my model of trucking freight with geographic

[6]This system represents the main internal water shipping in the United States, and covers the navigable components of major river systems such as the Mississippi, the Missouri, the Ohio, the Arkansas, the Columbia, and others, major artificial waterways such as the Tennessee-Tombigbee Waterway, and the Gulf and Atlantic Intracoastal Waterways.

specialization. For additional descriptive figures, see Appendix A.

2.3.1 Carrier homes are unevenly distributed across states

In Figure 1, I document the unequal distribution of carriers across the United States. To select for firms actively engaged in inter-state freight, I combine carrier registrations with highway inspections to measure the population of active carriers. I define an active carrier as any U.S.-licensed tractor inspected in the U.S. at least once in 2019. I focus on tractors because tractors are more difficult to register outside one's state of residency than trailers.

In Figure 1a, I plot the distribution of active carriers across U.S. states. Compared to the distribution of all carriers, the distribution of active carriers is much more concentrated in a few states: California, Texas, Illinois, and Indiana. In Figure 1b, I divide by state population to plot the number of active carriers per capita from each state.

2.3.2 Carriers are more likely to work close to home

In Figure 2, I document that carriers are more likely to be inspected in states that are close to their home state. Each highway inspection records the home (registration) state and current state of the inspection. I compute the distance between the centroids of the home and inspection states and plot a density histogram of those distances. Carriers are more likely to be inspected in their home state or in adjacent states than random. For scale, a randomly drawn pair of U.S. states has on average 1,000 miles between their centroids. By comparison, inspected carriers are on average 871 miles away from their home state centroid.

2.3.3 The composition of carriers in a state predicts differences in prices

In Figure 3, I present evidence that carrier location decisions predict differences in prices. Using the inspection dataset, I compute the share of active carriers in each state i from each home state h. This share reflects a combination of the underlying distribution of carrier home locations (Figure 1) and the equilibrium location decisions of carriers as they travel through the economy.

In the figure, I plot a bin scatter of prices from i to h on the share of carriers in i from h. For a given origin-destination route, having a higher share of carriers inspected in the origin state be from the destination state is associated with lower prices. Of course, both prices and the distribution of working carriers are determined in equilibrium, so this regression is endogenous. In addition, if carriers are likely to stay close to home, they will also be taking shorter distance routes with lower prices.

To think more carefully about this relationship, I now turn to my model.

3 Model

I develop a dynamic spatial equilibrium model to explore the effects of geographic specialization. In this model, trucking carriers sell freight services to shippers and move across the economy.

3.1 Setup, Agents, and Timing

There is a set of locations in the economy, L. There are two types of infinitesimal agents: shippers who demand shipping and carriers who supply shipping. Shippers are short-lived, myopic, and differentiated by their origin-destination. Carriers are risk-neutral, long-lived, and differentiated by their home location h.

Each carrier may either begin the period in a location $i \in L$, or begin the period en-route from i to j for $i, j \in L$. There is a fixed total quantity of carriers of each type h, C^h, and the number of carriers in each location i, C_i^h, or en-route along each route ij, C_{ij}^h, must sum up.

$$C^h = \sum_i C_i^h + \sum_{i,j} C_{ij}^h \tag{1}$$

Each period is one day, and the timing is:

1. Potential shippers arise.
2. Shippers and carriers draw idiosyncratic cost and demand shocks.
3. Prices are set to clear shipper demand & carrier supply.
4. Carriers begin traveling, or traveling carriers may arrive.

3.2 Carrier Choices / Freight Supply

Each period, a carrier c of type h in location i can choose to either accept a job to any destination $j \in L$, or choose to take an outside option and remain in i.

A carrier which begins the period in its home location $h(c)$ receives a home bias flow payoff, b. Economically, b can represent both positive preferences for being at home as well as costs associated with being away at home.

A carrier who accepts a job to j receives the price p_{ij} and pays cost κ_{ij}[7], where κ_{ij} is the sum of an observable component $\bar{\kappa}_{ij}$, a systematic unobservable cost component ξ_{ij}, and an idiosyncratic cost shock ϵ_{cj} which is i.i.d. Logit across all carriers. For example, distance may be an observable component of $\bar{\kappa}_{ij}$, while unobserved congestion or scarce public bathrooms may be unobserved components of ξ_{ij}.

$$\kappa_{ij}(c) = \bar{\kappa}_{ij} + \xi_{ij} + \epsilon_{cj} \tag{2}$$

A carrier who takes the outside option receives a common flow payoff $\delta_{i,OO}$ and an idiosyncratic cost shock $\epsilon_{c,OO}$.

$$\delta_{i,OO} + \epsilon_{c,OO} \tag{3}$$

Putting these together, the carrier's per-period flow payoffs are

$$b \times 1_{h(c)=i} + \begin{cases} \alpha p_{ij} + \bar{\kappa}_{ij} + \xi_{ij} + \epsilon_{cj} & \text{Accept job to } j \\ \alpha p_{ik} + \bar{\kappa}_{ik} + \xi_{ik} + \epsilon_{ck} & \text{Accept job to } k \\ \dots & \\ \delta_{i,OO} + \epsilon_{c,OO} & \text{Outside Option} \end{cases} \tag{4}$$

For convenience, let δ_{ij} denote the component of flow payoffs which are common across drivers.

$$\delta_{ij} = \alpha p_{ij} + \bar{\kappa}_{ij} + \xi_{ij} \tag{5}$$

A carrier which takes a job to j arrives at the destination with probability λ_{ij}. If they arrive, they may immediately take another job the following period. With probability $1 - \lambda_{ij}$, the carrier does not arrive and instead begins the next period en-route from i to j. Each period, an en-route carrier arrives with probability λ_{ij}. The expected days of travel for a job from i to j is therefore $1/\lambda_{ij}$.

[7] The carrier pays the entire cost of a trip at the beginning of the trip. Equivalently, κ_{ij} can be interpreted as the expected discounted value of flow costs that the carrier pays during the trip.

To complete the carrier optimization problem, let V_{ic}^h be the expected value function of a carrier with home h which starts a period available in i. Let W_{ijc}^h be the expected value function of a carrier with home h which starts a period en-route from i to j. Carriers have a discount factor of β.

$$V_{ic}^h(\epsilon) = b \times 1_{h(c)=i} + \max \begin{cases} \delta_{ij} + \epsilon_{cj} + E[W_{ij}^h] & \text{Accept job to } j \\ \delta_{ik} + \epsilon_{ck} + E[W_{ik}^h] & \text{Accept job to } k \\ \dots & \\ \delta_{i,OO} + \epsilon_{c,OO} + \beta E_\epsilon[V_{ic}^h] & \text{Outside Option} \end{cases} \tag{6}$$

Given the stochastic arrival probabilities, the value function in the en-route state is a weighted average of the value function in the destination and the value function of being in the en-route state.

$$E[W_{ij}^h] = \lambda_{ij} E_\epsilon[V_j^h] + (1 - \lambda_{ij})\beta E[W_{ij}^h] \tag{7}$$

Given the logit cost shocks, the share of carriers of type h in origin i who choose destination j is given by the usual logit formula. I call this the type-specific choice probability, as it is specific to carriers of type h.

$$s_{ij}^h(p) = \frac{\exp(\delta_{ij} + E[W_{ij}^h])}{\sum_{k \in L} \exp(\delta_{ik} + E[W_{ik}^h]) + \exp(\delta_{i,OO} + \beta E_\epsilon[V_{ic}^h])} \tag{8}$$

The aggregate share weights the choice probabilities by the mix of carrier types h available at i. Intuitively, a larger share of shipping flows from origin i to destination j if destination j is very popular (high s_{ij}^h) or if origin i has a large share of carriers who like destination j (high $\frac{C_i^h}{\sum_{h'} C_i^{h'}}$).

$$s_{ij} = \sum_h \left(\frac{C_i^h}{\sum_{h'} C_i^{h'}} \right) s_{ij}^h \tag{9}$$

Aggregate supply S_{ij} is the sum of choice probabilities weighted by the distribution of available carriers.

$$S_{ij} = \sum_h C_i^h s_{ij}^h \tag{10}$$

3.3 Shipper Optimization / Freight Demand

In each period, a mass of N_{ij} potential shippers arise with fixed origin $i \in L$ and destination $j \in L$.

Each shipper draws a willingness-to-pay for freight, where ω_{ij} is a common demand shock, and υ is an idiosyncratic shock distributed exponential with mean σ. Shipper profits are willingness to play less prices.

$$\pi = \omega_{ij} + \nu - p_{ij}$$

The shipper's outside option is to ship outside the trucking spot market, with payoff normalized to 0.

$$\max\{\omega_{ij} + \upsilon - p_{ij}, 0\} \tag{11}$$

Aggregating over the mass of potential shippers, aggregate demand is

$$D_{ij} = N_{ij} \times P(\omega_{ij} + \upsilon > p_{ij}) = N_{ij} \exp(\sigma p_{ij} + \omega_{ij}) \tag{12}$$

Since shippers have a fixed origin and destination, there is no substitution across destinations and the price of shipping along other routes does not enter demand for shipping from i to j. When I take logs, I find that the log share of shippers who choose trucking is linear in price.

$$\log s_{ij}^{shipper} = \log D_{ij} - \log N_{ij} = \sigma p_{ij} + \omega_{ij} \tag{13}$$

3.4 Equilibrium

A steady-state equilibrium of this model is a set of prices p_{ij}, quantities Q_{ij}, and carrier locations C_i^h, C_{ij}^h , such that (1) markets clear, (2) the geographic distribution of carriers is constant over time, (3) carriers make optimal choices, and (4) shippers make optimal choices. Specifically, the following must hold:

- For each $i, j \in L$, total supply equals total demand

$$Q_{ij} = S_{ij}(p) = D_{ij}(p) \tag{14}$$

- For each available state i, for each carrier type h, inflows equal outflows.

$$\sum_k \lambda_{ki}(\underbrace{C_{ki}^h}_{\text{inflows from en-route carriers}} + \underbrace{C_k^h s_{ki}^h}_{\text{inflows from new trips}}) = C_i^h \underbrace{\sum_j s_{ij}^h}_{\text{outflows}} \tag{15}$$

- For each en-route state $i \to j$, for each carrier type h, inflows equal outflows.

$$\underbrace{C_i^h s_{ij}^h (1-\lambda_{ij})}_{\text{new trips beginning to travel}} = \underbrace{\lambda_{ij} C_{ij}^h}_{\text{en-route carriers arriving}} \tag{16}$$

- For each $h, i \in L$, carrier market shares are optimal

$$s_{ij}^h(p) = \frac{\exp(\delta_{ij} + \beta E[W_{ij}^h])}{\sum_{k\in L} \exp(\delta_{ik} + \beta E[W_{ij}^h]) + \exp(\delta_{i,OO} + \beta E_\epsilon[V_{ic}^h])} \tag{17}$$

- For each $h, i \in L$, carrier value functions are consistent

$$E_\epsilon[V_{ic}^h] = 1_{h(c)=i} \times b + E_\epsilon[\max\{\max_{j\in L} \delta_{ij} + \beta E[W_{ij}^h], \delta_{i,OO} + \beta E[V_{ic}^h]\}] \tag{18}$$

$$E[W_{ij}^h] = \lambda_{ij} E_\epsilon[V_{jc}^h] + (1-\lambda_{ij})\beta E[W_{ij}^h] \tag{19}$$

- For each $i, j \in L$, shipper decisions are optimal

$$\log s_{ij}^{shipper} = \sigma p_{ij} + \omega_{ij} \tag{20}$$

3.5 Discussion

I make several simplifying assumptions to tailor my model for the long-haul truckload market.

First, I assume that all shipments are of equal size. This is true of the truckload market where a shipper purchases an entire truck's worth of capacity. Unlike less-than-truckload (LTL) and parcel markets, there are no complementarities across shipments along a route. For example, trucks have no reason to take a detour to drop off a portion of their load before continuing to their final destination.

Second, I assume that all carriers are optimizing independently. My model therefore rules out large carriers who may be able to exert market power. The existing literature characterizes the truckload market as more competitive than the less-than-truckload market (e.g. Corsi et al. (1992), Keeler (1989), Savage (1995), Laing and Nolan (2009)). In the less-than-truckload market, there are strong scale economies due to large firms' ability to operate hubs and repack freight efficiently. At the extreme end, the parcel market is dominated by just a few major firms.

Third, I abstract away from considerations of the spot, contract, and private fleet markets. This model focuses on the cross-sectional variation in freight prices, rather than the time-series interaction of spot and contract prices, or the contracting problem of whether to develop a private fleet. In practice, the spot and contract prices are highly correlated.

Fourth, I assume that there is a single market-clearing price for each origin-destination route. This prevents carriers of different types from charging different prices from shippers for a given route. Since I focus on the general freight market, there is less differentiation that would be true if I were considering a broader market including refrigerated or hazardous materials carriers.

4 Estimation

I begin by making parametric assumptions. I estimate the demand side of my model using a linear IV. I construct an estimator for my supply-side parameters. Finally, I discuss my estimated parameters and interpret their magnitudes.

4.1 Parametric Assumptions

For the remainder of this section, I assume that the observable route cost κ_{ij} is linear in observable route characteristics X_{ij}.

$$\kappa_{ij} = \gamma X_{ij} \tag{21}$$

The common component of the flow payoff δ_{ij} is linear in prices, route characteristics, and an unobservable route cost shock.

$$\delta_{ij} = \alpha p_{ij} + \gamma X_{ij} + \xi_{ij} \tag{22}$$

For details on how I construct route characteristics and other elements of the data, see Appendix D.

	OLS	IV
price	-0.166***	-0.305***
	(0.0122)	(0.0503)
Constant	-0.326***	-0.0773
	(0.0219)	(0.0876)
Observations	2025	2025

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Demand Estimation Results

Notes: Regression of log shipper trucking share $\log s_{ij}^{shipper}$ from i to j on the price of trucking p_{ij}. IV uses snowiness of the route from i to j as a cost shifter. Robust standard errors.

4.2 Demand Estimation

From my model, I can derive a linear equation for the share of shippers who choose trucking.

$$\log s_{ij}^{shipper} = \sigma p_{ij} + \omega_{ij} \tag{23}$$

This equation faces the classic simultaneity problem: equilibrium prices p are a function of demand shocks ω. I can use a linear IV strategy to estimate σ.

Specifically, I use supply shifters which affect prices but are independent of demand shocks ω: the snowiness of the route from i to j as a cost shifter. Snowy conditions make driving more difficult and intensify traffic, and multiple routes from the same origin or to the same destination may have different degreees of snow risk.

In Table 1, I report results from the regression in Equation 24, at the state-state level.

The price coefficient is significant and negative. For interpretation, the estimated price coefficient on -0.305 corresponds to an average demand elasticity of -0.547, which is comparable in magnitude to previous work in the trucking freight literature. Beuthe et al. (2001) estimate short distance trucking demand elasticities at -0.58 and long distance elasticities at -0.63. In one survey of the literature, Litman (2021) reports truck demand elasticities between -0.25 and -0.47. In another survey, Graham and Glaister (2004) report that 66 percent of estimates fall between -0.5 and -1.3. Trucking demand appears comparable and slightly less elastic compared to rail or water. Chen (2021) estimates a rail freight demand elasticity of -0.739, which is in line with earlier literature surveyed in that paper. Brancaccio, Kalouptsidi, and Papageorgiou (2020) finds a trade elasticity with respect to ocean freight shipping prices of -1.03.

4.3 Supply Estimation

The remaining structural parameters of my model are the discount factor β, the expected travel time λ_{ij}^{-1}, the home bias b, the supply price coefficient α, and the observable cost coefficients γ. I will calibrate β and λ and estimate the home bias and price and cost coefficients.

4.3.1 Overview

My problem is a standard dynamic discrete choice problem with two differences.

First, the home bias is reflected in differences in choice probabilities across types, but I do not have data on type-specific shares s_{ij}^h. To handle this, I use highway inspections where I observe the geographic distribution of carriers of different types.

Intuitively, suppose that the home bias is zero. All carriers are homogenous, so they will have identical inspection patterns across states. California carriers will make up the same share of inspected carriers in California as in Massachusetts. Alternatively, let the home bias go to infinity. Carriers will choose to only stay in their home state and do within-state jobs, so carriers will have very different inspection patterns. If the observed world is somewhere in the middle (i.e. Figure 2), then the degree of carrier geographic specialization will identify the level of home bias b.

More formally, I assume that inspections are generated by the following process. For origin i, destination j, and intermediate location k, let m_{ijk} be the mileage share of the total ij route spent in k. A carrier is inspected in location k with probability ρ_k if the carrier is available in k, or with probability $\rho_i m_{ijk}$ if the carrier is en-route in ij. Carriers which take the outside option are not inspected. This process allows different states to have different inspection intensities, but restricts states from discriminating against carriers registered in any particular state.

The probability of inspecting a type h carrier, conditional on making an inspection in k, is

$$\iota_k^h = \frac{\rho_k C_k^h + \sum_{i,j} \rho_k m_{ijk} C_{ij}^h}{\sum_{h'}(\rho_k C_k^{h'} + \sum_{i,j} \rho_k m_{ijk} C_{ij}^{h'})} = \frac{C_k^h + \sum_{i,j} m_{ijk} C_{ij}^h}{\sum_{h'}(C_k^{h'} + \sum_{i,j} m_{ijk} C_{ij}^{h'})} \tag{24}$$

Second, I allow unobservables shocks ξ_{ij} to enter the cost function. To handle this, I will use an approach similar to BLP for demand estimation where I use demand shifters as instruments independent of the ξ_{ij} cost shocks.

Recall the mean payoff of a route from i to j,

$$\delta_{ij} = \alpha p_{ij} + \gamma X_{ij} + \xi_{ij} \quad \forall (i,j) \tag{25}$$

For every level of home bias b, I can find a vector of mean payoffs which matches observed shares s_{ij}^O.

$$\delta^*(b, s^O) = \delta \quad .s.t \quad s_{ij}(b, \delta) = s_{ij}^O \in (0,1) \quad \forall (i,j) \tag{26}$$

For this vector to be unique, I must make L normalizations. I choose to normalize the flow payoff of taking the outside option $\delta_{OO,i}$ to zero for all locations i. I find this ex-ante more plausible than normalizing the payoff or the value of the unobservable cost for any other choice; the value of not working is probably more comparable across states than e.g. the value of a within-state trip. This creates a convenient interpretation for b: it is the difference in utils between not working at home versus not working somewhere else.

I solve for δ^* using an iterative algorithm which is analogous to the BLP contraction mapping, with the addition of accounting for how value functions and the equilibrium location of carriers depend on δ. For details on this algorithm, see the following section 4.4.2.

$$\delta'_{ij}(b) = \delta_{ij}(b) + \log s_{ij}^O - \log s_{ij}(\delta) \tag{27}$$

Given a value of δ^*, and a price instrument which is orthogonal to ξ_{ij}, I can recover price and cost coefficients with IV. Specifically, I use the availability of river and internal waterway shipping between i and j. Rivers increase the availability of substitutes for trucking (barge shipping), thereby shifting demand for trucking and varying prices independent of ξ_{ij}.

4.3.2 Computational Details of $\delta^*(b)$

I will compute $\delta^*(b)$ using the following iterative algorithm analogous to the nested fixed point of Berry, Levinsohn, and Pakes (1995).

Iterative Algorithm Recall that a carrier which starts traveling from i to j has a probability λ_{ij} of arriving next period.

$$W_{ij}^h = \lambda_{ij} E[V_j^h] + (1 - \lambda_{ij}) \beta W_{ij}^h \tag{28}$$

I can rearrange this to find W_{ij}^h as a function of V_j^h.

$$W_{ij}^h = \frac{\lambda_{ij}}{1 - \beta(1 - \lambda_{ij})} V_j^h \tag{29}$$

For notational convenience, let $\tilde{\beta}_{ij} = \frac{\lambda_{ij}}{1-\beta(1-\lambda_{ij})}$ be the effective route-specific "discount factor." This allows me to dispense with tracking the en-route state value functions W_{ij}^h.

Step 1. Given a guess for (b, δ), compute V_i^h.

In a steady-state equilibrium, conditional on δ, a carrier does not need to know what any other carrier is doing in the future. Let T be the following operator defined on a space $B(X)$ of functions $f : X \to \mathbb{R}$ where $X = L \times L$.

$$Tf(h, i) = b \times 1_{h=i} + E_\epsilon[\max\{\max_j\{\delta_{ij} + \tilde{\beta}_{ij} f(j) + \epsilon_j\}, \beta f(i)] \tag{30}$$

T is a contraction mapping, so V_i^h can be computed using value function iteration.

Step 2. Given V_i^h, compute the type-specific choice probabilities s_{ij}^h using Equation 8.

$$s_{ij}^h(p) = \frac{\exp(\delta_{ij} + \tilde{\beta}_{ij} V_j^h)}{\sum_{k \in L} \exp(\delta_{ik} + \tilde{\beta}_{ik} V_k^h) + \exp(\beta V_i^h)} \tag{31}$$

Step 3. Given $s_{i \to j}^h$, compute equilibrium carrier locations C_i^h.

The en-route state steady-state condition implies that the population of the en-route carriers is a multiple of the origin location carriers.

$$(1-\lambda_{ij})C_i^h s_{ij}^h = \lambda_{ij}C_{ij}^h \implies C_{ij}^h = \frac{(1-\lambda_{ij})s_{ij}^h}{\lambda_{ij}}C_i^h \tag{32}$$

Substitute this into the available state steady-state condition to find a relationship between all available carrier locations.

$$\sum_k \lambda_{ki}(C_{ki}^h + C_k^h s_{ki}) = C_i^h \sum_j s_{ij}^h \implies C_i^h = \frac{\sum_j s_{ji}^h C_j^h}{\sum_j s_{ij}^h} \tag{33}$$

Finally, the carriers must sum up.

$$C^h = \sum_i C_i^h + \sum_{i,j} C_{ij}^h = \sum_i C_i^h(1 + \sum_j \frac{(1-\lambda_{ij})s_{ij}^h}{\lambda_{ij}}) \tag{34}$$

I can combine these two equations as a linear system

$$\begin{pmatrix} A \\ B \end{pmatrix} (C_1^h \dots C_L^h) = \begin{pmatrix} C_1^h \\ \dots \\ C_L^h \\ C^h \end{pmatrix} \tag{35}$$

where A is an $L \times L$ matrix where $A_{ij} = \frac{s_{ji}^h}{1-\sum_j s_{ij}^h}$ and B is an $1 \times L$ matrix where $B_i = 1 + \sum_j \frac{(1-\lambda_{ij})s_{ij}^h}{\lambda_{ij}}$. This system can be solved for C^h. Intuitively, A captures the flows across locations, and B enforces that the distribution of carriers sums to $\bar{C}^h$.

Step 4. Given (C_i^h, s_{ij}^h), compute predicted aggregate shares $s_{ij}(b,\delta)$ using Equation 10.

$$s_{ij} = \sum_h (\frac{C_i^h}{\sum_{h'} C_i^{h'}}) s_{ij}^h \tag{36}$$

Step 5. Repeat Steps 1-4 and iterate $\delta'_{ij} = \delta_{ij} + \log s_{ij}^O - \log s_{ij}(\delta)$ until convergence[8].

4.3.3 Supply-side Estimation Steps

I conduct the supply-side estimation in two steps.

[8]For one carrier type, it is straightforward to prove that this δ^*-algorithm is a contraction mapping. For multiple carrier types, the algorithm converges quickly to a solution in practice.

In the first step, I estimate the home bias by maximizing the likelihood of observed inspections. For each guess of the home bias parameter b, I use the δ^*-algorithm to solve for mean payoffs which match observed shares. As part of computing δ^*, I also find equilibrium carrier locations $C(b, \delta)$ which are consistent with b and $\delta^*(b, s^O)$. These imply the probability of inspecting a carrier from h conditional on drawing an inspection in k.

$$\iota_k^h(b, \delta) = \frac{C_k^h(b, \delta) + \sum_{i,j} m_{ijk} C_{ij}^h(b, \delta)}{\sum_{h'}(C_k^{h'}(b, \delta) + \sum_{i,j} m_{ijk} C_{ij}^{h'}(b, \delta))} \tag{37}$$

Combine with the probability of drawing an inspection in k, ρ_k, to form the first stage optimization problem.

$$b^* = \arg\min_{b, \rho_k} \quad \sum_{h,i} I_k^h \times \log \iota_k^h(b, \delta^*(b, s^O)) \times \rho_k \tag{38}$$

where

$$\delta^*(b, s^O) = \delta \quad .s.t \quad s_{ij}(b, \delta) = s_{ij}^O \quad \forall i, j \tag{39}$$

In the second step, I take the mean payoffs corresponding to the optimal home bias, $\delta^*(b^*, s^O)$ and I estimate price and cost coefficients using linear IV. I use the availability of rivers as a price instrument.

Observing the Outside Share To operationalize this estimation, I need to be able to compute empirical aggregate shares, s_{ij}. In my DAT RateView dataset I only observe carriers who choose to sell shipping. On the other hand, the DAT Trucks in Market dataset should include both carriers chose to work, as wells carriers who searched and decided not to work.

Let T_i be the number of searches made by carriers in 2019. I assume that number of available carriers are distributed proportional to the share of searching carriers in the Trucks in Market dataset.

$$C_i = (\frac{T_i}{\sum_i T_i}) \times (\sum_h C^h) \tag{40}$$

I can then compute empirical aggregate shares:

$$s_{ij}^O = \frac{Q_{ij}}{C_i} \tag{41}$$

Calibrated Parameters The expected arrival time for a trip is $1/\lambda_{ij}$. For across-state trips, I set $\lambda_{ij} = \frac{500}{d_{ij}}$ to fit the expected numbers of days to travel distance d_{ij}, under the assumption that carriers average speed 45 miles per hour and drive the DOT-mandated maximum of 11 hours a day[9]. For within-state trips of distance less than 250 miles, I set λ_{ij} to 1 because a carrier can make a round trip in one day. Otherwise, I set $\lambda_{ii} = \frac{250}{d_{ii}}$. In practice, only California has average within-state trips above 250 miles; this accounts for the lower probability that a carrier taking a within-California trip can return home and receive a home bias.

I calibrate the discount factor β to 0.995. Specifically, since the time periods are short, I set the discount factor to reflect carrier exit rates rather than time preferences. Suppose that carriers are patient but have an exogenous $1 - \beta = 0.005$ probability of exiting the market each period and being replaced by an identical carrier. This generates a discount factor of β, a daily exit probability of 0.5 percent, and an annual attrition rate of 84 percent which is consistent with 2019 industry annual attrition rates of 70-100 percent (e.g. American Trucking Association (2020)).

4.4 Estimation Results

I present my estimates in Table 2. Confidence intervals are taken from 450 bootstrap sample draws. Given my estimated price coefficient, the daily flow payoff of being at home is about \$71 per day. This is one-third of the average daily wage of about \$200 (Williams and Murray (2020)).

Turning to the coefficients in Table 2, I find a positive coefficient on price and negative coefficients on the components of the cost function: diesel, distance, cracking, faulting, and rutting.

For interpretation of the magnitudes, I divide the coefficients by the estimated price coefficient α to convert into dollar units. I estimate the marginal cost of distance at \$1.64 per mile. This marginal cost is comparable with industry average cost estimates of \$1.55 per mile[10].

[9] See Williams and Murray (2020) for survey-based statistics and average moving speed. See Federal Motor Carrier Safety Administration (2020) for the full hours-of-service regulations.

[10] See Williams and Murray (2020) for this analysis using an accounting approach. They sum over fuel costs, capital lease and maintenance, license and toll expenses, and driver wages to arrive at their number.

Parameter	Estimate (Utils)	95% Bootstrap CI	Estimate ($)
Home Bias (Utils)	0.0206	[0.0205, 0.0216]	71.30
Price (000 $)	0.2889	[0.2711, 0.3076]	-
Diesel ($/gal x 000 miles)	-0.1422	[-0.1667, -0.1321]	-492.2
Distance (000 miles)	-0.4732	[-0.4755, -0.4709]	-1637
Cracking (std)	-0.0313	[-0.0326, -0.0301]	-108.3
Faulting (std)	-0.0542	[-0.0549, -0.0527]	-187.6
Rutting (std)	-0.0887	[-0.0902, -0.0877]	-307.0

Table 2: Supply Structural Estimates

I find that carriers value a route with $1 per gallon higher average diesel prices at -$0.49 per mile. This is fairly high: it implies that carriers are acting if they average two miles per gallon when choosing routes, rather than the six or seven miles per gallon found in carrier survey data. A possible explanation is that changes in national fuel prices are typically passed on to shippers through fuel surcharges, but carriers have to pay when local fuel prices deviate from a national index. This might make carriers more sensitive to route-specific fuel prices.

Carriers appear to be sensitive to road quality. A route with one standard deviation higher cracking, faulting, or rutting increases the cost of travelling along a route by $108, $187, and $307. Equivalently, carriers would be different between a route with one standard deviation higher cracking, faulting, or rutting and a comparable route of 66, 112, and 188 miles respectively.

To examine the effect of different model assumptions, I compare price and cost estimates across three specifications in Table 3. The first column contains estimates from my main specification as in Table 2. In the second column, I use OLS instead of my river shipping IV in the second stage of estimation. Compared to my main specification, the coefficient on price is close to zero and implies an unrealistically high marginal cost of distance of $12 per mile. The difference between the IV and OLS coefficients is consistent with prices being correlated with unobserved cost shocks, which would cause a downward bias in the price coefficient.

In the third column, I force the home bias b to be zero. The price coefficient becomes negative, and the distance coefficient drops in magnitude. Intuitively, trips returning to driver-rich states like California are more affected by home bias. If these trips also tend to be longer distance and lower price, then failing to consider home bias would give the illusion that carriers like longer distance and lower price trips.

Parameter	IV	OLS	OLS ($b = 0$)
Price (000 $)	0.2889	0.0400	-0.2592
Diesel ($/gal x 000 miles)	-0.1422	-0.0989	-0.1537
Distance (000 miles)	-0.4732	-0.4986	-0.1566
Cracking (std)	-0.0313	-0.0308	-0.0492
Faulting (std)	-0.0542	-0.0499	-0.0545
Rutting (std)	-0.0887	-0.0894	-0.0921

Table 3: Comparing Estimates Across Specifications

5 Counterfactual Simulations

I present two main sets of counterfactuals. My first counterfactual removes home bias while holding costs constant, to study the effects of home bias in isolation. My second counterfactual considers home bias along with two other major shifts from automation, lower per-mile costs and longer daily range, to set it in context.

5.1 Counterfactual 1: No Geographic Specialization

The first counterfactual studies a setting without incentives for geographic specialization where I set the counterfactual home bias b to zero for all carriers and compute a new equilibrium. To remain agnostic about the other effects of self-driving trucks (e.g. decreases in per-mile costs), I hold costs and demand constant.

Since I hold the value of the outside option constant, carrier can still choose not to operate. In the counterfactual, this would capture mechanical breakdowns or maintenance which stop work both at home and on the road.

5.1.1 Method

I compute counterfactual equilibria using a tatonnement procedure. Beginning at a random candidate price vector p^0, I iterate the price vector with excess supply until convergence. For a given level of prices, I update the value of δ, re-compute value functions, and re-compute the equilibrium distribution of carriers.

$$p_{ij}^{t+1} = p_{ij}^{t} + (S_{ij}(p^t) - D_{ij}(p^t)) \tag{42}$$

where demand and supply are computed as

$$D_{ij}(p^t) = N_{ij}\exp(\sigma p_{ij}^t + \hat{\omega}_{ij}) \tag{43}$$

$$S_{ij} = \sum_h C_i^h(\delta) \frac{\exp(\alpha p_{ij}^t - \bar{\kappa}_{ij} - \xi_{ij} + \tilde{\beta}_{ij} V_j^h(b,\delta))}{\sum_{k\in L}\exp(\alpha p_{ik}^t - \bar{\kappa}_{ik} - \xi_{ik} + \tilde{\beta}_{ik} V_k^h(b,\delta)) + \exp(\beta V_i^h(b,\delta))} \tag{44}$$

5.1.2 Results

There are two main effects. First, carriers reallocate from working in driver-rich states to working in driver-poor states. This benefits certain locations rather than others. Second, the overall attractiveness of taking the outside option when in the home location falls. This effectively shifts the supply curve out, thereby lowering prices and increasing quantities.

In Figure 4, I plot the percentage change in the number of available carriers C_i in each state. States with a high number of truckers per capita — California, Texas, Illinois, and Indiana — see large declines as carriers no longer choose to stay local. By comparison, previously low-value states such as northeastern states like Massachusetts see an increased number of available carriers.

I next compute the change in export prices-per-mile for each state using a Laspeyres index.

$$\Delta p_i^{export} = \frac{\sum_j (p_{ij}^{CF}/D_{ij}) q_{ij}}{\sum_j (p_{ij}/D_{ij}) q_{ij}} - 1 \tag{45}$$

I plot the change in this export price index in Figure 5. Compared to the observed equilibrium, prices fall across the board due to increase capital utilization. Notably, California sees an increase in prices: the high number of carriers per capita in California have subsidized shipping to and from California, so when those carriers are dispersed across the economy, California suffers relatively.

I plot changes in average export quantity in Figure 6. On average, trade increases more between states outside of the nexus of California, Texas, Illinois, and Indiana.

These aggregated plots mask a significant amount of heterogeneity across states. I consider Massachusetts as an example in Figure 7. Most carriers live far from New England, so New England is an undesirable region to work. When home preferences are removed, there are two effects: (1) there are more carriers in Massachusetts, and (2) New England destinations are more desirable. As a result, the price of intra-New England shipments falls.

5.2 Counterfactual 2: Full Automation

In this second counterfactual, I put the effect of home bias in context by comparing it to two other effects of self-driving trucks.

First, self-driving trucks are expected to experience decreases in marginal costs per mile along several dimensions[11]. Labor costs are eliminated, a decreased risk of accidents lowers depreciation and insurance costs, and more efficient driving increases fuel economy. Estimates of the total cost difference from the transportation literature range from 15 percent (Wadud (2017)) to 33 percent (Engholm, Pernestal, and Kristoffersson (2020)) for 40-ton trucks. Following Huang and Kockelman (2020), I consider a moderate scenario where costs-per-mile decrease by 25 percent. In the context of my model, $\gamma_{distance}$ and γ_{diesel} would decrease by 25 percent.

Second, self-driving trucks would no longer be subject to hours-of-service regulation which caps daily driving times for safety reasons. A 2021 Deloitte report suggests that without hours-of-service regulation, daily driving ranges would double. In my model, I set the stochastic arrival rate, λ_{ij}, to double the daily driving range.

I run counterfactual simulations with each of the eliminating home bias, lowering costs, and increasing range counterfactuals, as well as a full counterfactual with all three changes. In Table 4, I present the effects of each counterfactual on three measures: aggregate prices, total quantities, and shipper welfare. Under the full counterfactual, prices fall by 25.6 percent and shipper welfare increases by \$8.1B per year. For scale, U.S. Census reported annual expenditure on long-distance general freight trucking at \$111.1B for 2019.

Counterfactual	Price Index	Total Quantity	Shipper Welfare (\$B/year)
No Home Bias	-5.4%	+2.5%	+1.50
Lower Per-Mile Costs	-13.3%	+6.2%	+4.12B
Longer Daily Range	-7.6%	+3.5%	+2.29B
Full Counterfactual	-25.6%	+12.5%	+8.10B

Table 4: Full Automation Counterfactual Results

On average, eliminating home bias would be responsible for about 20 percent of the total impact of automation on prices, quantities and welfare. Looking at the cross-section, home bias's effect is negatively correlated with the effect of lower costs or longer range. In Figure

[11] Engholm, Pernestal, and Kristoffersson (2020) provides a detailed cost analysis of self-driving trucks.

8, I plot the change in average export prices for each U.S. state under no home bias (x-axis) and under lower costs and longer range (y-axis). Each marker represents one US state, and the negative correlation indicates that states which gain more from home bias will gain less from the other effects of automation. Intuitively, driver-rich states also tend to have longer average trip lengths.

In Figure 9, I plot the change in average export prices by state. Compared to the counterfactual where I only eliminate home bias, decreases per-mile costs and increasing range tends to benefit states in the West and Midwest. These regions are more likely to export longer distances, so they benefit more when long-range trips become cheaper and faster. The biggest winners are driver-poor states with long average export distances: examples include Iowa, Idaho, and New Mexico. Among the larger states, California benefits more than Texas from full automation because of its prevalence to export long distances to the East Coast.

In this counterfactual, I hold demand fixed and ignore externalities from trucking. Longer daily driving ranges would decrease travel times, which would further improve shipper welfare if shippers care about delivery time. In addition, time-sensitive shippers may substitute more from air (the next fastest mode) in ways which are not captured by my demand estimation.

Major externalities from trucking include emissions, congestion, and road wear and tear. The increase in quantity under the full counterfactual yields 2.27 billion additional miles driven per year. Using EPA estimates of emissions (65 grams per ton-mile) and gas mileage (7 miles per gallon), this translates into 325 million additional gallons of diesel consumed per year and 3.33 million additional metric tons of CO2 per year. By comparison, Liu, Kockelman, and Nichols (2018) estimates a 3 percent decrease in CO2 emissions for self-driving vehicles, suggesting that greater efficiency from self-driving vehicles is not enough to counteract the effect of increased quantity.

5.3 Additional Counterfactuals

I present additional counterfactuals in Appendix C.

In my main counterfactuals, I focus on a long-run outcome where all trucks are replaced with self-driving trucks. In counterfactual C.1, I consider a transition path to automation using a set of counterfactuals where X percent of the trucking fleet becomes self-driving while the remainder is human. I find a smooth transition path in terms of overall prices and quantities.

In counterfactual C.2, I consider a transition path to automation where self-driving trucks are geographically constrained along the transition path. At first, self-driving trucks gain access to technically simple routes in the sunny Southwest, before expanding North and East. I find that geographic restrictions cause trucks to be misallocated and freight costs can increase even if self-driving trucks have lower per-mile costs and longer driving range. Intermediate levels of automation, combined with geographic restrictions, can lead to price increases and welfare losses for states which do not have yet access to self-driving trucks.

In all self-driving truck counterfactuals, total mileage rises. Given that trucking freight contributes about 7 percent of global CO2 emissions, I conduct an electrification counterfactual in C.3 which studies the effect of a transition from diesel to electric trucks. In this counterfactual, I replace regional variation in diesel prices with equivalent regional variation in electricity prices. Given current benchmarks for electric trucks, per-mile costs would fall everywhere, but some regions such as New England and California would face relative increases in fuel costs. I find that prices overall fall, and a shift to electric trucks especially benefits shippers exporting from the Pacific Northwest, which has low electricity prices relative to diesel prices.

6 Conclusion

In this paper, I have developed a dynamic spatial model of trucking freight, estimated demand, cost, and carrier preference parameters, and conducted a counterfactual simulation where I remove carrier home bias. I have found that human preferences to return home are significant and shape the cost of transportation across the United States today.

Drivers' preferences to return home systematically subsidize driver-rich states and create a divide between short-haul and long-haul shipping. From the perspective of a driver, short-haul routes are much less lucrative than long-haul routes to compensate for being able to return home. From the perspective of a shipper, short-haul routes are attractively cheaper on a per-mile basis than longer routes - unless those long routes are to destinations which can routinely bring a driver home with return traffic. Under automation, the distinction between short- and long-haul routes collapses, and the two markets integrate. My findings suggest a new way that automation and artificial intelligence can affect our economy. When human labor cannot be substituted with capital, worker preferences will shape how and where production occurs. Artificial intelligence can de-link workers from production, and workers' preferences from outcomes.

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Figures

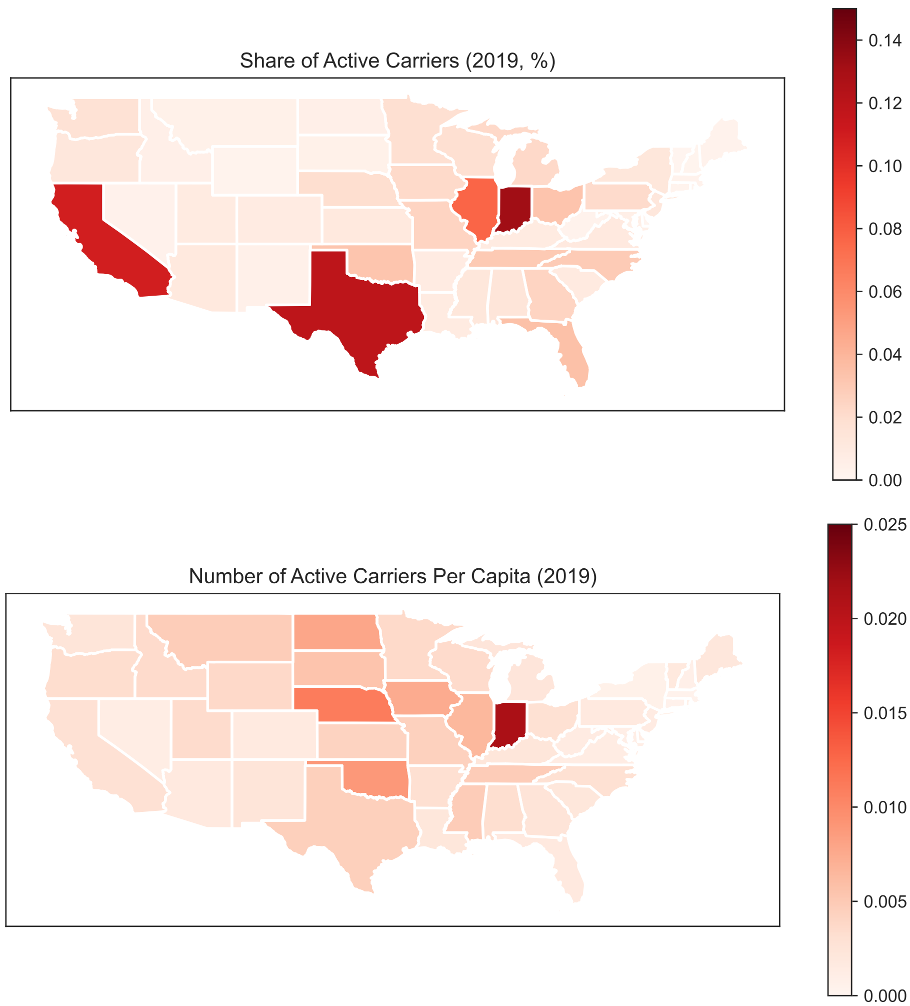

Figure 1: Geographic Distribution of (a) Active Carriers, (b) Active Carriers per Capita

Note: Figure 1a shows the share of active carriers, defined as registered drivers with at least one inspection in 2019, in each US state. Figure 1b normalizes the number of active carriers by the 2010 Census population in each state.
Data sources: 2019 FMCSA Motor Carrier Inspections, 2010 US Census.

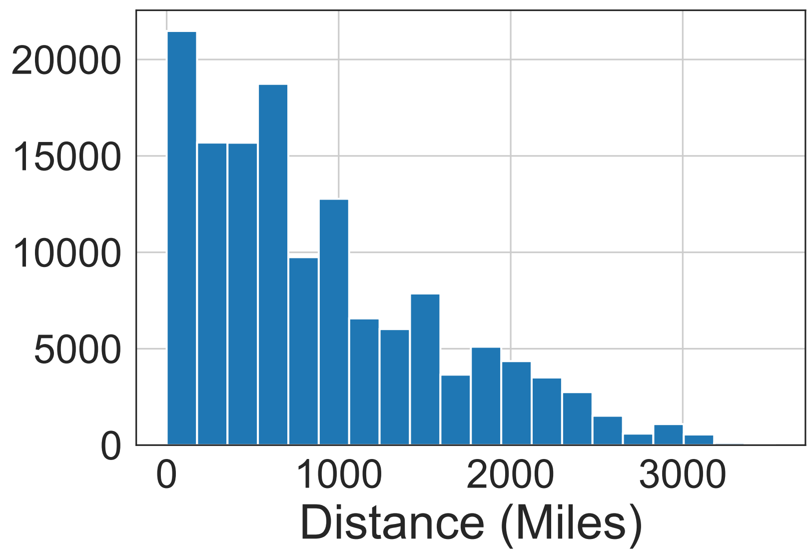

Figure 2: Carriers are more likely to be inspected closer to home

Note: Figure 2 plots a histogram of carrier inspections by the distance from the state of inspection to the home state of the carrier. Distances are measured between state centroids.
Data sources: 2019 FMCSA Motor Carrier Inspections

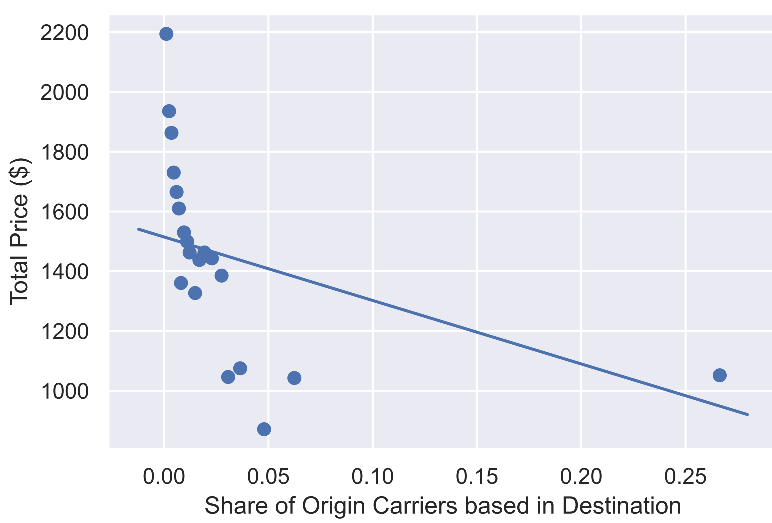

Figure 3: Carrier geography predicts prices

Note: Figure 3 plots a binned scatter plot of the average price of truck shipping along a route from i to j against the share of carriers in i with home location j.
Data sources: 2019 FMCSA Motor Carrier Inspections, 2019 DAT RateView

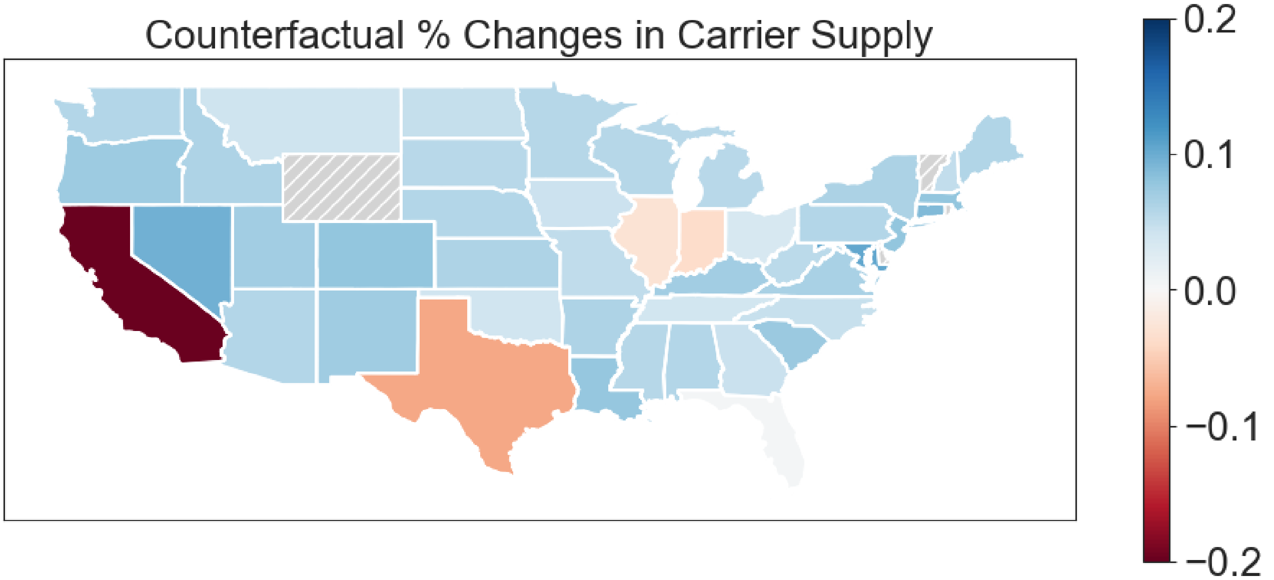

Figure 4: Counterfactual I: Carrier supply shifts from driver-rich states to driver-poor states

Note: In the first self-driving truck counterfactual, I eliminate home bias while holding carrier costs fixed. Figure 4 plots the percentage change in the number of available carriers working in each state. States which gain carrier supply are blue, while states which lose carrier supply are red. Larger magnitudes are indicated by darker colours.

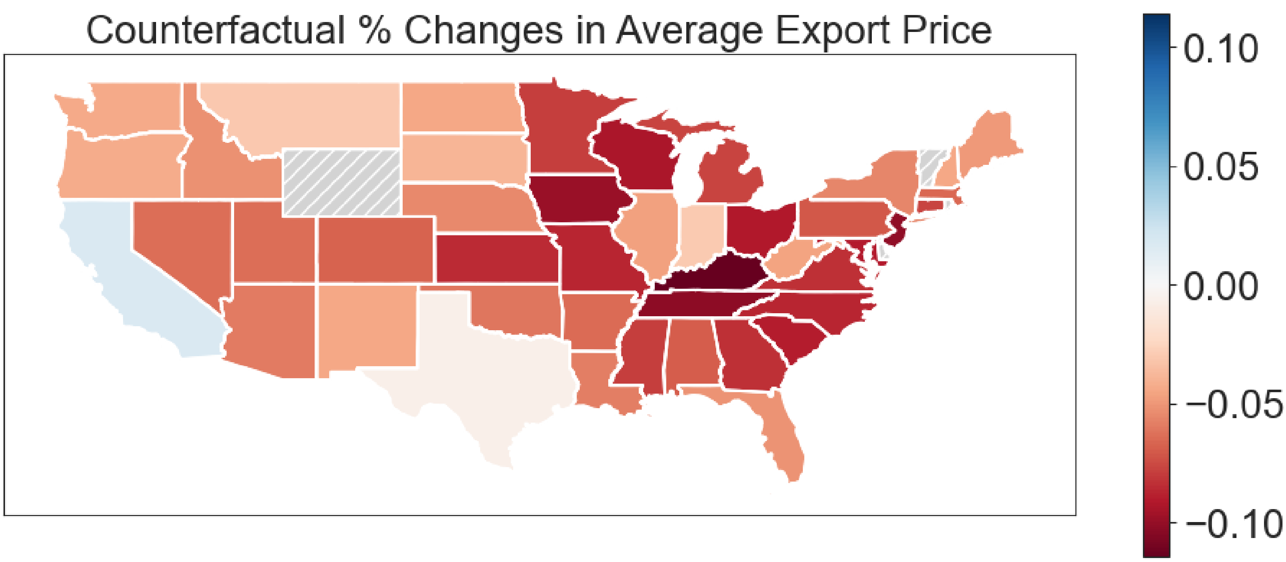

Figure 5: Counterfactual I: Export prices fall, but not for driver-rich states

Note: Figure 5 plots the percentage change in the average trucking export price from each U.S. state, as defined by a Laspeyres index which weights prices by quantity in the baseline. States which see rising export prices are blue, while states which see falling export prices are red. Larger magnitudes are indicated by darker colours.

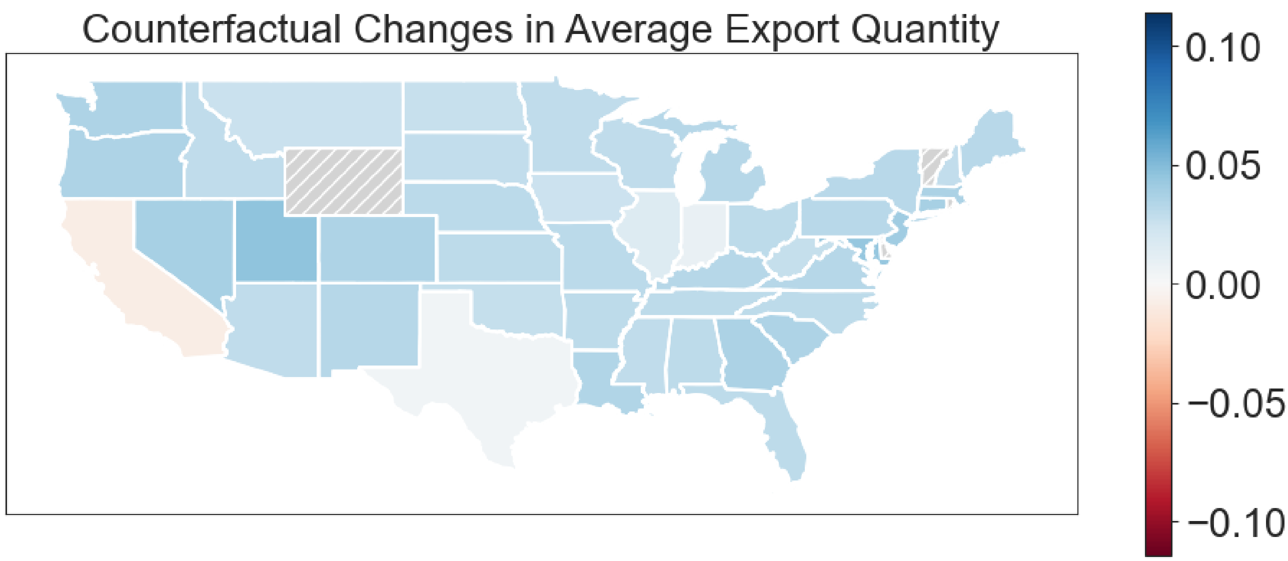

Figure 6: Counterfactual I: Export quantities rise, but not for driver-rich states

Note: Figure 6 plots the percentage change in total annual trucking exports from each U.S. state. States which see rising export quantity are blue, while states which see falling export quantity are red. Larger magnitudes are indicated by darker colours.

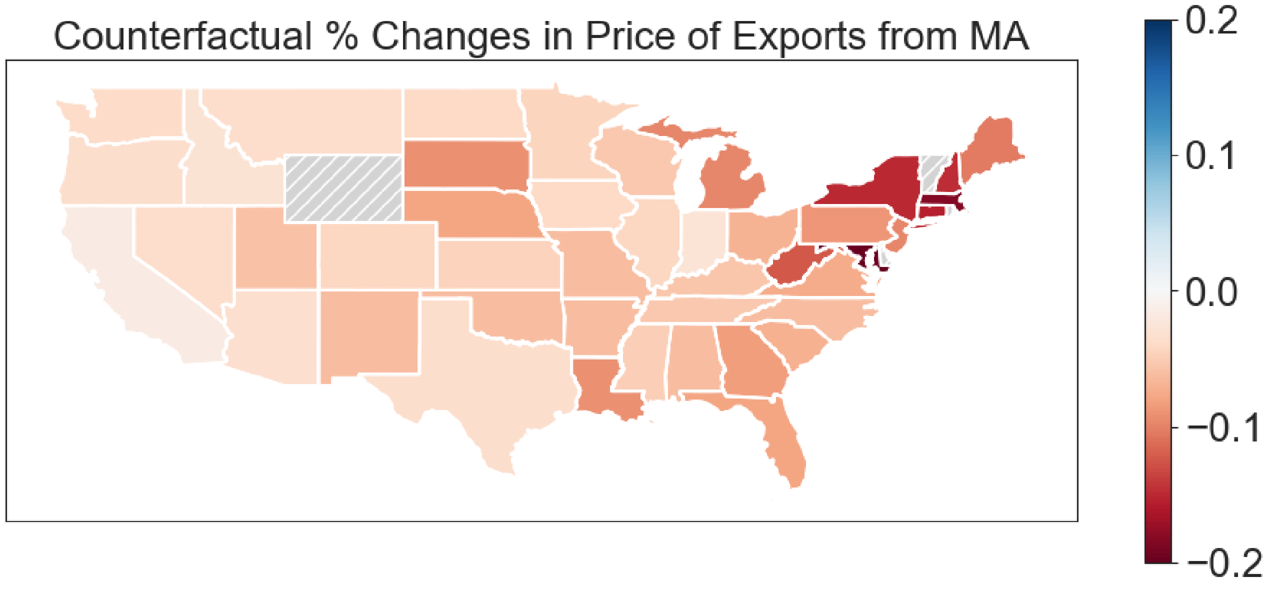

Figure 7: Counterfactual I: Massachusetts sees lower local export prices, especially to other Northeastern states

Note: Figure 7 plots the percentage change in export prices from Massachusetts to every other state. States which become more expensive shipping destinations from Massachusetts are blue, while states which become cheaper shipping destinations from Massachusetts are red. Larger magnitudes are indicated by darker colours.

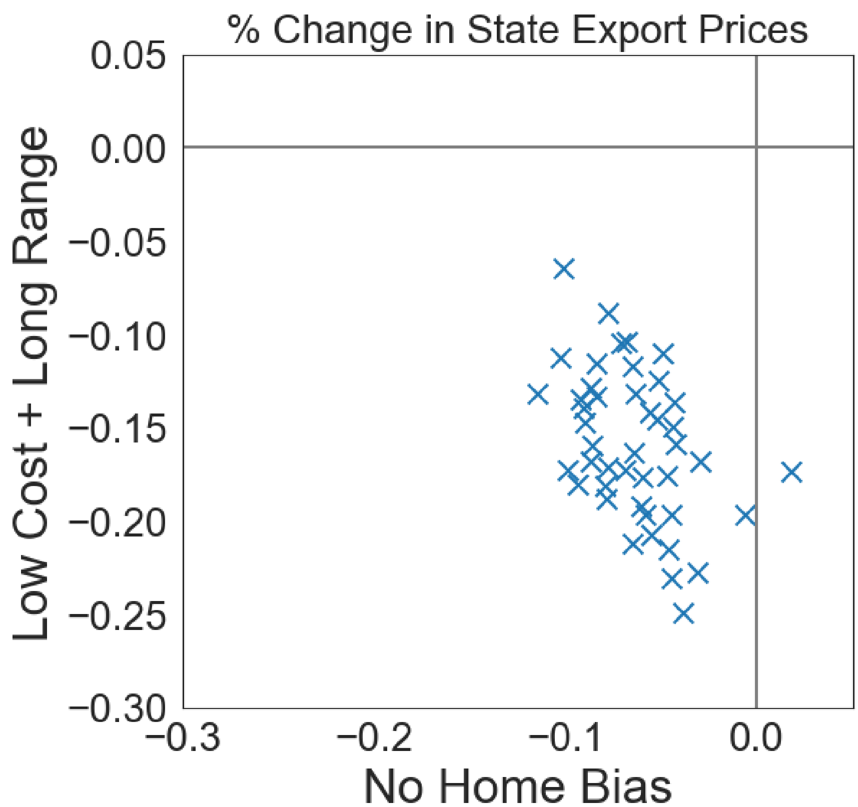

Figure 8: Counterfactual Comparison: Home Bias Effects are negatively correlated with Low Cost / Long Range

Note: I compare a first self-driving truck counterfactual where I eliminate home bias with a second counterfactual where I implement other effects of self-driving trucks (lower per-mile costs by 25 percent and double daily driving range). Figure 8 is a scatter plot of state export prices under these two counterfactuals: (1) no home bias (x-axis) and (2) low cost and longer range (y-axis). Each cross represents one US state. The cross's x-axis position is the percentage change in export prices when home bias is removed. The cross's y-axis position is the percentage change in export prices when per-mile costs fall and ranges increase.

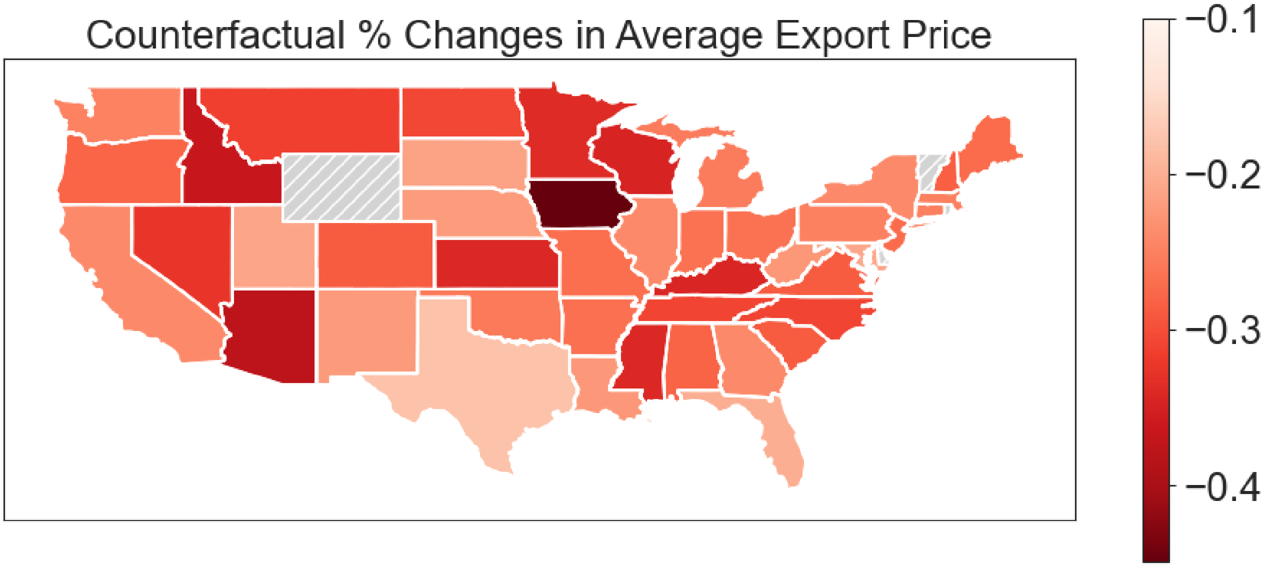

Figure 9: Counterfactual II: Changes in Export Prices

Note: In a second "full" self-driving truck counterfactual, I eliminate home bias while lowering per-mile costs by 25 percent and doubling daily driving range. Figure 9 plots the percentage change in export prices from each state as defined by a Laspeyres index which weights prices by quantity in the baseline. States which see rising export prices are blue, while states which see falling export prices are red. Larger magnitudes are indicated by darker colours.

Appendix A: Summary Figures

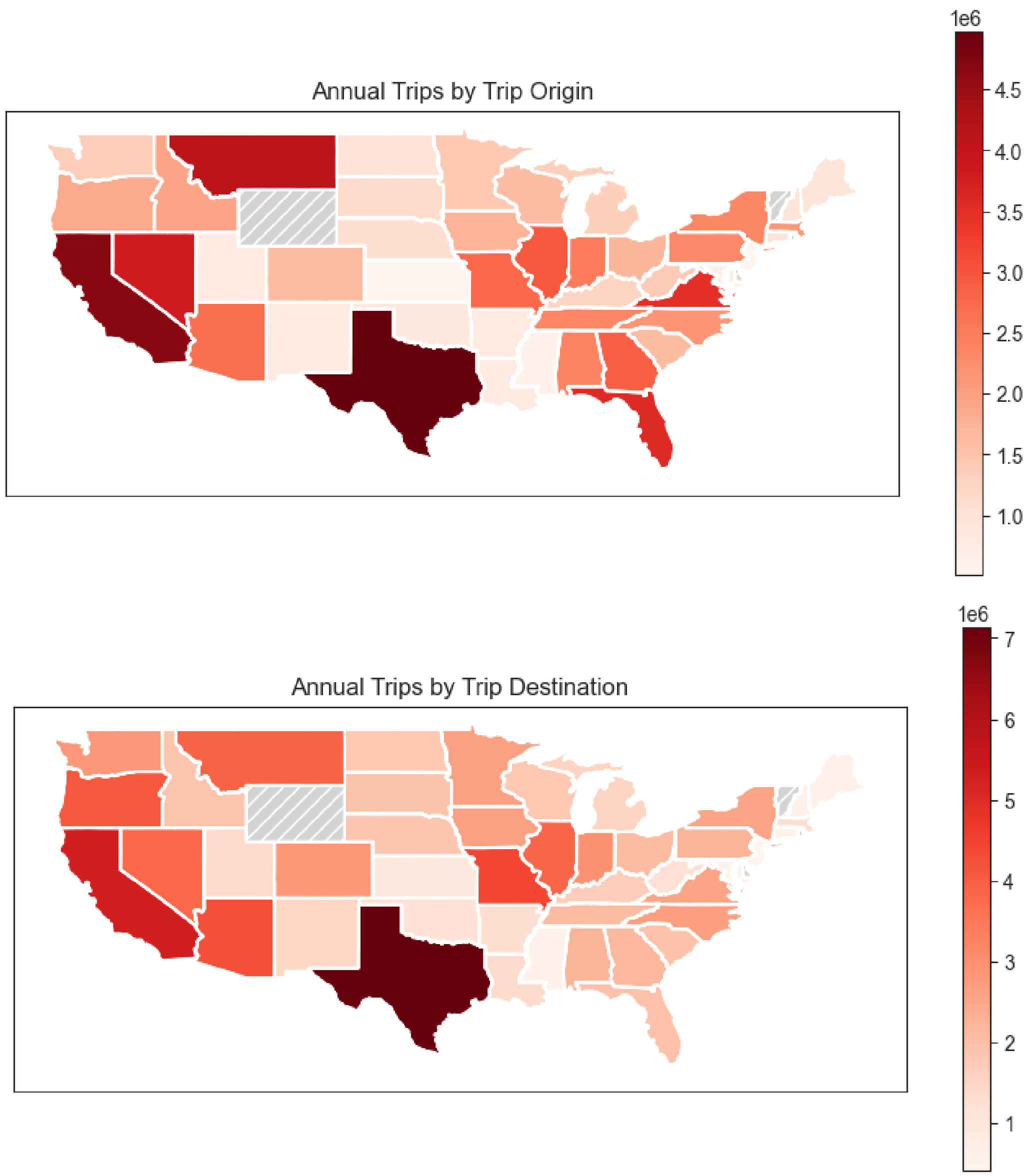

Figure 10: Annual Trips by Trip by Origin / Destination

Note: Figure 10a plots the total number of annual trips from each state as an origin. Figure 10b plots the total number of annual trips to each state as a destination. Larger magnitudes are indicated by darker colours. The largest origins and destinations for trucking freight are California and Texas.
Data source: 2019 DAT RateView

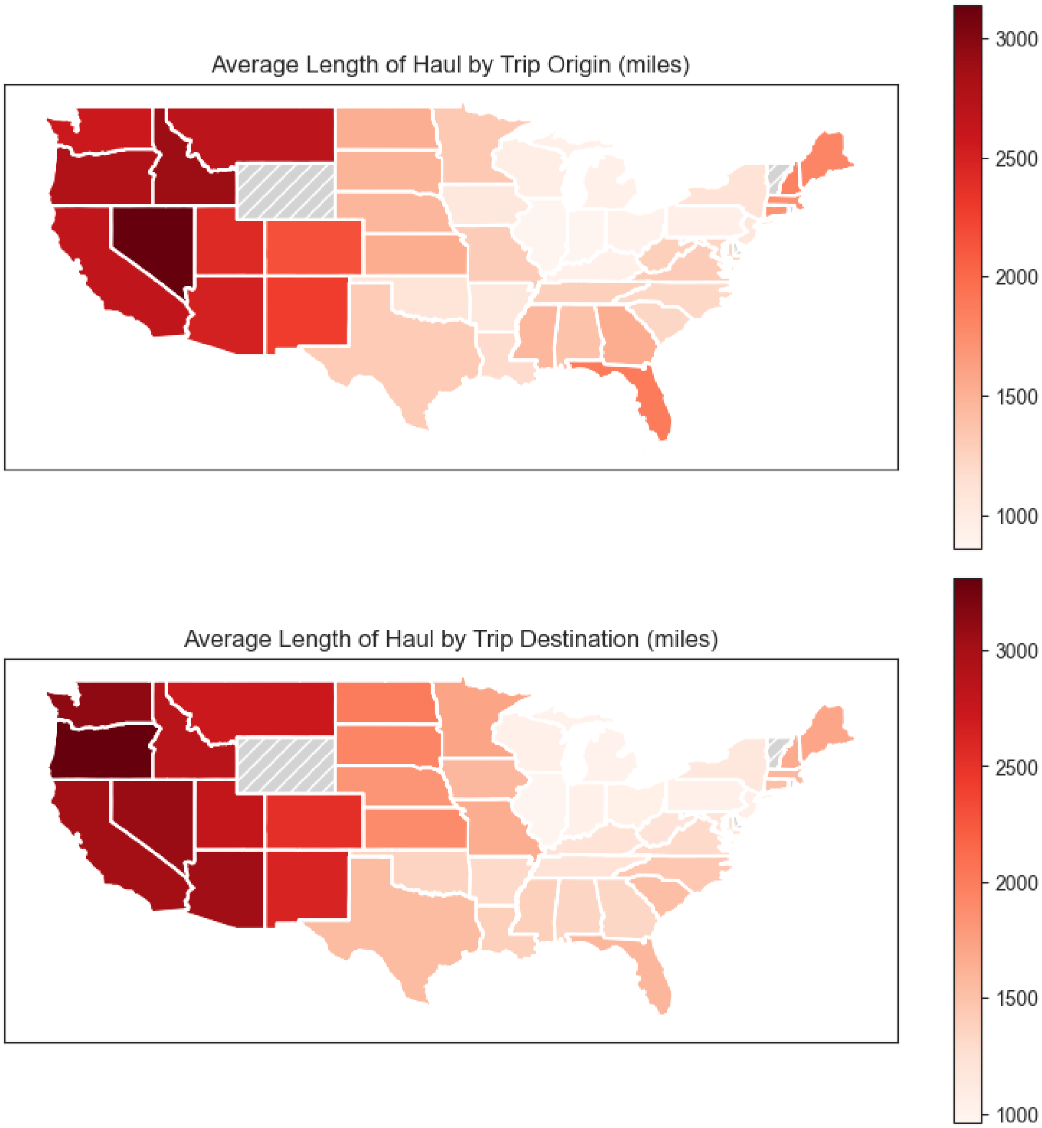

Figure 11: Average Length of Haul by Origin / Destination

Note: Figure 11a plots the average length of haul (trip distance) for trips from each state as an origin. Figure 11b plots the average length of haul for trips to each state as a destination. The West Coast has the longest average trip distances, while the Midwest has the shortest average trip distances.
Data source: 2019 DAT RateView

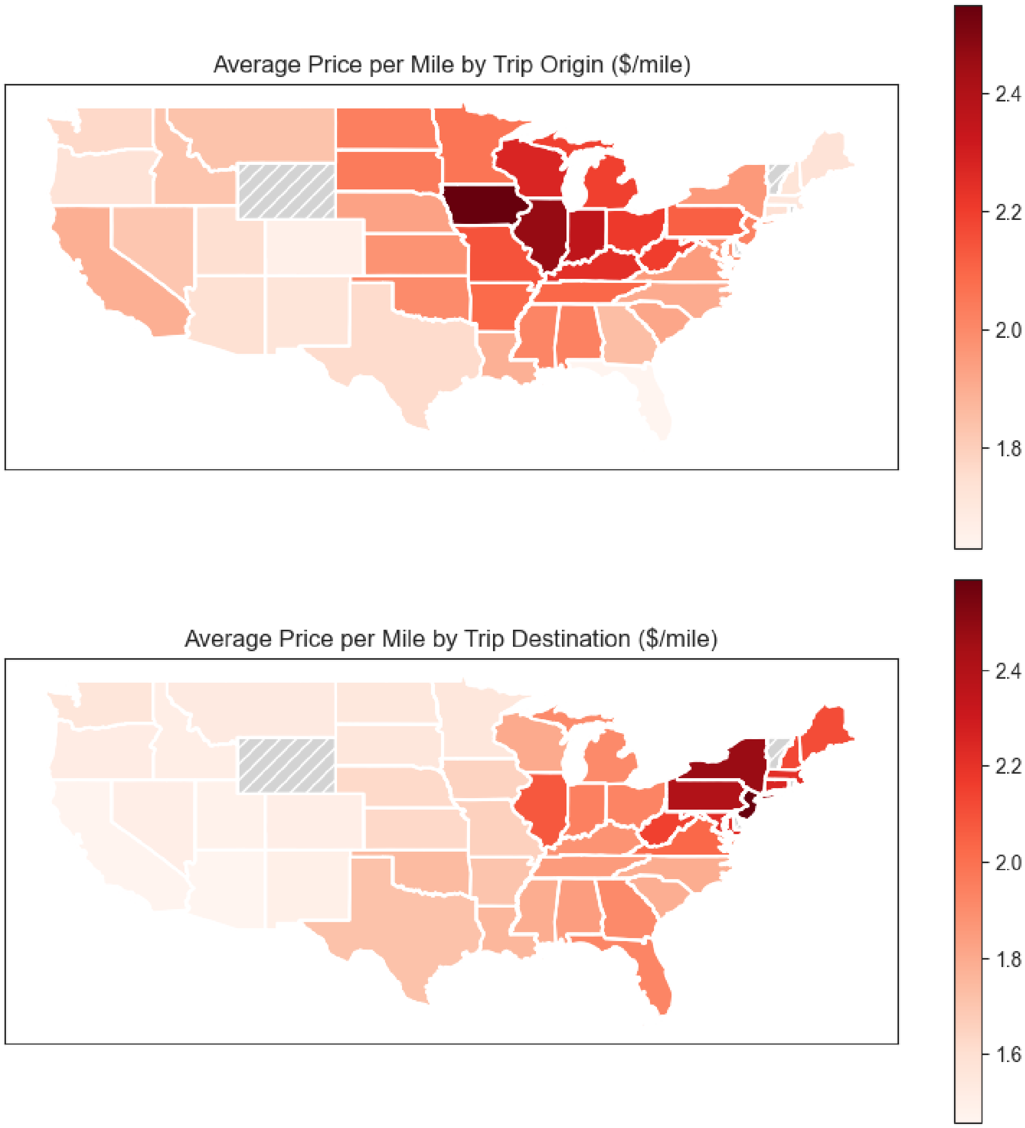

Figure 12: Average Price per Mile by Origin / Destination

Note: Figure 12a plots the average price per mile of trucking freight for each state as an origin. Figure 12b plots the average price per mile for each state as a destination. The Midwest has the highest average export prices, while the coastal states have lower average export prices. Destination states which are further east have higher prices per mile for imports.
Data source: 2019 DAT RateView

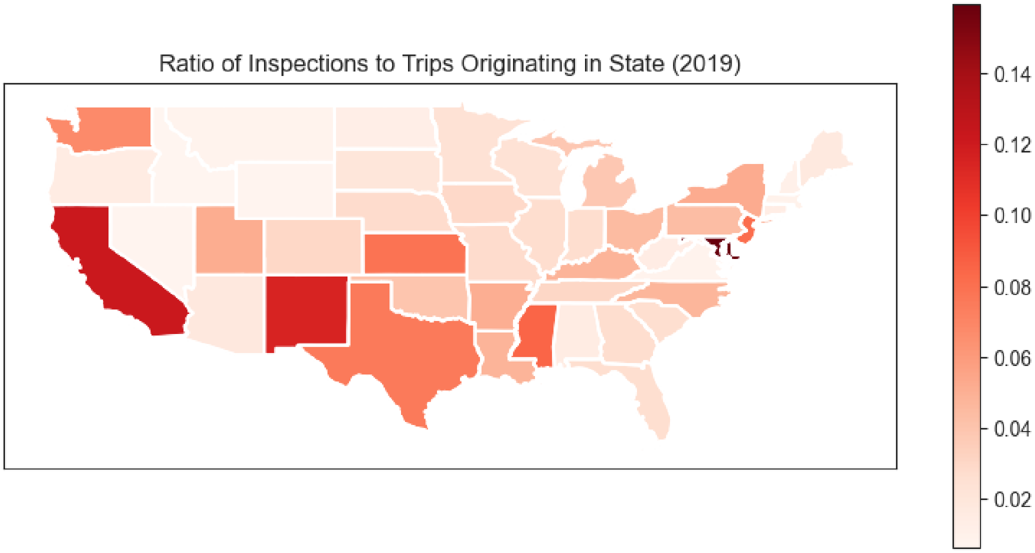

Figure 13: Ratio of Inspections to Trips Originating from Each State

Note: Figure 13 plots the ratio of inspections conducted to number of trips for each state. Consistent with industry interviews, several states appear to be more likely to inspect, including California, Texas, Arizona, and Maryland.
Data source: 2019 DAT RateView, 2019 FMCSA Motor Carrier Inspections

Appendix C: Additional Counterfactuals

Counterfactual C.1: Transition to Automation

In my main counterfactuals, I consider a complete transition from human drivers to self-driving trucks. In this set of counterfactuals, I could consider a transition path where a share of trucks convert to self-driving while the remainder retain their home bias.

In Figure 14, I plot average prices and total quantity for a variety of automation levels between 0 percent and 100 percent. The 0 percent counterfactual is the baseline, and the 100 percent counterfactual is the counterfactual studied in 5.1. I find a relatively smooth transition path from 0 percent automation to 100 percent automation.

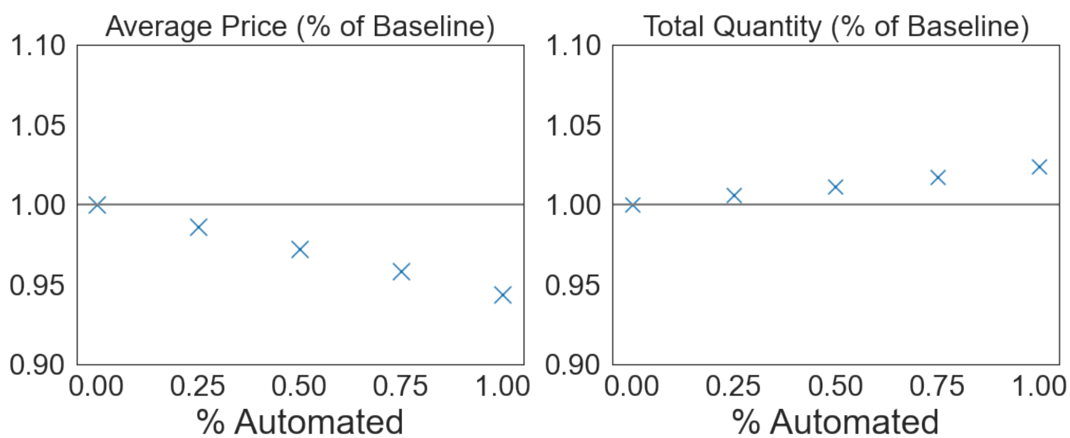

Figure 14: Prices and Quantities on Transition to Automation

Note: Figure 14 plots average prices (Laspeyres Index) and total quantity under transitional counterfactuals where 0 percent, 25 percent, 50 percent, 75 percent, and 100 percent of existing trucks are replaced with self-driving trucks.

Counterfactual C.2: Geographic Transition to Automation

Geographic rollout of self-driving trucks may not be instant across the United States. For example, while highways are much more regular than city streets, snowy northern highways may be a more challenging automation problem than sunny southern highways. A Deloitte report projects that in a first stage, southwestern states from Oregon and California down through Texas may be feasible first. In a second stage, snowier states from Nevada east through Illinois to Virginia may become feasible. Finally, in the third stage automated trucks would be able to travel through any state. In Figure 15, I plot the geographic distribution of these stages.

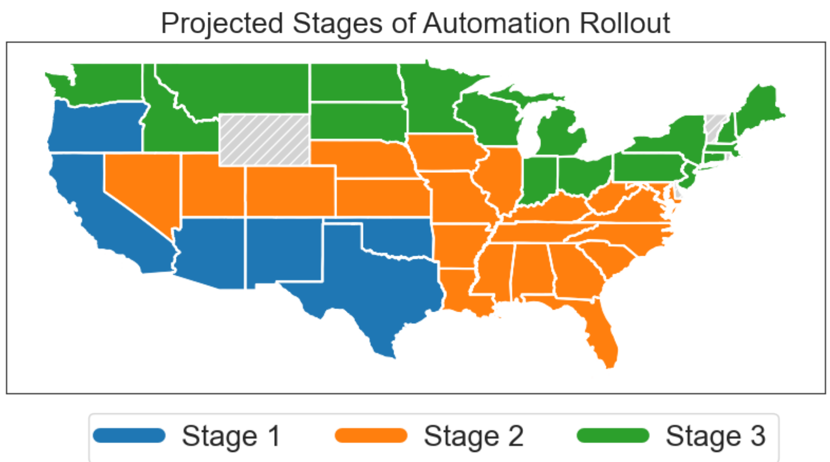

Figure 15: Rollout Stages of Self-Driving Trucks

Note: Figure 15 plots the three stages of automation rollout identified in Zarif, et al. (2021). The first stage covers southwestern states from Oregon to Texas. The second stage expands north and east. The third stage covers the northernmost U.S. states.

In this set of counterfactuals, I consider progressive rollout of self-driving trucks in stages.

In the first counterfactual, I convert 25 percent of trucks from Stage I states to self-driving, and I restrict self-driving trucks to only travel to Stage I states. In this counterfactual, self-driving trucks have no home bias, and also benefit from the 25 percent reduced per-mile costs and doubled daily range of the full counterfactual. In the Stage I counterfactual, I find that overall export prices increase everywhere as shown in Figure 16. Although self-driving trucks have lower costs and longer range, constraining some trucks to the Stage I states decreases overall efficiency. These two effects moderate each other for Stage I states such as California and Texas, which see minimal changes in export prices. Meanwhile, Midwestern states see the largest decline in carriers and increase in export prices.

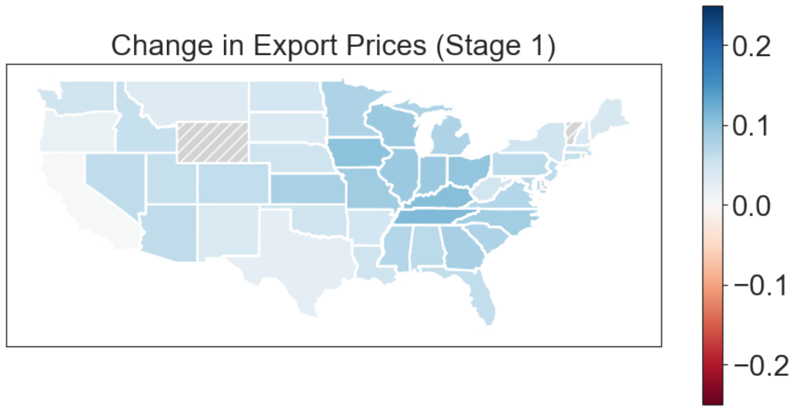

Figure 16: Counterfactual export prices under Stage I rollout

Note: In the Stage I rollout counterfactual, I convert 25 percent of trucks in Stage I states to self-driving and restrict self-driving trucks to Stage I states. Figure 16 plots the percentage change in the average trucking export price from each U.S. state, as defined by a Laspeyres index which weights prices by quantity in the baseline. States which see rising export prices are blue, while states which see falling export prices are red. Larger magnitudes are indicated by darker colours.

In the second counterfactual, I convert 25 percent of trucks from Stage I or Stage II states to self-driving, and I restrict self-driving trucks to only travel to Stage I or Stage II states. In the Stage II counterfactual, I find that export prices fall for Stage I and II states with access to self-driving trucks, but rise for Stage III states without access, as shown in Figure 17. Compared to the Stage I counterfactual, self-driving trucks are less constrained so overall efficiency is higher. However, Stage III states now lose significantly more carrier supply than in the Stage I counterfactual, since more trucks are now automated. This is particularly pronounced in the Midwest, where Illinois is a Stage II state but many of its main export destinations (Michigan, Ohio, Iowa, and Minnesota) are not. This figure suggests that short-run economic consequences of self-driving trucks may depend importantly on the geography of rollout.

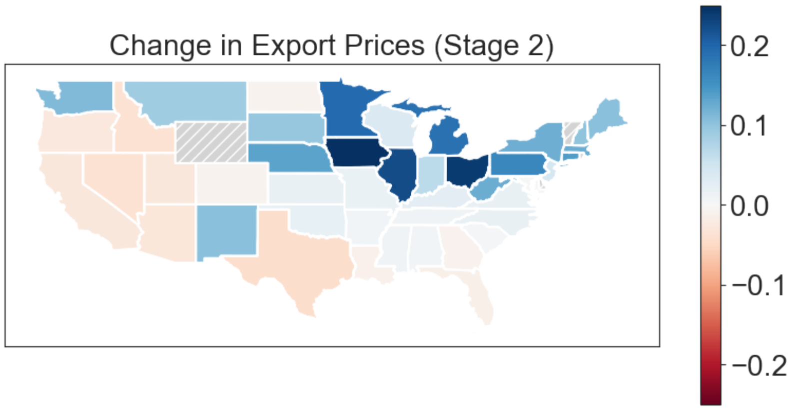

Figure 17: Counterfactual export prices under Stage II rollout

Note: In the Stage II rollout counterfactual, I convert 25 percent of trucks in Stage I and Stage II states to self-driving and restrict self-driving trucks to Stage I or Stage II states. Figure 17 plots the percentage change in the average trucking export price from each U.S. state, as defined by a Laspeyres index which weights prices by quantity in the baseline. States which see rising export prices are blue, while states which see falling export prices are red. Larger magnitudes are indicated by darker colours.

In the third counterfactual, I convert 25 percent of trucks from all states to self-driving, and I allow trucks unrestricted access to all states. Without the geographic restrictions, self-driving trucks efficiently distribute across the economy. Figure 18 shows that export prices fall for all states, and the pattern mirrors that of the "full" counterfactual.

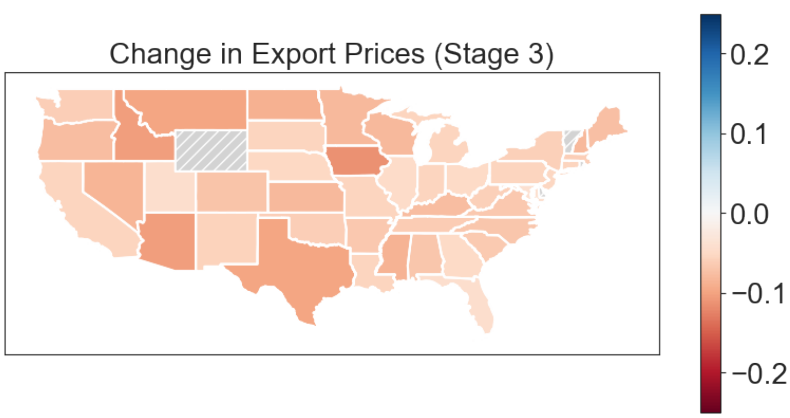

Figure 18: Counterfactual export prices under Stage III rollout

Note: In the Stage III rollout counterfactual, I convert 25 percent of trucks in all states to self-driving and do not restrict self-driving trucks. Figure 18 plots the percentage change in the average trucking export price from each U.S. state, as defined by a Laspeyres index which weights prices by quantity in the baseline. States which see rising export prices are blue, while states which see falling export prices are red. Larger magnitudes are indicated by darker colours.

Counterfactual C.3: Electrification

This counterfactual studies the effect of a transition from diesel to electric trucks by considering the effect of alternate fuel prices on shipping. Electric trucks have drawn immense investment over the past few years, comparable to self-driving trucks. Trucking freight is responsible for a significant share of environmental damages from the transportation sector. Road freight consumes about 20 percent of global oil, and accounts for 7 percent of total CO2 emissions (IEA (2017)). Major competitors in this area include the Tesla Semi, the Daimler/Freightliner eCascadia, and the Volvo VNR Electric. On the policy side, the Department of Energy announced its SuperTruck 3 initiative to fund truck electrification projects, and the Department of Transportation has made investing in charging infrastructure a priority.

Methodology In my estimation section, I estimated the effect of local diesel prices along a route on the carrier cost function. To explore the electrification counterfactual, I convert local electricity prices into comparable units.

I use monthly state-level and sector-level electricity prices from the U.S. Energy Information Administration. Within each state, electricity prices range from low (Industrial) or high (Residential) across different sectors. To be agnostic about the price of charging in this scenario, I use the average price for all sectors. To convert cents-per-kilo-watt-hour into dollars-per-gallon equivalents, I assume that carriers under the diesel status quo averages seven miles per gallon, and that carriers under the electric counterfactual will average two kilowatt hours per mile[12]. In Figure 19, I plot the percentage difference between state average diesel and electric prices. In all states, prices fall, prices fall least in the Northeast and in California, and prices fall the most in the northwest.

[12] In 2019, a North American Council for Freight Efficiency survey reported a fleet average of 7.27 miles per gallon. In 2021, Tesla's Semi claims "$<$2 kWh/mile," the Freightliner Class 8 eCascadia claims 1.9 kWh/mile, and Volvo's short-range Class 8 VNR claims 1.76 kWh/mile.

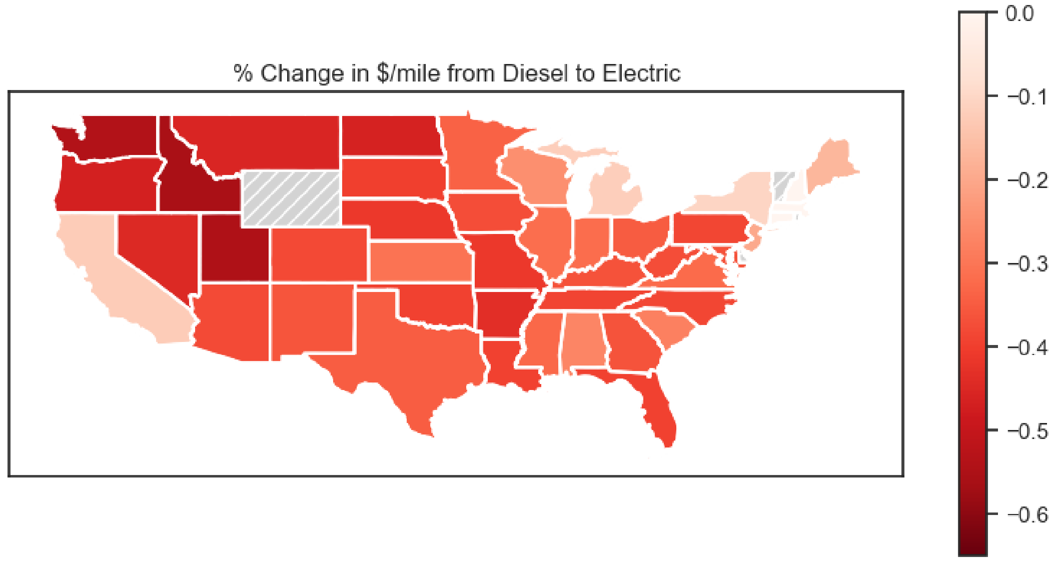

Figure 19: Electricity vs. Diesel Prices

Note: Figure 19 plots the ratio of local diesel prices to local electricity prices. Diesel prices are 2019 state averages from AAA. Electricity prices are 2019 state averages across all sectors from EIA. To make the figures comparable, I assume a fleet average of 7 miles per gallon and energy efficiency of 2 kilowatt-hours per mile.
Data sources: 2019 AAA diesel prices, 2019 EIA electricity prices.

I replace the role of local diesel prices in the cost function with local electricity prices and I compute new price equilibria using the procedure as described in 6.1.1.

Results There are two main effects: (1) overall marginal per-mile costs fall, reducing prices and increasing quantity, and (2) carriers shift away from jobs transiting through states with relatively higher electric prices, and toward jobs through states with relatively lower electric prices.

In Figure 20, I plot the change in average export prices and quantities. Since the highest electricity prices are in California and the East Coast, Midwestern and Western states ex-California see the greatest prices decreases. In terms of quantities, the greatest growth in freight shipping comes from the Pacific Northwest. Compared to the full automation counterfactual, electrification more clearly benefits one region of the country above others.

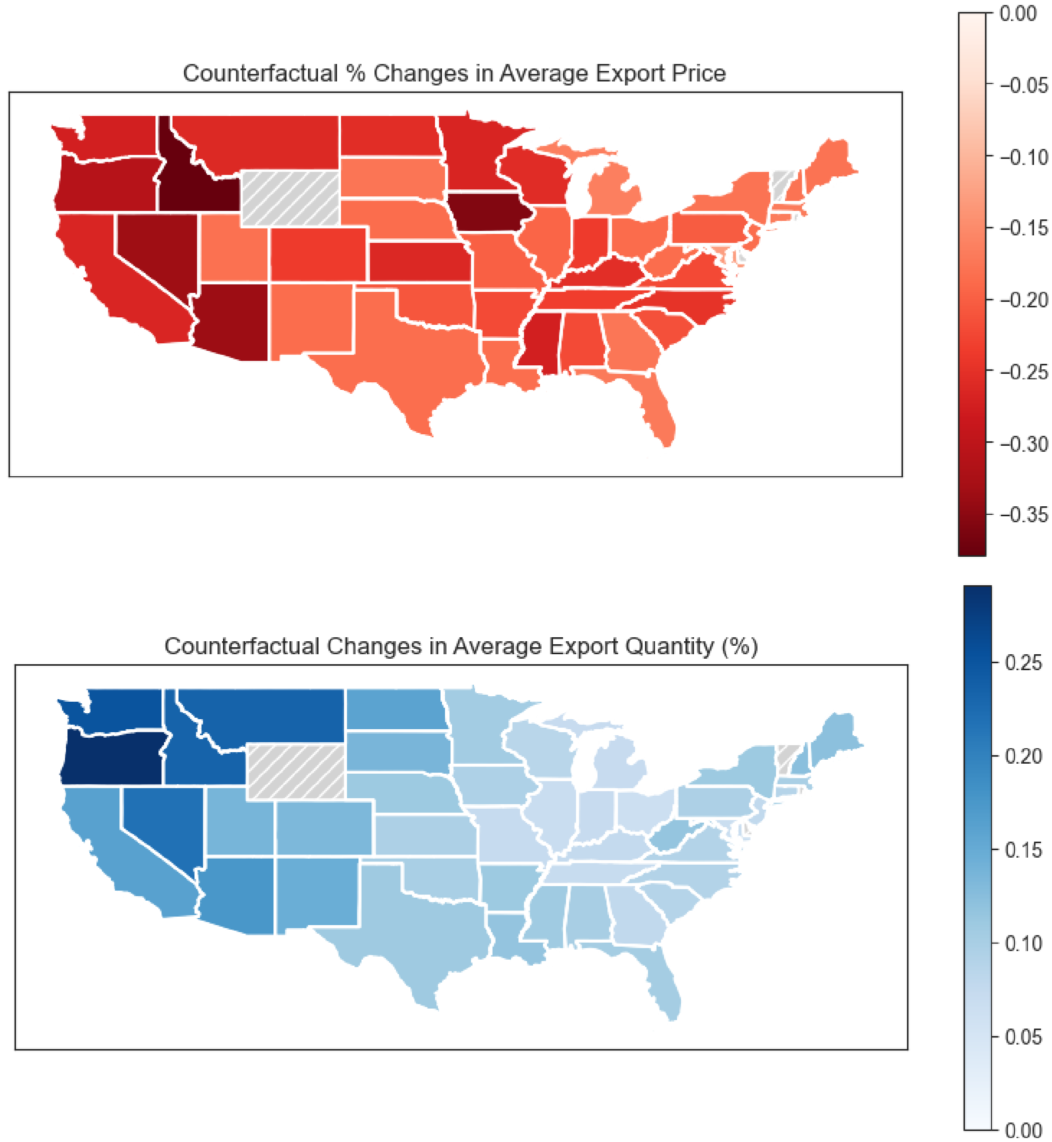

Figure 20: Counterfactual Changes in Prices and Quantities

Note: Figure 20 plots the change in average export prices (a) and export quantity (b) in an electric truck counterfactual where carriers are sensitive to local electricity prices rather than local diesel prices.

In practice, range, charging, and battery capacity are important issues for electric trucks which are not considered in this counterfactual. Limited range may have similar economic effects as home bias: carriers would have to specialize in shorter-range trips closer to their home charging infrastructure.

Appendix D: Data Construction

Since locations in highway inspections are observed at the state level, I aggregate my data to the state-state level and let L be the set of U.S. states[13].

For distance, I use the PC-Miler Effective Distance from i to j, an engineering estimate of the distance between origin and destination along truck-legal routes.

For diesel, I use a route-mileage-weighted average of state average diesel prices from AAA. I scale the dollar-per-gallon price by the distance, and I de-mean diesel prices so I can interpret my distance coefficient as an all-in marginal cost per mile.

For road quality, I filter road segments from the 2019 Highway Performance Monitoring System for interstate and principal arterial roads. For each segment, I observe cracking, faulting, and rutting as continuous measures[14]. I standardize these quality measures to have mean zero and standard deviation one, so that positive values indicate lower quality roads. I take compute state averages for each quality measure, and I weight states by the route mileage shares to compute route road quality measures.

I begin by finding the centroid of the origin and destination state and using OpenStreetMaps to compute the shortest route using U.S. highways. Let m_{ijk} be the share of miles on the shortest route from i to j spent in state k. For each route, I use the mileage shares to weight these state averages.

I measure quantity Q_{ij} using total daily trips in DAT RateView, and the share of shippers who choose trucking $s_{ij}^{shipper}$ using freight shipments in the 2017 Commodity Flow Survey (CFS). I use the total shipping across all modes in the Commodity Flow Survey as my measure of N_{ij}. Since the Commodity Flow Survey is reported in tons, I assume that 22 tons corresponds to a full truckload[15]. I use average 2019 prices in DAT RateView for p_{ij}.

[13] Due to discontinuity from the main U.S. highway system, I omit Alaska, Hawaii, and Puerto Rico from my analysis. In addition, due to data limitations in DAT RateView, I also omit Delaware, Rhode Island, and Vermont. Due to data limitations in DAT Trucks in Market, I omit Wyoming from analyses which depend on Trucks in Market.

[14] Cracking measures the percentage of road area which exhibits fissures and discontinuities. Faulting measures the average vertical misalignment of pavement joints. Rutting measure the average depth of surface depressions.

[15] Staff (2020) reports average payload for a dry van at 44,000 to 45,000 pounds