Freight in the Time of Covid

Estimating a Model of Transport Supply

Jacob Lefler

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Abstract

Trade models typically ignore the freight transportation industry. I develop a model of the US trucking industry that can replicate several stylized facts that I document, including inverse and spatial correlations in transportation prices, while remaining tractable enough to be embedded within a trade model and quantified using market-level data. Rather than being treated as fixed and exogenous, trade costs emerge endogenously as the market-clearing prices of the freight transportation industry. I quantify driver supply using instruments based on Covid-era shocks to US container import quantities. Finally, I use a simple calibration of my spatial model to estimate how changes in freight transportation prices affected goods prices and consumer welfare following the onset of Covid, and I find that changes in transport markets were primarily demand-driven.

1 Introduction

Freight transportation is a key industry. Different theories of trade explain how consumers can benefit from access to traded goods, including comparative advantage and increasing returns to scale in production, but all gains from trade rely on freight carriers that physically move the products. Despite its importance, trade economists usually ignore the role of the freight transportation industry and assume trade costs take a fixed, iceberg form where a constant fraction of goods melts in transit. This assumption makes the transport sector invisible. In reality, freight carriers are active agents who reallocate capacity across locations when demand shifts and whose actions affect equilibrium prices. If transport supply is itself elastic, forward-looking, and subject to physical frictions, then trade costs are not fixed objects, but are determined in equilibrium.

This paper develops and estimates a model of trucking supply in the United States that embeds the behavior of freight carriers directly into a spatial trade environment. The model is designed to be (i) rich enough to match key features of observed trucking prices and quantities, and (ii) tractable enough to take to market-level data and to integrate with a standard Armington-style demand system. I use the model to quantify how trucking capacity reallocated during the Covid-era import boom, how that reallocation affected transport prices across U.S. cities, and how much of the heterogeneity in goods inflation across cities can be attributed to changes in transport costs.

The first part of the paper documents four empirical facts about U.S. trucking in 2017–2023. I construct a quarterly panel of lane-level (origin–destination) prices and quantities for full truckload shipments across 51 U.S. metro areas. I begin by showing that transport prices have two striking features in the cross section. First, they are inversely correlated across directions: cities that are expensive to ship *from* are relatively cheap to ship *to*, and vice versa. Second, they are spatially smooth: neighboring cities tend to have similar origin premia, even after controlling for distance. I argue that both patterns are consistent with forward-looking behavior by truck drivers who can travel empty — "deadhead" — between cities when searching for their next load. A driver who delivers to a high-price outbound market is willing to accept a low inbound price to get there, generating the inverse correlation; and the ability to deadhead limits the extent to which prices can diverge sharply across neighboring cities. Consistent with this interpretation, I show that some cities experience large net outflows of loaded trucks while others experience persistent net inflows, which is only possible if drivers routinely move empty between markets.

Next, I link transport prices to downstream consumer prices. Using a partial-equilibrium Armington calibration, I map observed changes in trucking prices into predicted changes in local goods price indices. I compare these predictions to Bureau of Labor Statistics consumer price indices for goods in U.S. metro areas. I find that cities facing larger increases in incoming trucking costs experienced higher goods inflation, and that variation in transport prices can explain a meaningful share (on the order of 8%) of the cross-city dispersion in goods inflation over this period. This result does not imply that trucking costs were the primary driver of Covid-era inflation. Rather, it shows that the timing and spatial pattern of goods inflation is consistent with pass-through of transport prices into goods prices.

Finally, I show that increases in containerized imports to major U.S. gateways (e.g., Los Angeles/Long Beach, Houston, Savannah, New York/New Jersey, and key crossings on the U.S.–Mexico border) generated large movements in trucking prices and market shares. Following an import surge at a port, outbound trucking prices from that port increase and the port's share of outbound loads rises. At the same time, inbound prices into that port *fall*, and inbound volume increases. This pattern is difficult to rationalize with a purely static, one-period view of supply. It is natural if carriers are forward-looking and treat the port as a high-value location to be in next period: they are willing to accept lower inbound pay now in order to gain access to high-paying outbound freight tomorrow.

Guided by these facts, I build a model of transport supply based on forward-looking drivers who choose which lanes to serve in each period. The model draws on the dynamic discrete choice framework used to study worker migration across regions (Artuç et al., 2010; Caliendo et al., 2019), adapted to the trucking setting. In the model, a driver who ends the period in city i chooses a lane (j, k) for the next period: she may deadhead from i to j, haul a paying load from j to k, earn current-period revenue r_{jk} net of operating costs, and then begin the following period in city k. Drivers care not only about current profits but also about the *continuation value* of being in k, since k may offer attractive outbound opportunities. For tractability, I assume i.i.d. Gumbel preference shocks across lanes. This delivers expressions for two key objects: (i) the expected value V_i of starting a period in city i, and (ii) the probability that a driver in city i chooses any given lane (j, k). Allowing drivers to deadhead implies that every city is mutually reachable with positive probability, which guarantees that the system has a unique steady-state distribution of drivers across cities and a unique steady-state flow of trucks on every lane. This steady state is what I call transport supply.

I then estimate the model using market-level data. There are two main ingredients. First, I calibrate the per-mile cost of deadheading, d, using industry evidence on variable operating costs (fuel, driver time, and maintenance), and treat all remaining per-lane operating costs as unobserved cost shifters ξ_{jk}. Second, for any candidate value of the key behavioral parameter α — the parameter that governs how sharply drivers reallocate toward more profitable lanes — I invert the model quarter-by-quarter to recover the cost shifters $\xi_{jk,t}(\alpha)$ that rationalize observed prices and quantities in that quarter. This inversion is a high-dimensional nonlinear problem: changing $\xi_{jk,t}$ affects drivers' payoffs, which affects their location values V_i, which affects lane choice probabilities, which determines the steady-state allocation of drivers across cities, which determines predicted quantities. I solve this numerically using gradient-based optimization in JAX.

With these recovered costs in hand, I estimate α using a GMM procedure that leverages import surges as demand shocks. The logic mirrors the demand-estimation strategy in empirical industrial organization. If I guess an α that is too high, the model assumes that drivers are "too responsive," and therefore attributes too little of an import-driven quantity increase to reallocation and too much to rising costs: import shocks will appear positively correlated with inferred cost increases. If I guess an α that is too low, the opposite happens. I choose α so that changes in recovered costs are orthogonal to changes in port-level imports at the lane's origin and destination, controlling flexibly for time effects, city-by-quarter effects, and lagged changes in imports. The resulting estimates imply that drivers are responsive but not frictionless.

Finally, I use the estimated model to run two counterfactual exercises. First, I simulate a localized outbound demand shock at each of several major ports by increasing those ports' outbound demand for trucking and resolving for equilibrium prices and flows. The model reproduces a key feature of the data: shocks at Los Angeles/Long Beach generate large price increases not only in Los Angeles but also in nearby markets. The mechanism is that Los Angeles is a massive net exporter of loaded trucks. When outbound demand at Los Angeles rises, shippers in nearby cities are forced to pay drivers higher lest the drivers exercise the option of driving emtpy to Los Angeles. Second, I decompose the Covid-era changes in trucking prices and market shares between 2019 and 2021 into a "demand" component and a "cost" component. Holding costs fixed but allowing demand for specific lanes to surge captures the large reallocation of freight across lanes observed in the data. Holding demand fixed but allowing operating costs to rise captures much of the change in trucking prices, but none of the change in market shares. Together, these counterfactuals suggest that Covid-era market turbulence in trucking was driven primarily by a shift in where shippers wanted goods moved, though cost changes contributed to observed changes in transport prices.

This paper contributes to two literatures. First, it contributes to the quantitative spatial trade literature that studies how trade costs shape welfare (Redding and Rossi-Hansberg, 2017). In that literature, trade costs are almost always assumed to be exogenous iceberg costs. I replace that reduced-form object with an explicit transport sector whose prices and capacity allocation arise in equilibrium. In doing so, I show how to plug a model of trucking supply into a standard spatial demand system. Second, this paper is related to work that models transportation itself. Brancaccio et al. (2020) estimate a rich model of global bulk shipping; Yang (2024) build on that framework to study U.S. trucking. I build in the same spirit, retaining tractability in a flexible dynamic discrete choice model with (i) forward-looking, location-valuing drivers who choose where to be next, and (ii) the ability to drive empty between cities. These features are necessary to match the inverse and spatially smooth price patterns I document, as well as the asymmetric inbound/outbound price responses to port shocks. The result is a framework in which transportation is not just a cost wedge in a gravity equation, but an allocative sector whose behavior can be measured and used to interpret how transport supply interacts with the broader economy in equilibrium.

2 Data and Setting

2.1 Trucking Data

My data on US trucking comes from DAT Freight & Analytics. Among other services, DAT hosts one of the industry's largest "load boards," where shippers (transport customers) post the details of loads they need moved. Carriers (motor carriers, which in practice are often individual owner-operators or small trucking firms) observe available loads and contact shippers to negotiate a one-off contract for that specific load. These one-off transactions take place in the "spot market," in contrast to longer-term "contract market" arrangements. My data from DAT are primarily drawn from spot market transactions, but about 25% of observed shipments are associated with longer-term contracts.

DAT defines origins and destinations using "Key Market Areas," which roughly correspond to major Metropolitan Statistical Areas. I combine adjacent Key Market Areas in New York City, Los Angeles, and Dallas-Fort Worth so that they better match economically integrated metro regions. After this aggregation, I work with 51 hubs, which I will refer to as metro areas.

For each origin–destination pair ("lane") and quarter, I observe the average all-in price actually paid per loaded trip (dollars per load, including line-haul charges). I pool spot and contract transactions and treat this shipment-weighted average as the effective price to move one truckload between two cities. Furthermore, I use data on "dry van" loads, which are loads in standard 53-foot containers (as opposed to refrigerated containers or flat-bed trailers). For each origin–destination pair and each quarter from 2017Q1 through 2023Q4, I observe the average transport price for loads between 51 US metro areas. I also observe the number of completed dry van shipments on each lane in that quarter, which I use as a measure of shipped quantity. I focus on freight transport between, rather than within, cities; shipments whose origin and destination fall in the same hub are excluded.

2.2 Import Shocks and Border Crossings

To measure plausibly exogenous shocks to US freight demand, I assemble data on imported container volumes at major seaports and truck crossings from Mexico. These series report the number of loaded import containers (measured in full truckload-equivalent units) arriving each quarter. I convert seaborne container counts to truckload-equivalent units using standard container-to-truck ratios (2 twenty-foot equivalent units to 1 truck). I assign each port or border crossing to their corresponding market area (for example, the Ports of Los Angeles and Long Beach are mapped to the Los Angeles hub) and treat changes in inbound volume as shocks to outbound trucking demand from that hub in that quarter.

Data for seaports were downloaded from port websites for the ports of Los Angeles, Long Beach, New York-New Jersey, Savannah, Houston, Oakland, Tacoma-Seattle, and Virginia. I also use information on the number of loaded trucks that cross the US-Mexico border at each point of entry, available from the US Department of Transportation "Border Crossing Entry Data."

Under US cabotage rules, most Mexican-domiciled carriers cannot haul a load deep into the US interior. Instead, they typically hand off freight near the border to US-domiciled carriers which creates a localized surge in outbound truck demand originating near that crossing. By contrast, Canadian carriers are often permitted to move goods directly to US interior destinations before unloading. For identification, I therefore treat changes in inbound Mexican truck traffic and seaborne container imports as shocks that raise outbound truck demand in the corresponding US cities in that quarter, while I exclude Canadian crossings, which are less geographically anchored to the border.

2.3 Auxiliary Data for Demand Calibration

I use data from the Freight Analysis Framework dataset (FAF5) to calibrate my demand system (U.S. Department of Transportation, 2017). I use FAF5 to measure bilateral expenditure shares across city pairs (i.e., the share of a destination city's total trucked spending that is sourced from each origin). Mapping from my freight hubs to FAF5 regions is straightfoward, and expenditure shares are reported in terms of these 51 hubs. FAF5 also reports the average dollar value per pound of trucked goods. I use this to infer the share of final-goods prices that can be attributed to transportation costs. Together, the bilateral expenditure shares and this transport-cost share serve two roles. First, they allow me to estimate how changes in trucking prices pass through into goods inflation in the descriptive facts. Second, they discipline the CES demand system I use in the counterfactual simulations.

Finally, to study pass-through into consumer prices, I use Bureau of Labor Statistics Consumer Price Index series for goods ("Commodities") at the metro level (U.S. Bureau of Labor Statistics, 2025). I use the indices available for nine large metro areas (San Francisco, Miami, Atlanta, Chicago, Boston, New York, Dallas-Fort Worth, Houston, and Seattle) and match them to the corresponding freight hubs in my data to compare local retail goods inflation with changes in local trucking prices.

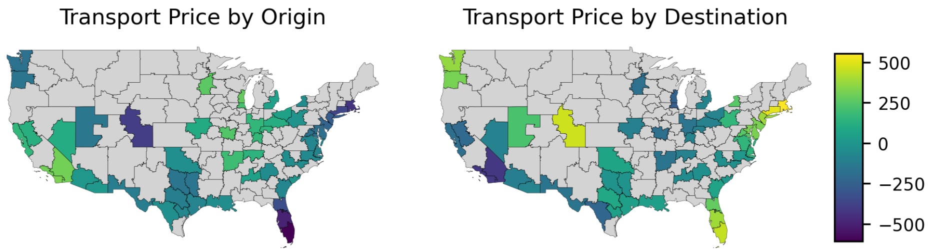

Figure 1: Origin (left) and destination (right) price premia across U.S. metro areas in 2017. Each panel shows the estimated fixed effect from a regression of lane-level transport prices on origin and destination dummies, controlling for distance. Lighter colors indicate higher prices.

3 Stylized Facts

Fact 1: Transport Prices are Spatially and Inversely Correlated

I begin by characterizing the cross-sectional pattern of trucking prices in 2017. I focus on 2017 because it predates the large import-driven shocks of 2020-2022 and reflects a relatively stable pre-pandemic trucking market. Let r_{jk} denote the average all-in price per loaded trip (in dollars per load) to move one truckload from origin j to destination k. I estimate the following regression:

$$r_{jk} = \gamma_j + \delta_k + \beta \, \mathrm{dist}_{jk} + \epsilon_{jk},$$

where γ_j is an origin fixed effect, δ_k is a destination fixed effect, and dist_{jk} is shortest-route distance (in miles) between j and k.. The origin effect γ_j measures how expensive it is, on average, to ship *out of* city j (holding distance and destination constant), and the destination effect δ_k measures how expensive it is to ship *into* city k.

Figure 1 plots these estimated origin and destination premia across the 51 freight hubs in my data. Two robust patterns emerge:

(i) Prices are spatially correlated. Nearby cities look similar. High-price origins tend to be surrounded by other high-price origins, and the same is true for destinations. In other words, the color gradient in each panel changes smoothly across geography rather than jumping discretely at city borders. This spatial smoothness in γ_j and δ_k suggests that whatever is driving high or low prices in one metro area is not purely local, but spills over to its neighbors.

(ii) Origins and destinations are inversely correlated. Cities that are expensive to ship *from* tend to be cheap to ship *to*, and vice versa. Los Angeles, for example, has a high origin premium (it is expensive to ship out of Los Angeles) but a low destination premium (it is relatively cheap to ship into Los Angeles).

I make this more explicit in Figure 2, which plots each city's estimated origin premium $\hat{\gamma}_j$ against its estimated destination premium $\hat{\delta}_j$. The relationship is strongly negative.

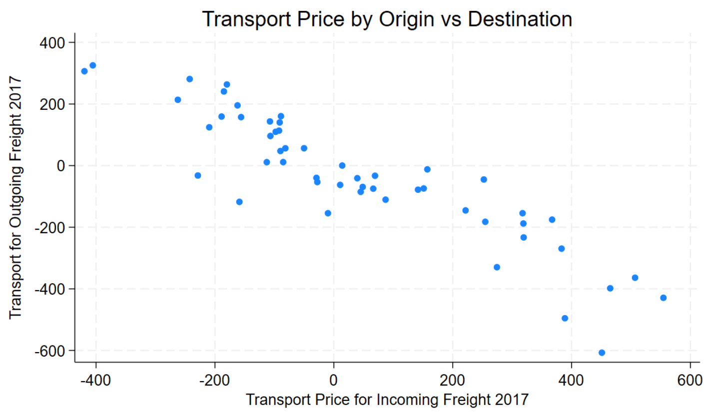

Figure 2: Origin vs. destination price premia for each metro area in 2017. Each point is a city. The y-axis is the estimated origin fixed effect $\hat{\gamma}_j$; the x-axis is the estimated destination fixed effect $\hat{\delta}_j$.

I interpret these two empirical facts—spatial smoothness and an inverse origin–destination relationship—as evidence of forward-looking, supply-driven pricing. In particular, both patterns arise naturally if truck drivers (i) choose where to position themselves next, and (ii) can drive empty when it is profitable to relocate.

To see the intuition, consider a city with abundant outbound freight demand. In such a city, shippers that need to move goods *out* must pay high prices because outbound capacity is scarce; this produces a high origin premium γ_j. At the same time, carriers are eager to end up in that city to access those lucrative outbound loads. They are therefore willing to haul freight *into* that city at relatively low prices—driving down its destination premium δ_j. This mechanism generates exactly the negative relationship between γ_j and δ_j in Figure 2.

Could these patterns be explained by demand alone? Pure demand stories struggle on two fronts. First, explaining the *inverse* correlation is difficult with demand: if a city is an attractive destination (strong demand to ship *into* it), there is no obvious reason why demand to ship *out of* that same city should simultaneously be weak. If anything, large and active cities should have high shipping demand in both directions. Second, while spatial correlation in prices could in principle reflect spatial correlation in demand (e.g., neighboring cities having similar production structure), the degree of spatial smoothness in Figure 1 is stronger than what we observe in population or output alone.

Instead, both stylized facts line up naturally with a supply system in which carriers are forward-looking and mobile: carriers internalize the value of being in a particular city next period, and are willing to reposition (even empty) across nearby cities to capture that future value. In Section 4 I build a dynamic model of transport supply with exactly these features, and I show that the model reproduces both the spatial pattern and the inverse origin–destination relationship in observed prices.

Fact 2: Drivers Frequently Deadhead

The spatial correlation in prices from Fact 1 suggests that drivers can reposition across cities, even without carrying freight. In the industry this is called "deadheading"—driving empty to a new location to access better outbound loads. Here I show direct evidence that such repositioning must be occurring at scale. I focus on 2017, which predates the large Covid-era import surges and associated capacity shocks, and reflects typical pre-pandemic routing patterns. All volumes are dry van truckloads.

For each metro area, I compare the number of loaded trips arriving in 2017 to the number of loaded trips departing in 2017. If every truck that arrived with a load also left with a load, then arrivals and departures would necessarily match in every city. In practice, they do not.

Figure 3 plots net outbound volume, defined as (loads departing j) $-$ (loads arriving j). Some cities are strong net exporters of outbound truckloads, and others are strong net importers. For example, I observe roughly 530,000 loaded trips arriving in Los Angeles in 2017, but nearly 800,000 departing. Miami shows the opposite pattern: about 200,000 arrivals but only 75,000 departures.

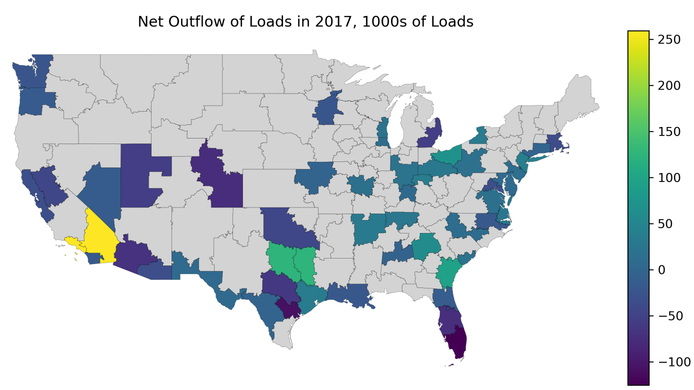

Figure 3: Net outbound truckload volume (dry vans) by metro area in 2017. For each city j, I compute (loads departing j) $-$ (loads arriving j). Positive values indicate net exporters of freight; negative values indicate net importers.

These imbalances are only possible if trucks frequently move between cities without carrying freight. A city like Los Angeles cannot ship out 800,000 paid loads while only receiving 530,000 paid loads unless additional trucks are flowing in empty. Likewise, Miami cannot absorb vastly more inbound loads than it ships outbound unless trucks are leaving Miami empty to reposition elsewhere.

The magnitudes of these net flows indicate that deadheading is not a rare, last-resort behavior—it is a first-order feature of how U.S. long-haul trucking operates. This motivates a model in which drivers are forward-looking and choose where to locate next period, and in which empty repositioning is an explicit option.

Fact 3: Transport Prices Help Predict Cross-City Differences in Goods Inflation

I now study how changes in transport prices line up with changes in retail goods prices, both over time and across cities. Figure 4 plots the average all-in trucking price (dollars per loaded trip) alongside the Consumer Price Index for goods ("Commodities") from 2017 through 2023. Both series rise sharply after the onset of Covid: average trucking prices nearly double between 2020 and 2021 before falling back, while the goods CPI increases by almost 30% and then levels off rather than returning to its pre-pandemic level.

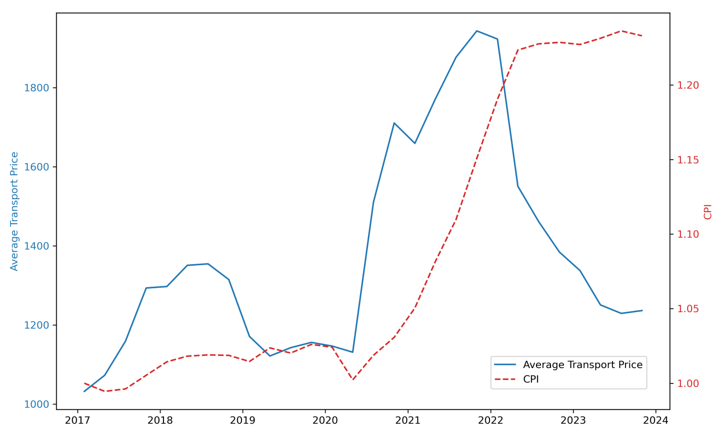

Figure 4: Average trucking prices and the Consumer Price Index for goods in U.S. cities, 2017–2023. Trucking prices are shipment-weighted averages across all lanes in each quarter; the CPI series is the BLS "Commodities" index, normalized to 1 in 2017Q1.

The aggregate comovement in Figure 4 suggests that high transport prices coincided with high goods inflation, but it does not imply that transport prices were the main driver of national inflation. To get closer to the role of trucking costs, I next ask whether *differences* in transport prices across cities line up with *differences* in goods inflation across those same cities.

For goods prices, I use the "Commodities" Consumer Price Index series reported by the Bureau of Labor Statistics for nine large metro areas (San Francisco, Miami, Atlanta, Chicago, Boston, New York, Dallas-Fort Worth, Houston, and Seattle). For each city, I normalize its CPI to 1 in 2017Q1 and then subtract the national mean in each quarter. This yields a series that captures "how much more (or less) goods inflation this city experienced than the U.S. average" over time.

For transport prices, I estimate destination–time effects from a panel regression of shipment prices on origin-time and destination-time terms. Let r_{jkt} be the average all-in price per loaded trip from origin j to destination k in quarter t. I estimate

$$r_{jkt} = \gamma_{jt} + \delta_{kt} + \beta_t \,\mathrm{dist}_{jk} + \epsilon_{jkt},$$

where γ_{jt} is an origin-by-quarter fixed effect, δ_{kt} is a destination-by-quarter fixed effect, and dist_{jk} is the shortest-route distance between j and k, interacted with quarter t through β_t to allow distance-related operating costs to vary over time. The destination-time effect δ_{kt} captures how expensive it is, in quarter t, to ship a typical load *into* city k, relative to other cities in that same quarter.

Figure 5 plots these two objects. The top panel shows heterogeneity in goods inflation across cities. The bottom panel shows heterogeneity in destination-specific trucking prices across cities. Both panels reveal large and persistent geographic gaps. For example, the top panel shows that Seattle experiences roughly 10 percentage points more cumulative goods inflation than Houston over this period. In the bottom panel, the price gap between shipping into Boston versus shipping into San Francisco widens from roughly \$500 per load in early 2020 to nearly \$2,000 per load at the end of 2021, before narrowing in 2022.

The basic prediction from a standard spatial trade framework is that higher inbound transport costs into a city should raise that city's retail goods prices. I now take that prediction to the data.

Consider a simple Armington environment in which each origin j produces a truckload of a distinct good at constant marginal cost b_j, and goods are sold in destination k. Under perfect competition, the delivered price of good j in market k is

$$p_{jk} = b_j + r_{jk},$$

where r_{jk} is the transport price to move one truckload from j to k. If consumers in k have CES preferences with elasticity of substitution σ, then the (log) change in k's CES price index P_k from a small change in transport prices is approximately

$$d\log P_{kt} = \sum_j s_{jk} \, \frac{r_{jk}}{b_j + r_{jk}} \, d\log r_{jkt}, \tag{1}$$

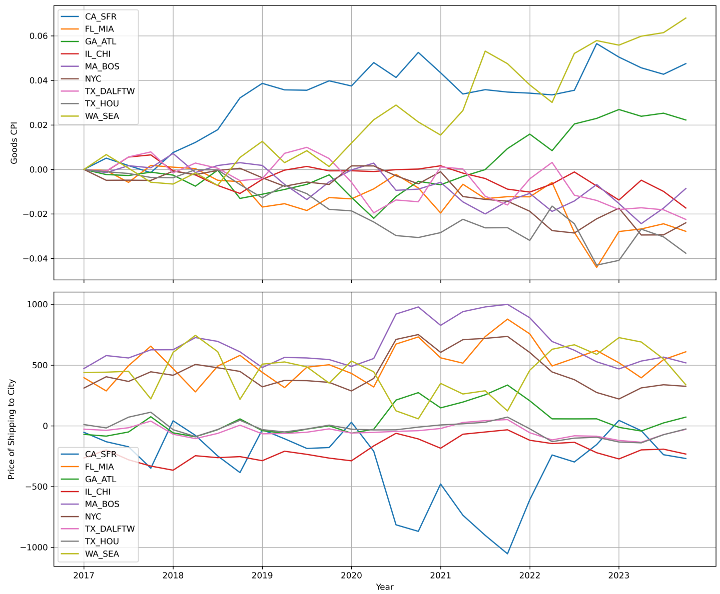

Figure 5: Cross-city variation in goods inflation (top) and destination-specific trucking prices (bottom), 2017–2023. Top panel: each city's goods CPI, normalized to 1 in 2017Q1 and demeaned by quarter. Bottom panel: destination-by-quarter fixed effects $\hat{\delta}_{kt}$ from the price regression, demeaned by quarter.

where s_{jk} is the share of destination k's total spending on trucked goods that comes from origin j and where $\frac{r_{jk}}{b_j + r_{jk}}$ is transport price's share of the goods price (in practice, about 2%). Intuitively: a destination's cost of living is most sensitive to transport price changes (i) on the origins it buys a lot from, and (ii) on lanes where transport costs make up a large share of delivered cost.

To implement (1), I proceed as follows. I treat a truckload as 40,000 pounds of goods, and I use FAF5 to measure two objects as of 2017: (i) bilateral expenditure shares s_{jk}, i.e. the share of k's trucked spending sourced from j, and (ii) the average dollar value per 40,000 pounds shipped from j, which I use as b_j (the production cost of one truckload). Holding b_j and s_{jk} fixed at their 2017 levels, I feed in observed two-year changes in lane-level trucking prices, $d \log r_{jkt}$, and compute the implied change in P_{kt} for each destination k and period t. By construction, this counterfactual attributes *all* price-index movements to transport-cost changes alone.

Finally, I compare these model-predicted changes in P_{kt} to the actual changes in the goods CPI for the nine cities where the BLS reports a "Commodities" index. In Figure 6, I plot observed goods inflation (y-axis) against model-predicted inflation driven purely by transport costs (x-axis). By demeaning by year-quarter, I difference out nationwide macro shocks and focus on cross-sectional gaps across cities within a given year.

Figure 6 shows a positive relationship: cities that experienced larger increases in inbound trucking

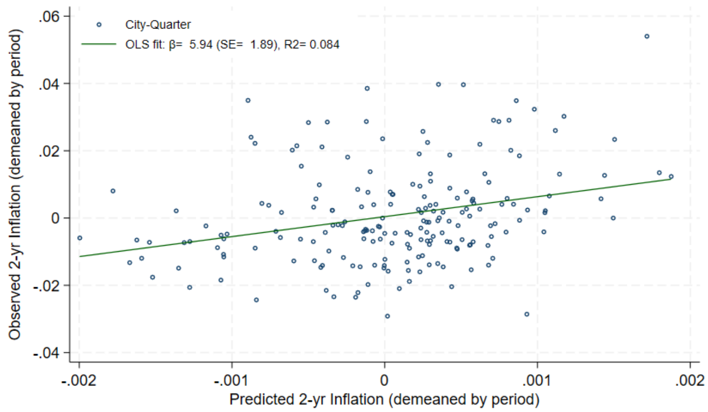

Figure 6: Observed goods inflation vs. model-predicted inflation from transport prices alone. Each point is a city-year. Both series are demeaned by year so that the scatter captures cross-city differences in inflation within each year. The fitted line reports the slope and the year-clustered standard error.

costs also tended to experience higher goods inflation in the same period. The fitted line has a slope of about 6, with a year-clustered standard error of about 1.9 and R^2 of 0.08. One way to interpret this is that the part of goods inflation that my simple model can explain—the part that is mechanically driven by changes in transport prices holding production costs and sourcing patterns fixed—accounts for on the order of 8% of the observed cross-city dispersion in goods inflation.

Two points of interpretation are important. First, this exercise is deliberately partial equilibrium: I hold production costs b_j and sourcing shares s_{jk} fixed at their 2017 values and ask what would happen to local price indices if only trucking costs moved. In reality, many other forces were driving inflation during 2020–2022. Second, I am not claiming that trucking costs explain the nationwide rise in goods prices after 2020. Instead, I am showing that the *geography and timing* of goods inflation across U.S. cities is consistent with transport price shocks passing through into local consumer prices.

Fact 4: Import Surges Reshape Local Trucking Prices and Flows

The previous facts focused on cross-sectional structure and spatial reallocation. I now show that large, plausibly external shocks to freight demand at U.S. ports are followed by sharp, local changes in trucking prices and quantities.

Figure 7 plots containerized import volumes for six major U.S. seaports. Following the onset of Covid-19 and associated social-distancing restrictions, U.S. consumers shifted spending toward goods and away from in-person services. In the second half of 2020, container imports into these ports rose and remained elevated through mid-2022.

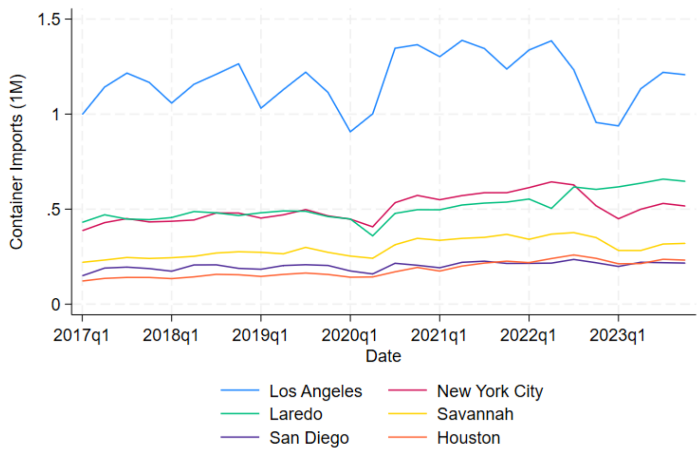

Figure 7: Loaded container imports at major U.S. container ports, 2017–2023.

To test whether these surges in inbound freight demand affected local trucking markets, I estimate reduced-form regressions relating changes in import volumes to changes in trucking prices and market shares on nearby lanes.

Let r_{jkt} denote the average all-in price per loaded trip from origin j to destination k in year-quarter t. I measure Δr_{jkt} as the quarter-to-quarter change in that price. Let ΔImp_{jt} be the quarter-to-quarter change in loaded import volume assigned to city j's port (and analogously for destination k). If a lane does not originate from or terminate at a port city, then its corresponding ΔImp is zero. I estimate

$$\Delta r_{jkt} = \beta_1 \, \Delta \text{Imp}_{jt} + \beta_2 \, \Delta \text{Imp}_{kt} + \eta_t + \epsilon_{jkt}, \tag{2}$$

where η_t are year-quarter fixed effects that absorb aggregate shocks to trucking prices and to national import volumes. Intuitively, β_1 captures how outbound trucking prices from a port respond when that port experiences an import surge, while β_2 captures how inbound prices into that same port respond.

I then estimate two extensions. First, I add origin-by-quarter and destination-by-quarter fixed effects to flexibly control for local seasonality and persistent differences in costs by city and time. Second, I include lagged changes in imports to test for pre-trends. I run the same set of specifications with $\Delta \log(\text{market share}_{jkt})$ as the dependent variable, where market share is the share of all observed truck-load movements in quarter t accounted for by lane (j, k).

Table 1 reports the results. The first three columns use Δr_{jkt} as the dependent variable. The coefficients on ΔImp_{jt} are large and positive: a one-million-container increase in imports assigned to an origin city is associated with an increase in that city's outbound trucking prices on the order of \$700 per load. By contrast, the coefficients on ΔImp_{kt} are negative: increased imports at a destination city are associated with *lower* prices to haul freight into that city, on the order of $300 per load.

The last three columns repeat the exercise using changes in log market share (lane-level volume share). Here, a one-million-container increase in imports is associated with an increase in the share of loads *leaving* the port of roughly 9% and an increase in the share of loads *arriving* to the port of roughly 14%.

Table 1: Effects of Container Imports on Transport Prices and Market Shares

	Change in Transport Price			Change in Log Market Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Chng Orig Imp	794.13***	561.67**	698.59**	0.14***	0.15***	0.13***
	(218.98)	(254.66)	(271.44)	(0.04)	(0.04)	(0.05)
Chng Dest Imp	-282.23***	-246.40**	-352.48***	0.08*	0.09**	0.10*
	(102.51)	(105.08)	(115.98)	(0.04)	(0.05)	(0.06)
(Lag 1-Orig)			-273.96			-0.06
			(214.69)			(0.04)
(Lag 2-Orig)			120.03			-0.01
			(151.73)			(0.05)
(Lag 3-Orig)			206.67			-0.08
			(196.09)			(0.05)
(Lag 1-Dest)			31.15			0.01
			(108.91)			(0.05)
(Lag 2-Dest)			-170.49**			0.01
			(79.27)			(0.06)
(Lag 3-Dest)			-171.86*			0.06
			(102.34)			(0.06)
Observations	68,850	68,850	61,200	68,850	68,850	61,200
Num Periods	27	27	24	27	27	24
Num Lanes	2,550	2,550	2,550	2,550	2,550	2,550
Period FEs	Yes	Yes	Yes	Yes	Yes	Yes
Orig-Qtr FEs	No	Yes	Yes	No	Yes	Yes
Dest-Qtr FEs	No	Yes	Yes	No	Yes	Yes

Notes: The dependent variable in columns (1)–(3) is the quarter-to-quarter change in average all-in trucking price (dollars per load) on lane (j, k). The dependent variable in columns (4)–(6) is the quarter-to-quarter change in the log of that lane's share of total observed truckloads. "Chng Orig Imp" is the quarter-to-quarter change in loaded import volume at the lane's origin market, in millions of containers; "Chng Dest Imp" is defined analogously for the destination market. If a market is not assigned a port, its change in imports is coded as zero. All specifications include quarter fixed effects η_t; columns (2), (3), (5), and (6) also include origin-by-quarter and destination-by-quarter fixed effects. Standard errors (in parentheses) are clustered by origin-quarter and destination-quarter. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The pattern of coefficients suggests a forward-looking and mobile supply side. When a port experiences an import surge, outbound trucking from that port becomes more expensive (capacity is scarce and shippers there must pay more), while inbound trucking to that port becomes cheaper (carriers are willing to accept lower prices to get into a hot market). At the same time, the share of total truckload movements both *leaving* and *arriving at* that port increases, consistent with carriers actively reallocating toward that location.

Importantly, I treat these results as descriptive and not as structural estimates of driver behavior. In particular, the regression in (2) does not correspond to a single-equation representation of the dynamic supply model in Section 4, and the coefficients on ΔImp_{jt} and ΔImp_{kt} cannot be directly mapped into the model's parameters (for example, they cannot simply be scaled to recover the elasticity of driver reallocation). In particular, these regressions fail to control for how changes in transport prices are correlated with changes in the option value of being in the origin or destination. Instead, I interpret these reduced-form responses as evidence that (i) port-level demand shocks visibly move local trucking prices and traffic patterns, and (ii) carriers respond in a way that is consistent with forward-looking repositioning of capacity.

4 Supply of Transportation

Guided by the stylized facts in Section 3, I develop a model of transport supply in which truck drivers are forward-looking and can reposition across cities even without carrying freight ("deadheading"). The goal of this section is to map observed transport prices into implied supply behavior and, ultimately, to recover a key supply parameter that governs how sensitively drivers respond to incentives.

The structure of the section is as follows. First, I model the behavior of an infinitely lived driver who chooses, in each period, which lane to serve next, analogous to the labor migration model developed by Artuç et al. (2010) and used by Caliendo et al. (2019). The driver takes current transport prices and costs as given, and internalizes both the immediate profit from hauling a load and the continuation value of being in the next city. Deadheading is explicitly allowed: a driver can deliver in city i, drive empty to some pickup city j, and then haul a load to destination k. The cost of deadheading is assumed to be linear in distance, with per-mile cost d. I treat d as a calibrated parameter based on industry evidence.

Second, to keep the problem tractable and estimable, drivers are homogeneous and have no persistent "home" location or preference for returning to a particular city. Instead, all drivers solve the same dynamic problem and ultimately induce a stationary supply of trucking capacity across origin–destination pairs. The simplification here is intentional: it allows me to write supply as the fixed point of a Markov decision process and to estimate a single key parameter governing driver responsiveness, which I denote α below.

Third, I assume that each period the driver receives i.i.d. extreme-value preference shocks over feasible lanes. This implies that (i) choice probabilities take a logit form, and (ii) each city's expected value function satisfies a closed-form "log-sum" expression familiar from dynamic discrete choice. Finally, given transport prices and costs, the spatial distribution of drivers in steady state can be recovered from the Perron–Frobenius eigenvector of the induced transition matrix. This gives me an internally consistent mapping from prices and costs to flows, which I will bring to the data in Section 5.

4.1 The Driver's Problem

Consider a single representative driver.[1] Time is discrete and indexed by $t = 0, 1, 2, \ldots$. At the start of period t, the driver is physically located in some city i. The driver must decide which lane to serve next.

A "lane" is defined by an ordered pair (j, k): pick up a load in origin j and deliver it to destination k, with $j \neq k$ (I ignore within-city transport). Importantly, the driver's current location i does not need to equal the pickup city j. The driver may first travel empty from i to j, then haul a loaded trip from j to k. This empty repositioning is what the industry calls "deadheading."

Let r_{jk} denote the all-in transport price (revenue per loaded trip) for hauling a load from j to k. Let ξ_{jk} denote the operating cost of actually performing that loaded move from j to k (fuel, driver's time, wear, etc.). If the driver begins the period in i, chooses to pick up in j, and then delivers to k, the total cost incurred is

$$d \cdot \mathrm{dist}_{ij} + \xi_{jk},$$

where dist_{ij} is the distance in miles between i and j, and d is the per-mile cost of deadheading. The term $d \cdot \mathrm{dist}_{ij}$ captures the resource and opportunity costs of driving empty from i to j. In estimation, d is treated as calibrated, while ξ_{jk} will be absorbed as a (potentially city-pair-specific) cost shifter. I will collect prices r_{jk} and costs ξ_{jk} in vectors r and ξ.

After completing the trip from j to k, the driver ends the period in location k. The continuation value of ending the period in k depends on the future opportunities available from k. To capture this, I define V_{kt} as the driver's ex ante expected value (before idiosyncratic shocks are realized) of being located in city k at the start of period t. Because different lanes take different amounts of time, a trip that requires more travel time is discounted more heavily. Let β_{ijk} denote the effective discount factor associated with completing the move $i \to j \to k$ and being in k when it is time to make the next decision. For example, if the per-day discount factor is $\beta^{\mathrm{day}} = 0.9997$ (corresponding to 10% annual discounting), and it takes 0.5 days to drive empty from i to j and 2 full days to haul a loaded trip from j to k, then $\beta_{ijk} = (\beta^{\mathrm{day}})^{2.5}$.

Each period, after seeing prices and costs, the driver also receives an idiosyncratic preference shock $\varepsilon_{jk,t}$ associated with choosing lane (j, k). These shocks are i.i.d. across lanes and periods and are assumed to follow the Type I Extreme Value (Gumbel) distribution. This assumption will imply a logit form for

[1] Throughout, I assume drivers are ex ante identical and do not have a preferred home city. This is a deliberate simplification for tractability. Drivers behave like mobile capacity that chases profitable opportunities across cities.

choice probabilities and will allow me to derive a contraction mapping for the value function.

Given these ingredients, the driver's problem can be written recursively as

$$U_{it}(\varepsilon) = \max_{j \neq k} \left[r_{jk} - d \cdot \text{dist}_{ij} - \xi_{jk} + \beta_{ijk} V_{kt+1} + \varepsilon_{jk,t} \right], \tag{3}$$

where $U_{it}(\varepsilon)$ is the realized value of being in city i at time t given the current shock vector $\varepsilon_t = \{\varepsilon_{jk,t}\}_{j \neq k}$, and V_{kt+1} is the expected (shock-averaged) value of starting the next decision problem in city k at time $t+1$:

$$V_{it} = \mathbb{E}_{\varepsilon} \left[U_{it}(\varepsilon) \right]. \tag{4}$$

A few points are worth emphasizing:

1. **Forward-looking behavior.** The term $\beta_{ijk} V_{kt+1}$ means that the driver cares not only about the current trip's profit, $r_{jk} - d \cdot \text{dist}_{ij} - \xi_{jk}$, but also about how attractive it will be to start the next period in city k. This is the mechanism behind the patterns in Fact 1 and Fact 4: drivers are willing to accept a cheaper inbound load into a "hot" city if that city will offer high-paying outbound loads next.

2. **Deadheading option.** Because i and j need not match, the driver can choose to reposition empty if the continuation value in k justifies it. This is where the deadhead cost parameter d matters. Lower d makes it easier to chase future opportunities and tends to smooth prices spatially.

3. **Homogeneous, unrooted drivers.** I assume that drivers do not have a persistent home preference, family constraint, or maximum days-out constraint. Every driver plays the same dynamic program, and the only state variable is current city i. This assumption is nonstandard relative to some previous studies which emphasizes home time (e.g., Allen et al. (2024) and Yang (2024)), but it is key for tractability. In particular, it lets me characterize steady-state flows of trucking capacity using a stationary Markov transition matrix implied by drivers' optimal choices.

4. **Timing and within-city moves.** I restrict attention to $j \neq k$ and therefore exclude purely within-city movements of freight. Empirically, my data focus on intercity (long-haul) truckload movements across 51 metro markets, not local pickup and delivery within a single metro. The state space for i is therefore the set of these 51 cities.

In the next subsection, I use the Gumbel assumption on $\varepsilon_{jk,t}$ to derive two key objects. First, the expected value V_i of being in city i, which can be expressed implicitly using a contraction mapping. Second, the probability that a driver currently in i chooses to serve lane (j, k). These choice probabilities define a system of flows across cities. By standard Perron–Frobenius arguments, the resulting system has a unique stationary distribution of drivers across cities given (r, ξ, d) and the driver's responsiveness parameter α, which I will estimate.

4.2 Driver Choices in a Steady State

I now characterize steady-state driver behavior. I drop time subscripts and assume that the environment is stationary: prices r_{jk}, costs ξ_{jk}, and travel times (which determine β_{ijk}) do not change over time. Drivers face the same decision problem in every period.

I assume that in each period the driver draws an idiosyncratic preference shock ε_{jk} for each feasible lane (j, k). These shocks are i.i.d. across lanes and drivers and are Type I Extreme Value (Gumbel), with scale parameter $1/\alpha$. The parameter $\alpha > 0$ governs how sensitive drivers are to payoff differences across lanes: when α is large, even small differences in profits generate large differences in choice probabilities; when α is small, drivers are less responsive to changes in transport prices or costs.

Under these assumptions, the driver's ex-ante (i.e., pre-shock) value of being in city i, denoted V_i, satisfies the familiar log-sum formula from dynamic discrete choice:

$$V_i = \frac{1}{\alpha} \log \sum_{j \neq k} \exp\left\{\alpha\left[r_{jk} - d \cdot \mathrm{dist}_{ij} - \xi_{jk} + \beta_{ijk} V_k\right]\right\} + \frac{\gamma}{\alpha}, \tag{5}$$

where $\gamma \approx 0.577$ is the Euler–Mascheroni constant. Economically, V_i is the expected (shock-averaged) lifetime value to a driver who starts the decision problem in city i. Because $\beta_{ijk} \in (0, 1)$, the operator that maps a guess of V into the right-hand side of (5) is a contraction. As a result, there exists a unique fixed point $V = (V_1, \ldots, V_N)$ that solves (5), given transport prices r, transport costs ξ, the deadhead cost parameter d, and the responsiveness parameter α. Numerically, we can solve for V by iterating on (5) until it converges, so we have V as a function of transport prices r and costs ξ, and model parameters: $V_i(r, \xi, \alpha, d)$.

Given the value function V, I can now characterize drivers' route choices. Let λ_{ijk} denote the probability that a driver who is currently located in city i chooses to pick up in j and deliver to k. The logit structure of the problem implies

$$\lambda_{ijk} = \frac{\exp\left\{\alpha\left[r_{jk} - d \cdot \mathrm{dist}_{ij} - \xi_{jk} + \beta_{ijk} V_k\right]\right\}}{\sum_{\ell \neq m} \exp\left\{\alpha\left[r_{\ell m} - d \cdot \mathrm{dist}_{i\ell} - \xi_{\ell m} + \beta_{i\ell m} V_m\right]\right\}} \tag{6}$$

for all i, j, and k with $j \neq k$. That is, a driver in i chooses lane (j, k) with probability λ_{ijk}. And since λ_{ijk} only depends on transport prices r, costs c, parameters α and d, and driver welfare $V_i(r, \xi, \alpha, d)$, we have that choice probabilities are a function of those same objects: $\lambda_{ijk}(r, \xi, \alpha, d)$.

Using (5), this can be rewritten in a way that highlights how the choice for (j,k) compares to the overall attractiveness of being in i:

$$\lambda_{ijk} = \exp\left\{\alpha\left[r_{jk} - d\cdot \mathrm{dist}_{ij} - \xi_{jk} + \beta_{ijk}V_k - V_i\right]\right\}. \tag{7}$$

In words, a lane (j,k) is chosen with higher probability when: it pays a high price r_{jk}, it requires little costly deadheading from i to j (small dist_{ij} and/or low d), operating costs ξ_{jk} are low, it delivers the driver to a city k with a high continuation value V_k, and the driver's current location i has relatively poor outside options (low V_i).

Equations (5) and (7) are the key building blocks for the supply side of the model. The vector V summarizes the dynamic attractiveness of each city as a place to end up, and λ_{ijk} gives the probability flow of drivers from i into k via lane (j,k). In the next subsection, I use λ_{ijk} to construct the implied Markov transition matrix over cities, and I show how the resulting stationary distribution of drivers across cities can be recovered via a Perron–Frobenius argument.

4.3 Distribution of Drivers in the Steady State

The previous subsection characterized drivers' optimal route choices via the choice probabilities λ_{ijk}. For a driver who *starts the period* in city i, λ_{ijk} is the probability that she (i) repositions, if necessary, to pick up in j, (ii) delivers a load to k, and (iii) ends the period in city k.

To describe how drivers are distributed across cities in the long run, I aggregate these route-level probabilities into a Markov transition matrix over cities. Define

$$\Lambda_{ik}(r,\xi,\alpha,d) \;\equiv\; \sum_j \lambda_{ijk}(r,\xi,\alpha,d),$$

the probability that a driver who begins the period in city i ends the period in city k, regardless of which pickup city j she used along the way. Intuitively, Λ_{ik} tells us how drivers flow between locations i and k from one decision to the next. Collecting these elements produces an $N\times N$ transition matrix

$$\Lambda(r,\xi,\alpha,d) = \begin{bmatrix} \Lambda_{11} & \cdots & \Lambda_{1N} \\ \vdots & & \vdots \\ \Lambda_{N1} & \cdots & \Lambda_{NN} \end{bmatrix}.$$

By construction, each row of Λ sums to one and every element is strictly positive: from any current city

i, the driver always eventually ends the period in some destination k, and every destination is reachable with positive probability.

Let π_i denote the steady-state mass of drivers who *begin* a period in city i, and let $\boldsymbol{\pi}$ be the $1 \times N$ row vector collecting these masses. In a stationary equilibrium, the distribution of drivers across cities must be constant over time. That is, the mass of drivers who start in each city this period must equal the mass implied by last period's distribution after they make their choices and move. This stationarity condition is

$$\boldsymbol{\pi}\, \Lambda(r, \xi, \alpha, d) \;=\; \boldsymbol{\pi}. \tag{8}$$

Equation (8) says that $\boldsymbol{\pi}$ is a (left) eigenvector of Λ with eigenvalue 1. Because Λ is a strictly positive, row-stochastic matrix (every element is > 0, each row sums to 1), the Perron–Frobenius Theorem implies that there exists a unique eigenvector $\boldsymbol{\pi}(r, \xi, \alpha, d)$ associated with eigenvalue 1, up to scale. Economically, this means there is a unique steady-state cross-sectional distribution of drivers across cities for any given (r, ξ, α, d).

I normalize $\boldsymbol{\pi}$ so that its elements sum to 1, having the interpretation of market shares. Once $\boldsymbol{\pi}$ is determined, the model delivers steady-state lane-level supply.

In particular, define $T_{jk}(r, \xi, \alpha, d)$ as the steady-state flow of drivers (in market shares) that pick up in j and deliver to k. This is obtained by summing over all possible starting locations i:

$$T_{jk}(r, \xi, \alpha, d) \;=\; \sum_i \pi_i(r, \xi, \alpha, d)\, \lambda_{ijk}(r, \xi, \alpha, d). \tag{9}$$

Intuitively, π_i is "how many drivers start in i," and λ_{ijk} is "what fraction of them choose to run $i \to j \to k$." Adding over all i gives the total mass of drivers serving lane (j, k) in steady state.

Let $\mathbf{T}(r, \xi, \alpha, d)$ denote the vector collecting all $T_{jk}(r, \xi, \alpha, d)$ across lanes (j, k). The object $\mathbf{T}$ is the model's implied steady-state supply of loaded truck trips on each lane, given: observed transport prices r_{jk}, unobserved operating costs ξ_{jk}, the deadheading cost parameter d, and the responsiveness parameter α.

In Section 5, I will use this mapping from (r, ξ, α, d) to $\mathbf{T}$ to recover unobserved costs and to estimate the key behavioral parameter α.

4.4 First-Order Approximation of Driver Welfare

The value function $V_i(r, \xi, \alpha, d)$ is central to the model: it summarizes how attractive it is for a driver to be located in city i. However, equation (5) characterizes V only implicitly, through a system of fixed-point equations. In this subsection, I use a first-order approximation to provide economic intuition for what V is capturing.

Suppose transport prices change by a small amount Δr and/or operating costs change by a small amount $\Delta\xi$. Consider first only the *direct*, one-period effect on a driver who currently starts in city i. Let

$$\Delta\psi_i := \sum_{j,k} \lambda_{ijk}\, \Delta r_{jk} \;-\; \sum_{j,k} \lambda_{ijk}\, \Delta\xi_{jk}. \tag{10}$$

This object $\Delta\psi_i$ is the instantaneous change in expected current-period payoff for a driver in city i, holding fixed all continuation values. The logic mirrors Shephard's Lemma intuition: if the price on lane (j, k) goes up by \$1, then a driver in city i benefits in proportion to the probability of choosing that lane, λ_{ijk}. Likewise, if the operating cost on lane (j, k) rises, expected payoff falls in proportion to that same probability.

But drivers are forward-looking and infinitely lived, so $\Delta\psi_i$ is not the whole story. A change in prices or costs on lane (j, k) also matters because it changes the attractiveness of ending up in k, which changes where drivers choose to position themselves today in order to exploit those future opportunities. In other words, a shock on lane (j, k) in period 0 affects not just the drivers who take that lane immediately, but also the drivers who plan to get to k (or near k) in order to *eventually* take that lane in future periods.

We can make this forward-looking component explicit. Totally differentiating the fixed-point system in (5) and applying the Implicit Function Theorem yields

$$\Delta V = (I - \widetilde{\Lambda})^{-1} \Delta\psi, \tag{11}$$

where ΔV is the vector collecting ΔV_i for all cities i, $\Delta\psi$ is the vector collecting $\Delta\psi_i$ from (10), I is the $N \times N$ identity matrix, and $\widetilde{\Lambda}$ is an $N \times N$ matrix with elements

$$\widetilde{\Lambda}_{ik} := \sum_{j} \beta_{ijk}\, \lambda_{ijk}.$$

The element $\widetilde{\Lambda}_{ik}$ has a natural interpretation: it is the discounted probability that a driver who *starts* in city i will *end* the current period in city k. It is like the transition matrix Λ from the previous subsection, but weighted by the appropriate discount factors β_{ijk} to reflect travel time. If $\widetilde{\Lambda}_{ik}$ is large, then drivers in i frequently and quickly move into k, so the continuation value in k matters a lot for V_i.

Equation (11) says that the total effect of a small change in prices or costs on V can be written as a discounted ripple process. Using the Neumann series for the matrix inverse,

$$(I - \widetilde{\Lambda})^{-1} = I + \widetilde{\Lambda} + \widetilde{\Lambda}^2 + \widetilde{\Lambda}^3 + \cdots ,$$

we can rewrite (11) as

$$\Delta V = \Delta\psi \ + \ \widetilde{\Lambda}\,\Delta\psi \ + \ \widetilde{\Lambda}^2\,\Delta\psi \ + \ \widetilde{\Lambda}^3\,\Delta\psi \ + \ \cdots . \tag{12}$$

This decomposition makes the economics transparent. The first term, $\Delta\psi$, is the direct effect: how today's price/cost changes affect a driver's current expected payoff in each city. The second term, $\widetilde{\Lambda}\,\Delta\psi$, captures one-step spillovers: how those shocks matter for the cities that are most likely to be reached next. The third term, $\widetilde{\Lambda}^2\Delta\psi$, captures two-step spillovers, and so on. In other words, a lane-specific shock in one part of the network propagates through the entire spatial system of cities, attenuating with probabilistic distance and with discounting via β_{ijk}.

This characterization highlights two features of the model. First, V_i is not just "the best lane out of i;" it also reflects the option value of reaching profitable locations in one or two moves. Second, because drivers can deadhead, $\widetilde{\Lambda}$ is dense: shocks in Los Angeles can quickly affect the value of being in Phoenix, Dallas, or even Chicago. This is the same forward-looking repositioning behavior that underlies the inverse origin–destination price relationship in Fact 1 and the asymmetric inbound/outbound price responses to import shocks in Fact 4.

5 Estimation

This section describes how I take the supply model in Section 4 to the data. The estimation proceeds in three steps.

Step 1 (Calibrate deadheading cost d). I discipline the cost of driving empty using industry evidence on per-mile operating costs. The parameter d governs how costly it is for a driver to reposition without a load. I treat d as calibrated rather than estimated.

Step 2 (Invert the model to recover costs). For any candidate value of the driver responsiveness parameter α and an assumed value of d, the model maps costs ξ and observed prices r into steady-state lane-level quantities $T(r, \xi, \alpha, d)$ (Section 4). Empirically, I observe lane-level quantities and prices. I therefore invert the model quarter-by-quarter to recover the cost matrix $\xi_t(\alpha, d)$ that rationalizes observed quantities given observed prices and a candidate (α, d).

Step 3 (Estimate α). I use variation in import surges at U.S. ports as demand shocks (see Section 3) to form moment conditions. Intuitively, if I guess an α that is "too high," the model will attribute too little of an import-driven quantity increase to supply reallocation and too much to rising costs; if I guess α that is "too low," the opposite happens. I choose α to make these import shocks orthogonal to the recovered cost changes. I implement this using GMM over a grid of α values.

At the end of this section, I report $\hat{\alpha}$, interpret its magnitude, and discuss precision.

5.1 Calibrating Deadhead Cost

The parameter d is the per-mile cost of driving empty. In the model, a driver who ends a period in city i, then deadheads to j and hauls a loaded trip from j to k, incurs a total cost of $d \cdot \text{dist}_{ij} + \xi_{jk}$, where ξ_{jk} is the operating cost of the loaded trip from j to k (see equation (5)). Thus d should reflect variable, per-mile operating costs of moving a truck without revenue: fuel, driver time, and wear/maintenance. It should *not* include fixed or quasi-fixed costs such as insurance premia, equipment leases, or licensing fees.

Industry studies place variable costs for long-haul trucking at roughly \$1.20 per mile in 2019, after excluding fixed costs such as truck and trailer lease payments. I therefore treat d as calibrated to match this per-mile benchmark (expressed in the same dollar units as my observed prices r_{jk}). This pins down how costly it is for drivers to reposition empty across cities. All remaining heterogeneity in effective costs of serving lane (j, k) is then absorbed into ξ_{jk}, which I recover in the next subsection.

5.2 Model Inversion: Recovering Cost Shifters

For a given year-quarter t, I observe (i) the average all-in trucking price per loaded trip on each lane (j, k), denoted r_{jkt}, and (ii) the number of loaded trips on that lane in that quarter, which I convert into a lane-level share of total observed trips in that quarter, denoted T_{jkt}^{data}. These shares are the empirical analogue of the model's steady-state lane-level supply $T_{jk}(r, \xi, \alpha, d)$ defined in equation (9).

Given (r_t, α, d), the model maps any candidate cost matrix $\xi_t = \{\xi_{jk,t}\}$ into predicted steady-state lane shares

$$T_{jk}(r_t, \xi_t, \alpha, d) \quad \text{for all lanes } (j, k).$$

Intuitively, lower $\xi_{jk,t}$ makes lane (j, k) more attractive to drivers (higher net payoff), which increases the probability that drivers choose that lane in equilibrium and therefore raises its predicted share.

Empirically, I treat $\xi_{jk,t}$ as a set of structural residuals: the unobserved effective operating cost of hauling from j to k in quarter t. To recover ξ_t, I invert the model by choosing ξ_t so that the model's predicted supply matches the observed supply in that quarter, given prices r_t and parameters (α, d).

Because there is no closed-form solution that directly expresses ξ_t as a function of $(r_t, \alpha, d, T_t^{\text{data}})$, I solve for ξ_t numerically. Specifically, I choose ξ_t to minimize a loss function of the form

$$\mathcal{L}_t(\xi_t\,;\,\alpha, d) = \sum_{j,k} \left[T_{jk}(r_t, \xi_t, \alpha, d) - T_{jkt}^{\text{data}}\right]^2,$$

i.e., the sum of squared differences between predicted and observed lane shares. This is a high-dimensional nonlinear problem: each $\xi_{jk,t}$ enters expected payoffs, which affect drivers' value functions V_i, their route choice probabilities λ_{ijk}, the implied transition matrix Λ, the stationary distribution $\boldsymbol{\pi}$, and ultimately T_{jk}. I solve this minimization using gradient-based numerical optimization (L-BFGS) implemented in JAX, a high-performance automatic differentiation and GPU/accelerator computing library Bradbury et al. (2018), and the associated optimization routines in Rader et al. (2024).

I repeat this inversion for each quarter t from 2017Q1 through 2023Q4 and for each candidate value of α on a grid (1.0, 1.5, ..., 10.0), holding d fixed at its calibrated value of $d = 1.2$ from Section 5.1. The result is a panel $\{\hat{\xi}_{jk,t}(\alpha, d)\}$: the recovered lane-specific cost shifters consistent with observed prices and quantities, conditional on (α, d).

5.3 Identifying the Driver Responsiveness Parameter α

The parameter α controls how sharply drivers reallocate capacity in response to profit differences across lanes. Large α means drivers are very selective: they aggressively chase high-paying opportunities and quickly reposition toward "hot" markets. Small α means drivers are more diffuse: they are less responsive to payoff differences and behave more like a random allocator of capacity.

To estimate α, I exploit variation in import surges at U.S. ports (Fact 4). These import shocks act like plausibly exogenous shifts in local trucking demand at specific origins (the port city from which goods exit the port by truck) and at specific destinations (the port city viewed as a place drivers want to be next). I use these shocks as instruments to discipline how much of a quantity increase my model attributes to (i) higher willingness of drivers to serve a lane versus (ii) a change in the unobserved cost $\xi_{jk,t}$ recovered in Section 5.2.

Here is the key idea. Fix a guess for α and hold d fixed at its calibrated value. For each quarter t, I invert the model and obtain $\hat{\xi}_{jk,t}(\alpha, d)$. If my guess of α is *too high*, the model thinks drivers are extremely sensitive to payoffs and will overpredict how much they reallocate toward a port after an import surge. To reconcile the observed data (big increases in quantities out of the port, higher outbound prices, etc.), the inversion will be forced to assign *higher* recovered costs $\hat{\xi}_{jk,t}$ to those same lanes. Intuitively, the model says: "drivers would have moved *even more* than we saw unless costs went up." As a result, changes in imports at the *origin* (the port) will be *positively* correlated with changes in recovered costs on outbound lanes if α is too high.

If my guess of α is *too low*, the model thinks drivers barely respond to incentives. After an import surge, the model underpredicts the increase in supply pointed at that port. To reconcile the data, inversion must drive *costs down*: the only way to get that much observed quantity with a sluggish driver response is to infer that lanes got "cheap to run." So when α is too low, changes in imports at the origin will be *negatively* correlated with changes in recovered costs.

A similar logic applies on the inbound side. When a port experiences a surge in imports, we observe (i) falling prices *into* the port and (ii) rising inbound volume (Fact 4 / Table 1). In the model, this pattern means that drivers view the port as a high-continuation-value location V_k: they are willing to accept lower inbound pay now because they care about tomorrow's outbound options. But how strongly they care about V_k depends on α. When α is very small (drivers are "looser"), the continuation value V_k plays a disproportionately large role relative to one-period revenue r_{jk}, so the model tends to overpredict how attractive it is to drive *into* the port after an import shock. The inversion then compensates by pushing up inferred costs on inbound lanes. When α is very large, the opposite happens.

We can summarize this logic statistically. For each candidate α, I run regressions of the form

$$\Delta\hat{\xi}_{jkt}(\alpha, d) = \beta_1(\alpha)\,\Delta\text{Imp}_{jt} + \beta_2(\alpha)\,\Delta\text{Imp}_{kt} + \eta_t + \epsilon_{jkt}, \tag{13}$$

where $\Delta\hat{\xi}_{jkt}(\alpha, d)$ is the quarter-to-quarter change in the recovered cost for lane (j,k), ΔImp_{jt} and ΔImp_{kt} are quarter-to-quarter changes in loaded import volume assigned to the origin j and destination k, and η_t are year-quarter fixed effects. This regression uses the same functional form as equation (2) from Section 3, but now the dependent variable is *recovered cost* instead of price.

Figure 8 plots the estimates $\beta_1(\alpha)$ and $\beta_2(\alpha)$ across values of α. Consistent with the intuition above, $\beta_1(\alpha)$ (the origin-side coefficient) tends to increase with α, while $\beta_2(\alpha)$ (the destination-side coefficient) tends to decrease with α. The value of α that makes both $\beta_1(\alpha)$ and $\beta_2(\alpha)$ close to zero is the value at which import shocks are orthogonal to cost changes. Visually, this occurs for α in the range of roughly 3 to 7.

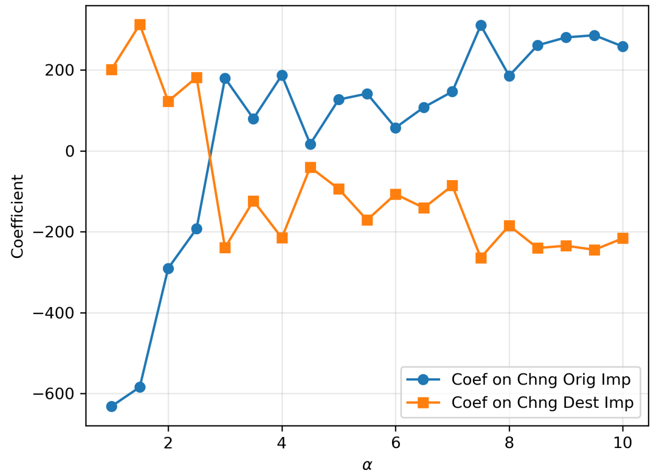

Figure 8: Regression coefficients of cost changes on import shocks across candidate values of α. Each point is an estimate of $\beta_1(\alpha)$ or $\beta_2(\alpha)$ from equation (13).

5.4 GMM Implementation and Results

The discussion above suggests a set of orthogonality conditions: after controlling flexibly for time effects and seasonal patterns, changes in recovered costs on a lane should not be systematically related to import surges at that lane's origin or destination if α is correctly chosen.

Formally, the moment conditions are

$$\mathbb{E}\Big[\Delta\hat{\xi}_{jkt}(\alpha,d)\cdot\Delta\text{Imp}_{jt}\Big|X_{jkt}\Big]=0,\quad\text{and}\quad\mathbb{E}\Big[\Delta\hat{\xi}_{jkt}(\alpha,d)\cdot\Delta\text{Imp}_{kt}\Big|X_{jkt}\Big]=0,$$

where X_{jkt} denotes controls. In practice, I implement this in two steps. First, I residualize both $\Delta\hat{\xi}_{jkt}(\alpha,d)$ and $\Delta\text{Imp}_{jt},\Delta\text{Imp}_{kt}$ on the same set of controls X_{jkt} used in Table 1: year-quarter fixed effects; then, in richer specifications, origin-by-quarter and destination-by-quarter fixed effects (to allow for city-specific seasonality); and finally, three lags of ΔImp at the origin and destination to absorb pre-trends in import volumes. Second, I compute the sample analogue of the covariance between these residualized series. The result is a two-element sample moment vector $g(\alpha)$.

I then compute the standard GMM objective $Q(\alpha)=g(\alpha)'Wg(\alpha)$, where W is the optimal weighting matrix given the covariance of the sample moments. Because I have two moment conditions and one scalar parameter α, I can also compute the associated J-statistic to test the overidentifying restrictions.

Figure 9 plots the J-statistic across values of α in my grid (1.0, 1.5, …, 10.0), using the specification with all controls included. The objective is somewhat noisy in α, but it is broadly bowl-shaped, with low values between roughly 2 and 7. In this specification, the minimum occurs at $\hat{\alpha} = 4.5$.

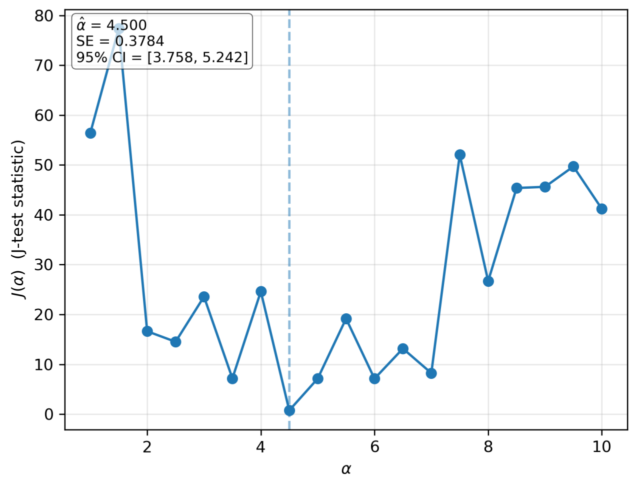

Figure 9: GMM J-statistic across candidate values of α. Lower values indicate better fit of the orthogonality conditions between recovered cost changes and import shocks.

Table 2 reports the resulting point estimates and standard errors from three specifications. Column (1) uses only year-quarter fixed effects. Column (2) adds origin-by-quarter and destination-by-quarter fixed effects to flexibly absorb local seasonality. Column (3) additionally controls for three lags of import changes to reduce concerns about pre-trends. Across specifications, the implied $\hat{\alpha}$ lies between 3 and 7, consistent with Figures 8 and 9.

How should we interpret $\hat{\alpha}$? In the driver's choice probabilities (equation (7)), the utility of serving lane (j, k) from starting location i is proportional to

$$\alpha \left[r_{jk} - d \cdot \mathrm{dist}_{ij} - \xi_{jk} + \beta_{ijk} V_k \right].$$

Thus α scales how strongly drivers react to payoff differences across lanes. A value of $\hat{\alpha} \approx 4.5$ implies that, holding costs and continuation values fixed, an increase in lane revenue of about \$1,000 raises the model-implied probability that a driver selects that lane by roughly 4–5%. In other words, the estimated α implies that drivers are responsive but not frictionless in their reallocation.

6 Simulations

In this section, I use the estimated supply model to run two sets of counterfactuals.

Table 2: GMM estimates of α

	(1)	(2)	(3)
Estimated $\hat{\alpha}$	3.0	6.5	4.5
	(0.106)	(0.775)	(0.378)
Observations	46,494	46,494	41,328
Num Periods	27	27	24
Num Lanes	1,722	1,722	1,722
Yr-Qtr FEs	Yes	Yes	Yes
Orig×Qtr FEs	No	Yes	Yes
Dest×Qtr FEs	No	Yes	Yes
Lagged ΔImp Controls	No	No	Yes

Notes: Standard errors (in parentheses) are based on numerical derivatives of the sample moments with respect to α. All specifications use changes (quarter-to-quarter differences) in recovered costs and import volumes.

(1) Local import demand shocks at ports. I ask: if a major U.S. port experiences a surge in outbound freight demand, how do trucking prices and capacity adjust in that port *and in nearby cities*? This speaks directly to the spatial spillovers in trucking supply and to the "ripple" logic in Section 4 (Fact 1, Fact 2, Fact 4).

(2) Covid-era changes in prices and quantities. I ask: between 2019 and 2021, how much of the observed change in trucking prices and market shares can be attributed to shifts in freight demand (import-driven) versus shifts in trucking supply (driver costs)? This lets me quantify the relative roles of demand shocks and cost shocks in the pandemic period.

To implement these counterfactuals, I combine the estimated supply system from Section 4 with a demand system derived from a simple partial-equilibrium Armington framework. The demand system maps transport prices into trade flows for shipped goods across cities. I calibrate that system using data expenditure shares between US cities.

6.1 Transport Demand

To simulate counterfactual equilibria, I need a model of transport demand. I adopt a standard Armington structure in which each origin j produces a differentiated good, demand is CES across origins, and trade is perfectly competitive.

Let E_k denote total expenditures on the relevant class of tradable goods in destination city k. I treat E_k as exogenous in each counterfactual. Quantities are measured in truckload-equivalents (roughly 40,000 pounds, consistent with a standard full truckload). Assume that production in each origin j has constant marginal cost b_j, and that hauling a truckload from j to k adds a transport price r_{jk}. Then the delivered price of good j in k is

$$p_{jk} = b_j + r_{jk}.$$

Under CES preferences with elasticity of substitution σ, demand in k for the variety produced in j is

$$Q_{jk} = \frac{a_{jk}\, p_{jk}^{-\sigma}}{\sum_\ell a_{\ell k}\, p_{\ell k}^{1-\sigma}}\, E_k, \tag{14}$$

where a_{jk} is a bilateral demand shifter.

To calibrate the demand system, I proceed as follows. I set $\sigma = 4$, consistent with estimates of trade elasticities in the spatial trade literature (Head and Mayer, 2014). From the Freight Analysis Framework (FAF), I observe the average value per truckload shipped from each origin j and the allocation of expenditures across origins for each destination k (i.e., bilateral expenditure shares). From the DAT data, I observe lane-level trucking quantities Q_{jk} and transport prices r_{jk}. Combining these gives delivered prices $p_{jk} = b_j + r_{jk}$ and destination expenditure totals E_k. I then back out the implied a_{jk} in the baseline year by choosing a_{jk} so that equation (14) is satisfied for observed (Q_{jk}, p_{jk}, E_k).

In counterfactuals, I will shock either the demand shifters a_{jk} (to mimic shifts in expenditures toward imported goods) or the supply-side cost terms ξ_{jk} (to mimic changes in driver costs), and then resolve for equilibrium trucking prices r_{jk} and quantities Q_{jk}.

6.2 Port Demand Shocks and Spatial Spillovers

I begin by asking: when a port experiences a sudden surge in outbound freight demand, how far does that shock propagate across the trucking network?

What the data show. Figure 10 plots origin fixed effects from a regression of the change in lane-level trucking prices between 2019 and 2021 on origin and destination fixed effects, controlling for distance. Lighter colors correspond to cities that became more expensive to ship *from* over this period. The pattern is stark: Los Angeles saw very large outbound price increases, consistent with the increase in imports documented in Figure 7, and outgoing prices also rose in nearby markets.

Counterfactual experiment. To isolate the role of port demand, I simulate a localized demand shock. For four major U.S. freight gateways (Los Angeles/Long Beach, Houston, Savannah, and New York/New Jersey), I increase the corresponding bilateral demand shifters a_{jk} by 10% for lanes that originate in that port. Intuitively, this mimics an increase in demand for outbound freight at that port.

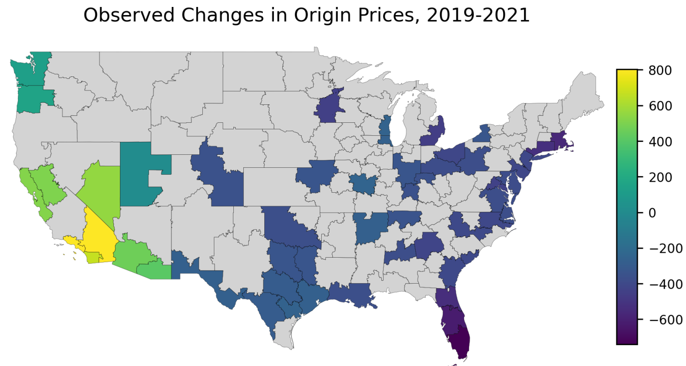

Figure 10: Observed change in outbound trucking prices, 2019–2021. Figure shows origin fixed effects from regressions of Δr_{jk} on origin and destination fixed effects and distance. Lighter colors indicate larger price increases to ship *from* that city.

I then resolve for the new equilibrium using the 2017 baseline cost structure ξ_{jk} and the estimated supply parameters $(\hat{\alpha}, d)$. With higher a_{jk} for port j, destination markets want to buy more truckloads sourced from that port. Transport prices and continuation values V_i rise until enough drivers reallocate their supply to the port to meet the shift in demand, determining new steady-state trucking prices r_{jk} and lane-level quantities Q_{jk}. I recover origin fixed effects for the simulated *change* in outbound prices (controlling for distance and destination fixed effects) and normalize each port's own shock to have value 1. This lets me compare the pattern of spillovers across ports of different sizes.

The resulting spatial price responses are shown in Figure 11.

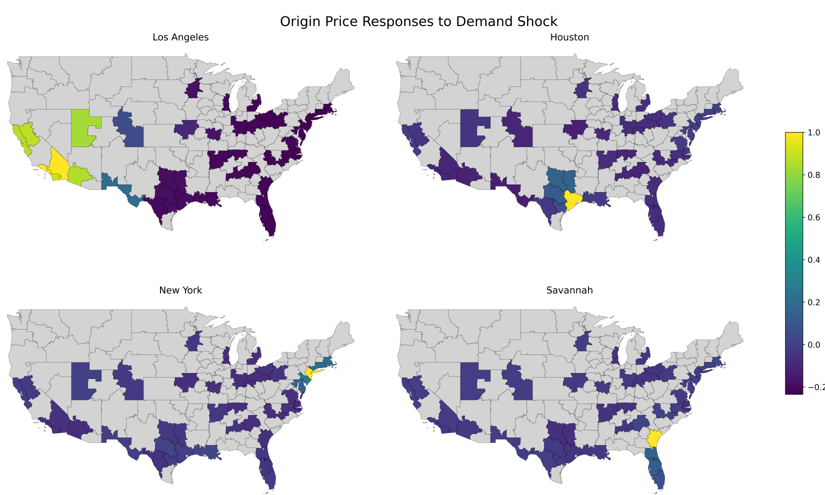

Figure 11: Simulated spillovers from a 10% outbound demand shock at each of four major ports. Plotted values are normalized so that the originating port's own outbound price effect equals 1.

Findings. A 10% demand shock in Los Angeles generates much larger and more diffuse spillovers than the same-sized shock in Houston, Savannah, or New York. In the Los Angeles case, simulated outbound prices rise not only in Los Angeles itself but also in nearby markets. In contrast, shocks in the other ports remain more geographically contained.

The model explains this asymmetry through mechanisms already highlighted in the empirical facts: Los Angeles is a net "exporter" of truckloads: many more loads leave than arrive. That means many drivers serving Los Angeles arrive empty from neighboring markets. When outbound demand at Los Angeles jumps, those neighbors suddenly become staging areas for profitable outbound loads. Thus, shippers must pay more to move goods out of Phoenix, for example, because drivers in Phoenix can exercise the option to drive empty to Los Angeles to pick up lucrative loads. This is exactly the mechanism captured in the first-order approximation in Section 4: price shocks in one market propagate through $\widetilde{\Lambda}$ to nearby markets that feed it capacity. Markets linked tightly to Los Angeles inherit part of the shock.

In short, the model reproduces two empirical features of the Covid freight boom: (i) import surges at large West Coast ports drove significant local price increases, and (ii) those price pressures spilled over into inland markets that serve as feeder capacity, not just the port city itself.

6.3 Covid-Era Reallocation: Demand vs. Supply

Finally, I use the model to decompose the Covid-era shock into a "demand" component and a "supply" component.

Between 2019 and 2021, U.S. truckload markets experienced dramatic changes: outbound prices from key ports spiked, quantities on certain lanes surged, and capacity visibly reallocated (Figures 7 and 10). I ask: how much of these changes can be explained by shifts in freight demand, and how much by shifts in trucking supply (i.e., changes in effective operating costs ξ_{jk})?

Setup. For each lane (j, k), I recover: - baseline driver costs $\xi_{jk,2019}$ and $\xi_{jk,2021}$ from the model inversion in Section 5.2; - baseline bilateral demand shifters $a_{jk,2019}$ and $a_{jk,2021}$ from the Armington system in Section 6.1.

I then construct two counterfactual scenarios:

1. **Demand-only change.** I allow the demand shifters to move from $a_{jk,2019}$ to $a_{jk,2021}$, holding supply-side costs fixed at $\xi_{jk,2019}$. Intuitively: "What if all that happened between 2019 and 2021 was that downstream buyers wanted more (or less) of particular lanes, but driver costs never changed?"

2. **Cost-only change.** I allow supply-side costs to move from $\xi_{jk,2019}$ to $\xi_{jk,2021}$, holding demand

shifters fixed at $a_{jk,2019}$. Intuitively: "What if the only thing that changed was that it got more expensive (or cheaper) to run certain lanes — due to fuel prices, labor scarcity, congestion — but underlying freight demand never shifted?"

In each counterfactual, I solve for equilibrium transport prices and quantities. I then compare, across lanes: the *observed* change from 2019 to 2021 in prices and market shares, the model-predicted change under Demand shifts only, and the model-predicted change under Cost-shifts only.

Figure 12 plots these comparisons. Each panel is a scatterplot of observed 2019–2021 changes (horizontal axis) against predicted 2019–2021 changes under one counterfactual (vertical axis). The top row compares trucking price changes; the bottom row compares changes in lane market shares.

Findings. Three patterns emerge:

1. **Quantities (market shares) require demand shifts.** The bottom panels of Figure 12 show that shifting driver costs ξ_{jk} while holding demand fixed (a_{jk} at 2019 levels) produces essentially no explanatory power for changes in observed market shares. In contrast, letting demand move while holding costs fixed captures the broad reallocation of freight across lanes. Interpretation: which lanes grew (or shrank) in volume during Covid was overwhelmingly driven by where downstream buyers wanted goods moved, not by changes in trucking costs.

2. **Prices reflect both demand pressure and cost pressure.** The top panels show that both counterfactuals — demand-only and cost-only — generate meaningful variation in lane-level price changes. Demand shocks (import surges, consumption reorientation toward goods) pushed up prices on lanes serving ports and their feeder markets. At the same time, increases in effective operating costs ξ_{jk} (driver scarcity, congestion, time costs) also contributed to higher observed prices.

3. **Demand dominates quantities, costs contribute materially to prices.** Put differently: Covid changed *where* trucks had to go (a demand story), and it also affected *how expensive* it was to get them there (a cost/supply story).

That changes in demand are necessary to explain the shifts in quantities is intuitive. In this setting, given transport price's relatively small share (about 2%) of goods prices, transport demand behaves inelastically. As a result, changes in driver costs will affect transport prices but not enough to shift market shares enough to match observed changes.

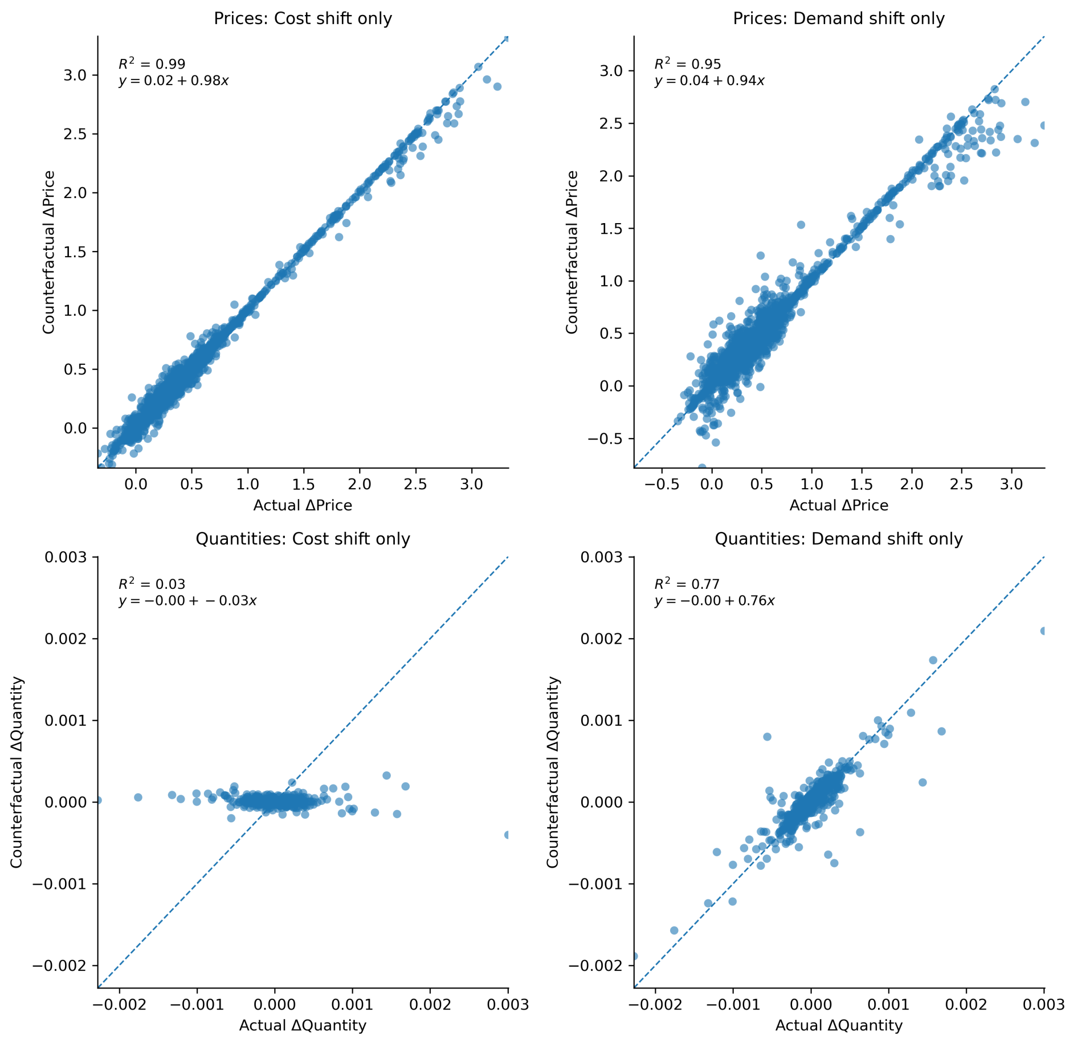

Figure 12: Observed vs. counterfactual changes in lane-level trucking prices (top row) and market shares (bottom row), 2019–2021. "Demand only" means a_{jk} updated to 2021 levels with ξ_{jk} held at 2019; "Cost only" means ξ_{jk} updated to 2021 with a_{jk} held at 2019.

7 Conclusion

This paper develops and estimates a model of trucking supply in which transport prices are outcomes of a forward-looking allocation problem, rather than fixed iceberg costs. The main contribution of the paper is to endogenize trade costs in a way that is both behaviorally meaningful and empirically usable. Rather than assuming that goods "melt in transit" at an exogenous rate, I model the transport sector as a set of forward-looking agents who choose where to be and which loads to haul. I show how to estimate this model using market-level data, discipline it with quasi-experimental shocks, and embed it in a tractable spatial demand system. In doing so, I provide a framework for thinking about how congestion at a port, a surge in import demand, or a disruption to driver availability propagates through trucking markets and into downstream consumer prices.

At the same time, the analysis is intentionally partial. I treat downstream expenditure levels as exogenous when I solve counterfactuals, so the model does not close general equilibrium in product markets. I also focus on the cost of line-haul trucking and model "trade costs" as dollars per truckload, even though time is likely an important contributor to effective trade costs. A full general-equilibrium treatment would allow shippers to substitute across modes, adjust sourcing patterns, or compress margins in response to both dollar prices and time delays.

These limitations point to several directions for future work. First, an important step is to close the model in general equilibrium by allowing destination expenditure E_k to adjust endogenously when transport prices change. Doing so would allow welfare analysis of infrastructure improvements, port congestion, or environmental policy in freight, in a way that is disciplined by observed behavior rather than imposed iceberg assumptions. Second, while I show that changes in trucking prices predict cross-city differences in goods inflation, I do not directly estimate pass-through at the product level. Linking lane-level transport prices to scanner data or customs-level unit values would allow for a direct measurement of how, and how quickly, transport shocks feed into consumer prices.

The broader lesson of this paper is that transportation is not just a wedge in a gravity equation. It is an allocative sector that can absorb, redirect, and amplify shocks. Bringing that sector inside spatial models changes how we interpret episodes like the Covid import boom and creates a path for evaluating policies that operate through logistics rather than production.

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