

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

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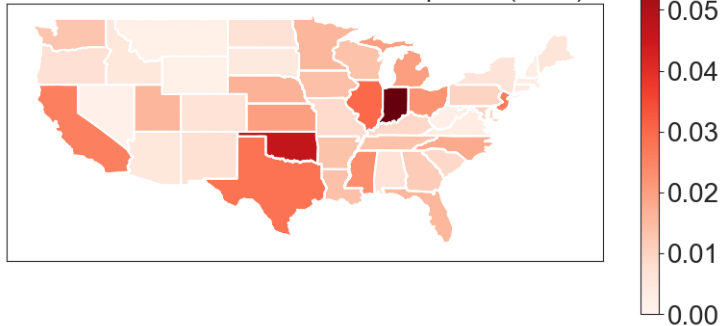
2021 Fall IO Seminar

Self-Driving Trucks are on the horizon



Trucker (Carrier) home locations are unevenly spread through US

Number of Active Carriers Per Shipment (2019)



► Map: All Carriers

► Map: Carriers per Capita

Question

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I argue that

- ① Human drivers' preference to return home ("home bias") generates geographic specialization in freight
- ② + uneven geographic distribution of homes → freight prices in driver-rich vs driver-poor states
- ③ Self-Driving trucks will eliminate this home bias.

This Paper

Overview

- ① Build model of trucking freight with home bias
- ② Estimate home bias and route costs using highway inspection and transaction data
- ③ Simulate self-driving-truck counterfactuals without home bias (w/ and w/o other effects)

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Preview

- ① I estimate a home bias of 70 dollars-per-day and per-mile marginal costs of 1.61 dollars-per mile.
- ② A transition to self-driving trucks without home bias would see carriers shift toward driver-poor states, lowering trade costs vs. driver-rich states.
- ③ The elimination of home-bias explains about 20% of full effect of automation.

Overview

- ① Background and Data
- ② Model
- ③ Estimation
- ④ Counterfactuals

Background

Context

Trucking Freight is Important

- **Transportation:** 80% of total U.S. domestic freight by value in 2019.
- **Labor:** Over 2 million workers in truck transportation in 2019.
- **Environmental:** 1% of on-road vehicles, 28% of vehicle greenhouse gas emissions.

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► Freight Mode Shares (CFS)

► Spot vs. Contract Prices

Structure

- Focus on **general freight, over-the-road, truckload** market
- Large number of small firms
- Limited returns to scale (vs. less-than-truckload, parcel)
- Highway driving (vs. local delivery)

Literature Review

- **Economics and Transportation Literature on Trucking**


- Regulation (Rose 1985, 1987)
- Asset Ownership (Hubbard 2001, Baker and Hubbard 2003, Baker and Hubbard 2004)
- Contracts/Relationship (Masten 2009, Scott et al 2016, Aemireddy et al 2019, Acocella et al 2020, Harris and Nguyen 2021, ...)
- Dynamic and backhaul incentives (Behrens and Picard 2011, Allen et al 2020, Heilmann 2020)

- **IO of Transportation** Brancaccio et al 2020, Bucholz 2021, Frechette et al 2019, Chen 2020, Rosaia 2021

- **Trade on Networks** Fagjelbaum and Schaal 2020, Allen and Arkolakis 2020, ...

- **Transportation Costs and Cities** Redding and Turner 2015, Duranton and Turner 2012, Hummels 2007, Glaeser and Kohlhase 2004, ...

Data

- **Prices and Quantities:** DAT RateView
 - Transactions, 2016-2020
- **Carrier Locations:** Highway Inspections
 - Random inspections, 2018-2020
 - For each inspection, home state + current state 
- **Route Characteristics**
 - Routes: Open Street Map
 - Road Chars: Highway Performance Monitoring System
 - Diesel prices: AAA
 - Rivers: Army Corps of Engineers
 - Snowiness: Weather Stations

Model

Setup

- **Agents:** There are two types of agents:
 - ① **Carriers** (Supply)
 - ② **Shippers** (Demand).
- **Locations:** There is a set of locations L .



Setup

- **Agents:** There are two types of agents:
 - ① **Carriers** (Supply)
 - ② **Shippers** (Demand).
- **Locations:** There is a set of locations L .
- **Types:** Carriers are differentiated by their **home location** $h \in L$.
- **Timing:** Each period is 1 day.



Carrier Locations

Carriers may begin a period

① in a location $i \in L$, or



Carrier Locations

Carriers may begin a period

- 1 in a location $i \in L$, or
- 2 en-route $i \rightarrow j$ for $i, j \in L$.



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There are total C^h carriers of type h .

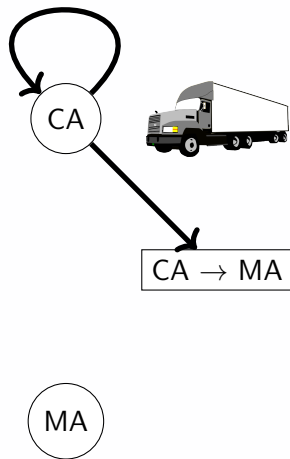
$$\sum_i C_i^h + \sum_{ij} C_{ij}^h = C^h \quad (1)$$



Carrier Choices

Each period, a carrier of type h in location i can choose to:

- 1 Accept a job to any destination $j \in L$
- 2 Choose to take an outside option and remain in i



Carrier Choices

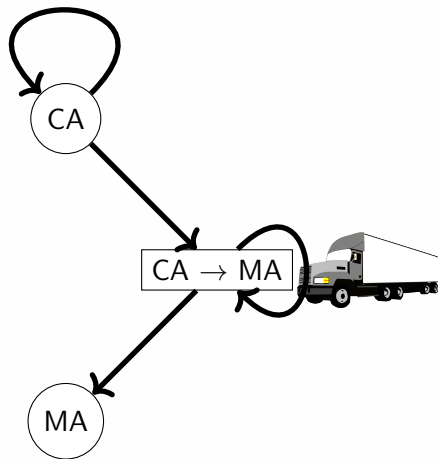
Each period, a carrier of type h in location i can choose to:

- 1 Accept a job to any destination $j \in L$
- 2 Choose to take an outside option and remain in i

If the carrier takes a job to j , or is travelling at $i \rightarrow j$,

- 1 With probability λ_{ij} , it arrives at the destination.
- 2 With probability $1 - \lambda_{ij}$, it continues travelling.

► Comparison with Fixed Travel Time



Carrier Static Payoffs

- A carrier c which begins the period in its home location $h(c)$ receives a **home bias** flow payoff, b .

$$b \times 1_{h(c)=i} + \begin{cases} \alpha p_{ij} + \gamma X_{ij} + \xi_{ij} + \epsilon_{cj} & \text{Accept job to } j \\ \dots & \\ \epsilon_{c,OO} & \text{Outside Option} \end{cases} \quad (2)$$

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- A carrier who takes the outside option receives an iid logit cost shock of $\epsilon_{c,OO}$.
- Let δ_{ij} denote the mean flow payoff of a route.

$$b \times 1_{h(c)=i} + \begin{cases} \overbrace{\alpha_{ij} + \gamma X_{ij} + \xi_{ij}}^{\delta_{ij}} + \epsilon_{cj} & \text{Accept job to } j \\ \dots & \\ \epsilon_{c,OO} & \text{Outside Option} \end{cases} \quad (2)$$

Carrier Value Function

Let V_i^h denote the carrier's value function in a location, and W_{ij}^h the value function when travelling.

$$V_{ic}^h = b \times 1_{h(c)=i} + \max \left\{ \begin{array}{l} \text{Begin Travelling} \\ \delta_{ij} + \epsilon_{cj} + \overbrace{\beta E \left[W_{ij}^h \right]} \\ \dots \\ \text{Start Again} \\ \epsilon_{c,00} + \overbrace{\beta E \left[V_i^h \right]} \end{array} \right. \quad (3)$$

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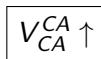
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Travelling value function depends on probability of arrival.

$$E[W_{ij}^h] = \underbrace{\lambda_{ij} E[V_j^h]}_{\text{Arrival}} + \underbrace{(1 - \lambda_{ij}) \beta E[W_{ij}^h]}_{\text{Continue Travelling}} \quad (4)$$

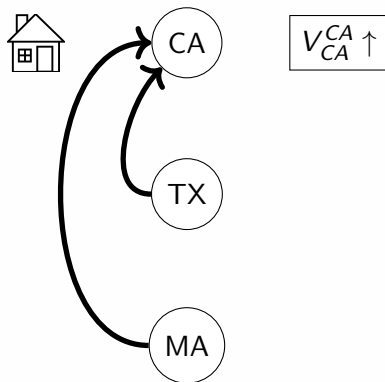
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- \rightarrow higher value function at locations likely to bring carrier home



CA

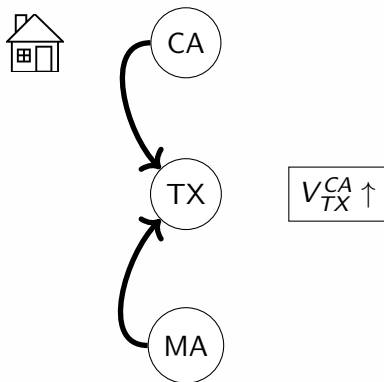
TX

$V_{TX}^{CA} \uparrow$

MA

Model: How does home bias affect carrier choices?

- Home bias raises the value function V_i^h of a carrier at home
- \rightarrow higher probability of choosing to go home
- \rightarrow higher value function at locations likely to bring carrier home
- \rightarrow higher probability of choosing to go to i



Aggregate Supply

Probability that a type h carrier currently in i chooses to go to j

$$s_{ij}^h = \frac{\exp(\delta_{ij} + \beta E[W_{ij}^h])}{\sum_{k \in L} \exp(\delta_{ik} + \beta E[W_{ik}^h]) + \exp(\beta E[V_i^h])} \quad (5)$$

Aggregate supply along a lane sums over types.

$$s_{ij} = \sum_h \frac{C_i^h}{\sum_{h'} C_i^{h'}} s_{ij}^h \quad (6)$$

Shippers

- In each ij lane, there is a mass of N_{ij} shippers, each with shipping value $\omega_{ij} + v$ where $v \sim_{iid} \text{Exp}(\sigma)$.
- Each shipper chooses between purchasing 1 unit of shipping and an outside option. The shipper's problem is

$$\max\{v + \omega_{ij} - p_{ij}, 0\}$$

- Aggregate demand is

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

Equilibrium Conditions

A steady-state equilibrium of this model is a vector of prices, quantities, and carrier locations such that:

- Carriers make optimal decisions
- Shippers make optimal decisions
- Markets clear in each lane

$$\forall i, j, \quad S_{ij}(p) = D_{ij}(p)$$

- For each location, number of carriers of each type constant

$$C_i^h = \underbrace{\sum_j C_j^h s_{ji}^h}_{\text{Inflows}} + \underbrace{C_i^h s_{i,oo}^h}_{\text{Outside Option}}$$

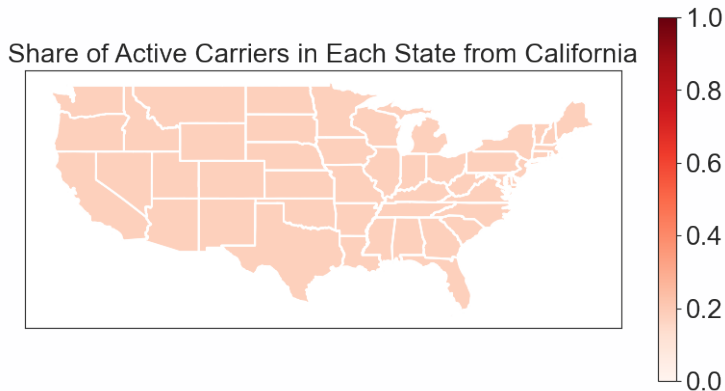
Model: Identification of Home Bias with Inspections

Consider the share of active carriers in each state who are from California.
What do different levels of home bias predict?

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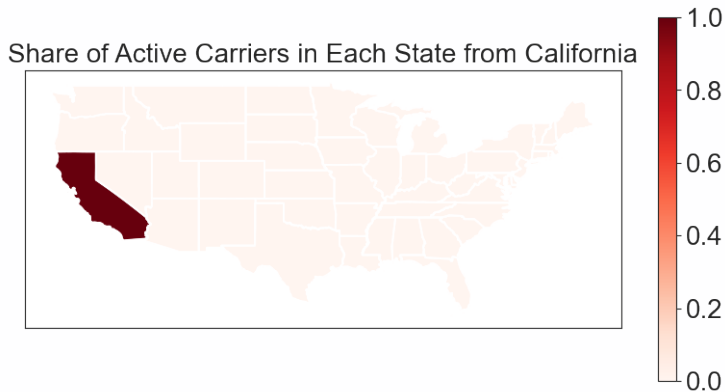
$b = 0$: No home bias, all carrier homogeneous



Model: Identification of Home Bias with Inspections

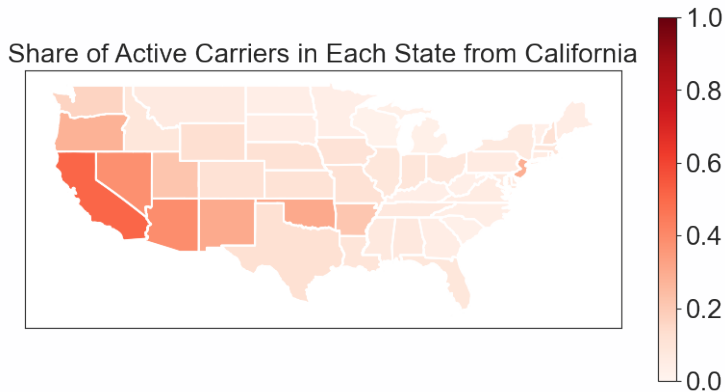
Consider the share of active carriers in each state who are from California.

$b \rightarrow \infty$: Carriers stay at home



Model: Identification of Home Bias with Inspections

Consider the share of active carriers in each state who are from California.
 b in the data identified by inspections



Estimation

Supply-side Estimation: Model Takeaways

Route mean payoffs δ_{ij} for a route from i to j :

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

Value function for a carrier from h to be in i

$$V_{ic}^h = b \times 1_{h(c)=i} + \max_j (\max_j \delta_{ij} + \epsilon_{cj} + \beta E[W_{ij}^h], \epsilon_{c,00} + \beta E[V_i^h])$$

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Data and Parameters

Supply-side Estimation: Big Picture

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- I need to estimate home bias b , but I don't have type-specific shares s_{ij}^h
 - Use inspections
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► Inspection Process Details

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- Inspection Process Details
- I allow unobservable shocks ξ_{ij} in my cost function
 - Use approach like BLP for demand estimation.

BLP Contraction Mapping Analog

- Recall the mean payoffs δ_{ij} :

$$\delta_{ij} = \alpha p_{ij} + \gamma X_{ij} + \xi_{ij} \quad (7)$$

- I can solve for predicted aggregate shares s_{ij} as a function of b and δ .

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- For every level of home bias, I can find mean payoffs which match observed shares.
- Differences:
 - Nested value function iteration
 - Equilibrium locations of carriers

► δ^* Algorithm Details

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► δ^* Algorithm Details

- Given δ_{ij} , I can use IV to recover price and cost coefficients.
- Price Instrument: Availability of River and Water Shipping

► Price Instrument Construction Details

Estimation Steps

Supply

- First step: estimate home bias by maximizing likelihood of observed inspections.
 - ① Guess home bias b .
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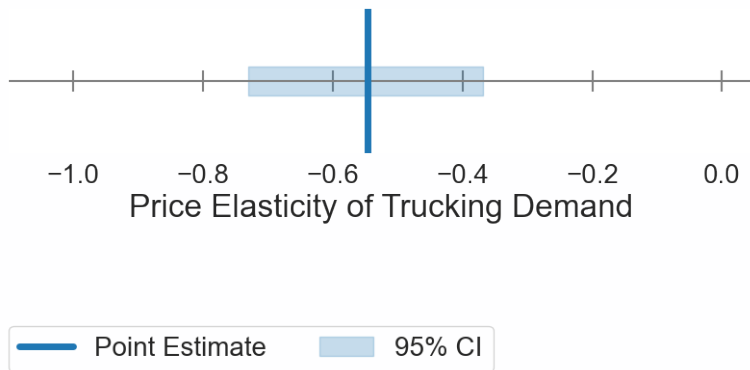
► Optimization Problem

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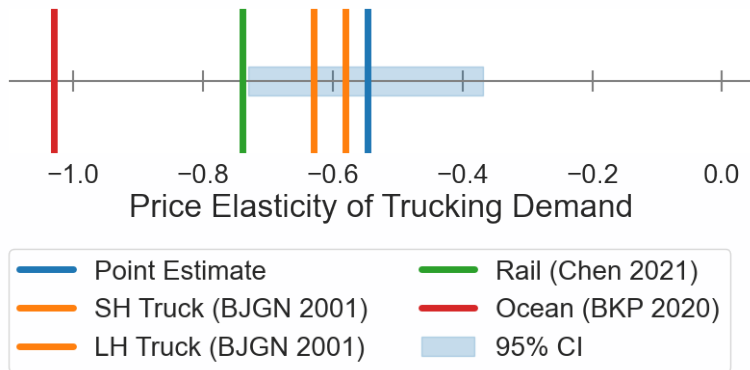
Demand

- Linear IV using route snowiness as cost shifter

Estimation: Demand-side Results



Estimation: Demand-side Results



Estimation: Supply-side Results

Parameter	Estimate (Utils)	95% Bootstrap CI	Estimate (\$)
Home Bias (Utils)	0.0206	[0.0204, 0.0212]	70.33
Price Sensitivity (000 \$)	0.2929	[0.2735, 0.3086]	-

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<i>Costs (γ)</i>			
Diesel (\$/gal \times 000 miles)	-0.1577	[-0.1697, -0.1447]	-538.4
Distance (000 miles)	-0.4734	[-0.4755, -0.4709]	-1616

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Cracking (std)	-0.0317	[-0.0326, -0.0303]	-108.2
Faulting (std)	-0.0535	[-0.0543, -0.0526]	-182.6
Rutting (std)	-0.0893	[-0.0903, -0.0878]	-304.8

Counterfactuals

Counterfactual I: Autonomous Trucks

Question: What is the effect of autonomous “homeless” trucks?

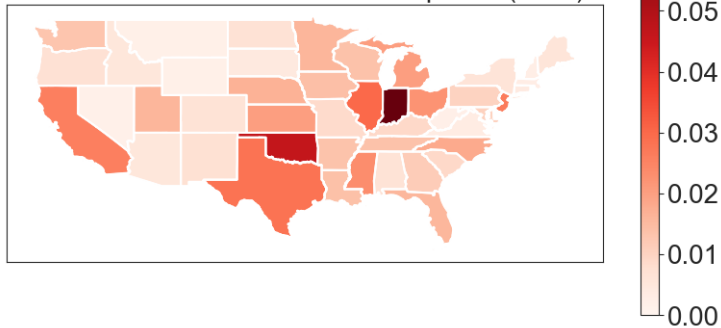
Setup

- Remove carrier heterogeneity and let $b = 0$.
- Agnostic about cost effects: Keep costs constant, consider dispersion.
- Hold demand constant.



Counterfactual I: Distribution of Carrier Homes

Number of Active Carriers Per Shipment (2019)



Counterfactual I: Counterfactual Results

Two forces:

- **Level effect:** Fewer carriers take outside option \rightarrow more capital utilization, supply shifts out.
- **Dispersion:** Carriers shift away from high trucker-per-capita states.
 - ① Fewer carriers \rightarrow lower supply \rightarrow higher export prices.
 - ② Fewer carriers wanting to return home \rightarrow higher import prices.
 - ③ Combination of (1) and (2) \rightarrow higher within-state prices.

Counterfactual I: Counterfactual Results

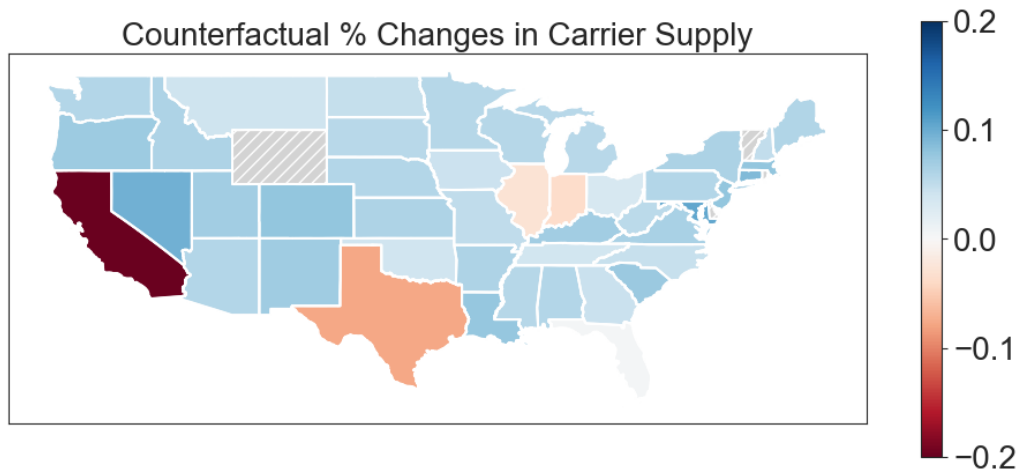
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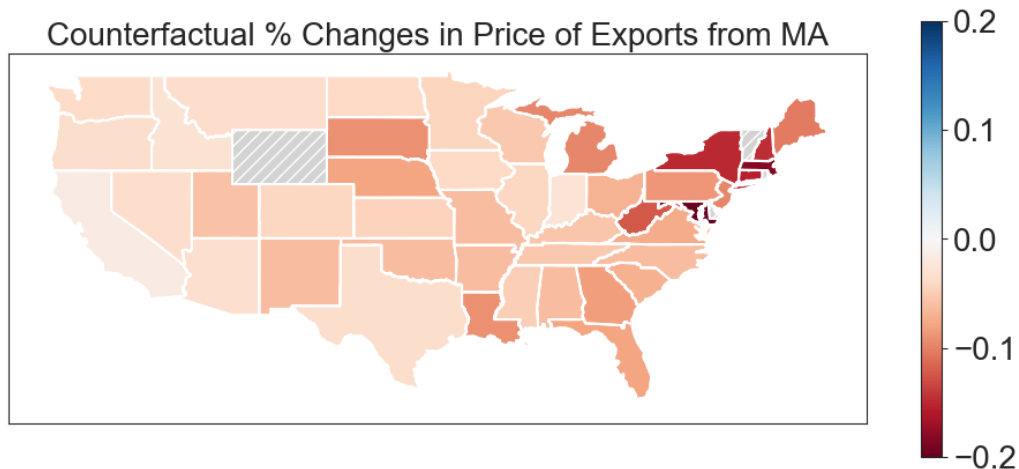
Big picture:

- 5.4% decrease in route prices (Laspeyres Index)
- 2.5% increase in total trucking freight

Counterfactual: Carriers reallocate from driver-rich states



Counterfactual: Short distance prices fall in driver-poor regions



Counterfactual II: Full Counterfactual

Full effects of automation include:

- ① No home bias
- ② Lower per-mile costs (labor, fuel, accidents)
- ③ Longer daily range

Counterfactual II: Full Counterfactual

Full effects of automation include:

- ① No home bias
- ② Lower per-mile costs (labor, fuel, accidents) [-25% (HK 2020)]
- ③ Longer daily range [2x (Deloitte 2021)]

I take estimates of 2 and 3 from transportation literature and industry and run simulations:

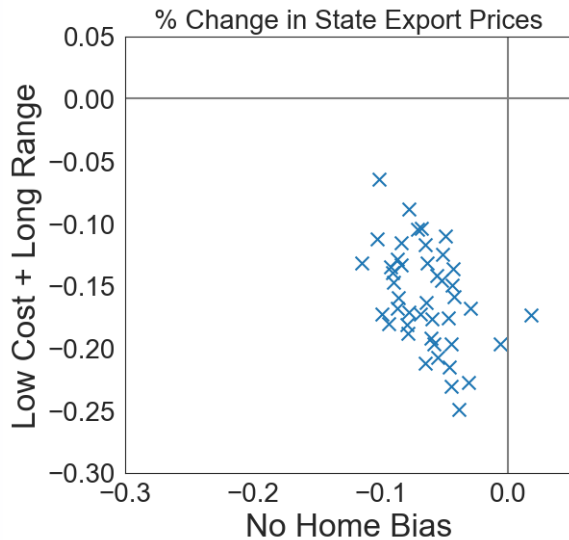
- With each effect alone
- With all 3 effects (“Full”)

Full Counterfactual: Home Bias \approx 20% of Total Effect

Counterfactual	Price Index	Total Quantity	Shipper Welfare (\$/year)
No Home Bias	-5.4%	+2.5%	+1.50B
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

Full Counterfactual: Home Bias negatively corr. with Other Effects

- Intuition: Carrier homes concentrated in states with long average hauls.
- States with long hauls benefits more from low cost / long range.



Conclusion

This paper:

- Estimate daily home bias \approx \$70 per day.
- Eliminating home bias:
 - shifts carriers from driver-rich states to driver-poor states.
 - increases capital utilization by reducing outside option
- Home bias effect \approx 20% of full effect of automation

Thank you!

Appendix

Appendix: Current Electrification Landscape

Appendix: Current Automation Landscape

Appendix: Data Summary Statistics

Appendix: Sample Selection

- 2019 Data only
- Exclude within-MSA trips
- Excluded states: Alaska, Hawaii, Nebraska, Wyoming, Vermont

Appendix: Choice of β

- Given flexible form of common cost shocks ξ_{ij} , it is likely β is not identified (Rust 1994, Magnac-Thesmar 2002).
- The industry sees exit rates of 70-90% annually, which corresponds to a daily discount factor of 0.9937-0.9967.

Appendix: Deterministic Arrival

Given the stochastic arrival probability, with risk-neutral carriers,

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

In expectation, a carrier arrives in $1/\lambda_{ij}$ days.

Under a deterministic arrival of T_{ij} days,

$$E[W_{ij}^h] = \beta^{T_{ij}} E[V_j^h]$$

For any λ_{ij} , there exists a T_{ij} which discounts the future equivalently.

In a steady-state equilibrium, the share of travelling carriers arriving will be exactly $1/T_{ij}$ under stochastic and deterministic arrival.

Appendix: Measurement Details

Appendix: Route Characteristic Construction

- For each (i, j) pair of origin and destination states, I take the centroid of the origin and destination.
- I use roads from the Highway Performance Measurement System and filter for highways on the National Truck Network.
- I compute the shortest distance route from the origin to the destination.
- The route characteristic is the average route characteristic over all intermediate states, weighted by the amount of distance travelled in each state.

$$X_{ij} = \sum_k s_{ijk} X_k$$

Appendix: Reduced Form Supply Derivation

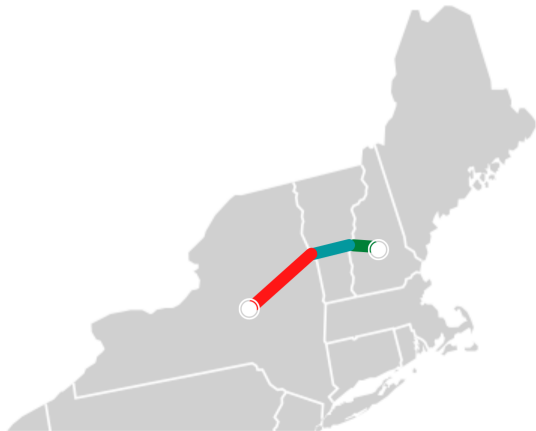
Recall choice probabilities.

$$s_{ij}^h = \frac{\exp\left(\alpha p_{ij} + \gamma X_{ij} + \beta E[W_{ij}^h] + \xi_{ij}\right)}{\sum_k \exp\left(\alpha p_{ik} + \gamma X_{ik} + \beta E[W_{ik}^h] + \xi_{ik}\right)}$$

Factor out common components of RHS, sum over carrier types h , and take logs.

$$\log S_{ij} = \underbrace{\log C_i + \alpha p_{ij} + \gamma X_{ij} + \xi_{ij}}_{\text{Error}} + \underbrace{\log \sum_h \frac{C_i^h}{C_i} \frac{\exp\left(\beta E[W_{ij}^h]\right)}{\sum_k \exp\left(\alpha p_{i+k} + \gamma X_{ik} + \beta E[W_{ik}^h] + \xi_{i+k}\right)}}_{\text{Error}} \quad (8)$$

Appendix: Inspection Process



Appendix: Supply Estimation Details

- ➊ Given a guess for (b, δ) , compute value function $E[V_i^h]$.
 - ➋ Given $E[V_i^h]$, compute type-specific shares s_{ij}^h
 - ➌ Given s_{ij}^h , compute steady-state carrier locations C_i^h
 - ➍ Given (s_{ij}^h, C_i^h) , compute aggregate shares $s_{ij}(\delta)$
 - ➎ Iterate $\delta'_{ij} = \delta_{ij} + \log s_{ij} - \log s_{ij}(\delta)$ until convergence
- In steady-state, conditional on δ , a carrier does not need to know choices of any other carriers.
 - Solve for $E[V_i^h]$ using value function iteration.

Appendix: Supply Estimation Details II

- ➊ Given a guess for (b, δ) , compute value function $E[V_i^h]$.
- ➋ Given $E[V_i^h]$, compute type-specific shares s_{ij}^h
- ➌ Given s_{ij}^h , compute steady-state carrier locations C_i^h
- ➍ Given (s_{ij}^h, C_i^h) , compute aggregate shares $s_{ij}(\delta)$
- ➎ Iterate $\delta'_{ij} = \delta_{ij} + \log s_{ij} - \log s_{ij}(\delta)$ until convergence

- With value functions, the model implies conditional choice probabilities

$$s_{ij}^h = \frac{\exp(\delta_{ij} + \beta_{ij}E[V_j^h])}{\sum_k \exp(\delta_{ik} + \beta_{ik}E[V_k^h]) + \exp(\beta E[V_i^h])}$$

- CCPs imply type-specific transition matrices, T^h . The steady-state location of carriers is the solution to

$$\begin{pmatrix} T^h \\ \vec{1} \end{pmatrix} C^h = \begin{pmatrix} C^h \\ \bar{C}^h \end{pmatrix}$$

Appendix: Supply Estimation Details III

- ➊ Given a guess for (b, δ) , compute value function $E[V_i^h]$.
 - ➋ Given $E[V_i^h]$, compute type-specific shares s_{ij}^h
 - ➌ Given s_{ij}^h , compute steady-state carrier locations C_i^h
 - ➍ Given (s_{ij}^h, C_i^h) , compute aggregate shares $s_{ij}(\delta)$
 - ➎ Iterate $\delta'_{ij} = \delta_{ij} + \log s_{ij} - \log s_{ij}(\delta)$ until convergence
- Aggregate shares are weighted averages of type-specific shares.

$$S_{ij}(\delta) = \sum_h C_i^h s_{ij}^h$$

$$s_{ij}(\delta) = \frac{S_{ij}(\delta)}{\sum_k S_{ik}(\delta)}$$

Appendix: Outside Option

- **Challenge:** I do not observe carriers which take the outside option.
- I observe the number of daily carrier searches for jobs on the DAT spot marketplace app, t_i , for each location i . This includes carriers who accept jobs as well as those who do not.
- I observe the total population of potential carriers C^h using registrations.
- Assume that the number of available carriers is proportional to the number of searches.

$$C_i^h = \frac{t_i}{\sum_j t_j} \times C^h$$

Appendix: Calibration of λ_{ij}

Appendix: Accounting Cost components

Building to Estimation: δ^*

Given a value of home bias b , I can find a vector of mean payoffs $\delta^*(b)$ which fits observed trip shares s_{ij}^O exactly.

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

I can find $\delta_{ij}^*(b)$ by iterating the following until convergence:

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

Following slides: How does model predict aggregate trip shares $s_{ij}(b, \delta)$?

Computing δ^* I: Solve for value function

- In steady-state, fixing δ , a carrier's problem looks like single-agent optimization.
- Given a guess for (b, δ) , compute value function $E[V_i^h]$ using value function iteration.

$$V_i'^h = b \times 1_{h=i} + E_\epsilon[\max(\max_j \delta_{ij} + \beta W_{ij}^h, \beta V_i^h)] \quad (9)$$

$$W_{ij}'^h = \lambda_{ij} V_j^h + (1 - \lambda_{ij}) \beta E[W_i^h j] \quad (10)$$

Computing δ^* II: Type-specific trip shares

With value functions V_j^h and W_{ij}^h , and δ , the model implies type-specific choice probabilities

$$s_{ij}^h = \frac{\exp(\delta_{ij} + \beta E[W_{ij}^h])}{\sum_k \exp(\delta_{ik} + \beta E[W_{ik}^h]) + \exp(\beta E[V_i^h])} \quad (11)$$

Computing δ^* III: Steady-state carrier locations

Each period, the number of type h carriers in i is

$$C_i^h = \underbrace{\sum_j C_j^h s_{ji}^h}_{\text{Inflows}} + \underbrace{C_i^h s_{i,00}^h}_{\text{Outside Option}}$$

L equations and L unknowns \rightarrow solve for C^h for each h .

► Back

Computing δ^* IV: Aggregate trip shares

Aggregate shares are carrier-weighted averages of type-specific shares.

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

I can find $\delta_{ij}^*(b)$ by iterating the following until convergence:

$$\delta'_{ij} = \delta_{ij} + \log s_{ij} - \log s_{ij}(\delta)$$

Building to Estimation: Inspection Process

- A carrier available in i is inspected at i with probability ρ_i .
- A carrier en-route from i to j is inspected at k with probability $\rho_k m_{ijk}$, where m_{ijk} is the mileage share of the total route from origin i to destination j spent passing through k .
- The share of type h carriers among inspections at k depends on the equilibrium locations of carriers:

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

Price Instrument Construction Details

- Idea: Geographic presence of rivers allows barge freight \rightarrow shifts demand for trucking freight independent of costs
- Construction: Use Army Corps of Engineers' Fuel-Taxed River and Internal Waterway System
- Let $Z_{ij} = 1$ if
 - A fuel-taxed river flows from i to j
 - An internal waterway (Gulf, Atlantic) connects i and j

Estimation Problem

First stage: Maximize likelihood of inspections I_i^h

$$\max_b LL(s^O \mid b, \delta^*(b)) = \sum_{hi} I_i^h \times \log \iota_i^h(b, \delta)$$

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

Second stage:

$$\min_{\alpha, \gamma} E[(\delta_{ij}^* - \alpha p_{ij} - \gamma X_{ij}) Z_{ij}]$$

Counterfactual III: Electric Trucks (Setup)

Question: What is the effect of electric trucks?

Setup

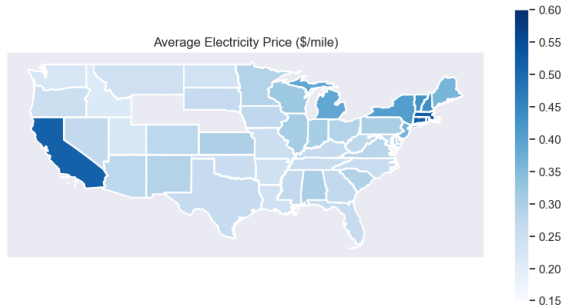
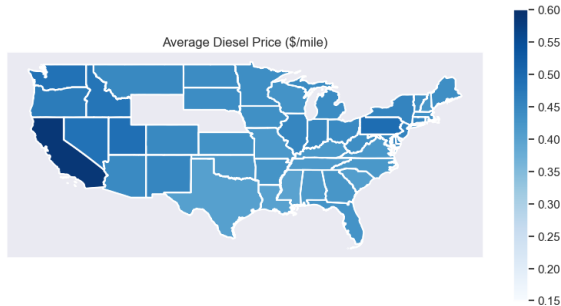
- Replace role of route diesel prices with route electricity prices.
- Agnostic about other cost effects: Keep costs constant, consider dispersion.
 - 3B trucking freight miles \rightarrow 6.6B kWh \rightarrow 0.17% US total electricity usage
- Hold demand and home locations constant.
- Abstract from range (more intense home preference), charging.



Counterfactual II: Input Price Differences

To make prices comparable, I make assumptions:

- Gas mileage: 6 mpg (industry survey of fleets)
- Electricity mileage: 2.2 kWh per mile (Freightliner eCascadia)
- Electricity prices: EIA average residential electricity price



Counterfactual II: Results

Two forces:

- **Level Effect:** Lower costs overall \rightarrow less outside option
- **Dispersion:** Shift toward routes with lower input prices

Counterfactual II: Results

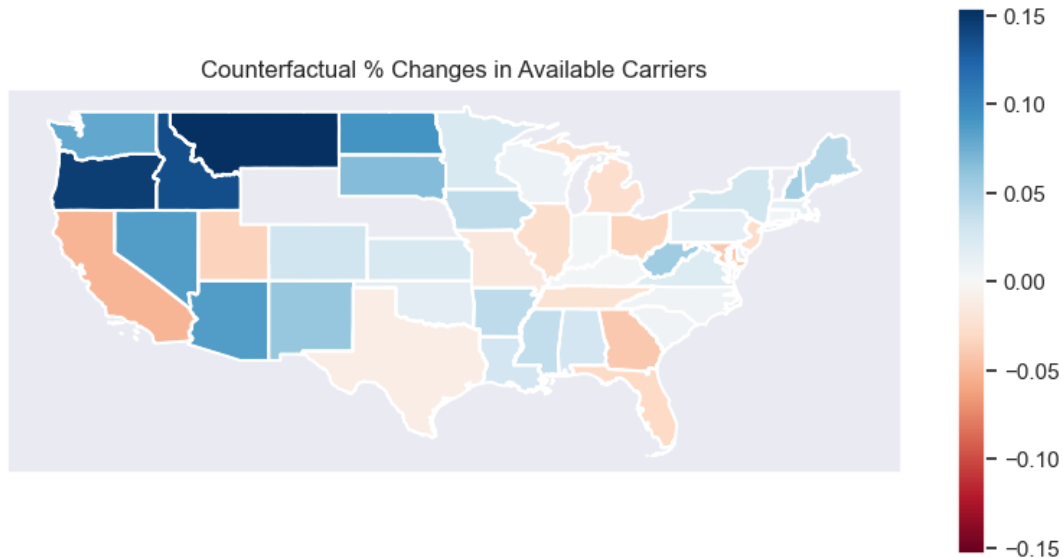
Two forces:

- **Level Effect:** Lower costs overall → less outside option
- **Dispersion:** Shift toward routes with lower input prices

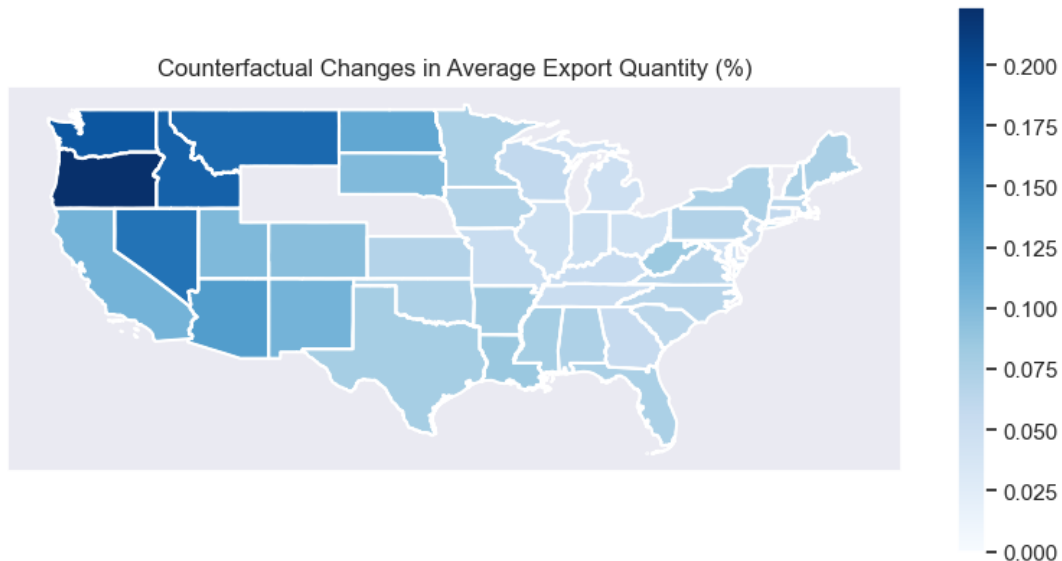
Big picture:

- 17.5% decrease in route prices (Laspeyres Index)
- 7.5% increase in total trucking freight
- 11% increase in distance travelled → biased toward longer trips

Counterfactual II: California carriers shift to work in NW



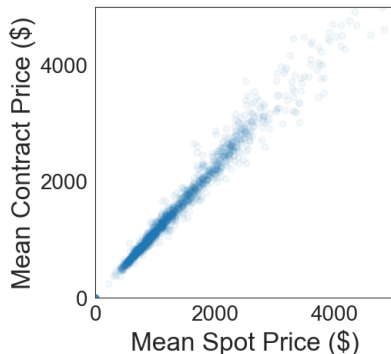
Counterfactual II: Pacific Northwest sees greatest increase in exports



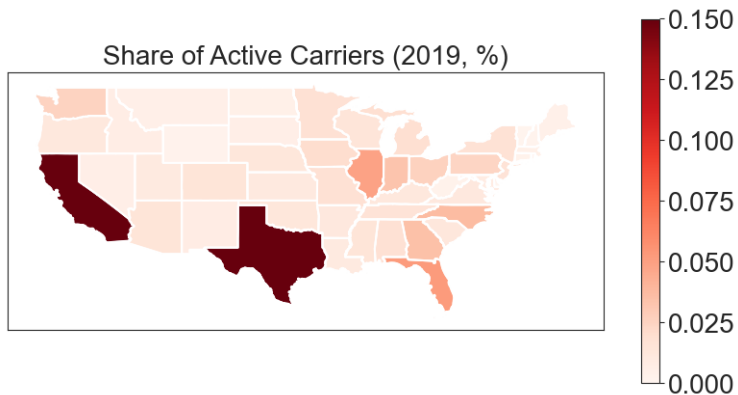
Appendix: Spot vs Contract Prices

Spot + Contract Price Correlation (2016)

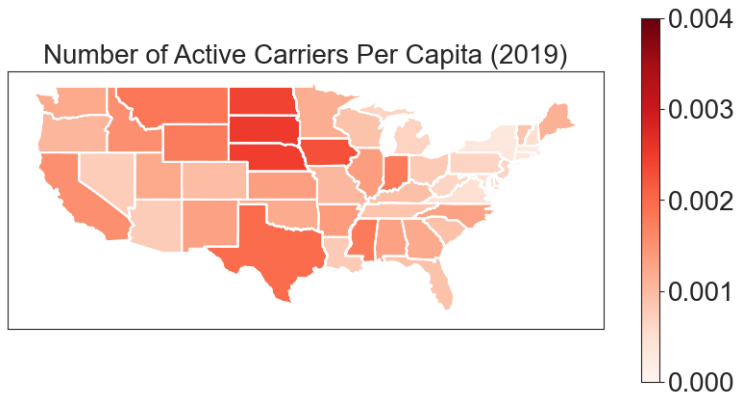
- Monthly average prices: 0.9804
- Annual average prices: 0.9909
- For more details, see literature: *Masten 2009, Scott et al 2016, Aemireddy et al 2019, Acocella et al 2020, Harris and Nguyen 2021.*



Active Carriers



Active Carriers per Capita



Estimation Details

Parameters

- Demand Parameters
 - σ : Price sensitivity
- Supply Parameters
 - b : Home preference
 - α : Price sensitivity
 - γ : Route observables
- Calibrated Parameters
 - β : Discount factor (0.995)
 - λ_{ij} : Arrival probabilities

Estimation Details

Parameters

- Demand Parameters
 - σ : Price sensitivity
- Supply Parameters
 - b : Home preference
 - α : Price sensitivity
 - γ : Route observables
- Calibrated Parameters
 - β : Discount factor (0.995)
 - λ_{ij} : Arrival probabilities

Data

- Q_{ij} : Quantity (DAT RateView)
- N_{ij} : Total Shippers (CFS - Total Shipping)
- p_{ij} : Average Price (DAT RateView)
- ι_{hi} : Inspection Shares (Highway Inspections)

Route Characteristics:

- $Dist_{ij}$: Distance (PC-Miler miles)
- $Diesel_{ij} \times Dist_{ij}$: Avg diesel price (\$/gal) \times Distance (demeaned)
- $Cracking_{ij}, Faulting_{ij}, Rutting_{ij}$: Road quality measures (std mean zero, std dev 1)

Inspection (Boston Globe 2020)

