Nexus tax laws and economies of density in e-commerce: A study of amazon's fulfillment center network.

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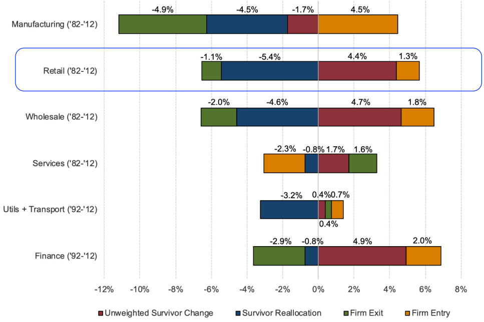
Superstar Hypothesis: Fast growing firms have declining labor costs and increasingly dominate their industries

Source: Autor et al. (2017)



Melitz-Polanec Decomposition:

$$\underbrace{\Delta \mathcal{S}_t}_{\text{Change in labor-cost share}} = \underbrace{\Delta \bar{S}_t}_{\text{Unweighted survivor change}} + \underbrace{\Delta \Gamma_t^c}_{\text{Survivor reallocation}} \underbrace{+ \sum_{i \in E} \omega_{it}(S_{it} - \mathcal{S}_t^c) - \sum_{i \in X} \omega_{it}(S_{it} - \mathcal{S}_{t-1}^c)}_{\text{Entry/exit reallocation}}$$

Implications for IO?

- **Superstar mechanism:**
  - Heterogeneity in technology implies that larger firms have lower variable cost
  - Market competition reallocate output towards low-cost firms
- **Takeaway:** Secular trends affecting most industries
  - Non-stationary increase in concentration
  - Decline in VC (esp. long-term), leading to $\uparrow$ in variable profits
  - Largest decline is concentrated among largest/fastest growing firms
- **Two examples:**
  - Walmart: Holmes (2011)
  - Amazon: Houde, Newberry, and Seim (2023)

Innovation in Logistic and Distribution

- The diffusion of Walmart and other "Big-Box" retailers illustrates a major shift the supply chain:
  - **Traditional model:** Manufacturer. $\rightarrow$ Wholesaler $\rightarrow$ Distributor $\rightarrow$ Retailer
  - **Big-Box model:** Manufacturer (or Wholesaler/importer) $\rightarrow$ Retailer-owned DC $\rightarrow$ Retailer
- The Big-Box model is based on: (i) large volume/variety ratio, (ii) economies of scale, (iii) "specific investments" from suppliers to manage inventories and share information.

Wallmart Rollout: Co-location of stores and DCs

Holmes (2011)

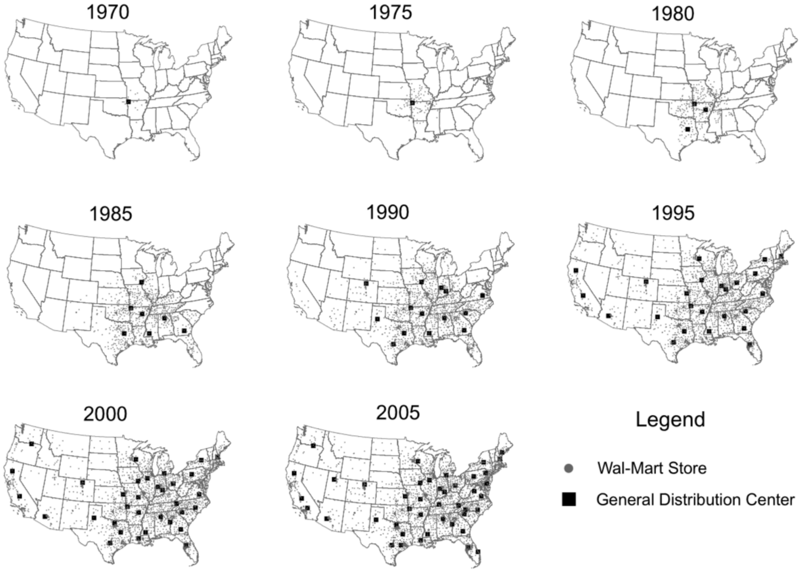


FIGURE 1.—Diffusion of Wal-Mart stores and general distribution centers.

Holmes (2011): Model overview

- Model the **location** of new stores and superstores in each period t, conditional on:
  - The location and timing of entry of distribution centers (DC),
  - And the number of new stores opened every year.
- **Assumptions:** (i) perfect foresight, and (ii) no location-specific unobserved preference shocks.
- **Dynamic control:** A sequence of opening $a = \{\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_\infty\}$

$$\max_a \underbrace{\sum_{t=1}^{\infty} (\rho_t \beta^t) \left[\sum_{j \in \mathcal{B}_t^{wall}} (\pi_{jt}^g - F_{jt}) + \sum_{j \in \mathcal{B}_t^{super}} (\pi_{jt}^f - F_{jt}) \right]}_{\Pi(a)}$$

- Economies of density:

$$F_{jt} = \tau d_{jt}^e + \omega_1 \ln \text{PopDensity}_j + \omega_2 \ln \text{PopDensity}_j^2$$

where d_{jt}^e is the distance to the closest DC for category $e \in \{f, g\}$.

Bounding Fixed-Costs

- Tradeoff b/w economies of density (F) and profit cannibalization (π)
  - Entering **early** in a state leads to $\uparrow \pi$, and greater distribution distance
  - Entering **late** in a state leads to $\downarrow \pi$, and lower distribution distance
- Ignoring the dynamics, this leads to bounds on the fixed-cost:

$$\pi(a^*) - \tau d^* > \pi(a') - \tau d', \qquad \text{where } a^* \text{ is opened earlier than } a'$$

$$\tau < \frac{\pi(a^*) - \pi(a')}{d^* - d'}$$

$$\pi(a^*) - \tau d^* > \pi(a') - \tau d', \qquad \text{where } a^* \text{ is opened later than } a'$$

$$\tau > \frac{\pi(a^{'}) - \pi(a^*)}{d' - d^*}$$

Bounding Fixed-Costs

- **Problem:** The choice is dynamic, and the comparison of observed choices (i.e. sequences) with counter-factual choices necessitate the calculate the value function (impossible!)
- **Simplification:** Focus on counter-factual sequences that **swap** the opening dates of two stores.

$$
\begin{aligned}
&\Pi(a^*) - \Pi(a') = \\
&\sum_{t=t_0(a')}^{t_1(a')} \Bigg\{ (\rho_t \beta^t) \left[\sum_{j \in \mathcal{B}_t^{wall}} (\pi_{jt}^g - F_{jt}) + \sum_{j \in \mathcal{B}_t^{super}} (\pi_{jt}^f - F_{jt}) \right] \\
&-(\rho_t \beta^t) \left[\sum_{j \in \mathcal{B}_t^{wall}} (a')(\pi_{jt}^g - F_{jt}) + \sum_{j \in \mathcal{B}_t^{super}} (a')(\pi_{jt}^f - F_{jt}) \right] \Bigg\} \\
&= y_{a'} - x_{a'}\theta \geq 0, \quad \forall a' \neq a^*
\end{aligned}
$$

- **Key insight:** Swapping entry dates eliminates the need to calculate the continuation-value

WSJ, August 29, 2019

BUSINESS

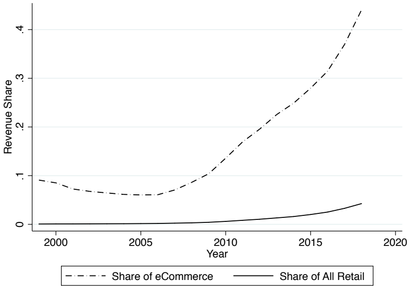
How Amazon's Shipping Empire Is Challenging UPS and FedEx

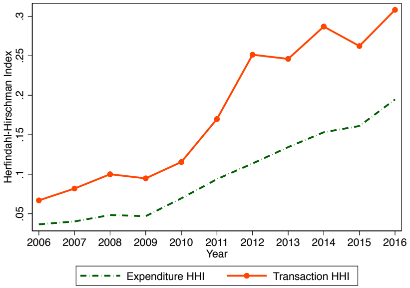
The e-commerce giant has blanketed the U.S. with warehouses and package-sorting centers, flooded the streets with vans and taken to the sky

...Amazon has quietly blanketed the nation with hundreds of sprawling suburban warehouses and neighborhood package-sorting centers...The **costly effort** *is enabling Amazon to* **control how goods reach its customers**.

Online Retailing: 1999-2018

- **Amazon US Sales:** \$1.4bn to \$226bn from 1999-2018
- **Online concentration:** HHI of 400 to 1,900 (2006-2016)





Amazon's Investment Strategy

- **Fulfillment Centers (FCs):**
  - Warehouses that hold a product until an order is placed.
  - From 5 in 5 states in 1999 to over 100 FCs in 32 states by 2018.
- **Sortation Centers (SCs):**
  - Downstream facilities where packages are sorted for local pickup.
  - Began in 2012, 40 by 2018.
- **Amazon Tradeoff:**
  - *Benefits:* Increase network density $\rightarrow \downarrow$ third-party shippers.
    - ⋆ Guaranteed delivery times at low shipping cost.
  - *Costs:* Additional/higher costs and sales tax exposure.
    - ⋆ *Loss of scale:* Higher order processing and fixed costs.
    - ⋆ *Tax disadvantage:* Reduced benefits from NEXUS tax laws.
- **NEXUS:** Retailers with "sufficient physical presence" in a state must collect and pay tax on sales in that state.

Nexus Tax Laws and Economies of Density in E-Commerce

Houde, Newberry, and Seim (2023)

1. Quantify cost-side effects of network expansion
   - Decompose aggregate order fulfillment cost into
     - **Network density:** Reduce demand for independent shippers
     - **Vertical integration:** In-house sortation (and delivery)
2. How does sales tax policy impact investment?
   - Distortion: Nexus tax laws affect the timing of entry and the location network nodes.
   - Use model to predict network configuration under alternative sales tax laws.

Dynamic Problem

- The network in year t, a_t, is:
  - The location ℓ_j and size k_j of FCs
  - The location of SCs
  - Facilities can be co-located: each location l accommodates multiple facilities
- *Dynamic control:* Where to locate new FCs and SCs?
- Amazon chooses the sequence of network expansion, $a = (a_0, a_1, ..., a_\infty)$, that solves:

$$\max_{a_t \forall t} \sum_{t=0}^{\infty} \beta^t \pi_t(N_t) \quad s.t. \quad N_t = N_{t-1} + a_t$$

- *Network configuration:* $N_t = \{n_{\ell t}^{fc}, n_{\ell t}^{sc}\}_{\ell=1,...,L}$
- *Important:* Focus on the decision *where* to put FCs/SCs, taking as given the number of new facilities (as in Holmes (2011))

Profit Components

- Profit flow:

$$\pi_t(N_t) = \underbrace{R_t(N_t) \times \bar{\mu}_t}_{\text{Net revenue}} - \underbrace{\left[\sum_i \sum_\ell D_{it}(N_t)\Omega_{i\ell}(N_t) sh_{i\ell}(N_t)\right]}_{\text{Shipping cost}}$$

$$- \underbrace{\sum_\ell L(q_{\ell t}) w_{\ell t}}_{\text{Labor cost}} - \underbrace{\sum_\ell F_{\ell t}}_{\text{Fixed Costs}}$$

Main objects to estimate:

- Revenue function: $R_t(N_t)$
- Cost of shipping an order: $sh_{i\ell} = d_{i\ell}(N_t)\theta_d + \mathbf{1}^{VI}_{i\ell t}(N_t)\theta_{vi}$
- Labor demand function: $L(q_{\ell t}) = A_\ell q^{\nu}_{\ell t}$
- Fixed-cost: $F_{\ell t} = K_{\ell t}\left(r_{\ell t} + \kappa \text{PopDens}_{\ell t}\right)$

CES Demand Model

- Representative consumer in county i and year t (Einav et al. 2014):

$$U_{it}(q_{i0t},..q_{i3t}) = \left(\sum_{j=0}^{3}\int(\alpha_{ijt}\omega)^{1/\sigma}q_{ijt}(\omega)^{\frac{\sigma-1}{\sigma}}dF_{jt}(\omega)\right)^{\frac{\sigma}{1-\sigma}}$$

  - **Modes**: (0) Offline; (1) Amazon; (2) Taxable; (3) Non-taxable
  - σ : constant elasticity of substitution between modes

- Tax-inclusive transacted price given by:

$$\tilde{p}_{ijt}(\omega) = p_{jt}(\omega)(1+\mathbf{1}_{ijt}^{taxable}\tau_{it}) = (\rho_{jt}\cdot\omega)(1+\mathbf{1}_{ijt}^{taxable}\tau_{it})$$

- Mode j's spending share relative to the offline mode:

$$\begin{aligned}\tilde{e}_{ijt} &= \ln(\alpha_{ijt}) - ln(\alpha_{i0t}) - (1-\sigma)\left(\ln(\rho_{jt}) - \ln(p_{i0t})\right) \\ &\quad +(1-\sigma)\underbrace{\left(\ln(1+\mathbf{1}_{ijt}^{taxable}\tau_{it}) - \ln(1+\tau_{it})\right)}_{\tilde{\tau}_{ijt}=\text{Tax Effect}} + \underbrace{\ln(\int\omega^{2-\sigma}dF_{jt}(\omega))}_{\xi_{jt}^{\omega}=\text{Variety Effect}}\end{aligned}$$

Estimation

- Linear estimating equation:

$$\begin{aligned}\tilde{e}_{ijt} &= (1-\sigma)\tilde{\tau}_{ijt} \\ &\quad + \ln(\alpha_{ijt}) - ln(\alpha_{i0t}) - (1-\sigma)\left(\ln(\rho_{jt}) - \ln(p_{i0t})\right) + \xi^{\omega}_{jt} \\ &= (1-\sigma)\tilde{\tau}_{ijt} + \xi_{jt} + \lambda_j Z_{it} + \gamma_j C_{it} + \Delta\xi_{i0t} + \epsilon_{ijt}\end{aligned}$$

  where:
  - ξ_{jt}: Mode-year effect includes variety, quality, convenience, prices.
  - $\lambda_j Z_{it}$: Impact of demographics.
  - $\gamma_j C_{it}$: Impact of offline competition.
  - $\Delta\xi_{i0t} = \bar{\xi}_i + \Delta\xi_{rt}$: county and region-year fixed effects.
  - $\Delta\xi_{i0t}$ and $\gamma_j C_{it}$ account for offline prices.
- Identification of σ: Change in expenditure in counties in state with FC entry, relative to states with or without FC throughout.

CES Demand Estimates

	Homogenous σ				Heterogeneous σ			
		Est	SE			Est	SE	
Elasticity of Substitution:								
σ		-1.541	0.399			-2.536	0.506	
$\sigma *$ (% income 100k +)						4.159	1.343	
	Amazon		Modes 2 & 3		Amazon		Modes 2 & 3	
	Est	SE	Est	SE	Est	SE	Est	SE
Demographics:								
λ_j^{age}	0.016	0.008	-0.021	0.01	0.014	0.008	-0.02	0.01
$\lambda_j^{\text{\% under 35}}$	1.744	0.397	-0.142	0.4	1.704	0.397	-0.04	0.402
$\lambda_j^{\text{log(income)}}$	0.156	0.218	0.016	0.008	0.33	0.214	0.014	0.008
$\lambda_j^{\text{\% income 100k +}}$	1.248	0.16	-1.501	0.514	1.096	0.139	-1.98	0.521
$\lambda_j^{\text{\% black}}$	-0.37	0.075	-0.659	0.62	-0.382	0.075	-0.658	0.636
$\lambda_j^{\text{\% asian}}$	0.862	0.208	2.268	1.172	0.866	0.208	2.25	1.215
Offline Competition:								
$\gamma_j^{\text{log(pop density)}}$	0.012	0.007	0.637	0.216	0.014	0.007	0.571	0.228
$\gamma_j^{\text{\# retailers per 10k people}}$	-0.354	0.305	-0.961	0.406	-0.386	0.307	-0.812	0.415
$\gamma_j^{\text{\# small retailers per 10k people}}$	0.363	0.315	1.009	0.416	0.398	0.317	0.878	0.425

- Tax elasticity: -1.5 w/significant heterogeneity.
- Amazon demographics: Younger and richer hh's
- Offline competition impacts other modes more than Amazon.

Cost Function Estimation

- Cost function given network configuration N_t:

$$C_t(N_t) = \underbrace{\left[\sum_i \sum_\ell D_{it}\Omega_{i\ell}(N_t) sh_{i\ell}(N_t)\right]}_{\text{Shipping cost}} + \underbrace{\sum_\ell L(q_{\ell t}) w_{\ell t}}_{\text{Labor cost}} + \underbrace{\sum_\ell F_{\ell t}}_{\text{Fixed Costs}}$$

- $\Omega_{i\ell}(N_t)$ and $L(q)$: Employment data
  - Cross-sectional variation in employment, demand, and capacity.
  - Order assignment function:
    - *Results:* most shipments (50-60%) from closest FC by 2018.
  - Cobb-Douglas labor demand function:
    - *Results:* economies of scale.
- $sh_{i\ell}(N_t)$ and $F_{\ell t}$: Revealed-preference inequalities
  - Shipping cost: $sh_{i\ell} = d_{i\ell}(N_t)\theta_d + \mathbf{1}^{VI}_{i\ell t}(N_t)\theta_{vi}$
  - Fixed cost: $F_{\ell t} = K_{\ell t}\left(r_{\ell t} + \kappa \text{PopDens}_{\ell t}\right)$

Profit Function and Optimal Rollout

- Amazon has perfect foresight and chooses the optimal sequence of FC and SC openings:

$$\mathbf{a}^* = \arg\max_{\mathbf{a}\in\mathcal{A}} \Pi(\mathbf{a};\theta^3) = \sum_{t=0}^{\infty} \beta^t \pi(N_t;\theta^3) \quad s.t. \quad N_t = N_{t-1} + a_t$$

  where $\theta^3 = (\theta_d, \theta_{vi}, \kappa)$.

- **Implication:** Choosing a counter-factual sequence in which the opening date of FC j is swapped with j' must be suboptimal:

$$\Pi(\mathbf{a}^*;\theta^3) - \Pi(\mathbf{a}^{j,j'};\theta^3) = \Delta\Pi(\mathbf{a}^*,\mathbf{a}^{j,j'};\theta^3) + \epsilon^{j,j'} \geq 0.$$

  - ϵ: measurement error in revenue and transactions

Revealed Preference Inequalities

- **Return function:** Linear NPV profit differences

$$\Delta\Pi(\mathbf{a}^*, \mathbf{a}^{j,j'}; \theta^3) = Y^{j,j'} - (\theta_d X_d^{j,j'} + \theta_{vi} X_v^{j,j'} + \kappa X_p^{j,j'})$$

- $\left(Y^{j,j'}, X_d^{j,j'}, X_{vi}^{j,j'}, X_p^{j,j'}\right)$ discounted differences in *estimated*:
  - Y: Gross profit (net revenue less labor and rent costs)
  - X: Shipping distance; VI transactions; Population density
- **Assumption:** Errors $\epsilon^{j,j'}$ independent of observed pre-determined differences between rollout $\mathbf{a}$ and $\mathbf{a}^{j,j'}$.
- Form a set of moment inequalities.

$$\frac{1}{M} \sum_{j,j'} z_{j,j'} \Delta\Pi(\mathbf{a}^*, \mathbf{a}^{j,j'}; \theta^3) = \bar{m} \geq 0,$$

where $z_{j,j'}$ are (positive) instruments.

Choice of Moments

- **Instruments:** $(z^{j,j'})$
  - Indicators: Swap grouping s.t. predetermined shifters of Y and X predict changes consistent with key trade-offs (i.e., predict rollout).
- **Predetermined Gross Profit/Cost shifters:**
  - $\hat{Y}$: Population-weighted taxes: $\Delta \text{Tax}^{j,j'}$
  - $\hat{Y}$: Average cost (wage and rent): $\Delta \text{Input prices}^{j,j'}$
  - $\hat{X}$ (order-weighted distance): Population-weighted distance
  - $\hat{X}$ (VI orders): Number of HHs served by SC
- **Swaps:** (M=5,577)
  - Entry date: $t(j') - t(j) > 1$
  - Same type: FC or SC
  - Similar size: $|K_j - K_{j'}| < \sigma_k$

Illustration: Tradeoffs and Parameter bounds

Identifying **lower bound estimates on θ_d:**

- Grouping: FC swaps such that satisfy two conditions:
  - $Z_h^{j,j'} = \mathbf{1}\left(\hat{X}_d^{j,j'} < 0 \text{ and } \Delta \text{Tax}^{j,j'} > 0\right)$.
  - chosen network has lower population-weighted average distances, but higher taxes than perturbed
  - favors proximity to population over tax savings
  - shipping cost savings exceed revenue losses: $\theta_d \geq \dfrac{E\left[Y^{j,j'} | Z_h^{j,j'}\right]}{E\left[X_d^{j,j'} | Z_h^{j,j'}\right]}$.

	Lower bound: θ_d		Upper bound: θ_d	
	$Z^{j,j'} = 1(\Delta\text{Shifter}^{j,j'} > 0 \ \& \ \hat{X}_d^{j,j'} < 0)$		$Z^{j,j'} = 1(\Delta\text{Shifter}^{j,j'} < 0 \ \& \ \hat{X}_d^{j,j'} > 0)$	
	$E(Y\|Z)$	$E(X_d\|Z)$	$E(Y\|Z)$	$E(X_d\|Z)$
ΔShifter (Gross Profit)				
(a) Tax	-13.30	-93.60	37.10	140.19
(b) Input prices	-5.94	-82.68	7.60	128.21
Bounds: $\frac{E(Y\|Z)}{E(X_d\|Z)}$				
(a) Tax	0.14		0.26	
(b) Input prices	0.07		0.06	

Notes: In selecting swaps for inclusion in each instrument category, we condition on population-weighted tax, input price, and distance changes. The statistics in the body of the table, however, represent order-weighted aggregates. The variable ΔShifter refers to the change in one of two population-weighted profit shifters: taxes and average input prices.

Confidence interval calculation: Bugni et al. (2017)

- For each dimension s, we want to estimate the set of parameter values that fail to reject the following null hypothesis with probability α

$$T_n(\theta_s) < \hat{c}_n^{MR}(\theta_s, 1-\alpha)$$

  where $T_n(\theta_s)$ is the *profiled* test statistic of the moment conditions evaluated under the null.

- The profiled test statistics is the smallest value of the objective function fixing θ_s:

$$T_n(\theta_s) = \inf_{\theta \in \Theta(\theta_s)} \sum_{k=1}^{K} \left[\frac{\sqrt{n}\bar{m}_{n,k}(\theta)}{\hat{\sigma}_{n,k}(\theta)} \right]_{-}^{2}$$

  where $x_{-} = \min\{0, x\}$.

- This differs from Anderson-Rubin's style test inversion CIs: Single-dimension vs Multi-dimension confidence sets
- Computational burden: Resampling algorithm to calculate $\hat{c}_n^{MR}(\theta_s, 1-\alpha)$ for each dimension s.

Algorithm 1 Algorithm to implement the minimum resampling test.

Inputs: λ_0, Θ, κ_n, B, $\lambda(\cdot)$, $\varphi(\cdot)$, $m(\cdot)$, α ▷ $\kappa_n = \sqrt{\ln n}$ recommended by Andrews and Soares (2010)
$\Theta(\lambda_0) \leftarrow \{\theta \in \Theta : \lambda(\theta) = \lambda_0\}$
$\zeta \leftarrow n \times B$ matrix of independent $N(0,1)$

function QSTAT(type, θ, $\{W_i\}_{i=1}^n$, $\{\zeta_i\}_{i=1}^n$) ▷ Computes criterion function for a given θ
  $\bar{m}_n(\theta) \leftarrow n^{-1}\sum_{i=1}^n m(W_i,\theta)$ ▷ Moments for a given θ
  $\hat{D}_n(\theta) \leftarrow \mathrm{Diag}(\mathrm{var}(m(W_i,\theta)))$ ▷ Variance matrix for a given θ
  if type $= 0$ **then** ▷ Type 0 is for Test Statistic
    $v(\theta) \leftarrow \sqrt{n}\hat{D}_n^{-1/2}(\theta)\bar{m}_n(\theta)$
    $\ell(\theta) \leftarrow \mathbf{0}_{k\times 1}$ ▷ Test Statistic does not involve ℓ
  else if type $= 1$ **then** ▷ Type 1 is for $T_n^{\mathrm{DR}}(\lambda)$
    $v(\theta) \leftarrow n^{-1/2}\hat{D}_n^{-1/2}(\theta)\sum_{i=1}^n(m(W_i,\theta) - \bar{m}_n(\theta))\zeta_i$
    $\ell(\theta) \leftarrow \varphi(\kappa_n^{-1}\sqrt{n}\hat{D}_n^{-1/2}(\theta)\bar{m}_n(\theta))$
  else if type $= 2$ **then** ▷ Type 2 is for $T_n^{\mathrm{PR}}(\lambda)$
    $v(\theta) \leftarrow n^{-1/2}\hat{D}_n^{-1/2}(\theta)\sum_{i=1}^n(m(W_i,\theta) - \bar{m}_n(\theta))\zeta_i$
    $\ell(\theta) \leftarrow \kappa_n^{-1}\sqrt{n}\hat{D}_n^{-1/2}(\theta)\bar{m}_n(\theta)$
  end if
  return $Q(\theta) \leftarrow \{\sum_{j=1}^p[v_j(\theta)+\ell_j(\theta)]_-^2 + \sum_{j=p+1}^k(v_j(\theta)+\ell_j(\theta))^2\}$
end function

function TESTMR(B, $\{W_i\}_{i=1}^n$, ζ, $\Theta(\lambda_0)$, α) ▷ Test MR
  $T_n \leftarrow \min_{\theta\in\Theta(\lambda_0)}$ QSTAT($0, \theta, \{W_i\}_{i=1}^n$) ▷ Compute test statistic
  $\hat{\Theta}_I(\lambda_0) \leftarrow \{\theta \in \Theta(\lambda_0) :$ QSTAT$(0,\theta,\{W_i\}_{i=1}^n) \le T_n\}$ ▷ Estimated set of minimizers
  for $b = 1,\dots,B$ **do**
    $T^{\mathrm{DR}}[b] \leftarrow \min_{\theta\in\hat{\Theta}_I(\lambda_0)}$ QSTAT$(1,\theta,\{W_i\}_{i=1}^n,\zeta[:,b])$ ▷ type $= 1$. Uses bth column of ζ
    $T^{\mathrm{PR}}[b] \leftarrow \min_{\theta\in\Theta(\lambda_0)}$ QSTAT$(2,\theta,\{W_i\}_{i=1}^n,\zeta[:,b])$ ▷ type $= 2$. Uses bth column of ζ
    $T^{\mathrm{MR}}[b] \leftarrow \min\{T^{\mathrm{DR}}[b], T^{\mathrm{PR}}[b]\}$
  end for
  $\hat{c}_n^{\mathrm{MR}} \leftarrow$ QUANTILE$(T^{\mathrm{MR}}, 1-\alpha)$ ▷ T^{MR} is $B\times 1$. Gets $1-\alpha$ quantile
  return $\phi^{\mathrm{MR}} \leftarrow 1\{T_n > \hat{c}_n^{\mathrm{MR}}\}$
end function

Results: Distribution Cost Parameters

	Specification 1			Specification 2			Specification 3		
	Est.	CI		Est.	CI		Est.	CI	
θ_d: Dist. (x100 miles)	0.16	0.15	0.17	0.59	0.41	0.88	0.34	0.26	0.49
θ_{vi}: VI orders							-0.52	-0.91	0.01
κ: Density (x100)				2.06	1.48	3.17	0.98	0.69	1.56
Moments	4			8			14		

- **Inference method:** Bugni, Canay, and Shi (2017)
  - Profiling method: Bootstrap 95% confidence set for individual parameters
- **Values for analysis:**
  - Parameters that minimize objective function:

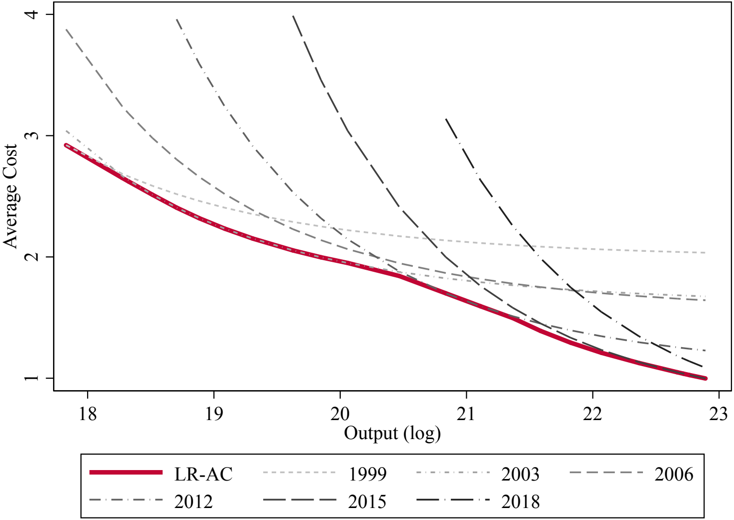
$$(\theta_d = 0.34, \theta_{vi} = -0.52, \kappa = 0.98)$$

Results: Average Cost under Network Expansion

			Average cost components				
	FC	SC	Shipping	Labor	Rent	Density	Total
2000	5	0	1.99	0.55	0.12	0.05	2.71
2003	7	0	1.61	0.60	0.11	0.08	2.41
2006	12	0	1.55	0.62	0.11	0.13	2.40
2009	16	0	1.39	0.53	0.08	0.10	2.11
2012	31	1	1.03	0.43	0.07	0.07	1.60
2015	67	21	0.50	0.51	0.09	0.19	1.28
2018	128	35	0.29	0.51	0.08	0.22	1.11
2018*	128	0	0.49	0.48	0.07	0.20	1.23

- 2018* corresponds to a counterfactual network with no sortation centers. Average cost components calculated using total network cost divided by predicted total orders.

Estimated Long-Run Average Cost



Counterfactual

- **Question:** how does tax policy impact realization of economies of density?
  - June, 2018: Supreme court decision allows states to collect sales tax from all online sales: ‘non-discriminatory tax’
  - Measure distortion from ‘tax nexus ’ policy:
    - ⋆ Compare optimal network decisions and corresponding costs under two tax regimes.
- **Intuition:**
  - Tax nexus $\rightarrow$ increased incentive to avoid high tax/high population states.
  - Distorted location choices

Implementation

- Solving optimal dynamic network problem difficult (what we wanted to avoid)
  - *Simplification:* solve static optimization problem, given the distribution of demand for year X.
  - *Simplification:* assume all other components (e.g., input costs) fixed at 2018 level.
- Set of locations/sizes large.
  - *Simplification:* Restrict to current Amazon locations and 'viable' Walmart, Target, and UPS locations (253 locations)
  - *Simplification:* Assume uniform size across FCs.
- **Method:** Population-Based Incremental Learning (Baluja 1994)
  - Simulation-based genetic algorithm combined with "hill-climbing"
  - Advantage: can deal with large set of locations

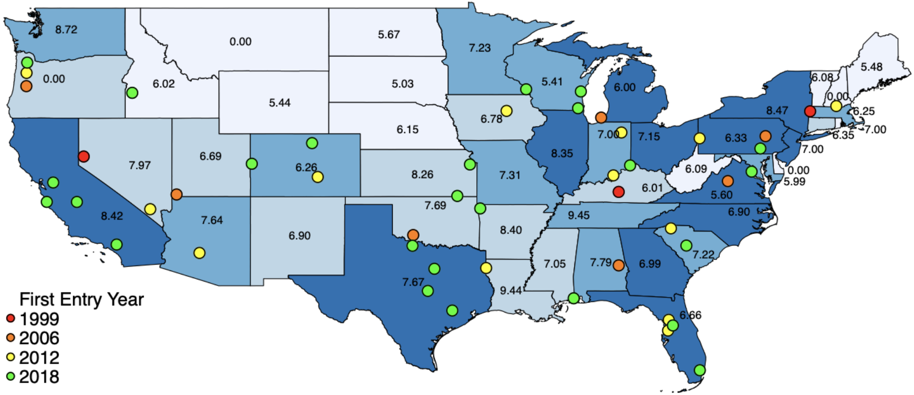
Optimal network solution

- Notation:
  - $A = \{a_{i,fc}, a_{i,sc}\}_{i=1,\ldots,N}$ where $a_{i,fc} \in \mathcal{N}^+$ and $a_{i,sc} \in \{0,1\}$.
  - $\lambda^k_{i,j}$ is the probability of placing a facility of type j in location i
  - Starting values: Uniform distribution $[0,1]^{N \times 2}$
  - Tuning param.: α (hill-climbing), η^1 (mutation prob.) and η^2 (mutation step)
- The following steps are repeated until $\Pi^{\max}$ is stable for K iterations

1. *Maximization step:*
   (a) Sample S network configurations from probability distribution Λ^k
   (b) For each s, calculate the flow of orders and the aggregate profits: Π^s_t
   (c) Identify the profit maximizing configuration: $A^{\max}_k = \arg\max_{s\in\{1,\ldots,S} \Pi^s$.
2. *Hill-climbing step:* Update network probability parameters using the convex combination of Λ^k and $A^{\max}_k$
$$\Lambda^{k+1} = (1-\alpha)\Lambda^k + \alpha A^{\max}_k$$
3. *Mutation step:*
   (a) For each location/facility type draw $u^k_{i,j} \sim U[0,1]$ and $e^k_{ij} \sim U[0,1]$
   (b) If $u^k_{i,j} < \eta^1$, perturb (i,j) choice probability according to:
$$\lambda^{k+1}_{i,j} = \lambda^k_{i,j}\eta^2 + e^k_{ij}(1-\eta^2)$$
4. If $\Pi^{\max} < \Pi^{\max}_k$ update the profit maximization network:
$$A^{\max} = A^{\max}_k \text{ and } \Pi^{\max} = \Pi^{\max}$$

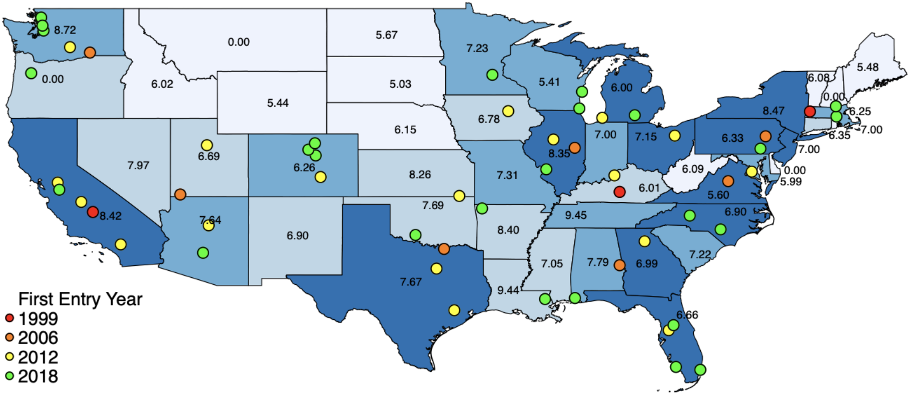
- To approximate the global network solution, the algorithm is repeated for a large number of starting values

Predicted FC Locations: Nexus Laws



Notes: Colors of dots denote the first year in which we predict entry into that location.

Predicted FC Locations: Non-discriminatory Taxes



Notes: Colors of dots denote the first year in which we predict entry into that location.

Predicted Networks under Alternative Tax Regimes

With Tax Distortions ('nexus')

		Average Cost ($/order)					Amazon Tax		Facilities	
	Profit	Shipping	Labor	FC	Total	Dist.	Avg.	% > 0	FC	SC
1999	88	1.29	0.86	0.32	2.47	377	0.26	0.05	3	0
2006	537	1.14	0.66	0.22	2.02	347	0.95	0.15	8	1
2012	4,784	0.71	0.48	0.14	1.32	233	1.71	0.24	25	4
2018	27,626	0.50	0.35	0.08	0.93	173	3.08	0.42	65	9

Without Tax Distortions

		Average Cost ($/order)					Amazon Tax		Facilities	
	Profit	Shipping	Labor	FC	Total	Dist.	Avg.	% > 0	FC	SC
1999	79	1.26	0.88	0.37	2.51	367	6.74	0.98	3	0
2006	488	1.10	0.69	0.24	2.03	336	6.75	0.98	8	1
2012	4,499	0.59	0.52	0.15	1.27	201	6.96	0.98	27	5
2018	26,406	0.39	0.39	0.10	0.88	150	7.13	0.98	74	11

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Welfare Effects of Uniform Tax Laws

Table: Changes in Amazons Profit Components

Year	Δ Net Revenue	Δ Variable Cost	Δ Fixed Cost	Variable Margin (nexus/uniform)	Δ Profit
1999	-18	-10	1	0.071/0.072	-9
2006	-93	-44	0	0.086/0.087	-49
2012	-504	-223	4	0.111/0.114	-285
2018	-1921	-768	66	0.124/0.126	-1220

Table: Changes in Other Components

Year	Δ Tax Revenue		Compensating Variation	Δ Revenue Rival	Δ Profit Rival	Fiscal Mutiplier s.t. Δ Welfare=0
	Amazon	Rival				
1999	74	3	-78	44	3	1.091
2006	372	15	-394	233	16	1.104
2012	2304	65	-2419	995	70	1.112
2018	9085	181	-9293	3539	250	1.108

Conclusion

Understanding one of the sources of Amazon's dominance:

- Quantified trade-offs associated with expansion of FC network.
  - Consumers sensitive to sales tax across wide range of retailers
    - $\rightarrow$ Tax implications of distribution networks matter to firm.
  - Endogenize distribution network for a large retailer
    - $\rightarrow$ Gains from VI: complementarity between SC and FC locations
- Examined how policy impacts costs/benefits of expansion.
  - Nexus laws distorted investments: Higher shipping costs + Distance

Future directions:

- Relationship between tax incentives and investment
- Upstream: Agglomeration effects from third-party sellers & Amazon's market power in supplying logistics services

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