

E-commerce and Regional Inequality: A Trade Framework and Evidence from Amazon's Expansion

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Brick-and-mortar vs. E-commerce

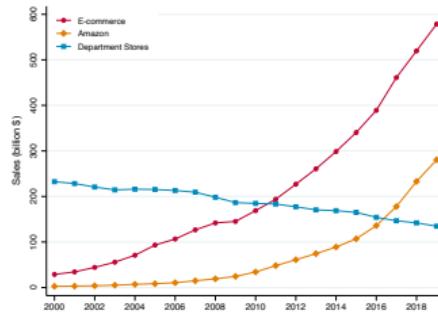
Motivation

Empirical Facts

A Spatial Retail Trade Model

Quantification

Amazon's Impacts



- Secular ↑ online retail sales (**e-commerce**)
- "Opening to trade" challenges *regional equality*
 - Comparative advantages, worker specializations, input-output linkages
 - The unique nature of online retailing may exacerbate

E-commerce as a
unique trade shock \Rightarrow Spatial GE and reallocation
(welfare, empl. dispersion)

- **Empirics:** New facts on Amazon sales, retailers, facilities
 - Online retailer agglomeration, sales & trade
- **Theory:** multi-region & -sector spatial (retail) trade model
 - Consumer search & shipping
 - Location choice of online retailer \Rightarrow \uparrow agglomeration
- **Policy:** place-based public finances

Contribution: new data & extend spatial trade theory \Rightarrow e-commerce

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Empirical Facts

The Online Retail Business Model

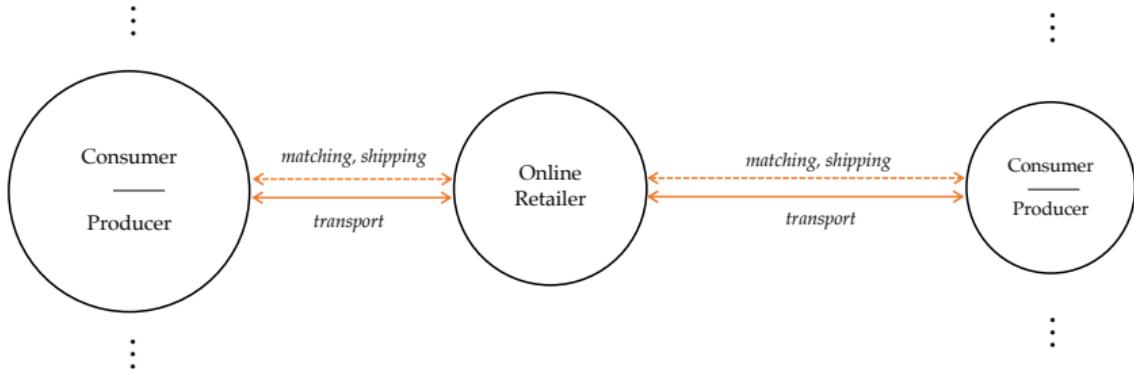
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Insights:

- **Agglomeration:** Trade frictions (HME, CA) \Leftrightarrow **Dispersion:** Factor prices
- Their agglomeration should be assoc. with different trade flows

Data Sources

Motivation

- Amazon Retailers and Products ([Keepa.com](#))

Empirical Facts

- Universe of products on Amazon (36 categories, 2016-2020, 0.5%)
- Information on prices, and sales ranking, converted to sales
- Collect sellers' addresses, FBA status

A Spatial Retail Trade Model

- Amazon Facilities ([MWPVL](#))

Quantification

- Addresses, square feet, date, type.[\[Houde, Newberry & Seim \(HNS,2021\)\]](#)
- Focus on large fulfill. & distr. centers; drop specialized, small-package

Amazon's Impacts

- DOT Commodity Flow Survey (CFS)

- Origin-destination data on trade value, volume, NAICS category

- Other Datasets

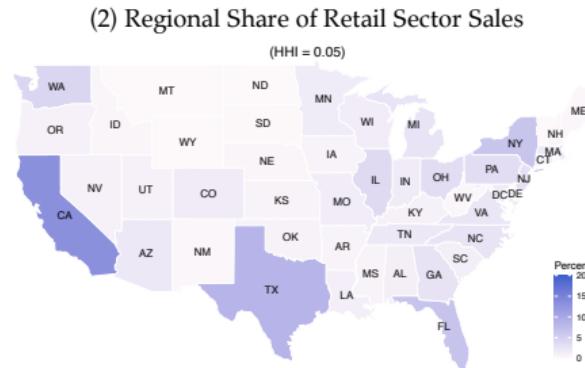
- Surveys: CBP, BEA, ACS
- Geography Datasets (topography, climate)

Motivation

Empirical Patterns

- 1a: Online retail sales is more concentrated than average retail sales...

Empirical Facts



Empirical Patterns

Motivation

- 1a: Online retail sales is more concentrated than average retail sales...
- 1b: ...and those that are FBA more concentrated than non-FBA

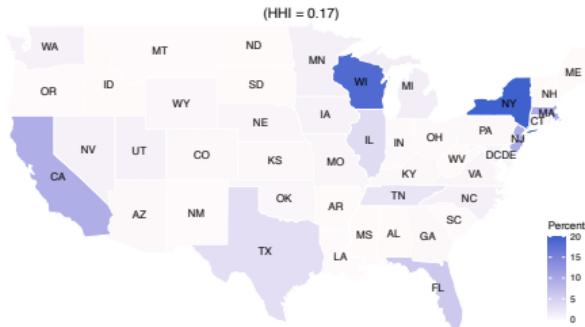
Empirical Facts

A Spatial Retail Trade Model

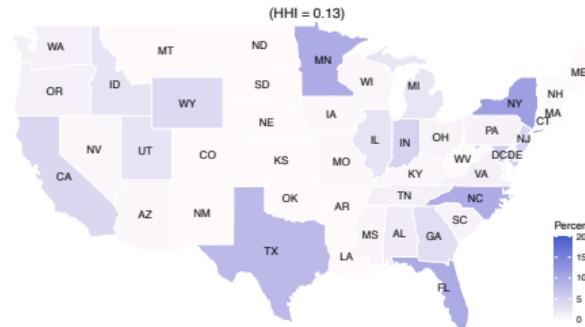
Quantification

Amazon's Impacts

(3) Regional Share of E-commerce Sales with FBA



(4) Regional Share of E-commerce Sales without FBA



- 2: Durable/standardized ones are less concentrated

Table: HHI Index by Product Categories

Category name	HHI Index
Toys & Games	0.12
Patio, Lawn & Garden	0.12
Arts, Crafts & Sewing	0.07
Sports & Outdoors	0.14
Office Products	0.16
Grocery & Gourmet Food	0.08
Tools & Home Improvement	0.21
Movies & TV	0.08
Musical Instruments	0.10

Empirical Patterns

Motivation

- 3a: Online retail is less correlated with population or taxes

Empirical Facts

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Amazon's Impacts

Dependent Variable (in %)	Online Retail	Overall Retail
In (corporate tax)	-0.01 [1.29]	0.03* [0.02]
Population share (%)	14.54* [7.92]	1.06*** [0.26]
Year, State FE	X	X
Observations	230	230
R-squared	0.52	1.00

Empirical Patterns

Motivation

- 3a: Online retail is less correlated with population or taxes
- 3b: ...and the concentration aligns with truck routes

Empirical Facts

A Spatial Retail Trade Model

Quantification

Amazon's Impacts



- 4a: Origins with ↑ online retailers **export more** tradable goods
- 4b: Destinations with ↑ online retailers **import less** tradable goods
- 5: Regions near to fulfillment centers have **more** trade flows

Dependent Variable:	$\Delta \ln(\text{Shipment})$
Δ share (%) of online sellers - origin	3.5*** [0.8]
Δ share (%) of online sellers - destination	-1.4* [0.7]
$\Delta \ln$ (bilateral distance via Amazon facility)	4.92* [2.53]
Origin, destination FE	✓
Industry FE	✓
Observations	24,693 24,693
R-squared	0.20 0.19

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A Spatial Retail Trade Model

- Environment

- N regions: n (destination), m (origin)
- J sectors: j (home production, service) & (durable, non-durable)
- 3 subsectors: M (manufacturer), R (online retailer), B (brick-and-mortar)

1. **Demand:** Sequential directed search → CES w/. demand shifter

2. **Intermediate:** Ricardian (EK) → manuf. trade flow

3. **Online Seller:** Location choice → agglomeration, retail trade flow

- Two approaches: Arkolakis et al. (2018, 2017) vs. Chaney (2008)
- Key difference: multiple destinations & origins, vertical production

4. **Worker:** Roy labor supply

Consumer Demand

Motivation

- Sequential Directed Search

Empirical Facts

- A continuum of consumers (n), sector share (η^j)

A Spatial Retail Trade Model

- Pick 1 among measure $1 + O^j$ sellers, $O^j = \sum_m \Psi_m^j$

Quantification

- $v_{nm}^j = \ln \eta^j y_n - \ln p_{nm}^{j,K} + \epsilon_{nm}^{j,K}$ (i.i.d. $E(\epsilon_{nm}^{j,B}) = 0$, and $E(\epsilon_{nm}^{j,R}) = \ln(\mu)$)

Amazon's Impacts

- Sequential directed search: pay k to see $\epsilon_{nm}^{j,K}$, or continue Weitzman ('79)

1. Any SDM has a discrete choice model (DCM) w/. same demand proof
2. CES demand is a special case of DCM with extreme type I error proof

Theorem

A rep. consumer in n with weights η^j has nest CD-CES demand as below under sequential ordered search and if $\epsilon_{nm}^{j,K}$ is distributed extreme type I

$$C_n = \prod_{j=1}^J (C_n^j)^{\eta^j}, \quad C_n^j = [(c_{nn}^B)^{\frac{\sigma^j-1}{\sigma^j}} + \mu \sum_{m=1}^N \int_0^{\Psi_m^j} (c_{nm}^R(i))^{\frac{\sigma^j-1}{\sigma^j}} di]^{\frac{\sigma^j}{\sigma^j-1}}$$

- Intermediate Varieties (M)

- A rep. firm in (n, j, M) produces varieties $e^j \in [0, 1]$

$$q_n^{j,M}(e^j) = a_n(e^j)l_n(e^j)$$

- Retail Sector (R/B)

- Collect varieties $e^j \in [0, 1]$: $q_n^{j,R/B} = [\int_0^1 q_n^{j,M}(e^j)^{\frac{\alpha^j-1}{\alpha^j}} d\phi^j(a^n(e^j))]^{\frac{\alpha^j}{\alpha^j-1}}$

$$Q_n^{j,R/B} = z_n^{j,R/B} \left[(h_n^{j,R/B})^{\beta_n} (l_n^{j,R/B})^{1-\beta_n} \right]^{\gamma_n^j} \left[q_n^{j,R/B} \right]^{1-\gamma_n^j}$$

- i.i.d. Fréchet (θ^j, T_n^j) . Intermediate exp. share: $x_{nm}^{j,M} = \frac{(\kappa_{nm}^M c_m^{j,M})^{-\theta^j} T_m^j}{\sum_{g=1}^N (\kappa_{ng}^M c_g^{j,M})^{-\theta^j} T_g^j}$

- Unit cost: $c_n^{j,R/B} = (\omega_n^{j,R/B})^{\gamma_n^j} (p_n^{j,M})^{1-\gamma_n^j} / z_n^j$. For online: $p_{nm}^{j,R} = c_m^{j,R} \kappa_{nm}^R$

Online Retailer Location

Motivation

Empirical Facts

A Spatial Retail Trade Model

Quantification

Amazon's Impacts

- Optimal Location (R) alternative

- Online retailers draw $(z_1^{j,R}, \dots, z_N^{j,R})$, entry cost f_m . Optimal location:

$$m^* = \arg \min_m \left\{ \sum_n \left(\tilde{\sigma} \frac{c_m^{j,R}}{z_m^{j,R}} \frac{\kappa_{nm}^R}{P_n^{j,R}} \right)^{\sigma^j - 1} \cdot \frac{1}{\eta^j X_n} \right\} \quad (\equiv \frac{\tilde{\sigma} \xi_m^j}{z_m^{j,R}})$$

Entry: $\sum_n \left(\frac{p_{nm}^{j,R}}{P_n^{j,R}} \right)^{1-\sigma^j} \eta^j X_n \geq \sigma^j w_m^{j,R} f_m$. Thold: $\bar{c}_m^{j,R} = \frac{\mu z_m^{j,R}}{\sigma^j} \left[\frac{\sigma^j}{\eta^j} \frac{w_m^{j,R} f_m}{\sum_n (\kappa_{nm}^R / P_n^{j,R})^{\sigma^j - 1} X_n^{-1}} \right]^{\frac{1}{1-\sigma^j}}$

- Aggregate Retail Trade

- Multi-var Pareto : $P(Z_1^j < z_1, \dots, Z_N^j < z_N) = 1 - \left(\sum_{m=1}^N [T_m^{j,R} z_m^{-\phi}]^{\frac{1}{1-\rho}} \right)^{1-\rho}$

$$\Psi_m^j = P(m = \operatorname{argmin}_m \{ \frac{\tilde{\sigma} \xi_m^j}{z_m^j} \} \cap c_m^{j,R} < \bar{c}_m^j) = \psi_m^j (\bar{c}_m^j)^\phi \quad \psi_m^j = \frac{T_m^{j,R} (\xi_m^j)^{\frac{-\phi}{1-\rho}}}{\sum_{m=1}^N [T_m^{j,R} (\xi_m^j)^{-\phi}]^{\frac{-\rho}{1-\rho}}}$$

Bilateral online retail exp. share

Regional brick-and-mortar exp. share

$$x_{nm}^{j,R} = \frac{\Psi_m^j (\kappa_{nm}^R c_m^{j,R} / \mu)^{1-\sigma}}{\sum_h \Psi_h^j (\kappa_{nh}^R c_h^{j,R} / \mu)^{1-\sigma} + \frac{1}{O} (c_n^{j,B})^{1-\sigma}}$$

$$x_n^{j,B} = \frac{\frac{1}{O} (c_n^{j,B})^{1-\sigma}}{\sum_h \Psi_h^j (\kappa_{nh}^R c_h^{j,R} / \mu)^{1-\sigma} + \frac{1}{O} (c_n^{j,B})^{1-\sigma}}$$

- Employment Share

- L_n HHs choose sector $\{j, K\}$ (home production $j = 0$)
 - ▶ $K = \{M, R, B\}$ the three subsectors for dur/non-dur sectors, \emptyset for others
- Draw $z_n^{j,K}$ from i.i.d. Fréchet $(\nu_n, A_n^{j,K})$

$$\pi_n^{j,K} = \frac{A_n^{j,K} (w_n^{j,K})^{\nu_n}}{\Phi_n}, \text{ where } \Phi_n = \sum_{j=0}^J \sum_{K=\{M,R,B,\emptyset\}} A_n^{j,K} (w_n^{j,K})^{\nu_n}$$

- Sectoral Wage Income

- Let $l_n^{j,K}$ efficiency units of labor provided to sector (j, K)
- Wage income in (j, K) becomes $w_n^{j,K} l_n^{j,K} = \Gamma(\frac{\nu_n - 1}{\nu_n}) \Phi_n^{1/\nu_n} \pi_n^{j,K} L_n$

E-commerce and General Equilibrium Outcomes

Motivation

- General Equilibrium

- Market clearing [details](#)
- Comparative statics w/. exact hat algebra [details](#)

Empirical Facts

- E-commerce

- ↑ Match efficiency μ (Dinerstein et. al 2018; Goldmanis et. al 2010)
- ↓ Bilateral frictions κ_{ni}^R (Houde, Newberry & Seim 2021)
- ↑ Online retailer agglomeration Ψ_m^j (Keepa, targeted)

A Spatial Retail Trade Model

Quantification

Amazon's Impacts

- Welfare

- Definition: real income per capita $W_n = \frac{Y_n}{P_n}$, its change:

$$\hat{W}_n = \underbrace{\hat{w}_n^0(\hat{\pi}_n^0)^{\frac{-1}{vn}}}_{\text{non-emp. worker special.}} \times \underbrace{\Pi_{j=1}^J (\hat{x}_{nn}^{j,B})^{\frac{-\eta_j}{\sigma^j - 1}}}_{\text{industry composition}} \underbrace{(\hat{c}_n^{j,R}/B)}_{\text{input-output local pref.}}$$

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Calibration: General

Motivation

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Section	Param.	Description	Estimation/Calibration
Consumer	η_n^j	Sector share of consumption	CFS 2007
	σ^j	Elasticity of subs. across retailers	Keepa + IV
Labor Supply	π_n^j	Share of empployment	CBP, ACS
	v^n	Fréchet shape of worker product.	Galle, Rodríguez-Clare & Yi (2022)
Production	β_n^j	Share of structures	BEA + Greenwood et. al (1997)
	θ^j	Fréchet shape of sector product.	Caliendo and Parro (2015)
	γ_n^j	Value-added share of retail goods	BEA, CFS
Expenditure	$x_{ni}^{j,M}$	Interm. expenditure share	CFS 2007
	$x_n^{j,B}$	Brick-and-motar expenditure share	CFS 2007, E-Stats
	$x_{nm}^{j,R}$	E-commerce expenditure share	CFS 2007, E-Stats
	$p_n^{j,B}$	Brick-and-motar price index	CFS 2007, E-Stats, CES

Baseline Economy (2007): Model vs. Data

Motivation

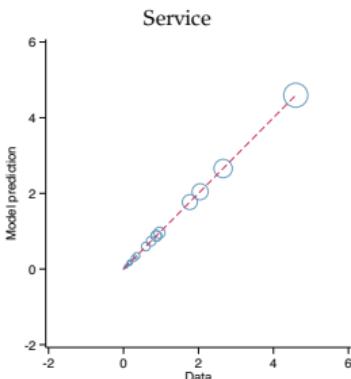
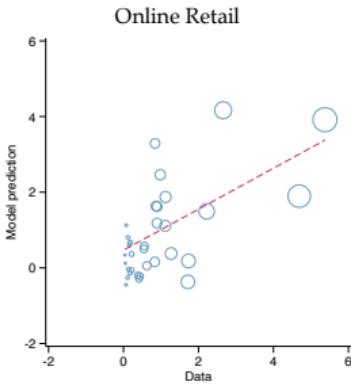
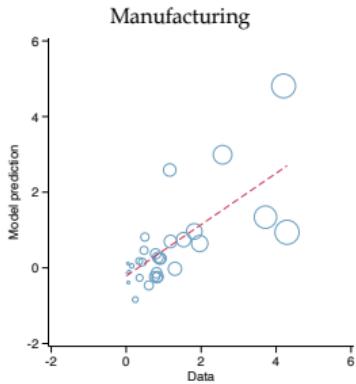
- Model implied regional income (untargeted)

Empirical Facts

A Spatial Retail Trade Model

Quantification

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Sequential Estimation: Amazon Shock

Motivation

Empirical Facts

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Amazon's Impacts

Section	Param.	Description	Estimation/Calibration
Amazon Shock	$\hat{\kappa}_{nm}^R$	Iceberg cost change	Amazon data + CFS 2007 + IV
	μ	Matching efficiency	E-stats + CES
	Ψ_m^j	Online retailer location probability	Keepa
	O	Measure of online retailers	E-stats
	T_n^j	Fréchet scale of sectoral product.	Assume constant
	A_n^j	Fréchet scale of labor product.	Assume constant

Sequential Estimation: Amazon Shock

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- Extrapolate Amazon Ice-berg cost shock

- **Intuition:** Ice-berg is increasing in distance
 - Estimate coefficient of ice-berg cost on shipping distance [details](#)

$$\ln(\kappa_{nm}^{j,R}) = \delta^j \text{Distance}_{nm} + X'_{nm}\theta + \delta_n^j + \delta_m^j + \epsilon_{nm}^j$$

- Estimate reduction in shipping distance due to Amazon
 - ▶ Build counterfactual facilities based on exog. factors as IV for actual ones

- Back-out online matching efficiency

- **Intuition:** % online exp. should inform matching, conditional on shipping

$$\sum_{m=1}^N x_{nm}^{j,R} / x_{nn}^{j,R} = (\mu)^{\sigma^j - 1} \sum_{m=1}^N M_m (p_m^{j,R} \kappa_{nm}^R / p_{nn}^{j,R})$$

- ▶ Use Keepa for M_m , above estimated κ_{nm}^R , CES for $p_m^{j,R}, p_{n0}^{j,R}$

δ^{dur}	δ^{nondur}	$\hat{\kappa}$	μ
1.5	2.1	0.97	1.27
[0.2]	[0.6]	[0.15]	[1.46]

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Amazon's Spatial GE Effects on Welfare and Employment

Welfare – Total

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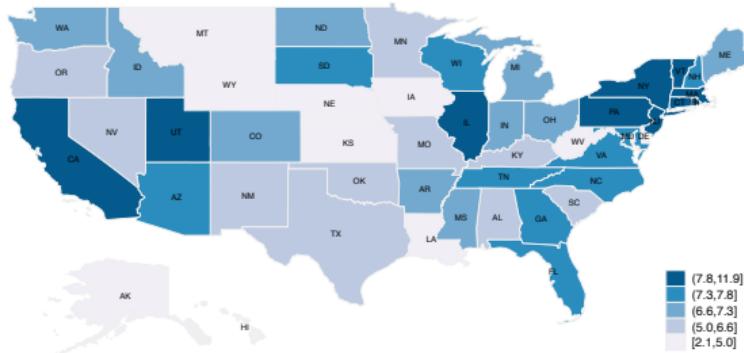


Figure: Total Welfare Change

- ↑ **welfare** overall (avg: 6.7 %)
 - States on the East and West Coasts experience larger welfare gains
 - Midwestern states see smaller increases

Welfare – Decomposition

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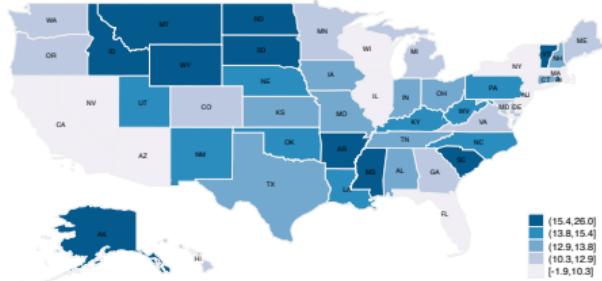


Figure: Price effects

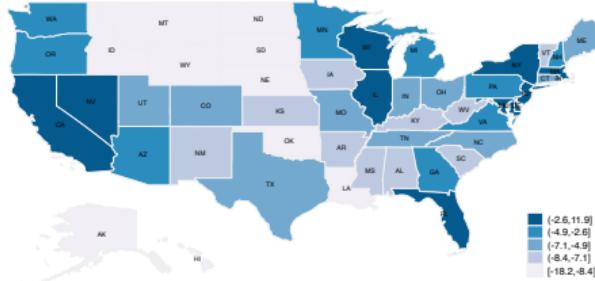


Figure: Income effects

- **Price effects ↑ welfare (13.1%); Income effects ↓ welfare (5.4%)**
 - States w/. CA in e-commerce and diverse industries (NY, MA, WI, CA, FL):
Positive income effects due to ↑ online sales, wages
 - Midwestern: Negative income effects from competition and labor shifts.
Lower initial online spending → Positive price effects

Result – Employment

Motivation

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A Spatial Retail Trade Model

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Sector	All States		Below 50th Percentile Online Sales Density	
	Mean	Std. Dev.	Mean	Std. Dev.
Manufacturing	-4.3	(7.6)	-1.8	(1.1)
Online Retail	109.8	(97.8)	63.3	(64.8)
Brick-and-Mortar	-11.1	(8.0)	-8.6	(1.2)
Service	-1.6	(7.9)	1.2	(1.2)
Non-Employment	-1.3	(8.1)	1.7	(0.8)

Table: Employment Changes by Sector and State Groups

- Reallocate from manufacturing/brick-and-mortar to online retail; non-employment ↓ by 0.5 ppts.
- Midwestern states shift more to service/non-employment sectors
- ↑ inequality: Gini 0.11→0.38

(Simple) Revenue Redistribution

Motivation

Empirical Facts

A Spatial Retail Trade Model

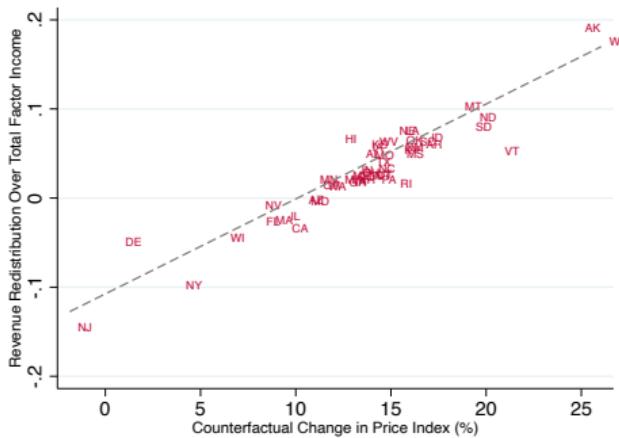
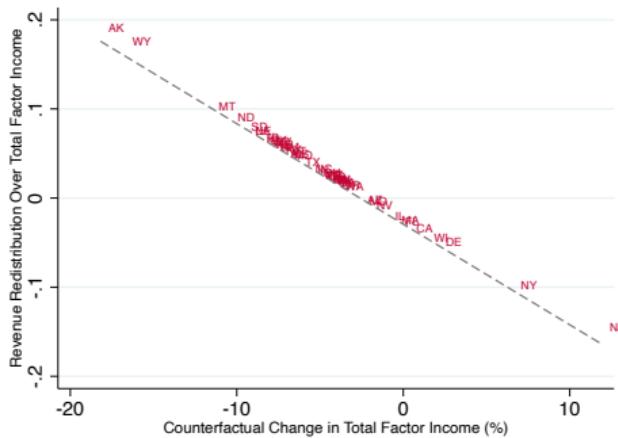
Quantification

Amazon's Impacts

- Government Objectives

- Common welfare changes ($\forall n, \hat{W}_n = \frac{\hat{Y}_n}{\hat{P}_n} = k$), by manipulating $Y'_n \rightarrow \tilde{Y}'_n$
- Same total surplus $\sum_{n=1}^{50} (\tilde{Y}'_n - Y_n) = B = \sum_{n=1}^{50} (Y'_n - Y_n)$

$$\Rightarrow k = \frac{B + \sum_{n=1}^{50} Y_n}{\sum_{n=1}^{50} Y_n \cdot \frac{\hat{P}_n}{P_n}} = 0.97; \text{redistrib. amt} = (\tilde{Y}'_n - Y'_n) = Y_n k \frac{\hat{P}_n}{P_n} - Y'_n$$



Conclusion

Motivation

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A Spatial Retail Trade Model

Quantification

Amazon's Impacts

- E-commerce as **unique trade** shock
- **New facts** on online retailer agglomeration (sellers, trade flows)
- **Spatial retail trade model** w/. location choices (search efficiency, elastic labor)
- **Amazon** ⇒ efficiency equality tradeoff on welfare, empl.
 - ↓ prices, ↑ variety, but ↓ income and empl. adjmnt in Midwestern
 - Need national level revenue redistribution

Appendix

Search is *ordered*: Weitzman (1979) optimal stopping

- Assign thresholds/scores \bar{v}_i st. $E[\max\{\hat{x}_i + \tilde{\epsilon}_i - \bar{v}_i, 0\}] = 0$, where
$$\hat{x}_i = \ln y - \ln p_i$$
- Therefore, $\bar{v}_i = \hat{x}_i + \gamma_{\epsilon_i}^{-1}(\ln s_i)$, where $\gamma_{\epsilon_i}(z) = E[\max\{\epsilon_i - z, 0\}]$,
decreasing function
- Search in decreasing order of the scores
- Stop if find a \bar{v}_i exceeding all remaining

Proposition: For any OSM, there is a DCM with same demand & payoff.

- Under OSM, consumer's optimal choice is the one for which

$v_i^* = \min\{v_i, \bar{v}_i\}$ is largest (Armstrong and Vickers (2015),

Armstrong(2017), Choi, Dai and Kim(2018)), where

$\bar{v}_i = \hat{x}_i + \gamma_{\epsilon_i}^{-1}(\ln \mu_i) = \hat{x}_i + r(\ln \mu_i)$, and $\gamma_{\epsilon_i}(z) = E[\max\{\epsilon_i - z, 0\}]$, the upside gain function

- Consumer's demand for i , D_i is thus:

$$P[v_i^* > \max_{j \neq i} v_j^*] = \int_{-\infty}^{\infty} P[z > \max_{j \neq i} v_j^*] f_{v_i^*}(z; x_i, \hat{x}_i) dz = \int_{-\infty}^{\infty} \prod_{j \neq i} F_{v_j^*}(z; x_j, \hat{x}_j) f_{v_i^*}(z; x_i, \hat{x}_i) dz$$

- Under advertised price, $x_j = \hat{x}_j, \forall j$. D_i then simplifies to

$$\int_{-\infty}^{\infty} \prod_{j \neq i} F_{\omega_j}(\epsilon_j) f_{\omega_i}(\epsilon_i) d\epsilon, \text{ where } \omega_i = \min\{\epsilon_i, r(\ln \mu_i)\}.$$

Thus, D_i is equivalent to the demand of a DCM: $v_i = x_i + \epsilon_i^{DC}$, iff

Proposition: The CES demand is a special case of DCM with extreme type I error.

The following proof follows Anderson, De Palma, and Thisse (1987, 1989) closely

- Consumer's utility $u_i = \ln c_i$, income y . Let price of i : $\tilde{p}_i = \mu_i p_i$
- Random utility/match value ϵ_i with i , st. net value:

$$v_i = \ln y - \ln \tilde{p}_i + \epsilon_i^{DC}$$

Further, re-scale $\epsilon_i^{DC} = \chi \tilde{\epsilon}_i$ st. $\tilde{\epsilon}_i$ mean 0 and unit variance

- The demand for i , D_i is then

$$P[v_i > \max_{j \neq i} v_j] = \int_{-\infty}^{\infty} \prod_{j \neq i} F_{\epsilon_j^{DC}}(\epsilon_j^{DC}) f_{\epsilon_i^{DC}}(\epsilon_i^{DC}) d\epsilon.$$

- And if $\tilde{\epsilon}_i$ is distributed extreme type I, D_i then simplifies to

- Retail and intermediate goods:

$$X_n^{R,j} = \sum_{i=1}^N x_{in}^{R,j} (I_i L_i), \text{ where } I_i L_i = \sum_{k=0}^J [r_i^{g,k} g_i^{R,k} + \sum_{K=M,R} (r_i^{h,k} h_i^{K,k} + w_i^k l_i^{K,k})] - \Omega_i,$$

$$X_n^{M,j} = \sum_{i=1}^N (1 - \gamma_i^j) x_{in}^{M,j} X_i^{R,j}.$$

- Trade balance:

$$\sum_{j=0}^J \sum_{i=1}^N (x_{ni}^{M,j} X_n^{M,j} + x_{ni}^{R,j} X_n^{R,j}) + \Omega_n = \sum_{j=0}^J \sum_{i=1}^N (x_{in}^{M,j} X_i^{M,j} + x_{in}^{R,j} X_i^{R,j}).$$

- Labor market:** $w_n^{M,j} l_n^{M,j} = \beta_n X_n^{M,j}, \quad w_n^{R,j} l_n^{R,j} = \gamma_n^j m_n^{R,j} \beta_n X_n^{R,j}$
- Structure:** $r_n^h h_n^{M,j} = (1 - \beta_n) X_n^{M,j}, \quad r_n^h h_n^{R,j} = \gamma_n^j \frac{1}{\rho_n^{R,j}} (1 - \beta_n) X_n^{R,j}$
- Capital:** $r_n^g g_n^{R,j} = (\frac{\rho_n^j - 1}{1 - \beta_n}) w_n^{R,j} \pi_n^{R,j} L_n$

- Employment shares:

$$\hat{\pi}_n^0 = \frac{\hat{A}_n^0(\hat{w}_n^0)^{\nu_n}}{\hat{\Phi}_n}, \quad \hat{\pi}_n^{K,j} = \frac{\hat{A}_n^{K,j}(\hat{w}_n^{K,j})^{\nu_n}}{\hat{\Phi}_n}, \text{ where } \hat{\Phi}_n = \sum_{h=0}^J \sum_{K=M,R} \pi_n^{K,h} \hat{A}_n^{K,h} (\hat{w}_n^{K,h})^{\nu_n}.$$

- Input costs: $\hat{c}_n^{M,j} = \hat{\omega}_n^{M,j}$, $\hat{c}_n^{R,j} = (\hat{\rho}_n^{R,j} \hat{\omega}_n^{R,j})^{\gamma_n^j} (\hat{P}_n^{M,j})^{1-\gamma_n^j}$, where

$$\hat{\omega}_n^{K,j} = \hat{w}_n^{K,j} (\hat{l}_n^{K,j})^{\beta_n} = (\hat{w}_n^{K,j})^{1+\beta_n} (\hat{\pi}_n^{K,j})^{\frac{(\nu_n-1)\beta_n}{\nu_n}}, \text{ and } \hat{P}_n^{M,j} = \left(\sum_{i=1}^N x_{ni}^{M,j} (\hat{\kappa}_{ni}^M \hat{c}_i^{M,j})^{-\theta_j} \hat{T}_i^j \right)^{\frac{-1}{\theta_j}}.$$

- Trade shares: $x_{ni}^{'M,j} = x_{ni}^{M,j} \left(\frac{\hat{\kappa}_{ni}^M \hat{c}_i^{M,j}}{\hat{P}_n^{R,j}} \right)^{-\theta_j} \hat{T}_i^j$, $x_{ni}^{'R,j} = x_{ni}^{R,j} \left(\frac{\hat{\kappa}_{ni}^R \hat{c}_i^{R,j}}{\hat{\mu}_{ni}^j \hat{P}_n^{R,j}} \right)^{1-\sigma_j}$.

- Market clearing:

$$X_n^{'R,j} = \sum_{i=1}^N x_{in}^{'R,j} \eta^j \left[\sum_{k=0}^J \left(\frac{1}{1-\beta_i} \right) (\hat{\rho}_i^{R,k} \hat{w}_i^{R,k} \hat{l}_i^{R,k} \rho_i^{R,k} w_i^{R,k} L_i^{R,k} + \hat{w}_i^{M,k} \hat{l}_i^{M,k} w_i^{M,k} L_i^{M,k}) - \Omega_i \right],$$

$$X_n^{'M,j} = \sum_{i=1}^N (1 - \gamma_i^j) x_{ni}^{'M,j} X_n^{'R,j},$$

- Pareto productivity: $P(Z^j < z) = G^j(z) = 1 - z^{-\rho}$
- Enter: $\sum_n \left(\frac{p_{nm}^j / \mu}{p_{nj}^R} \right)^{1-\sigma} \eta_n^j \geq \omega_m^j f_m^j$. $c_m^j = \mu \left(\frac{\sigma}{\tilde{\sigma}_n} \right)^{1-\sigma} \left[\frac{w_m^j f_m^j}{\sum_n (k_{nm}^R / p_{nj}^R)^{1-\sigma} \frac{1}{y_n}} \right]^{\frac{1}{1-\sigma}}$
- Bilateral trade shares

$$x_{nm}^{j,R} = \frac{\lambda Y_m \left(\left(w_m^{j,R} \right)^{\gamma^j} \left(P_m^{j,M} \right)^{(1-\gamma^j)} \frac{(\kappa_{nm}^R)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_m^{j,R} f_m}{\sum_n \left(\frac{w_m^{j,R}}{P_n^{j,R}} \right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}}}{\sum_h \lambda Y_h \left(\left(w_h^{j,R} \right)^{\gamma^j} \left(P_h^{j,M} \right)^{(1-\gamma^j)} \frac{(\kappa_{nm}^R)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_h^{j,R} f_h}{\sum_n \left(\frac{w_h^{j,R}}{P_n^{j,R}} \right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} + \left(\left(\omega_n^{j,B} \right)^{\gamma^j} \left(P_n^{j,M} \right)^{(1-\gamma^j)} \right)^{1-\sigma}}$$

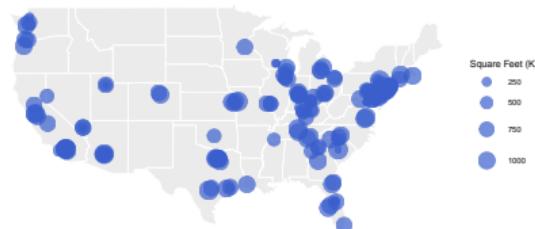
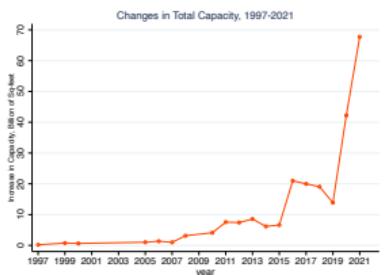
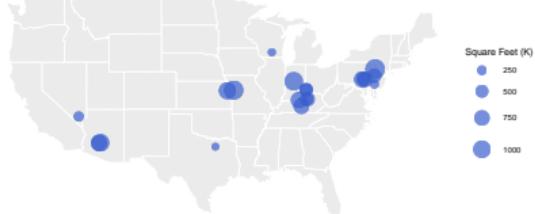
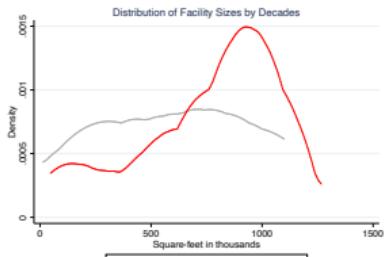
$$x_{nn}^{j,B} = \frac{\left(\left(\omega_n^{j,B} \right)^{\gamma^j} \left(P_n^{j,M} \right)^{(1-\gamma^j)} \right)^{1-\sigma}}{\sum_h \lambda Y_h \left(\left(w_h^{j,R} \right)^{\gamma^j} \left(P_h^{j,M} \right)^{(1-\gamma^j)} \frac{(\kappa_{nm}^R)^{\frac{\sigma-1}{\rho}}}{\mu} \right)^{-\rho} \left[\frac{w_h^{j,R} f_h}{\sum_n \left(\frac{w_h^{j,R}}{P_n^{j,R}} \right)^{1-\sigma} Y_n} \right]^{\frac{\sigma-\rho-1}{\sigma-1}} + \left(\left(\omega_n^{j,B} \right)^{\gamma^j} \left(P_n^{j,M} \right)^{(1-\gamma^j)} \right)^{1-\sigma}}$$

Estimation: Amazon Transportation Shock

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Appendix

- Data: Amazon's Facility Network
 - address, square feet, date, type. [Houde, Newberry & Seim (HNS,2021)]
 - focus on large fulfill. & distr. centers; drop specialized, small-package



- Need to specify how:

origin → facility → destination

- HNS (2021): 90% of orders from 3 closest centers to dest.
- Assume order is processed by among the 3 closest to destination, the closest to origin

Year	Mean	Std. Dev	P25	P75
2007	490.2	376.3	234.9	739
2017	287.9	225.6	124.7	409
Diff.	-202.2	295.6	-249.8	-12.5
Log Diff.	-.5	.6	-.9	0

- Spatial Simulated IV

- concern: endogeneity of facilities
- simulate facilities' locations based only on geo. cost factors, to be used as IV (Duflo et.al, 2007; Lipscomb et.al, 2013; Faber 2014)
- need orthogonality of geo. factors

Dependent 1{AMZ Center}		
<i>Temperature (Lag)</i>	Mean	-0.011 [0.018]
	Minimum	-0.002 [0.009]
	Maximum	0.046*** [0.012]
<i>Precipitation (Lag)</i>	Mean	-0.032 [0.040]
	Minimum	0.043 [0.044]
	Maximum	-0.015 [0.013]
<i>Elevation</i>	Mean	-0.001*** [0.000]
	Minimum	0.000 [0.000]
	Maximum	0.001*** [0.000]
<i>Tornado</i>	Magnitude	-0.051 [0.086]
	Injuries	-0.110 [0.153]
County, Year FE		X
Observations		55,259
Psudo R-squared		0.1663

- Spatial Simulated IV

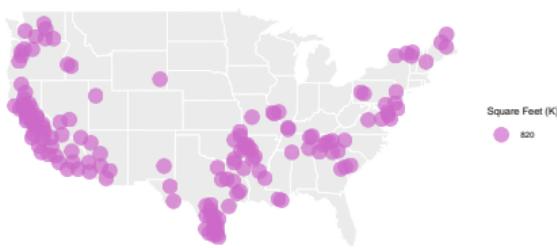
- concern: endogeneity of facilities
- simulate facilities' locations based only on geo. cost factors, to be used as IV (Duflo et.al, 2007; Lipscomb et.al, 2013; Faber 2014)
- need orthogonality of geo. factors

- Simulation Steps

- based on observed # of new centers, determine AMZ's budget
- rank counties by geo. factors
- highest ranks get new centers

Dependent 1{AMZ Center}		
<i>Temperature (Lag)</i>	Mean	-0.011 [0.018]
	Minimum	-0.002 [0.009]
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	Injuries	-0.110 [0.153]
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Estimation: Amazon Transportation Shock

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Year	Mean	Std. Dev	P25	P75	Corr
2007	623.4	400.3	349.6	897.4	0.10
2017	335.2	278.4	143.9	412.1	0.58
Diff.	-288.2	361.8	-355.9	0	-0.22
Log Diff.	-.7	.8	-1.1	0	-0.02

	Dependent Variables	
	Actual log distance	Counterfactual log distance
First Stage Results		
Counterfactual log distance	0.399*** [0.015]	
F-Stats	670	
Robustness		
Avg. lag GDP		0.000 [0.000]
Avg. GDP growth		-0.004*** [0.001]