

The Comparative Advantage of Cities

Donald R. Davis Jonathan I. Dingel

Columbia University and NBER

Chicago Booth

October 2014

Research questions

What determines the spatial distribution of...

- Skills
- Occupations
- Industries

Research questions

What determines the spatial distribution of...

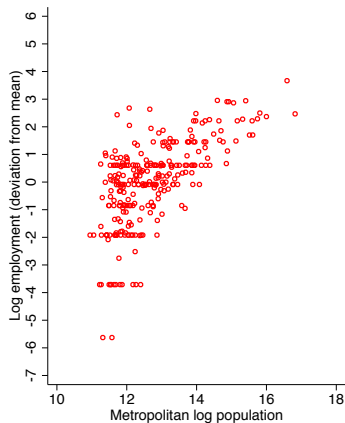
- Skills
- Occupations
- Industries

In particular, how are these related to cities' sizes?

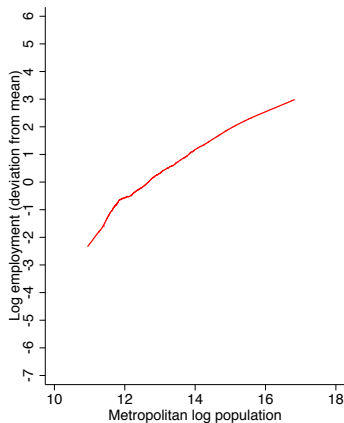
A first look: Wood product manufacturing

- Consider wood product manufacturing, whose employees average 11.8 years of schooling
- Plot employment in wood products against population for 276 metropolitan areas
- Will wood products be manufactured in every city?
- Will wood product employment be decreasing in city size, increasing in city size, or attain an interior maximum?

Industries and city size



- Wood products
- ▲ Machinery
- Computer and electronic products



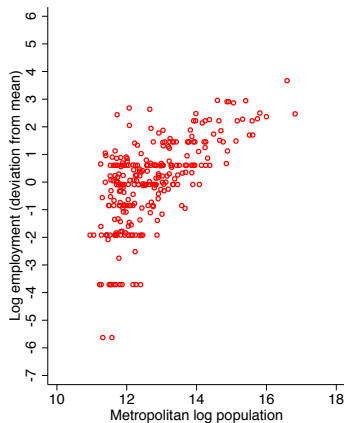
- Wood products
- Machinery
- Computer and electronic products

Adding more industries

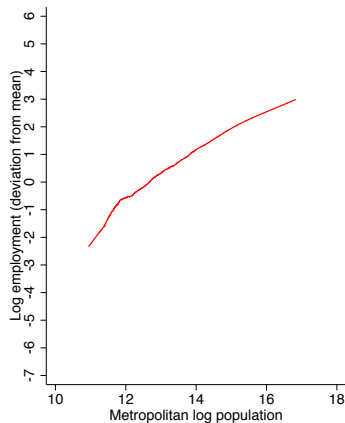
Now consider:

- Machinery manufacturing (12.9 years of schooling)
- Computer and electronic products (14.1 years of schooling)

Industries and city size

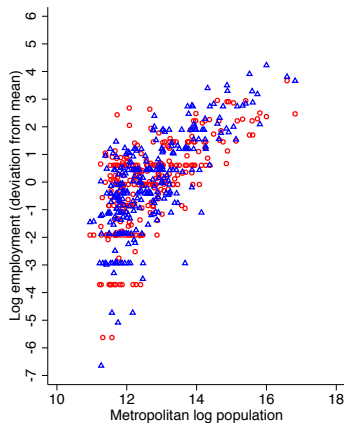


- Wood products
- ▲ Machinery
- Computer and electronic products

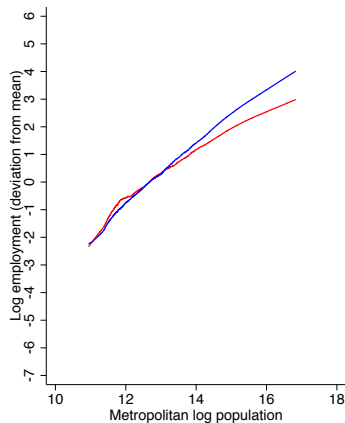


- Wood products
- Machinery
- Computer and electronic products

Industries and city size

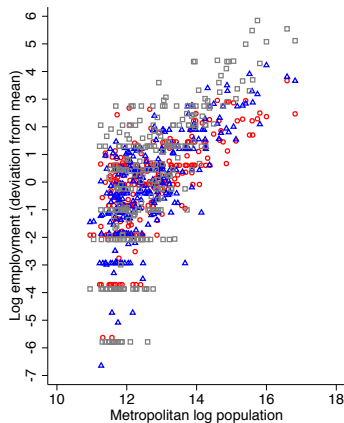


- Wood products
- △ Machinery
- Computer and electronic products

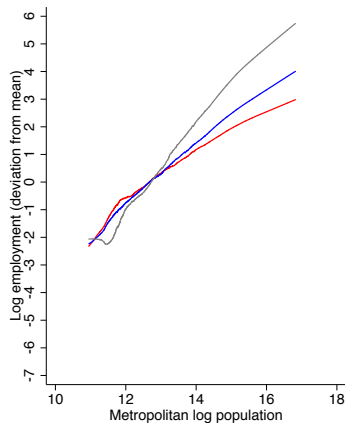


- Wood products
- Machinery
- Computer and electronic products

Industries and city size



- Wood products
- △ Machinery
- Computer and electronic products



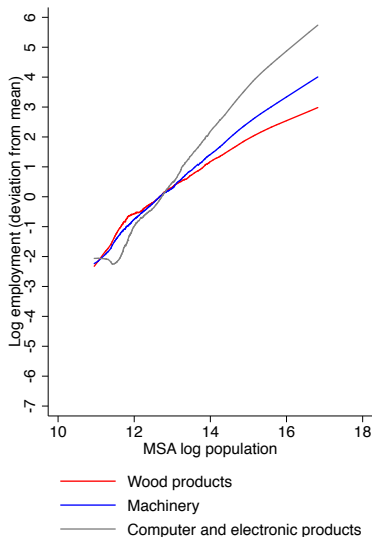
- Wood products
- Machinery
- Computer and electronic products

Comparative Advantage of Cities: Theory

- We describe comparative advantage of cities as jointly governed by individuals' comparative advantage and locational choices
- Cities endogenously differ in TFP due to agglomeration
- More skilled individuals are more willing to pay for more attractive locations
- Larger cities are skill-abundant in equilibrium
- By individuals' comparative advantage, larger cities specialize in skill-intensive activities
- Under a further condition, larger cities are larger in all activities

Comparative Advantage of Cities: Empirics (1/2)

- Use US data on skills and sectors
- Characterize the comparative advantage of cities with two tests
- Elasticity test of variation in relative population/employment
 - Compare elasticities of different skills, sectors
 - Steeper slope in log-log plot is higher elasticity
 - Elasticities may be positive for all sectors



Comparative Advantage of Cities: Empirics (2/2)

Pairwise comparison test (LSM)

- The function $f(\omega, c)$ is log-supermodular if

$$c > c', \omega > \omega' \Rightarrow f(\omega, c)f(\omega', c') \geq f(\omega', c)f(\omega, c')$$

- Our theory says skill distribution $f(\omega, c)$ and sectoral employment distribution $f(\sigma, c)$ are log-supermodular
- For example, population of skill ω in city c is $f(\omega, c)$. Check whether, for $c > c', \omega > \omega'$,

$$\frac{f(\omega, c)}{f(\omega', c)} \geq \frac{f(\omega, c')}{f(\omega', c')}$$

Are larger cities **larger in all sectors**?

- Check if $c > c' \Rightarrow f(\sigma, c) \geq f(\sigma, c')$

Related literature

- **Distribution of heterogeneous skills:** Behrens, Duranton, and Robert-Nicoud (2014); Eeckhout, Pinheiro, and Schmidheiny (2014); Davis and Dingel (2012); Acemoglu and Autor (2011); Baum-Snow and Pavan (2011)
- **Assignment models of differential rents:** Ricardo (1817), Alonso-Muth-Mills, Brueckner (1987); von Thünen (1826); Sattinger (1979); Fujita and Thisse (2002); Behrens and Robert-Nicoud (2011); Behrens, Duranton, and Robert-Nicoud (2014)
- **Assignment models of comparative advantage:** Sattinger (1975); Teulings (1995); Costinot (2009); Costinot and Vogel (2010, 2014)
- **Models of cities' industrial structure:** Henderson (1974); Duranton and Puga (2001); Helsley and Strange (2012)
- **A structural interpretation of prior estimates of sectors' population elasticities:** Henderson (1983, 1991, 1997); Holmes and Stevens (2004)

Outline

- 1 Theory
- 2 Empirical approach and data description
- 3 Empirical results
 - Elasticities tests
 - Pairwise comparisons tests
 - Larger cities are larger in all skills and sectors
- 4 Conclusions

Theory

Model components

Producers

- Skills: Continuum of skills indexed by ω (educational attainment)
- Sectors: Continuum of sectors σ (occupations, industries)
- Goods: Freely traded intermediates assembled into final good
- All markets are perfectly competitive

Places

- Cities are *ex ante* identical
- Locations within cities vary in their desirability
- TFP depends on agglomeration of “scale and skills”

$$A(c) = J \left(L, \int_{\omega \in \Omega} j(\omega) f(\omega, c) d\omega \right)$$

Analytical tool: log-supermodularity

- The skill distribution $f(\omega, c)$ is log-supermodular if
$$c > c', \omega > \omega' \Rightarrow f(\omega, c)f(\omega', c') \geq f(\omega', c)f(\omega, c')$$

Individual optimization

Perfectly mobile individuals simultaneously choose

- A sector σ of employment
- A city with total factor productivity $A(c)$
- A location τ (distance from ideal) within city c

The productivity of an individual of skill ω is

$$q(c, \tau, \sigma; \omega) = A(c)T(\tau)H(\omega, \sigma)$$

Utility is consumption of the numeraire final good, which is income minus locational cost

$$\begin{aligned} U(c, \tau, \sigma; \omega) &= q(c, \tau, \sigma; \omega)p(\sigma) - r(c, \delta) \\ &= A(c)T(\tau)H(\omega, \sigma)p(\sigma) - r(c, \delta) \end{aligned}$$


Sectoral choice

- Individuals' choices of locations and sectors are separable:

$$\arg \max_{\sigma} \underbrace{A(c) T(\tau)}_{\text{locational}} \underbrace{H(\omega, \sigma) p(\sigma)}_{\text{sectoral}} - r(c, \delta) = \arg \max_{\sigma} H(\omega, \sigma) p(\sigma)$$

- $H(\omega, \sigma)$ is log-supermodular in ω, σ and strictly increasing in ω
- Comparative advantage assigns high- ω individuals to high- σ sectors (Costinot, 2009; Costinot and Vogel, 2010)
- Absolute advantage makes more skilled have higher incomes ($G(\omega) = \max_{\sigma} H(\omega, \sigma) p(\sigma)$ is increasing)

Locational choice

- A location's attractiveness $\gamma = A(c)T(\tau)$ depends on c and τ
- $T'(\tau) < 0$ may be interpreted as commuting to CBD, proximity to productive opportunities, or consumption value 
- More skilled are more willing to pay for more attractive locations
- Equally attractive locations have same rental price and skill type
- Location in higher-TFP city is farther from ideal desirability

$$\begin{aligned}\gamma &= A(c)T(\tau) = A(c')T(\tau') \\ A(c) > A(c') &\Rightarrow \tau > \tau'\end{aligned}$$

- Locational hierarchy: A smaller city's locations are a subset of larger city's in terms of attractiveness: $A(c)T(0) > A(c')T(0)$

Equilibrium distributions

- Skill and sectoral distributions reflect distribution of locational attractiveness: Higher- γ locations occupied by higher- ω individuals who work in higher- σ sectors
- Locational hierarchy \Rightarrow hierarchy of skills and sectors
- The distributions $f(\omega, c)$ and $f(\sigma, c)$ are log-supermodular if and only if the supply of locations with attractiveness γ in city c , $s(\gamma, c)$, is log-supermodular

$$s(\gamma, c) = \begin{cases} \frac{1}{A(c)} V\left(\frac{\gamma}{A(c)}\right) & \text{if } \gamma \leq A(c)T(0) \\ 0 & \text{otherwise} \end{cases}$$

where $V(z) \equiv -\frac{\partial}{\partial z} S(T^{-1}(z))$ is the supply of locations with innate desirability τ such that $T(\tau) = z$

When is $s(\gamma, c)$ log-supermodular?

Proposition (Locational attractiveness distribution)

The supply of locations of attractiveness γ in city c , $s(\gamma, c)$, is log-supermodular if and only if the supply of locations with innate desirability $T^{-1}(z)$ within each city, $V(z)$, has a decreasing elasticity.

- Links each city's exogenous distribution of locations, $V(z)$, to endogenous equilibrium locational supplies $s(\gamma, c)$
- Informally, ranking relative supplies is ranking elasticities of $V(z)$

$$s(\gamma, c) \propto V\left(\frac{\gamma}{A(c)}\right) \Rightarrow \frac{\partial \ln s(\gamma, c)}{\partial \ln \gamma} = \frac{\partial \ln V\left(\frac{\gamma}{A(c)}\right)}{\partial \ln z}$$

- Satisfied by the canonical von Thünen geography

The Comparative Advantage of Cities

Corollary (Skill and employment distributions)

If $V(z)$ has a decreasing elasticity, then $f(\omega, c)$ and $f(\sigma, c)$ are log-supermodular.

- Larger cities are skill-abundant in equilibrium (satisfies Assumption 2 in Costinot 2009)
- Locational productivity differences are Hicks-neutral in equilibrium (satisfies Definition 4 in Costinot 2009)
- $H(\omega, \sigma)$ is log-supermodular (Assumption 3 in Costinot 2009)

Corollary (Output and revenue distributions)

If $V(z)$ has a decreasing elasticity, then sectoral output $Q(\sigma, c)$ and revenue $R(\sigma, c) \equiv p(\sigma)Q(\sigma, c)$ are log-supermodular.

The Comparative Advantage of Cities

Corollary (Skill and employment distributions)

If $V(z)$ has a decreasing elasticity, then $f(\omega, c)$ and $f(\sigma, c)$ are log-supermodular.

- Larger cities are skill-abundant in equilibrium (satisfies Assumption 2 in Costinot 2009)
- Locational productivity differences are Hicks-neutral in equilibrium (satisfies Definition 4 in Costinot 2009)
- $H(\omega, \sigma)$ is log-supermodular (Assumption 3 in Costinot 2009)

Corollary (Output and revenue distributions)

If $V(z)$ has a decreasing elasticity, then sectoral output $Q(\sigma, c)$ and revenue $R(\sigma, c) \equiv p(\sigma)Q(\sigma, c)$ are log-supermodular.

When are bigger cities bigger in everything?

We identify a sufficient condition under which a larger city has a larger supply of locations of a given attractiveness

Proposition

For any $A(c) > A(c')$, if $V(z)$ has a decreasing elasticity that is less than -1 at $z = \frac{\gamma}{A(c)}$, $s(\gamma, c) \geq s(\gamma, c')$.

Now apply this result to the least-attractive locations, so larger cities are larger in all skills and sectors

Corollary

If $V(z)$ has a decreasing elasticity that is less than -1 at $z = \frac{K^{-1}(\underline{\omega})}{A(c)} = \frac{\gamma}{A(c)}$, $A(c) > A(c')$ implies $f(\omega, c) \geq f(\omega, c')$ and $f(M(\omega), c) \geq f(M(\omega), c') \forall \omega \in \Omega$.

Empirical approach and data description

Empirical tests

Our theory says $f(\omega, c)$ and $f(\sigma, c)$ are log-supermodular.

Two tests to describe skill and sectoral employment distributions:

- Elasticities test:
 - Compare population elasticities estimated via linear regression
 - More skilled types should have higher population elasticities
 - More skill-intensive sectors should have higher population elasticities
- Pairwise comparisons test:
 - Compare any two cities and any two skills/sectors
 - Relative population of more skilled should be higher in larger city: $c > c', \omega > \omega' \Rightarrow \frac{f(\omega, c)}{f(\omega', c)} \geq \frac{f(\omega, c')}{f(\omega', c')}$
 - Relative employment of more skill-intensive sector should be higher in larger city: $c > c', \sigma > \sigma' \Rightarrow \frac{f(\sigma, c)}{f(\sigma', c)} \geq \frac{f(\sigma, c')}{f(\sigma', c')}$
 - “Bin” together cities ordered by size and compare bins similarly

Data: Skills

- Proxy skills by educational attainment, assuming $f(edu, \omega, c)$ is log-supermodular in edu and ω (Costinot and Vogel 2010)
- Following Acemoglu and Autor (2011), we use a minimum of three skill groups.

Skill (3 groups)	Population share	Percent US-born	Skill (9 groups)	Population share	Percent US-born
High school or less	.35	.77	Less than high school	.03	.21
			High school dropout	.07	.69
			High school graduate	.24	.87
Some college	.32	.88	College dropout	.24	.89
			Associate's degree	.08	.87
Bachelor's or more	.33	.85	Bachelor's degree	.21	.86
			Master's degree	.08	.83
			Professional degree	.03	.81
			Doctoral degree	.01	.69

Population shares and percentage US-born are percentages of full-time, full-year prime-age workers.

Source: Census 2000 microdata via IPUMS-USA

Data: Sectors

- 21 manufacturing industries (3-digit NAICS, 2000 County Business Patterns)
- 22 occupations (2-digit SOC, 2000 BLS Occupational Employment Statistics)
- Infer sectors' skill intensities from average years of schooling of workers employed in them

Occupational category	Skill intensity	Manufacturing industry	Skill intensity
Farming, Fishing, and Forestry	9.3	Apparel	10.7
Building & Grounds Cleaning & Maintenance	10.9	Textile Product Mills	11.4
Food Preparation and Serving	11.4	Leather and Allied Product	11.7
Construction and Extraction	11.5	Textile Mills	11.7
Production	11.6	Furniture and Related Products	11.7
Healthcare Practitioners and Technical	15.6	Beverage and Tobacco Products	13.1
Community and Social Services	15.8	Transportation Equipment	13.2
Education, Training, and Library	16.5	Petroleum and Coal Products	13.5
Life, Physical, and Social Science	17.1	Computer & Electronic Products	14.1
Legal	17.3	Chemical	14.1

Data source: Census 2000 microdata via IPUMS-USA

Empirical results

Elasticities tests

Three skill groups

Table: Population elasticities of educational groups

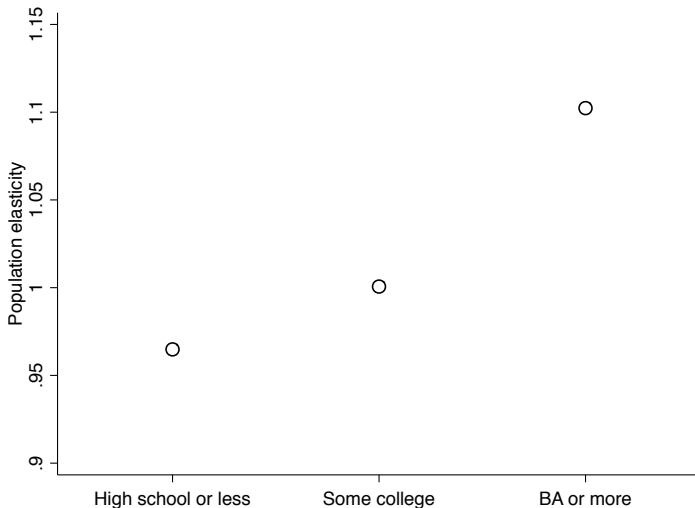
Dep var: $\ln f(\omega, c)$	All	US-born
β_{ω_1} HS or less	0.96	0.90
× log population	(0.011)	(0.016)
β_{ω_2} Some college	1.00	0.97
× log population	(0.010)	(0.012)
β_{ω_3} BA or more	1.10	1.07
× log population	(0.015)	(0.017)

Standard errors, clustered by MSA, in parentheses.

Sample is all full-time, full-year employees residing in metropolitan areas.

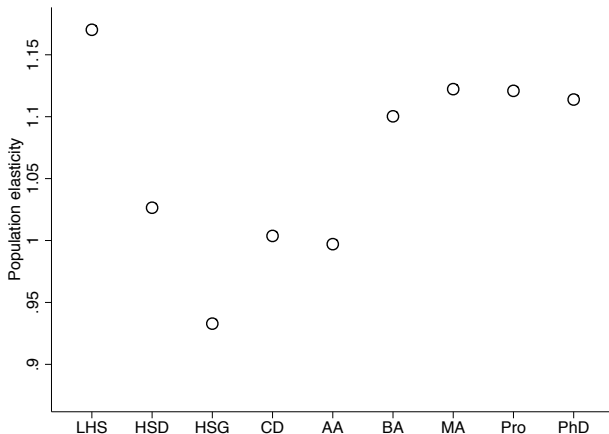
Three skill groups

Figure: Population elasticities of educational groups



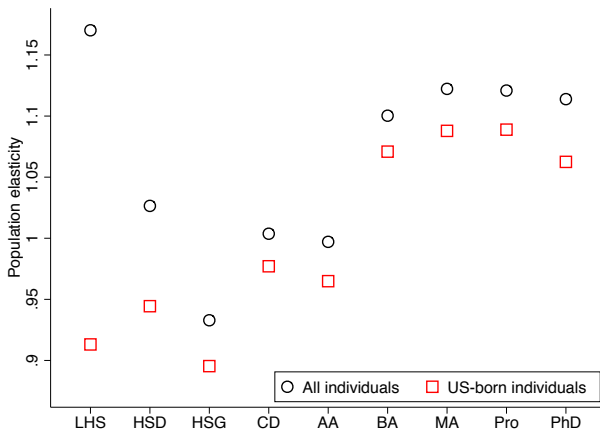
Nine skill groups

Figure: Population elasticities of educational groups



Nine skill groups

Figure: Population elasticities of educational groups



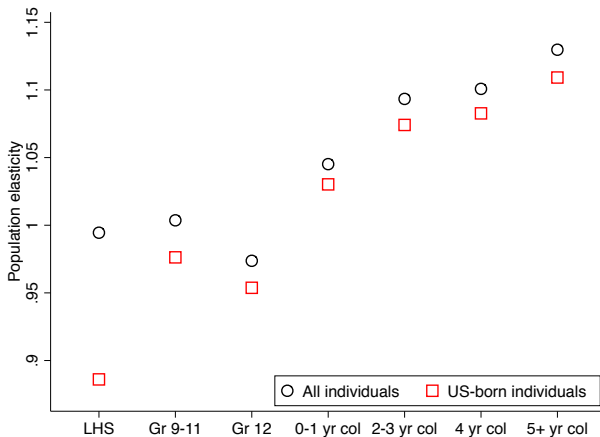
Cities, skills, and birthplaces

Why the difference between skill distribution of population as a whole and US-born individuals?

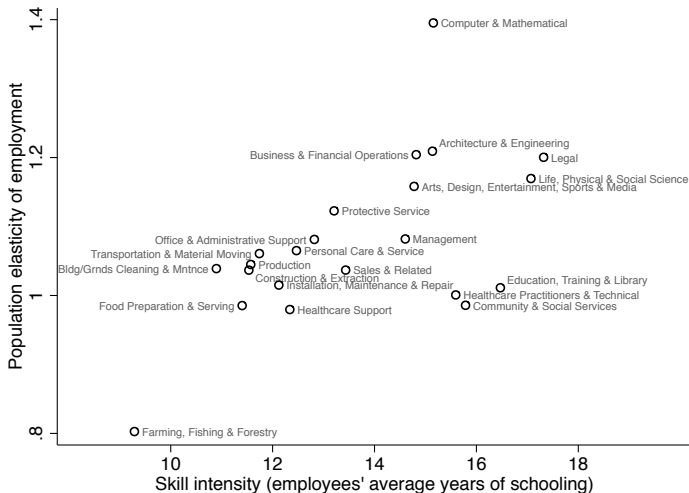
- One possibility: Extreme-skill complementarity (Eeckhout, Pinheiro, and Schmidheiny, 2014)
- Another possibility: Ethnic enclaves
- In 1980 foreign-born were 6% of US population; in 2000, 11%
- In 1980 foreign-born were 32% of lowest skill group; in 2000, they were 79%

Spatial distribution of skills in 1980

Figure: Population elasticities of educational groups, 1980

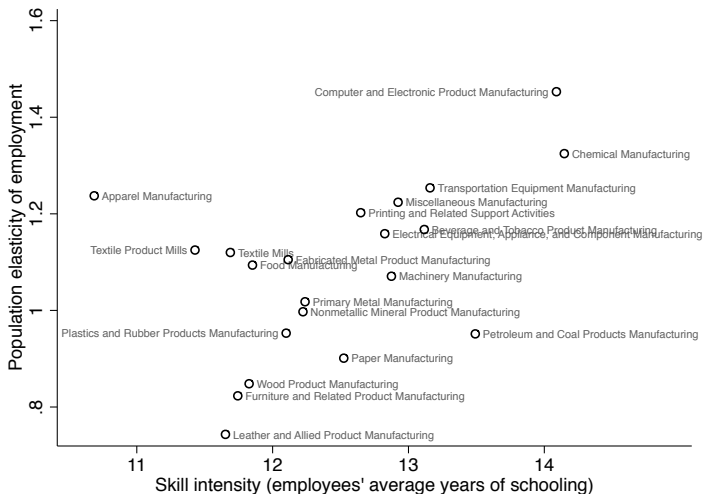


Occupations' elasticities and skill intensities



231 elasticity comparisons yield 80% success rate [▶ Table](#)

Industry population elasticities and skill intensities



210 elasticity comparisons yield 87% success rate [Table](#)

Pairwise comparisons tests

Pairwise comparisons test

If $f(\nu, c)$ is log-supermodular, where $\nu = \omega$ or $\nu = \sigma$,

- $c > c', \nu > \nu' \Rightarrow \ln f(\nu, c) + \ln f(\nu', c') \geq \ln f(\nu', c) + \ln f(\nu, c')$
- if \mathcal{C} and \mathcal{C}' are distinct sets and $\mathcal{C} \geq_s \mathcal{C}'$, then $\forall \nu > \nu'$

$$\sum_{c \in \mathcal{C}} \ln f(\nu, c) + \sum_{c' \in \mathcal{C}'} \ln f(\nu', c') \geq \sum_{c \in \mathcal{C}} \ln f(\nu', c) + \sum_{c' \in \mathcal{C}'} \ln f(\nu, c')$$

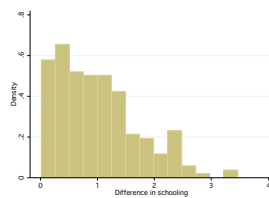
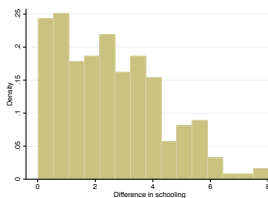
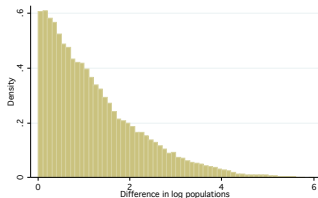
Example: Chicago > Kalamazoo; Bachelor's degree > HS graduate

- $c > c', \omega > \omega' \Rightarrow \frac{f(\omega, c)}{f(\omega', c)} \geq \frac{f(\omega, c')}{f(\omega', c')}$
- $\frac{f(BA, Chicago)}{f(HSG, Chicago)} = \frac{642,776}{611,054} > \frac{24,178}{36,425} = \frac{f(BA, Kalamazoo)}{f(HSG, Kalamazoo)}$ is true

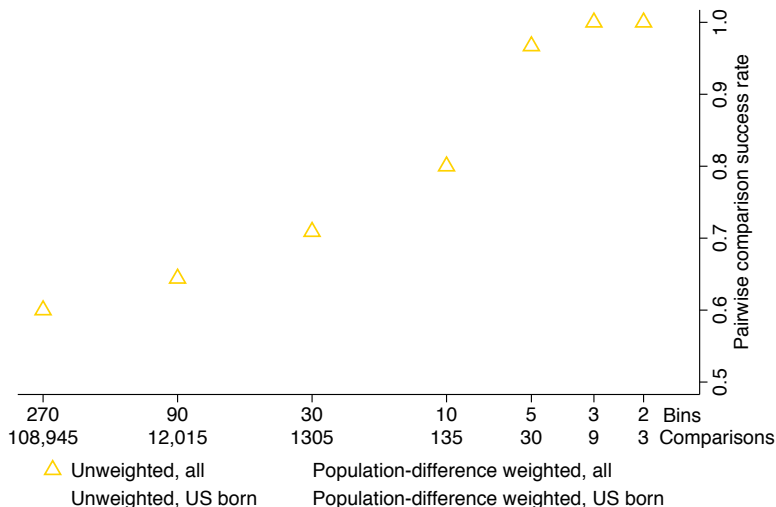
If there are n (bins of) cities and m skills/sectors, there are $\frac{n(n-1)}{2} \times \frac{m(m-1)}{2}$ pairwise comparisons.

Pairwise weights

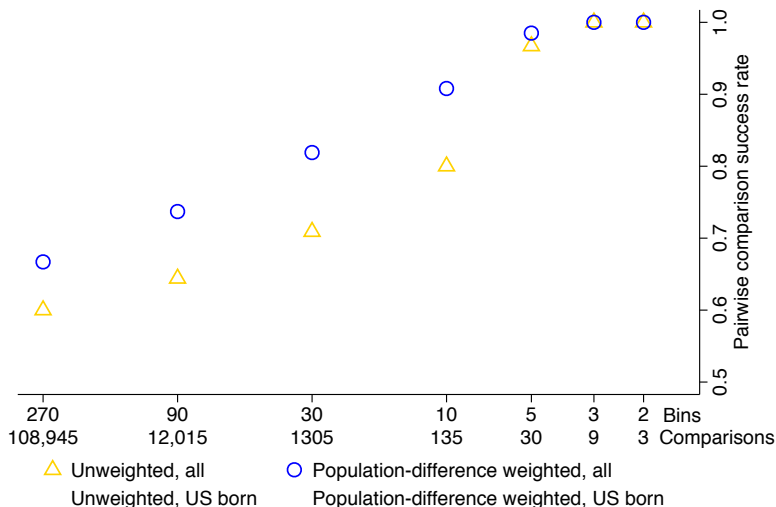
- With idiosyncratic errors, comparisons of cities of similar size and sectors of similar skill intensity are less informative
- Comparing Chicago (population 9 million) to Des Moines (population 456 thousand) is much more informative about the relevance of our theory than Des Moines vs Kalamazoo (population 453 thousand)
- In addition to simple success rate, we also report a weighted average of the success rate, weighting by differences in cities' log populations and differences in skill intensities



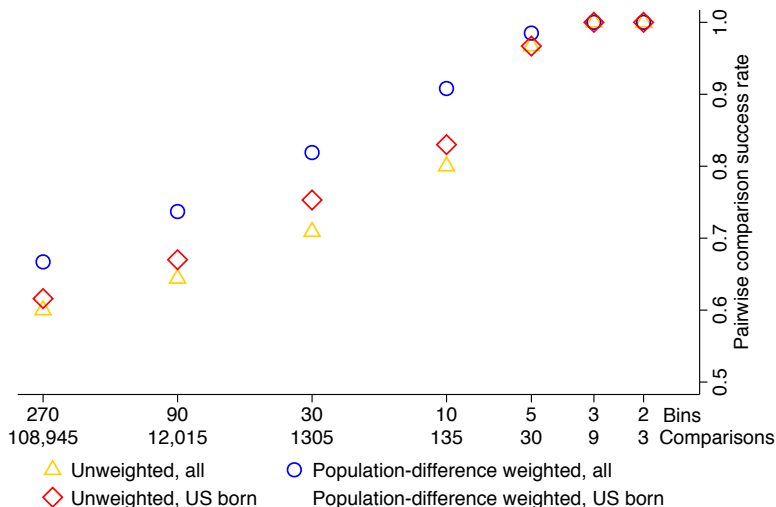
Pairwise comparisons: Three skill groups



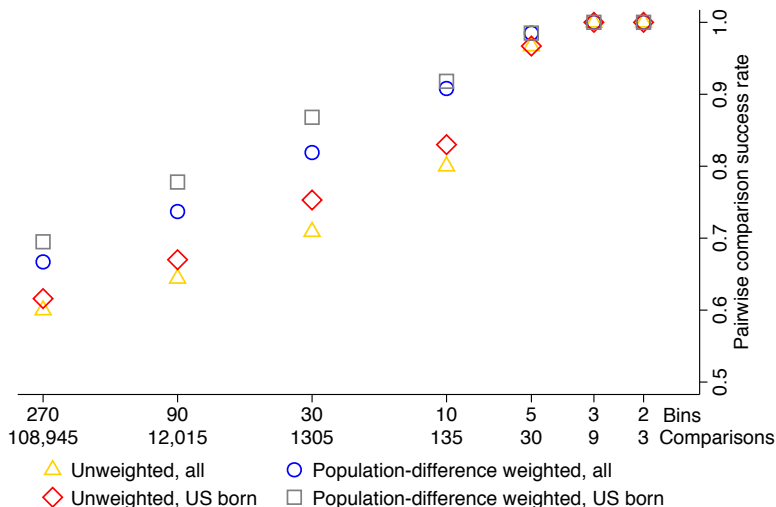
Pairwise comparisons: Three skill groups



Pairwise comparisons: Three skill groups

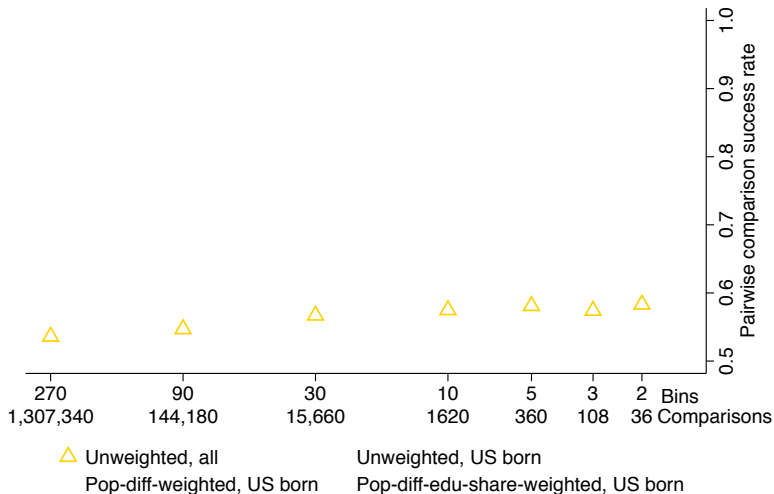


Pairwise comparisons: Three skill groups

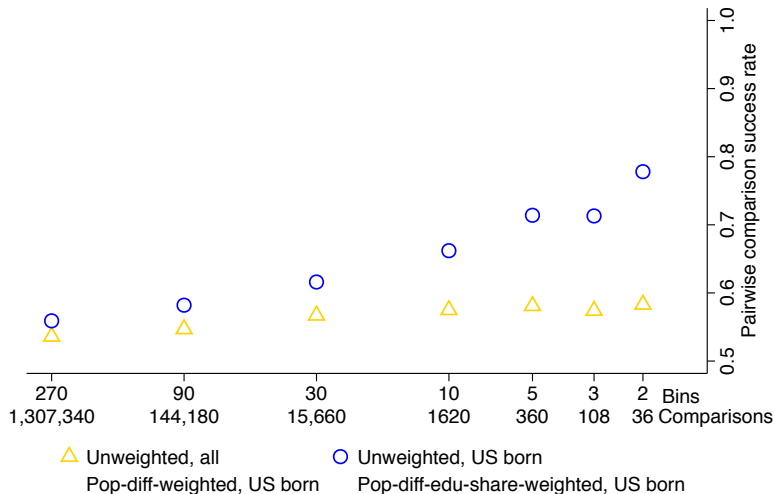


► Table

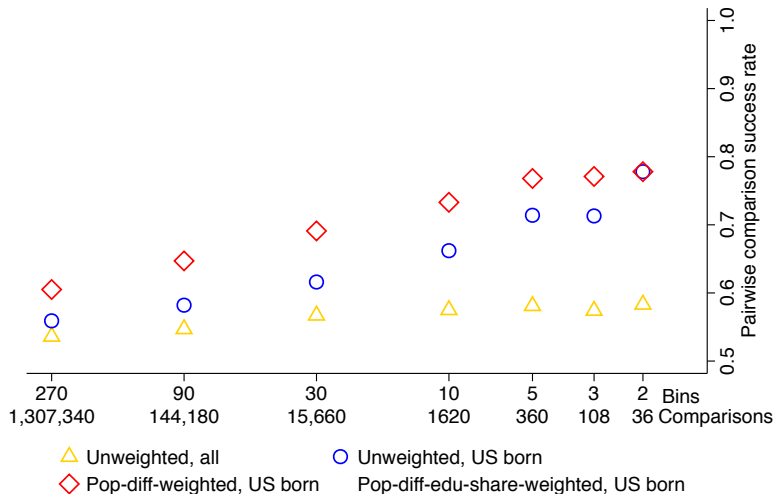
Pairwise comparisons: Nine skill groups



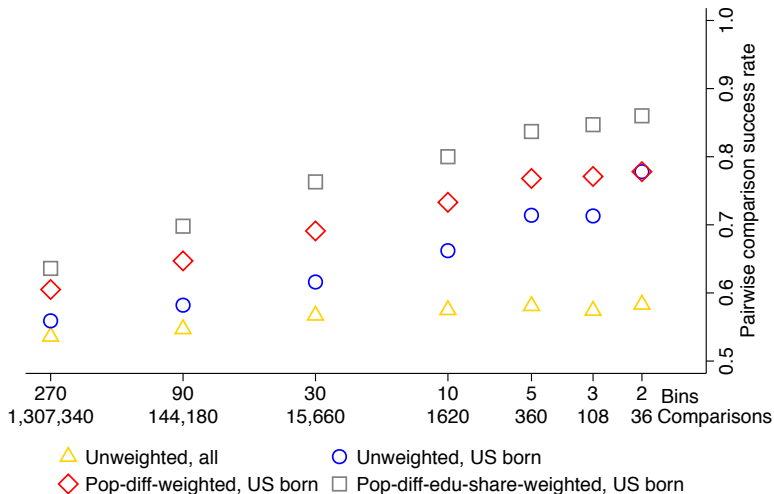
Pairwise comparisons: Nine skill groups



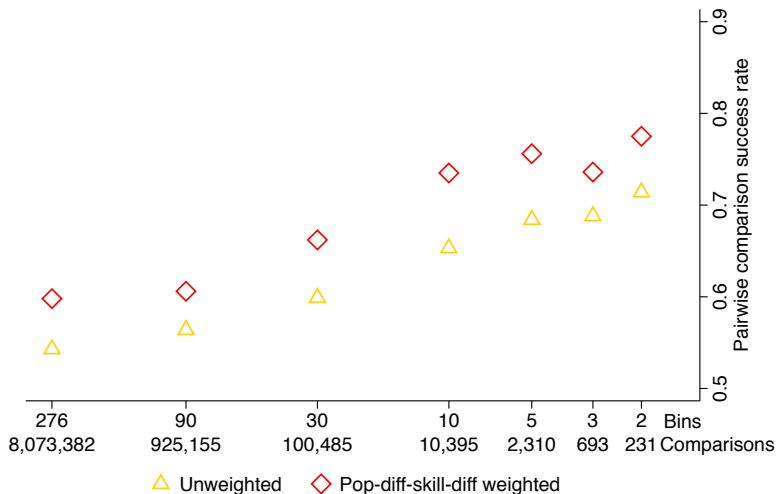
Pairwise comparisons: Nine skill groups



Pairwise comparisons: Nine skill groups

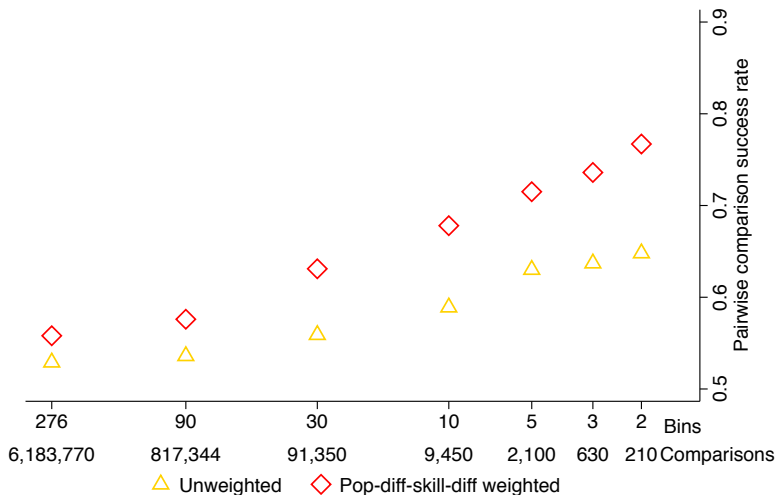


Pairwise comparisons: 22 occupations



► Table

Pairwise comparisons: 21 manufacturing industries



► Table

Larger cities are larger in all skills and sectors

- Larger cities are more populous in all educational attainment categories and employ more people in all sectors
- Every estimated population elasticity is strongly positive
- For manufacturing industries, the prediction that $c > c' \Rightarrow f(\sigma, c) \geq f(\sigma, c')$ is true in 77% of 796,950 cases
- 16 industries attain maximal size in NYC, LA, or Chicago
- Only industry outside top ten is textile mills (maximal in #52 Greenville-Spartanburg-Anderson)
- For occupations, $c > c' \Rightarrow f(\sigma, c) \geq f(\sigma, c')$ true for 88%
- 19 of the 22 occupations attain their maximal size in NYC

Conclusions

Conclusions: Theory

- Urban
 - Extends systems-of-cities approach to incorporate substantive locational heterogeneity within cities
 - Predicts that cities are neither completely specialized nor completely diversified
 - Predicts the pattern of economic activity based on observable characteristics of cities and sectors
- Trade
 - Integrate endogenous spatial distribution of skills with high-dimensional theory of comparative advantage
 - At equilibrium, economy exhibits properties of Costinot (2009) F-economy
 - Links ordering of locations by skills to city size
- Predict distributions of skills and sectors across cities are log-supermodular
- Derive empirically implementable tests of the theory

Conclusions: Empirics

- More disaggregated examination of distributions of skills and sectoral employment across cities than existing literature
- Provide evidence that LSM a good description of skills and cities
 - Theory-consistent elasticities in 35/36 comparisons with nine US-born skill groups
 - Stronger than simple correlation of city size and college share
 - 1980 data contra EPS's "extreme skill complementarity"
- Provide evidence that LSM plays a substantive role in cross-city distributions of sectoral employment
 - Theory-consistent elasticities in more than 80% of comparisons for both occupations and manufacturing industries

Thank you

Consumption interpretation

$$q(c, \tau, \sigma; \omega) = A(c)H(\omega, \sigma)$$

$$U(c, \tau, \sigma; \omega) = T(\tau) [A(c)H(\omega, \sigma)p(\sigma) - r(c, \tau)]$$

- Lower- τ locations complement consumption of the final good
- Higher-income individuals more willing to pay for more attractive location
- This consumption interpretation changes the expression for equilibrium rental prices
- This interpretation does not change the two propositions describing cities' sizes, skills, and sectors

Equilibrium (1/2)

- Denote the quantity of individuals of skill ω residing in city c at location τ and working in sector σ by $L \times f(\omega, c, \tau, \sigma)$.
- **Individuals maximize utilities** by choices of city, location, and sector

$$f(\omega, c, \tau, \sigma) > 0 \iff \{c, \tau, \sigma\} \in \arg \max U(c, \tau, \sigma; \omega) \quad (1)$$

- Final-good producers **maximize profits** by demanding

$$Q(\sigma) = I \left(\frac{p(\sigma)}{B(\sigma)} \right)^{-\epsilon} \quad (2)$$

- Absentee landlords **maximize profits** in Bertrand competition so that unoccupied locations have rental prices of zero

$$r(c, \tau) \times \left(S'(\tau) - L \int_{\sigma \in \Sigma} \int_{\omega \in \Omega} f(\omega, c, \tau, \sigma) d\omega d\sigma \right) = 0 \quad \forall c \quad \forall \tau \quad (3)$$

Equilibrium (2/2)

Agglomeration occurs and markets clear:

$$S'(\tau) \geq L \int_{\omega \in \Omega} \int_{\sigma \in \Sigma} f(\omega, c, \tau, \sigma) d\sigma d\omega \quad \forall c \quad \forall \tau \quad (4)$$

$$Q(\sigma) = L \sum_{c \in \mathbb{C}} \int_{\omega \in \Omega} \int_{\tau \in \mathcal{T}} q(c, \tau, \sigma; \omega) f(\omega, c, \tau, \sigma) d\omega d\tau \quad \forall \sigma \quad (5)$$

$$f(\omega) = \sum_{c \in \mathbb{C}} f(\omega, c) = \sum_{c \in \mathbb{C}} \int_{\sigma \in \Sigma} \int_{\tau \in \mathcal{T}} f(\omega, c, \tau, \sigma) d\tau d\sigma \quad \forall \omega \quad (6)$$

$$A(c) = J(L \int_{\omega \in \Omega} j(\omega) f(\omega, c) d\omega) \quad \forall c \quad (7)$$

A **competitive equilibrium** is a set of functions $Q : \Sigma \rightarrow \mathbb{R}^+$, $f : \Sigma \times \mathbb{C} \times \Delta \times \Omega \rightarrow \mathbb{R}^+$, $r : \mathbb{C} \times \Delta \rightarrow \mathbb{R}^+$, and $p : \Sigma \rightarrow \mathbb{R}^+$ such that conditions (1) through (7) hold.

Nine skill groups

Population share	Percent US-born	Dep var: $\ln f(\omega, c)$	Population elasticities	
			All	US-born
.03	.21	β_{ω_1} Less than high school × log population	1.17 (0.039)	0.91 (0.028)
.07	.69	β_{ω_2} High school dropout × log population	1.03 (0.017)	0.94 (0.020)
.24	.87	β_{ω_3} High school graduate × log population	0.93 (0.013)	0.90 (0.016)
.24	.89	β_{ω_4} College dropout × log population	1.00 (0.011)	0.98 (0.013)
.08	.87	β_{ω_5} Associate's degree × log population	1.00 (0.014)	0.96 (0.016)
.21	.86	β_{ω_6} Bachelor's degree × log population	1.10 (0.015)	1.07 (0.017)
.08	.83	β_{ω_7} Master's degree × log population	1.12 (0.018)	1.09 (0.019)
.03	.81	β_{ω_8} Professional degree × log population	1.12 (0.018)	1.09 (0.019)
.01	.69	β_{ω_9} PhD × log population	1.11 (0.035)	1.06 (0.033)

For US-born, only reject $\beta_{\omega} \geq \beta_{\omega'} \iff \omega \geq \omega'$ in $\beta_{\omega_3} < \beta_{\omega_2}$ comparison.

Spatial distribution of skills in 1980

Population share	Percent US-born	Dep var: $\ln f(\omega, c)$	Population elasticities	
			All	US-born
.06	.67	β_{ω_1} Less than grade 9 × log population	0.99 (0.028)	0.89 (0.030)
.11	.91	β_{ω_2} Grades 9-11 × log population	1.00 (0.019)	0.98 (0.021)
.33	.94	β_{ω_3} Grade 12 × log population	0.97 (0.013)	0.95 (0.015)
.08	.94	β_{ω_4} 1 year college × log population	1.04 (0.018)	1.03 (0.018)
.13	.92	β_{ω_5} 2-3 years college × log population	1.09 (0.018)	1.07 (0.018)
.13	.92	β_{ω_6} 4 years college × log population	1.10 (0.018)	1.08 (0.018)
.13	.90	β_{ω_7} 5+ years college × log population	1.13 (0.022)	1.11 (0.022)

Standard errors, clustered by MSA, in parentheses

Sample is all full-time, full-year employees residing in 253 metropolitan areas.

Occupations' population elasticities

β_{σ_1} Farming, Fishing, and Forestry Occupations	0.803	$\beta_{\sigma_{12}}$ Sales and Related Occupations	1.037
× log population	(0.048)	× log population	(0.010)
β_{σ_2} Building and Grounds Cleaning and Maintenance Occupations	1.039	$\beta_{\sigma_{13}}$ Management occupations	1.082
× log population	(0.011)	× log population	(0.015)
β_{σ_3} Food Preparation and Serving Occupations	0.985	$\beta_{\sigma_{14}}$ Arts, Design, Entertainment, Sports, and Media Occupations	1.158
× log population	(0.011)	× log population	(0.019)
β_{σ_4} Construction and Extraction Occupations	1.037	$\beta_{\sigma_{15}}$ Business and Financial Operations Occupations	1.204
× log population	(0.014)	× log population	(0.018)
β_{σ_5} Production Occupations	1.045	$\beta_{\sigma_{16}}$ Architecture and Engineering Occupations	1.209
× log population	(0.025)	× log population	(0.026)
β_{σ_6} Transportation and Material Moving Occupations	1.061	$\beta_{\sigma_{17}}$ Computer and Mathematical Occupations	1.395
× log population	(0.014)	× log population	(0.034)
β_{σ_7} Installation, Maintenance, and Repair Workers	1.015	$\beta_{\sigma_{18}}$ Healthcare Practitioners and Technical Occupations	1.001
× log population	(0.011)	× log population	(0.014)
β_{σ_8} Healthcare Support Occupations	0.980	$\beta_{\sigma_{19}}$ Community and Social Services Occupations	0.986
× log population	(0.013)	× log population	(0.020)
β_{σ_9} Personal Care and Service Occupations	1.065	$\beta_{\sigma_{20}}$ Education, Training, and Library Occupations	1.011
× log population	(0.017)	× log population	(0.017)
$\beta_{\sigma_{10}}$ Office and Administrative Support Occupations	1.081	$\beta_{\sigma_{21}}$ Life, Physical, and Social Science Occupations	1.170
× log population	(0.010)	× log population	(0.030)
$\beta_{\sigma_{11}}$ Protective Service Occupations	1.123	$\beta_{\sigma_{22}}$ Legal Occupations	1.200
× log population	(0.014)	× log population	(0.022)
Observations	5943	Observations	5943
R-squared	0.931	R-squared	0.931
Occupation FE	Yes	Occupation FE	Yes

Standard errors, clustered by MSA, in parentheses

Industries' population elasticities

β_{σ_1} Apparel Manufacturing	1.237	1.024	$\beta_{\sigma_{11}}$ Nonmetallic Mineral Product Manufacturing	1.018	0.955
× log population	(0.070)	(0.148)	× log population	(0.036)	(0.042)
β_{σ_2} Textile Product Mills	1.125	0.905	$\beta_{\sigma_{12}}$ Paper Manufacturing	0.901	0.539
× log population	(0.056)	(0.135)	× log population	(0.063)	(0.104)
β_{σ_3} Leather and Allied Product Manufacturing	0.743	0.147	$\beta_{\sigma_{13}}$ Printing and Related Support Activities	1.202	1.122
× log population	(0.099)	(0.284)	× log population	(0.036)	(0.047)
β_{σ_4} Furniture and Related Product Manufacturing	1.120	1.000	$\beta_{\sigma_{14}}$ Electrical Equipment, Appliance & Component	1.159	0.813
× log population	(0.050)	(0.076)	× log population	(0.074)	(0.111)
β_{σ_5} Textile Mills	0.823	0.352	$\beta_{\sigma_{15}}$ Machinery Manufacturing	1.071	0.960
× log population	(0.105)	(0.208)	× log population	(0.055)	(0.069)
β_{σ_6} Wood Product Manufacturing	0.848	0.608	$\beta_{\sigma_{16}}$ Miscellaneous Manufacturing	1.224	1.208
× log population	(0.055)	(0.085)	× log population	(0.044)	(0.059)
β_{σ_7} Fabricated Metal Product Manufacturing	1.094	1.036	$\beta_{\sigma_{17}}$ Beverage and Tobacco Product Manufacturing	1.168	1.010
× log population	(0.048)	(0.050)	× log population	(0.065)	(0.147)
β_{σ_8} Food Manufacturing	0.953	0.864	$\beta_{\sigma_{18}}$ Transportation Equipment Manufacturing	1.254	0.940
× log population	(0.050)	(0.067)	× log population	(0.075)	(0.101)
β_{σ_9} Plastics and Rubber Products Manufacturing	1.105	0.975	$\beta_{\sigma_{19}}$ Petroleum and Coal Products Manufacturing	0.951	0.393
× log population	(0.056)	(0.070)	× log population	(0.074)	(0.308)
$\beta_{\sigma_{10}}$ Primary Metal Manufacturing	0.997	0.449	$\beta_{\sigma_{20}}$ Computer and Electronic Product Manufacturing	1.453	1.254
× log population	(0.078)	(0.107)	× log population	(0.075)	(0.108)
			$\beta_{\sigma_{21}}$ Chemical Manufacturing	1.325	0.992
			× log population	(0.065)	(0.098)
Observations	5406	2130	Observations	5406	2130
R-squared	0.564	0.541	R-squared	0.564	0.541
Industry FE	Yes	Yes	Industry FE	Yes	Yes
Only uncensored obs		Yes	Only uncensored obs		Yes
Standard errors, clustered by MSA, in parentheses					

Pairwise comparisons: 3 skill groups

Bins	Birthplace	Weights	College vs some college	College vs HS or less	Some college vs HS or less	Total comparisons	Average
2	All	Unweighted	1	1	1	3	1
2	All	Population difference	1	1	1	3	1
2	US-born	Unweighted	1	1	1	3	1
2	US-born	Population difference	1	1	1	3	1
3	All	Unweighted	1	1	1	9	1
3	All	Population difference	1	1	1	9	1
3	US-born	Unweighted	1	1	1	9	1
3	US-born	Population difference	1	1	1	9	1
5	All	Unweighted	1	1	.900	30	.967
5	All	Population difference	1	1	.955	30	.985
5	US-born	Unweighted	1	1	.900	30	.967
5	US-born	Population difference	1	1	.955	30	.985
10	All	Unweighted	.844	.844	.711	135	.800
10	All	Population difference	.927	.944	.852	135	.908
10	US-born	Unweighted	.844	.889	.756	135	.830
10	US-born	Population difference	.927	.956	.870	135	.918
30	All	Unweighted	.768	.726	.632	1305	.709
30	All	Population difference	.887	.853	.716	1305	.819
30	US-born	Unweighted	.782	.784	.694	1305	.753
30	US-born	Population difference	.893	.898	.812	1305	.868
90	All	Unweighted	.684	.667	.58	12,015	.644
90	All	Population difference	.804	.779	.627	12,015	.737
90	US-born	Unweighted	.679	.693	.639	12,015	.670
90	US-born	Population difference	.799	.809	.727	12,015	.778
270	All	Unweighted	.629	.616	.556	108,945	.600
270	All	Population difference	.717	.695	.588	108,945	.667
270	US-born	Unweighted	.624	.635	.589	108,945	.616
270	US-born	Population difference	.712	.726	.647	108,945	.695

Pairwise comparisons: 9 skill groups

Table: Pairwise comparisons of nine skill groups with one city per bin

Unweighted comparisons									
		LHS	HSD	HS	CD	AA	BA	MA	Pro
2	HSD	.423							
3	HS	.399	.413						
4	CD	.428	.486	.587					
5	AA	.43	.483	.571	.483				
6	BA	.476	.555	.644	.619	.602			
7	MA	.484	.558	.643	.614	.615	.528		
8	Pro	.484	.57	.645	.617	.604	.524	.499	
9	PhD	.49	.548	.598	.576	.577	.521	.501	.511
Pop-diff weighted comparisons of US-born population									
		LHS	HSD	HS	CD	AA	BA	MA	Pro
2	HSD	.568							
3	HS	.488	.435						
4	CD	.583	.569	.649					
5	AA	.552	.53	.616	.453				
6	BA	.644	.65	.738	.695	.682			
7	MA	.648	.651	.738	.686	.695	.544		
8	Pro	.654	.654	.73	.676	.676	.533	.493	
9	PhD	.611	.605	.651	.605	.617	.502	.476	.497

Pairwise comparisons: 22 occupations

Bins	Weights	Comparisons	Success rate
2	Unweighted	231	.714
2	Population difference	231	.714
2	Population difference \times skill difference	231	.775
3	Unweighted	693	.688
3	Population difference	693	.694
3	Population difference \times skill difference	693	.736
5	Unweighted	2,310	.684
5	Population difference	2,310	.71
5	Population difference \times skill difference	2,310	.756
10	Unweighted	10,395	.653
10	Population difference	10,395	.689
10	Population difference \times skill difference	10,395	.735
30	Unweighted	100,485	.599
30	Population difference	100,485	.628
30	Population difference \times skill difference	100,485	.662
90	Unweighted	925,155	.564
90	Population difference	925,155	.582
90	Population difference \times skill difference	925,155	.606
276	Unweighted	8,073,382	.543
276	Population difference	8,073,382	.571
276	Population difference \times skill difference	8,073,382	.598

Pairwise comparisons: 21 manufacturing industries

Bins	Weights	Comparisons	Success rate
2	Unweighted	210	.648
2	Population difference	210	.648
2	Population difference \times skill difference	210	.767
3	Unweighted	630	.637
3	Population difference	630	.64
3	Population difference \times skill difference	630	.736
5	Unweighted	2100	.63
5	Population difference	2100	.629
5	Population difference \times skill difference	2100	.715
10	Unweighted	9450	.589
10	Population difference	9450	.604
10	Population difference \times skill difference	9450	.678
30	Unweighted	91,350	.559
30	Population difference	91,350	.577
30	Population difference \times skill difference	91,350	.631
90	Unweighted	817,344	.536
90	Population difference	817,344	.545
90	Population difference \times skill difference	817,344	.576
276	Unweighted	6,183,770	.529
276	Population difference	6,183,770	.538
276	Population difference \times skill difference	6,183,770	.558