# Geographic Fragmentation in a Knowledge Economy: Theory and Evidence from the US

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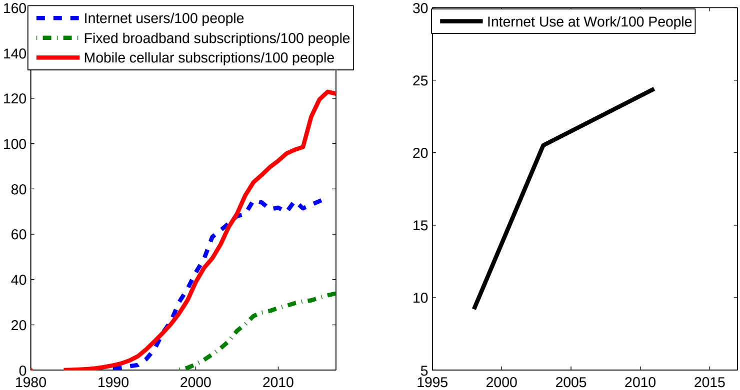
# Motivation

- Revolutionary development in ICT, e.g., Internet technology
- In the United States




Data Source: the WDI data in the left panel; authors' calculation from Current Population Survey Internet and Computer Use Supplement in the right panel

# Motivation

- Profound impacts on the labor market: geographic fragmentation, e.g., sourcing, headquarter-subsidiary relation
- Increasingly fragmented production process across geographic boundaries:
  - internationally: a huge literature (e.g., Hummels, Ishii and Yi, 2001; Antras, Garicano & Rossi-Hansberg, 2006; Grossman & Rossi-Hansberg, 2008; ...)
  - domestically: underexplored
    - ⋆ focus of this paper
- Domestic fragmentation:
  - Quantitatively important: e.g., 95% of sourcing done domestically (BCG survey, 2015)
  - Labor **mobile** across regions
    - ⋆ Spatial movement of economic activities $\Longrightarrow$ Inter-regional redistribution of skills
- Research question:

How the rise in *cross-region productions*, driven by internet improvement, shapes the distribution of skills across US cities and welfare?

# Preview of Results

- Stylized facts:
  - Spatial skill segregation: skilled workers $\uparrow$ disproportionally more in larger cities
  - Industries tend to **fragment** more see larger increases in spatial **skill segregation**
- A spatial eqm model of production fragmentation + heterogeneous agent
  - knowledge (skilled) + standardized production (unskilled)
  - $\downarrow$ communications costs: $\uparrow$ cross-city joint production, $\uparrow$ skilled share in larger cities; and $\downarrow$ skilled share in smaller cities
- Empirical support for model predictions on Internet improvement and skill flows
- Quantitatively evaluate the importance of proposed mechanism

# Related Literature

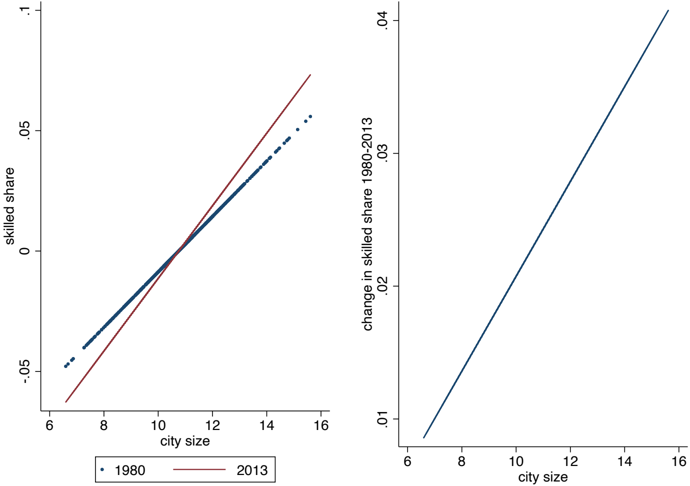
- International offshoring: Feenstra (1998); Hummels, Ishiii & Yi (2001); Antras, Garicano & Rossi-Hansberg (2006); Grossman & Rossi-Hansberg (2008)
- Domestic production fragmentation: Duranton & Puga (2005); Liao (2012); Santamaria (2018); Eckert (2019); Acosta (2020); Hsieh & Rossi-Hansberg (2020)
- Spatial equilibrium model in a system-of-cities: Behrens, Duranton & Robert-Nicoud (2014); Davis & Dingel (2012, 2019)
- Quantitative spatial equilibrium analysis: Allen & Arkolakis (2014); Allen, Arkolakis & Takahashi (2014)
- Impact of ICT technology on production organizations: Fort (2017); Tian (2019)

# Stylized Facts

# Data and Definitions

- Census Integrated Public Use Micro Samples (IPUMS):
  - 1980: 5 percent census; 2011-2013 three-year ACS: 3 percent sample
  - Individuals between age 16 and 64
- Local labor markets: 722 commuting zones
- City sizes: total labor supply (robust if population)
- Two skill groups (occupation based): high (mean wage rank above 75%); low (others)
  - robust to other thresholds: 80% or 67%
  - robust to education: COL+

# Skilled Empl Share & City Size




Notes: the left panel displays the regression line for the high skilled share (demeaned) in 1980 and 2013 against city size (log of 1980 population) . The right panel displays the change in the skilled share from 1980 to 2013.

# Change in Skilled Empl Share and City Size: 1980-2013

| Dependent variable: change in the skilled share | (1) | (2) |
|---|---|---|
| City Size | $0.004^{***}$ | $0.005^{***}$ |
| | (0.001) | (0.001) |
| State fixed effect | No | Yes |
| Observations | 722 | 722 |
| $R^2$ | 0.037 | 0.357 |

$* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, ***1%.

- Larger cities become increasingly specialized in skill-intensive activities

# Spatial Skill Segregation: 1980 - 2013

- Kremer & Maskin (1996) segregation index

$$\rho = \frac{1}{S}\sum_{s}\left[\frac{\sum_{c} N_{cs}\cdot(\pi_{cs}-\pi_{s})^{2}}{N_{s}\cdot\pi_{s}\cdot(1-\pi_{s})}\right].$$

  where

  - $N_{cs}$: employment in sector $s$ and city $c$
  - $N_{s}$: total sectoral employment
  - $\pi_{cs}=\frac{N_{cs}^{skilled}}{N_{cs}}$: high skilled employment share in sector $s$ and city $c$
  - $\pi_{s}=\frac{N_{s}^{skilled}}{N_{s}}$: high skilled employment share in sector $s$

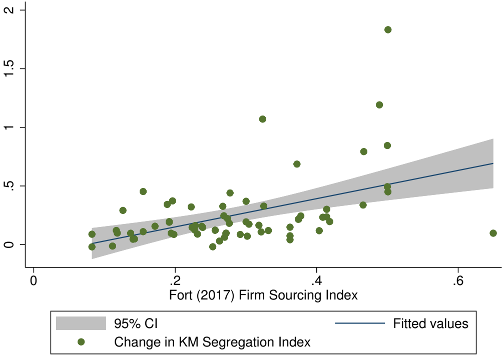
- Larger $\rho$: greater extent of segregation

- KM index more than tripled from 1980 - 2013

| Year | $\rho$ | 95% Confidence Interval |
|---|---|---|
| 1980 | 0.00746 | (0.00741, 0.00752) |
| 2013 | 0.0204 | (0.0202, 0.0205) |

# Production Fragmentation and Spatial Segregation

- Change in sector-level KM index and Fort (2017) sourcing index




Notes: each dot represents an NAICS4 industry. The correlation between change in KM skill segregation index and Fort sourcing index is 0.47.

- Industries that **source more** are also those that tend to undergo **greater skill segregation**

# Summary of Stylized Facts

- Three stylized facts:
  1. Larger cities have a comparative advantage in skill-intensive activities (Glaeser, 2008; Davis & Dingel, 2014)
  2. Pattern of specialization has become stronger, as skilled and unskilled workers become more segregated geographically
  3. Extent of segregation strongly associated with production fragmentation

- Central hypothesis
  - ICT (e.g., Internet technology) improvement reduces communication frictions:

$\Longrightarrow$ $\uparrow$ geographic fragmentation (cross-city joint productions)

$\Longrightarrow$ Reinforce initial patterns of specialization

$\Longrightarrow$ Spatial redistribution of skills

# Theory

# Set-up and Preferences

- Finite number of cities $n \in \mathcal{N}$, with exogenous housing supply $H_n$
- Continuum of agents, distinguished by their skill levels
  - $L^m$ skilled labor (called "managers")
  - $L^p$ unskilled labor (called "production workers")
- Agents inelastically supply labor, mobile across $n$
- Utility function:
$$U(x,h) = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}x^{\alpha}h^{1-\alpha},$$
  where
  - $x$: homogeneous good
  - $h$: housing

# Production

- Managers who live in city $n$ may hire workers in any city $c$ with:

$$y_{nc} = a_{nc} \cdot l_c^{\beta}, \;\; \beta < 1$$

- $a_{nc}$: manager's productivity

$$a_{nc} = f(L_n^m) \times \bar{a}_{nc}$$

  - $f(L_n^m) = (L_n^m)^{\gamma}$, $\gamma \geq 0$: agglomeration externalities in $n$.
  - $\bar{a}_{nc}$: a random draw
    - ⋆ Manager living in city $n$ draws $\bar{a}_{nc}$ for all $c \in \{1, \ldots, N\}$ cities

- $\bar{a}_{nc}$ follows Fréchet distribution

$$G(a) = \exp\left(-T_n a^{-\theta}\right)$$

  - $T_n$: exogenous technology parameter in $n$
  - $\theta > 0$: dispersion of manager's productivities across cities

# Manager's problem

- Income of a manager living in $n$, hiring workers in $c$:

$$\pi_{nc} = \frac{a_{nc}}{\tau_{nc}} l^{\beta} - w_c l = \beta^{\frac{\beta}{1-\beta}} (1-\beta) (\frac{a_{nc}}{\tau_{nc} w_c^{\beta}})^{\frac{1}{1-\beta}}$$

- $\tau_{nc} \geq 1$: "fragmentation" costs, e.g., cross-city communication, off-site coordination, search frictions...

- Given Fréchet productivity assumption, *fragmentation* gravity equation:

$$x_{nc} \equiv \frac{L_{nc}^m}{L_n^m} = \frac{T_n(\tau_{nc} w_c^{\beta})^{-\theta}}{\Phi_n},$$

  where $\Phi_n \equiv \sum_k T_n(\tau_{nk} w_k^{\beta})^{-\theta}$ ("fragmentation potential" of city $n$)

  - $x_{nc}$: share of managers in $n$ producing in $c$

- Expected income of a manager living in $n$:

$$E[\pi_n] = \zeta [[f(L_n^m)]^{\theta} \Phi_n]^{\frac{1}{\theta(1-\beta)}}$$

# Spatial Indifference Conditions

- In equilibrium, agents indifferent to living locations
- Production workers' indifference condition:

$$\frac{w_n}{p_n^{1-\alpha}} = \frac{w_{n'}}{p_{n'}^{1-\alpha}}, \quad \forall n, n'$$

- Managers' Indifference condition:

$$\frac{E[\pi_n]}{p_n^{1-\alpha}} = \frac{E[\pi_{n'}]}{p_n'^{1-\alpha}}, \quad \forall n, n'$$

# Equilibrium Properties

- WLOG, suppose $T_n > T_c$
- Internet Autarky: $\tau_{nc} = \infty$
  - Cities with higher $T_n$ are larger: more $L_n^m$ and $L_n^p$
  - Skilled share the same across cities
- Internet Openness: $\tau_{nc} < \infty$
  - $\tau_{nc} = \tau_{cn} \downarrow$ locally.
  - $L_n^m$ and $L_c^p \uparrow$; $L_c^m$ and $L_n^p \downarrow$
  - Skilled shares: $\uparrow$ in $n$; $\downarrow$ in $c$
  - Stronger agglomeration externality, $(L_n^m)^\gamma \implies$ Greater labor relocation for both managers and low-skilled workers

# Infinite Fragmentation Cost

- Set $f(L_n^m) = (L_n^m)^\gamma$ and assume $\gamma + 1 > \frac{\gamma}{1-\alpha}$, when $\tau_{nc} \to +\infty$, $\forall n \neq c$, the spatial equilibrium exists and is unique

- The number of managers in each city $L_n^m$ and the number of production workers in each city $L_n^p$

$$L_n^m \propto T_n^\kappa,$$

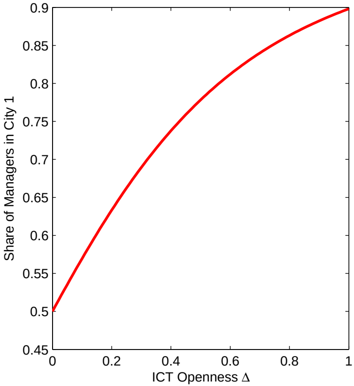
$$L_n^p \propto T_n^\kappa,$$

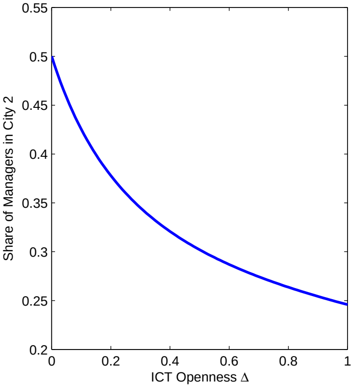
  where $\kappa = \frac{\frac{1}{1-\alpha} - 1}{1+\gamma-\frac{\gamma}{1-\alpha}} \frac{1}{\theta} > 0$

- Skilled share $L_n^m/(L_n^m + L_n^p)$ in each city the same across all cities

# Two-City Simulation: Skilled Shares

- Internet Openness $\triangle_{nc} = \tau_{nc}^{-\theta}$
  - $\triangle_{nc} \uparrow$
  - Suppose $T_1 > T_2$, then $L_1^m/(L_1^m + L_1^p) \uparrow$ and $L_2^m/(L_2^m + L_2^p) \downarrow$




Skill Premium | Welfare | Many City Simulation

# Heterogeneous effects of Internet

- Heterogeneous effects of Internet on city skill composition
  - Large city: $\uparrow$ share of skilled workers
  - Small city: $\downarrow$ share of skilled workers
- Empirical specification:

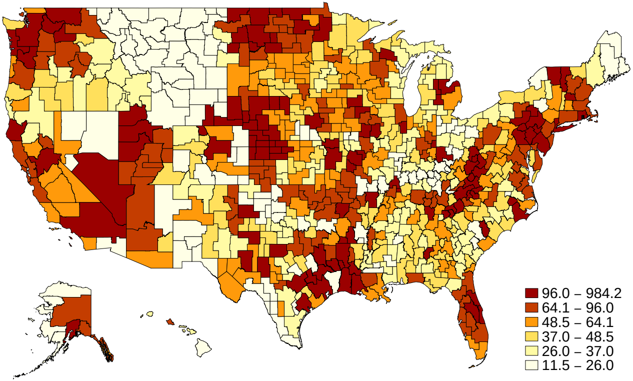
$$\Delta\text{skilled share}_i = \beta_0 + \beta_1\,\text{city size}_i + \beta_2\,\Delta\text{internet}_i + \beta_3\,\text{city size}_i * \Delta\text{internet}_i + \gamma \mathrm{X_i} + \epsilon_i$$

- $\mathrm{X_i}$:
  - State FEs
  - Telephone penetration rate in 1980
- $\beta_2 < 0$, $\beta_3 > 0$

# Empirical Support

# US Internet Infrastructure

- Data source: US Federal Communications Commission
- Block-level Internet download and upload bandwidths 2014
  - fixed broadband suppliers file Form 477 on maximum bandwidths
  - Population-weighted average CZ-level measures




Notes: Speeds are measured in Megabytes per second.

# Identification Challenges

$$\Delta \text{skilled share}_i = \beta_0 + \beta_1 \, \text{city size}_i + \beta_2 \, \Delta \text{internet}_i + \beta_3 \, \text{city size}_i * \Delta \text{internet}_i + \gamma \mathrm{X_i} + \epsilon_i$$

1. Long-run local employment trends
2. Unobserved local shocks affecting both internet quality and changes in skill share
3. Reverse causality: local labor demand shocks drive internet provision

# Identification Challenges

$$\Delta\text{skilled share}_i = \beta_0 + \beta_1\,\text{city size}_i + \beta_2\,\Delta\text{internet}_i + \beta_3\,\text{city size}_i * \Delta\text{internet}_i + \gamma \mathrm{X_i} + \epsilon_i$$

1. Long-run local employment trends
2. Unobserved local shocks affecting both internet quality and changes in skill share
   - (Large Cities) Omitted variable: + skilled share and + internet
   - (Small Cities) Omitted variable: − skilled share and + internet
3. Reverse causality: local labor demand shocks drive internet provision
   - (Large Cities) *Larger* skilled share $\implies$ internet improvement
   - (Small Cities) *Smaller* skilled share $\implies$ internet improvement

# Identification Strategies

- Falsification test to rule out long-run trends: replacing LHS by change in employment share between 1950 - 1980
- Instrumentation strategy to address OVB and reverse causality,
  - Instrument: **Average elevation of the local terrain** (Jaber, 2013; Amorim, Lima & Sampaio, 2015)
  - Higher elevation areas less costly for broadband infrastructure deployment and maintenance
  - e.g., proneness to flooding, summer temperature

More details Zero Stage

# Results

| Dependent variable: change in the share of high-skill employment | | | | | | |
|---|---|---|---|---|---|---|
| | 1980-2013 | | | 1950-1980 | | |
| | OLS | | 2SLS | OLS | | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Internet quality | -.023** | -.029** | -.138*** | -.005 | -.012 | -.013 |
| | (.009) | (.012) | (.034) | (.017) | (.020) | (.037) |
| Internet quality × city size | .0022** | .0028** | .0119*** | -0.000 | .001 | .001 |
| | (.0008) | (.0011) | (.003) | (.001) | (.001) | (.003) |
| State Fixed Effect | No | Yes | Yes | No | Yes | Yes |
| Observations | 722 | 722 | 722 | 722 | 722 | 722 |
| $R^2$ | .045 | .360 | .253 | .048 | .284 | -0.338 |
| S-W F-stats (First Stage) | | | | | | |
| Internet quality | | | 12.92 | | | 12.92 |
| Internet quality × city size | | | 11.15 | | | 11.15 |

Notes: City size is measured by log(population in 1980) and is always included as a control variable. Standard errors are in parentheses. Robust standard errors are used when there is no state fixed effect. Standard errors clustered at the state level when there is state fixed effect. We also report Sanderson-Windmeijer (S-W) F- statistics for the first stage regressions. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

# Dealing with "Exclusion Restriction"

- Concern:
  - Theory: Internet $\implies$ Production fragmentation $\implies$ Skill relocation
  - Empirics: Internet $\implies$ Skill relocation
- Some industries are more likely to fragment (Fort, 2017)
  - Cities with greater concentration of such industries would undergo greater extent of skill relocation
- Separate cities into two groups based on average fragmentation intensities

$$\sum_i \frac{\text{Sourcing Index}_i \times L_{ic}}{L_c}$$

- Repeat the IV regression separately for the two groups of cities
- Hypothesis: fragmentation-intensive cities would experience more skill relocation

# Results

| Dependent variable: change in share of high-skill employment | | | |
|---|---|---|---|
| | Baseline | Non-Fragment-Intensive | Fragment-Intensive |
| | (1) | (2) | (3) |
| Internet quality | -.138*** | -.102 | -.139* |
| | (.034) | (.062) | (.077) |
| Internet quality × city size | .0119*** | .0084 | .0122** |
| | (.0031) | (.0062) | (.0057) |
| State Fixed Effect | Yes | Yes | Yes |
| Observations | 722 | 361 | 361 |
| $R^2$ | .253 | .233 | .342 |
| S-W F-stats (First Stage) | | | |
| Internet quality | 12.92 | 11.02 | 18.09 |
| Internet quality × city size | 11.15 | 10.01 | 24.53 |

Notes: City size is measured by log(population in 1980) and is always included as a control variable. Standard errors are in parentheses. Robust standard errors are used when there is no state fixed effect. Standard errors clustered at the state level when there is state fixed effect. We also report Sanderson-Windmeijer (S-W) F- statistics for the first stage regressions. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

# Quantitative Analysis

# Model Extension

- Housing market (Ganong and Shoag, 2017; Giannone, 2019)

$$H_n = \bar{H}_n p_n^{\mu} \implies p_n = \left( \frac{(1-\alpha) W_n}{\bar{H}_n} \right)^{\frac{1}{\mu+1}}$$

- More extensions (in progress):
  - Endogenous amenity (Diamond, 2016)
    - ⋆ Differences in valuations of amenities between skill types

$$U_p = c^{\alpha} h^{1-\alpha}$$

$$U_m = c^{\alpha} h^{1-\alpha} A^{\zeta}$$

    - ⋆ Amenity supply

$$\log A_n = \kappa (\log L_n^m - \log L_n^p)$$

  - Skill-biased technical change

# Assigning Parameter Values

- Literature
  - Share of spending on housing: $(1 - \alpha) = 0.24$ (Davis & Ortalo-Magne, 2011; Behrens, Duranton & Robert-Nicoud, 2014)
  - Span of control: $\beta = 0.53$ (Buera & Shin, 2013)
  - Housing supply elasticity: $\mu = 0.135$ (Giannone, 2019)
- Strength of agglomeration $\gamma$: match elasticity of wage w.r.t. city size
- Dispersion of manager's productivity $\theta$: match high skilled hourly wage distribution
- Housing supply $\bar{H}_n$: match city-level wage and total income
- City technology $T_n$: match city-level differences on wage, size, and fragmentation potential $\Phi_n$

Skip to Counterfactual

# Bilateral Fragmentation Costs

- Semi-parametric form:

$$\log \tau_{nc} = \delta^d \log d_{nc} + \delta^I q_{nc} + \lambda_{nc}$$

  - Power functions of bilateral distance $d_{nc}$, and internet connectivity $q_{nc} = q_n \times q_c$
  - Other bilateral costs $\lambda_{nc}$

- Infer $\tau_{nc}$ from fragmentation gravity equation
  - Recall:

$$X_{nc} = L_n^m \frac{T_n \tau_{nc}^{-\theta} w_c^{-\beta\theta}}{\Phi_n}$$

  - Taking ratios, we get:

$$\tau_{nc} = \left( \frac{w_c^{\beta\theta} X_{nc}}{w_n^{\beta\theta} X_{nn}} \right)^{-1/\theta}$$

  - $X_{nc}$: number of subsidiaries in $c$ belonging to headquarters in $n$
    - ⋆ Obtained from Orbis Database More details Orbis database

# Elasticity Estimates

- Estimate

$$\log \tau_{nc} = \delta^d \log d_{nc} + \delta^I q_{nc} + \lambda_{nc}$$

using:

$$\log \tau_{nc} = \chi_n + \iota_c + \delta^d \log d_{nc} + \delta^I q_n q_c + \Theta \mathrm{H_{nc}} + \varepsilon_{nc}$$

where $\mathrm{H_{nc}}$:

  - Same state
  - Shared border
  - Racial affinity

| Estimates | OLS | PPML |
|---|---|---|
| $\hat{\delta}^d$ | .134*** | .231*** |
| | (.004) | (0.006) |
| $\hat{\delta}^I$ | -.010*** | -.010*** |
| | (.0027) | (.006) |
| City Fixed Effects | Yes | Yes |
| Controls | Yes | Yes |
| N | 44,203 | 505,008 |

Notes: Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, ***1%.

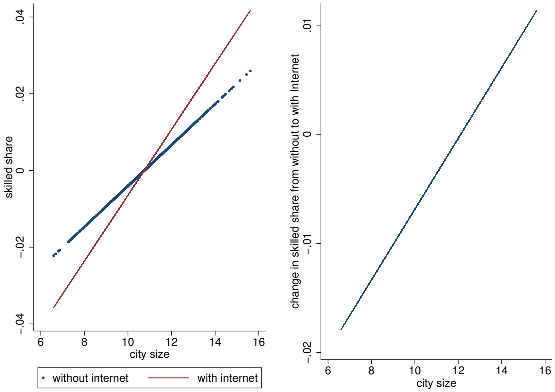
Internet and Trade in Goods | Calibration Results & Model Fit

# Role of the Internet in Skill Redistribution

- Assume no internet quality improvement between 1980 and 2013

$$\log \tilde{\tau}_{nc} = \log \tau_{nc} - \hat{\delta}^I q_{nc}$$

- Solve for counterfactual skilled share in each city.



# Skill Redistribution and Welfare

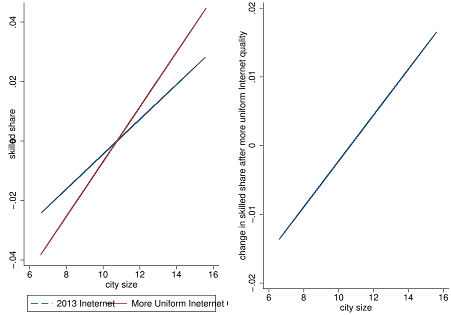
- Slope coefficient: $\triangle$ 0.0031**
  - Without internet, the observed skill redistribution in the US would have been reduced by about $0.00310/0.00503 = 61\%$
- Welfare effects
  - Unskilled: 3.88%
  - Skilled: 3.66%

| | $\Delta$ Managers' Welfare | $\Delta$ Workers' Welfare |
|---|---|---|
| Direct Effect | 2.93% | 2.89% |
| GE Effect | 0.95% | 0.77% |
| Total | 3.88% | 3.66% |

Table: Decomposition of Welfare Changes

# Narrowing the Digital Divide

- Policy experiment: programs improving internet quality in less connected places, e.g., Connect America Fund
    - Upgrade internet in cities with below-median level to the median level




- More spatial skill relocation: semi-elasticity of skill share wrt city size ↑ .0007
- Welfare implications: Unskilled +0.19%; Skilled +0.17%

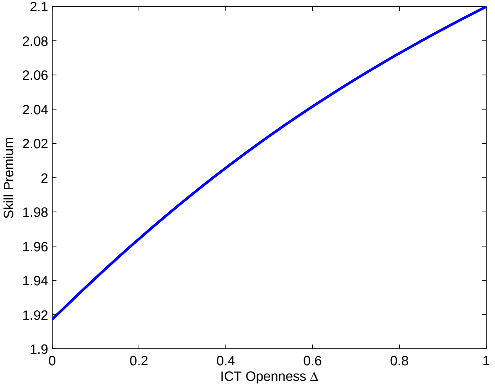
# Conclusion

- Document facts using US individual level data
  - Larger cities disproportionately attract the skilled 1980-2013
  - More skill segregation occurs in fragmentation intensive industries
- Develop a model of domestic production fragmentation with heterogeneous skills
  - skill distribution
  - communication cost, city size and skill flows
- Provide empirical support for key model predictions
- Quantify the importance of domestic production fragmentation, aided by Internet improvement, in shaping the spatial skill distributions and welfare

# Appendix

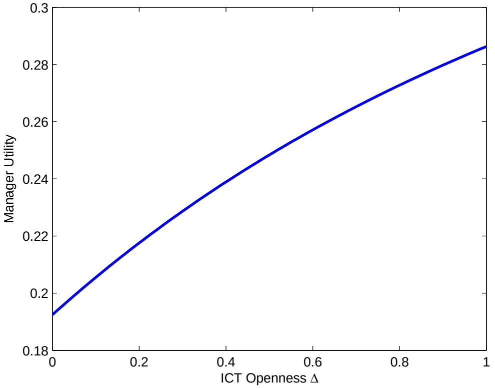
# Two-City Simulation: Skill Premium

$$\text{Skill Premium} = \log E[\pi_n] - \log w_n = \frac{1}{1-\beta}\log f(L_{mn}) + \frac{1}{(1-\beta)\theta}\log \Phi_n - \log w_n$$



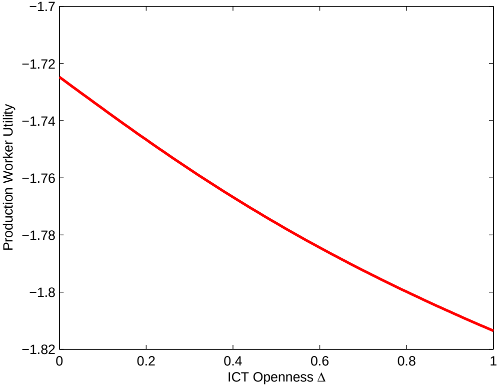

Welfare Many City Simulation Back

# N=2 Simulation: Welfare for Managers




Back

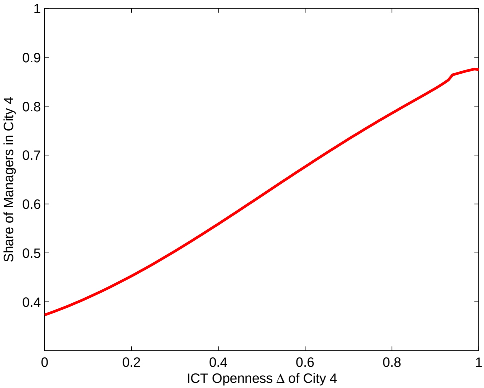
# N=2 Simulation: Welfare for Production Workers




Back

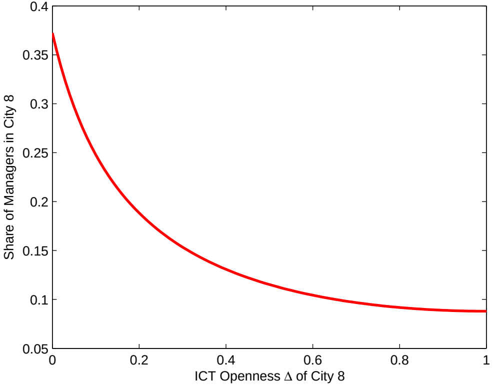
# Many-City Simulation: N=8

- Four big and four small: $T_1 = T_2 = T_3 = T_4 > T_5 = T_6 = T_7 = T_8$
- ICT improvement in the bigger city, $\tau \downarrow$




Back

# ICT Improvement In One Small City




Back

# Orbis Database

- Orbis: shareholders with strictly more than 50% ownership
- map zip code to CZ using Missouri Census Geocorr
- count the number of bilateral headquarter-subsidiary

Back

# Joint-production from Orbis Database

- $X_{nc}$: number of subsidiaries in $c$ belonging to headquarters in $n$
- Limitations: not all cross-city productions are captured
- Reasonable starting point:
  - Fits skilled-unskilled production setting in the theory well
  - Identifies one specific channel through which firms can achieve fragmented production

Back

# Instrument Variable

- Cable infrastructure prone to damage from flooding, high ground temperatures, and excessive precipitation (Zimmerman and Faris, 2010)

- Land elevation are strongly correlated with these natural conditions
  - Greater flooding risk (Michel-Kerjan et al., 2010, Landry and Parvar, 2011)

    $\Longrightarrow$ the need to safeguard broadband facilities from being submerged under water (Norhaus, 2010; Rosenzweig et al., 2011)

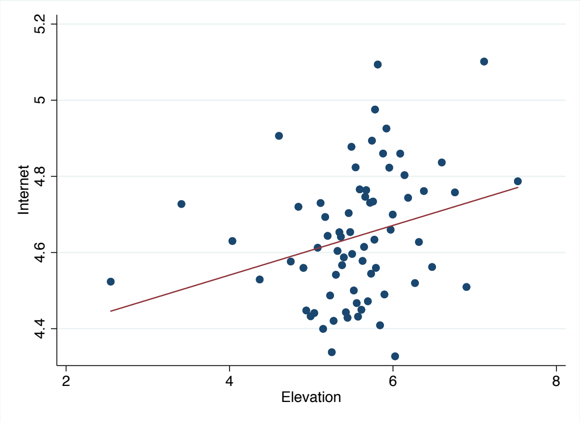
    $\Longrightarrow$ difficulty of burying cable underground (Bascom and Antoniello, 2011)
  - Higher summer temperature (Willmott and Matsuura, 1995)

    $\Longrightarrow$ higher installation costs, e.g., additional cables, artificial soil to absorb heat (Daly et al., 2008)

- Heavily associated with the use of cable technology: 90% of the broadband market in the US
  - ADSL technology in other countries, e.g., Western Europe (Jaber, 2013)

Back

# Zero Stage Results




$$Internet_n = \alpha_1 + \alpha_2 Elevation_n + \mathrm{X_n} + \epsilon_c$$

$$\hat{\alpha}_2 = .065(.029)$$

Back

# Does Internet Improve Trade in Goods

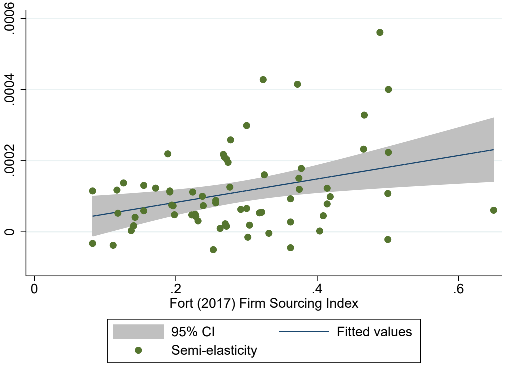
| Dependent variable | log(*shipment*) | log(*shipment*) |
| --- | --- | --- |
| | (1) | (2) |
| log (distance) | -1.236*** | -1.239*** |
| | (.0026) | ( .027) |
| $q_i * q_j$ | .058 | .039 |
| | (.094) | (.053) |
| $q_i$ | .489 | |
| | ( .349) | |
| $q_j$ | .379 | |
| | (.356) | |
| Fixed Effects | No | Yes |
| N | 4801 | 4801 |

Table: Gravity Equation Estimates for Trade in Good

Notes: Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, ***1%.

Back

# Production Fragmentation and Spatial Segregation




Notes: each dot represents an NAICS4 industry.

Back