The Global Value of Cities

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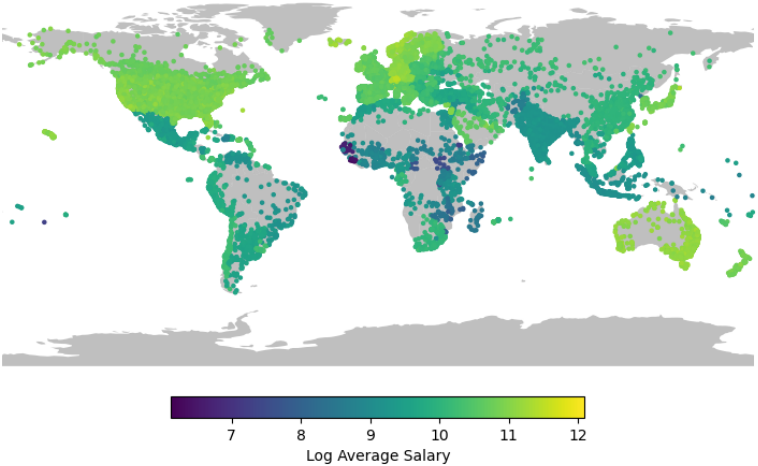
"Mostly in the world there aren't poor people. There are people in poor places."

Pritchett (2017)


7
8
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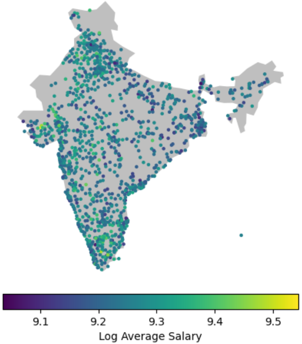
Log Average Salary


9.1
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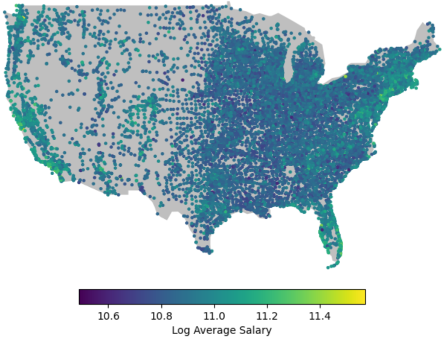
9.5
Log Average Salary

(a) India


10.6
10.8
11.0
11.2
11.4
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(b) USA

Questions

1. How much does place affect earnings?
   - Are wage differences between cities caused by city effects or sorting?
     - Between New York and Omaha? What about New York and Bangalore?

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2. What do productive cities look like?
   - Size? Amenities? Industry composition?

3. What are the potential gains from reallocation?
   - From low wage to high wage firms within a city? From low wage to high wage cities?
   - Do gains vary throughout the development process?

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- Interpreting city wage premia
  - Correlates with city effects — population, industry composition, amenities
- Allocation of people across cities and firms
  - How people move between productive cities
    - In developed and developing countries
  - Quantitative exercise: Wage gains from reallocating workers in developing countries

Part 1: Measuring City Effects

Data

- Profiles of 513 million users from 220,000 cities in 191 countries from professional networking websites (LinkedIn) Example Profiles

- Contains:
  - Education: Degree, Institution, Time
  - Jobs: Job Title (Mapped to O*NET), Start/End Date, Company (Mapped to NAICS), Location
  - Predicted: Seniority level (1-5), Salary (PPP adjusted, 3% growth rate applied) Salary by Occupation

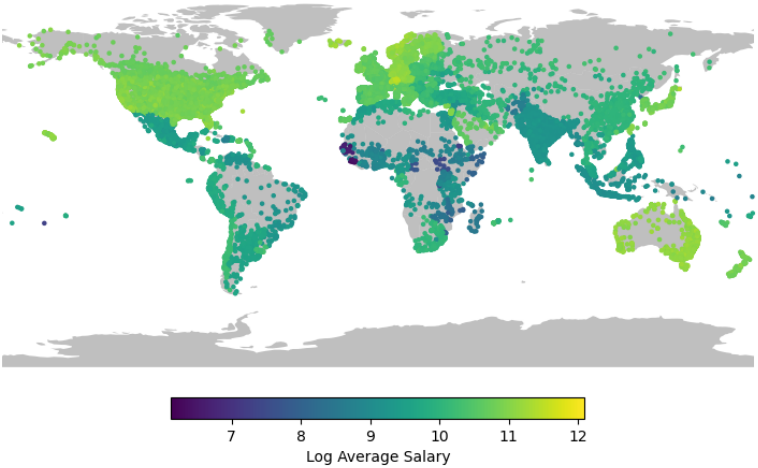
- High coverage, especially for high-skilled workers and developed countries

- Our Sample: Users who who move between two firms Are Movers Different?

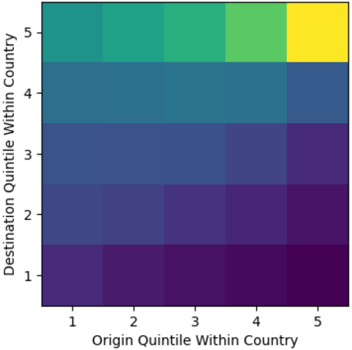
Salary Imputation

- Function of company, occupation, tenure, year, and city characteristics (population density, unemployment rate, poor share, median housing value)
- Relevant welfare measure — higher score for better jobs
  - Amanzadeh, Kermani, and McQuade (2024) validate with individual Glassdoor data and national surveys
- We develop a new method to bound bias of estimates using imputed data

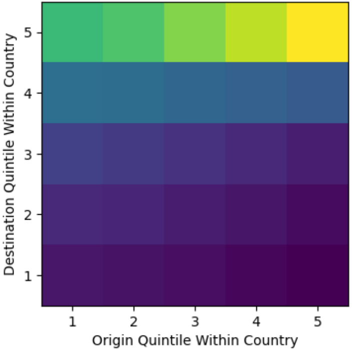
Coverage



Movers



(a) Wage Transition Matrix: Within Country Moves



(b) Wage Transition Matrix: Cross Border Moves

Event Study

- Do people earn more when they move to a higher-wage city?

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- Event study á la Finkelstein, Gentzkow, and Williams (2016):

$$\delta_i = \bar{y}_{d(i)} - \bar{y}_{o(i)}$$
$$y_{it} = \alpha_i + \tau_t + I_{r(i,t)} + \theta_{r(i,t)} I_{r(i,t)} \delta_i + \eta_{it}$$

δ_i: Diff. in avg. salary; α_i: User effect; τ_t: Time effect; $I_{r(i,t)}$: Relative years vector

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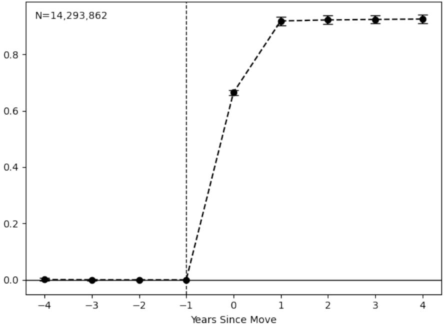
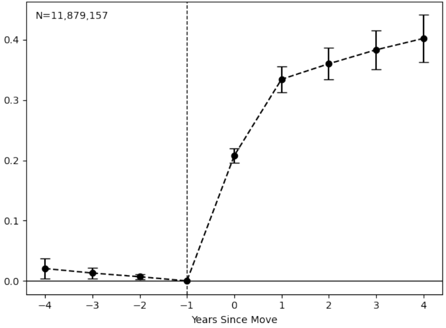
- Interested in $\theta_{r(i,t)}$
  - Frac. of diff. user earns

Results



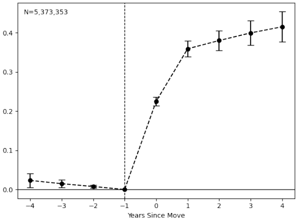
(a) All Moves



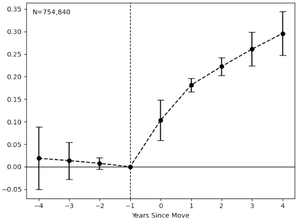
(b) Internal Moves

▸ Industry ▸ Occupation ▸ Seniority

Results Within Individual Countries



(a) United States



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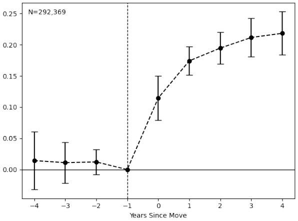
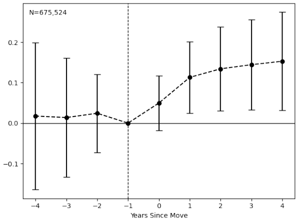
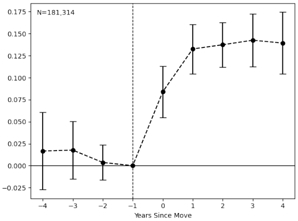


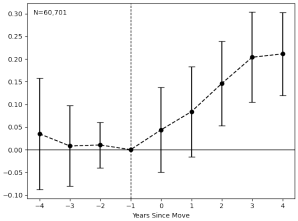
(c) Italy



(d) India

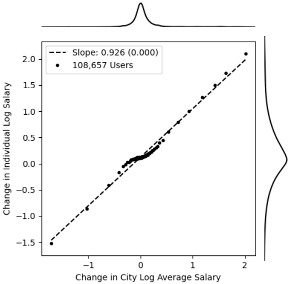


(e) Mexico



(f) Nigeria

Salary Gains by Origin-Destination Pairs



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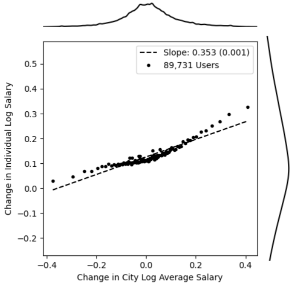
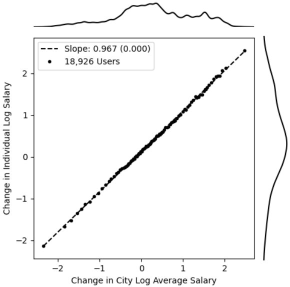
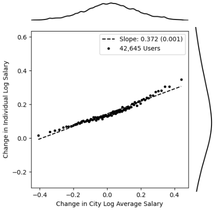


(b) Internal Moves



(c) International Moves

Salary Gains by Origin-Destination Pairs Within Individual Countries



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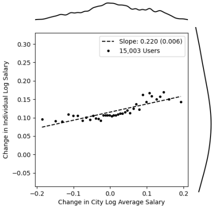
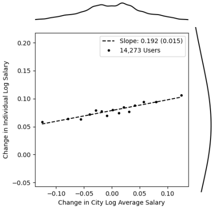


(b) United Kingdom



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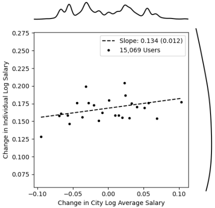

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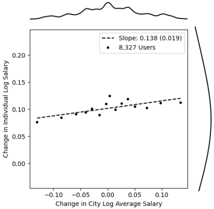

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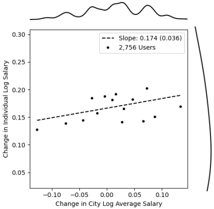

(f) Nigeria

Basic AKM

- Decompose salary into user effect (α_i) and city effect ($\psi_{\mathbf{J}(i,t)}$):

$$\log(\text{Salary})_{it} = \alpha_i + \psi_{\mathbf{J}(i,t)} + \tau_t + x'_{it}\beta + \epsilon_{it}$$

τ_t: Time effect; $x'_{it}\beta$: Time-varying controls

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- Allowed: Systematic mobility on individual and city characteristics
  - Productive workers are mobile
  - Productive cities are popular
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- Assumes:
  - Log additive separability of user and city effects
  - Exogenous mobility
    - No sorting based on user-city match quality
    - No drift in effects over time

Assumptions

- Event Studies:
  - No pre-trends
  - No spikes before or after moves (no Ashenfelter dip or signing bonus)

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- Event Studies:
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- Origin-Destination Pairs:
  - Symmetric wage increases and decreases (additive separability and match-based sorting)

Hierarchy Effects

- Still potential for misidentification due to within-city firm heterogeneity
  - Ex: Move from high-paying firms in low-wage cities to low-paying firms in high wage cities

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- Card, Rothstein, and Yi (2025) solution: Estimate firm effects ($\gamma_{\mathbf{f}(i,t)}$) using

$$\log(\text{Salary})_{it} = \alpha_i + \gamma_{\mathbf{f}(i,t)} + \tau_t + x_{it}'\beta + \epsilon_{it}$$

Then, aggregate to city effects (Γ_j)

$$\Gamma_j = \frac{\sum_{j(f)=j} N_f \gamma_f}{\sum_{j(f)=j} N_f}$$

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- Interpretation: Productive cities are where people work at productive firms

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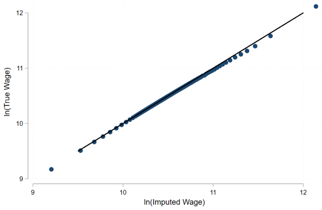
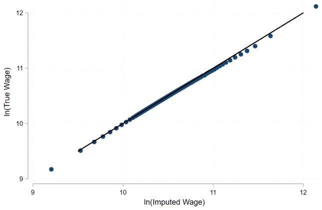
  - Can cause bias if there's assortative matching
- Use matched employer-employee data from Italy and create similar imputed salary
  - Compare city effects under different imputations

Imputation Bias



(a) True vs imputed wages

Imputation Bias



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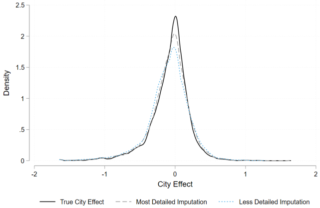

(b) City effects under different imputations

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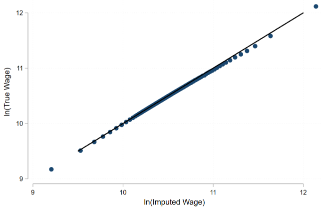

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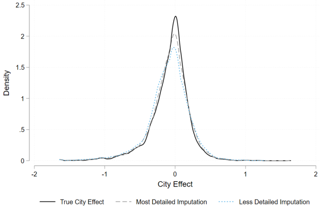

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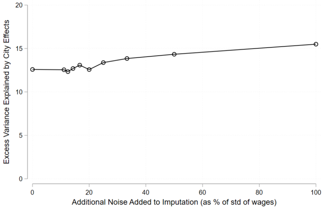
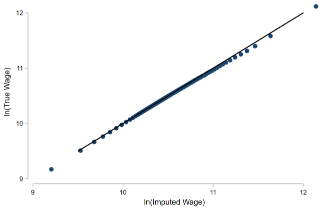


(c) Excess variance under added noise

Imputation Bias



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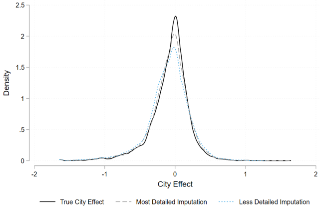

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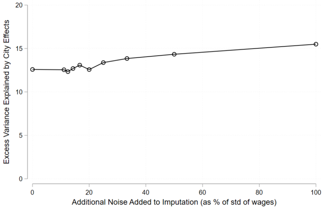
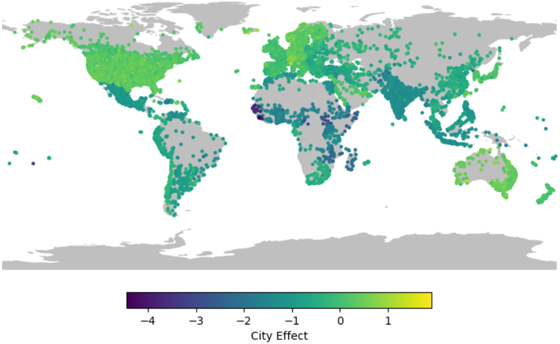


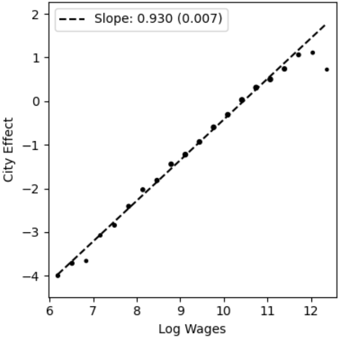
(c) Excess variance under added noise

Result: With a prediction R^2 of 0.875, bias is less than 12.5%

City Effects: Global

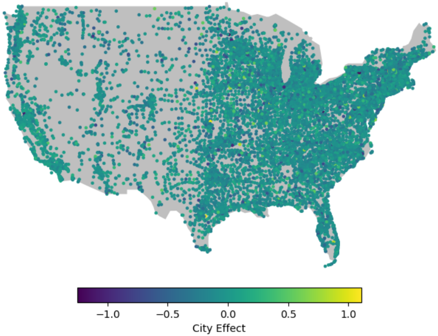


(a) Estimated City Effect



(b) Log Wages vs City Effect

City Effects: United States



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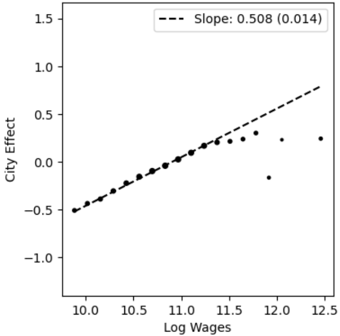

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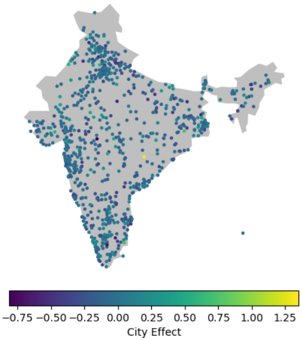
City Effects: India



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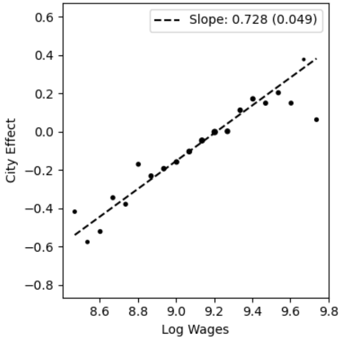
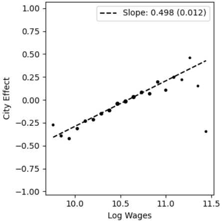
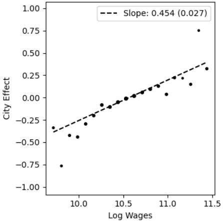


(b) Log Wages vs City Effect

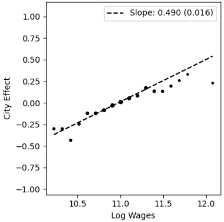
City Effects: Other Countries



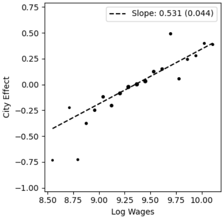
(a) United Kingdom



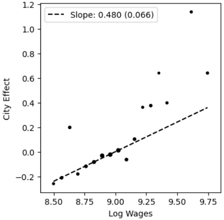
(b) Italy



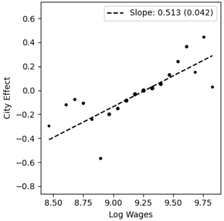
(c) Germany



(d) Mexico

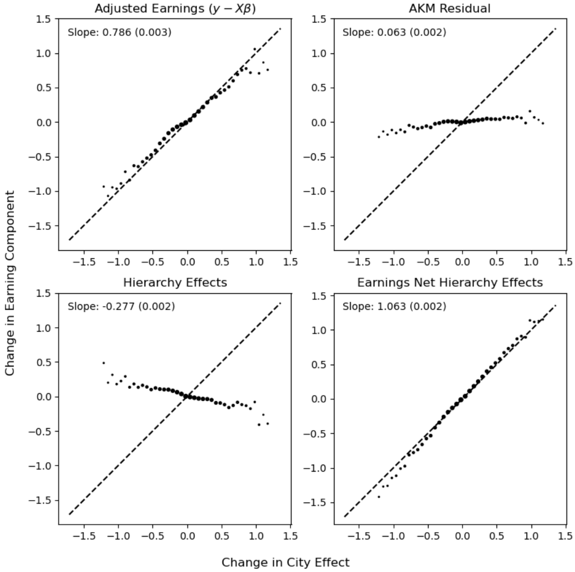


(e) Nigeria



(f) Philippines

Hierarchy Effects



Decomposition of Wage Differences: Global

	Below to Above Median (1)	Bottom to Top 25% (2)	Bottom to Top 5% (3)	Bangalore to San Francisco (4)	Var ($\bar{y}_j$) (5)
Difference in Ln Wages	0.75	1.27	2.39	1.1	–
Difference due to City	0.65	1.07	2.05	1.02	–
Share due to City	0.87	0.84	0.86	0.93	0.93
Bounded Share					(0.75)

Share Formula

Decomposition of Wage Differences: United States

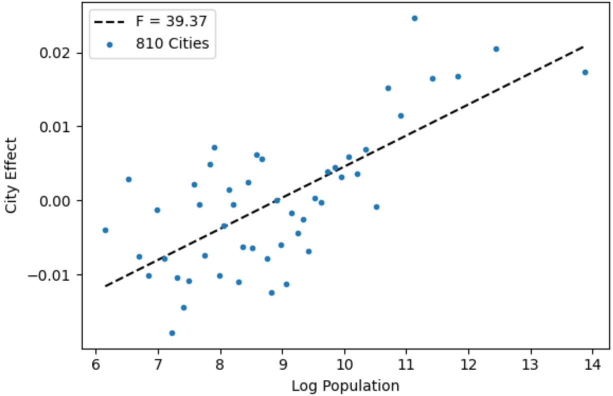
Panel A: United States	Below to Above Median (1)	Bottom to Top 25% (2)	Bottom to Top 5% (3)	San Diego to New York (4)	Var ($\bar{y}_j$) (5)
Difference in Ln Wages	0.32	0.52	1.0	0.2	–
Difference due to City	0.14	0.24	0.45	0.04	–
Share due to City	0.45	0.45	0.45	0.22	0.51
Bounded Share					(0.41)

Decomposition of Wage Differences: India

Panel A: India	Below to Above Median (1)	Bottom to Top 25% (2)	Bottom to Top 5% (3)	Kolkata to Bangalore (4)	Var ($\bar{y}_j$) (5)
Difference in Ln Wages	0.26	0.44	0.84	0.13	–
Difference due to City	0.17	0.29	0.47	0.1	–
Share due to City	0.65	0.65	0.56	0.74	0.73
Bounded Share					(0.59)

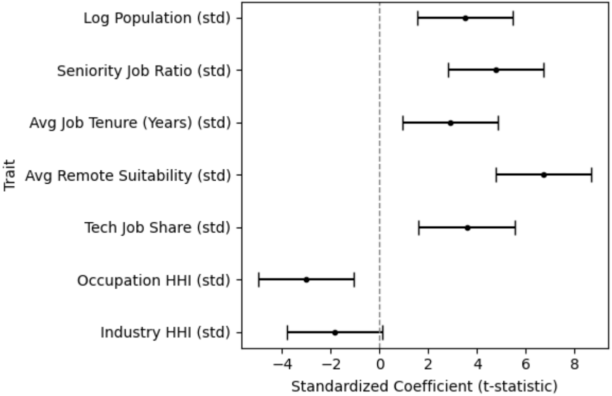
Part 2: City Characteristics

Agglomeration



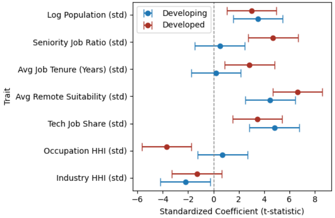
Population

Other Characteristics

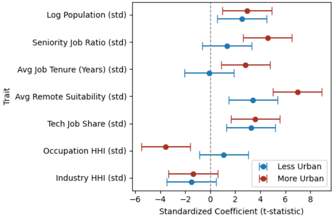


▸ Seniority ▸ Modern Firms ▸ Industrial Diversity

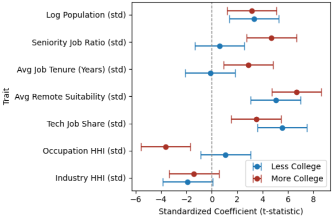
By Country Status



(a) By Development Status

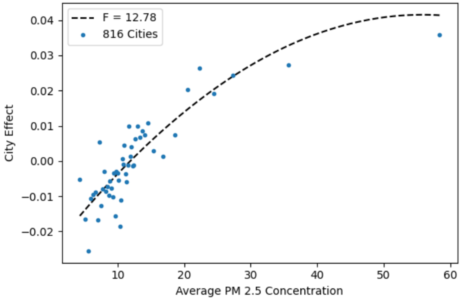


(b) By Urbanization Level

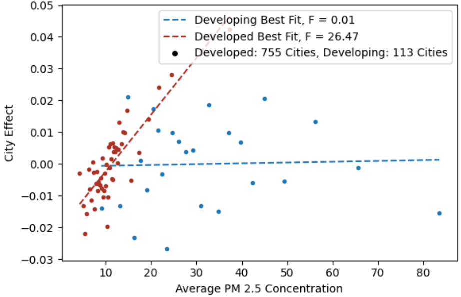


(c) By College Attainment

Pollution

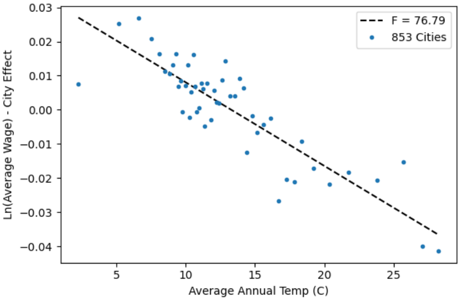


(a) Pollution

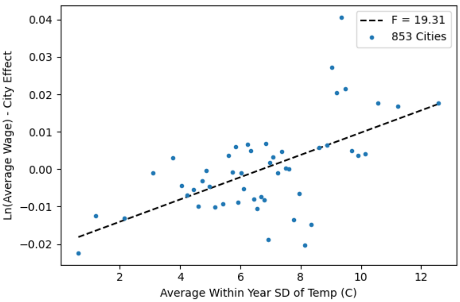


(b) Pollution by Dev. Status

Amenities and Compensating Differentials

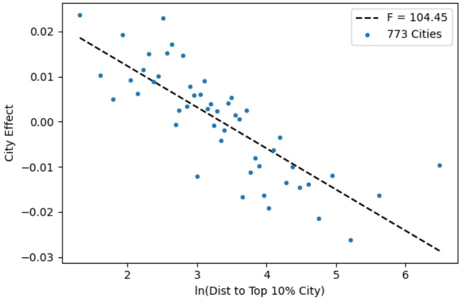


(a) Temperature Avg.

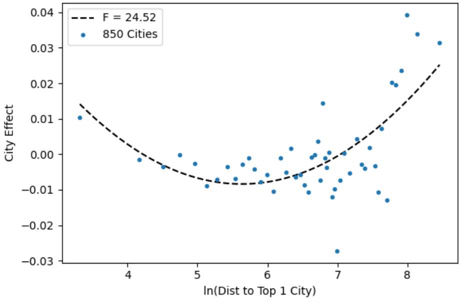


(b) Temperature St. Dev.

Shadows



(a) Distance to Top 10% Effect City in Country



(b) Distance to Highest Effect City in Country

Part 3: Allocation

Allocation

- Two types:

Allocation

- Two types:
  - Between firms within a city
    - Move from low- to high-productivity firms $\Longrightarrow$ higher city effect

Allocation

- Two types:
  - Between firms within a city
    - Move from low- to high-productivity firms $\implies$ higher city effect
  - Between cities within a country
    - Move from low- to high-productivity cities $\implies$ higher national production

Allocation Across Firms

- Olley and Pakes (1996): Decompose city effects into mean effect and allocative effect

Allocation Across Firms

- Olley and Pakes (1996): Decompose city effects into mean effect and allocative effect

$$\Gamma_j = \sum_{j(f)=j} s_f \gamma_f$$

s_f: Share of user-years at firm f

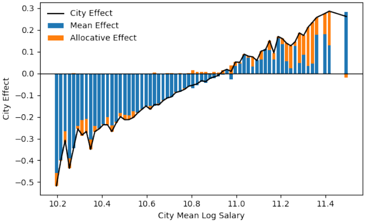
Allocation Across Firms

- Olley and Pakes (1996): Decompose city effects into mean effect and allocative effect

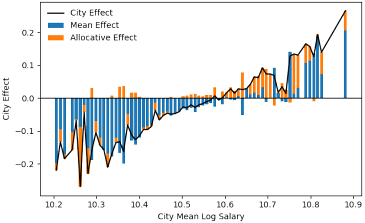
$$\Gamma_j = \sum_{j(f)=j} s_f \gamma_f = \underbrace{\bar{\gamma}_j}_{\text{Mean}} + \underbrace{\sum_{j(f)=j} \left(s_f - \bar{s}_j\right)\left(\gamma_f - \bar{\gamma}_j\right)}_{\text{Allocation}}$$

s_f: Share of user-years at firm f

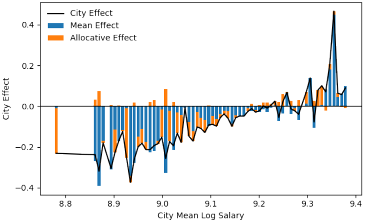
Olley-Pakes Decomposition



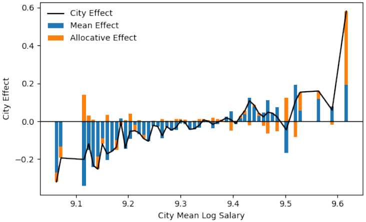
(a) United States



(b) United Kingdom

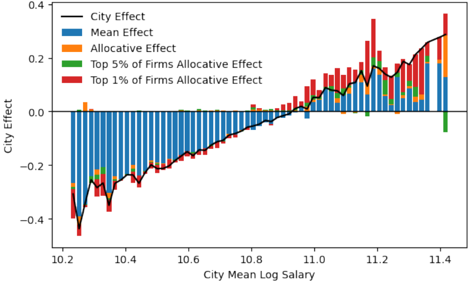


(c) India

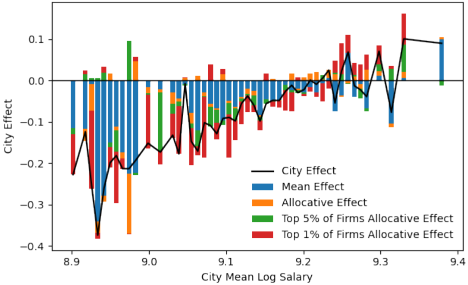


(d) Mexico

Large Firms

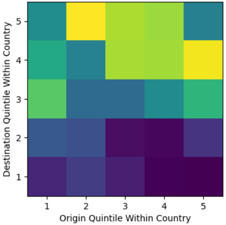


(a) United States

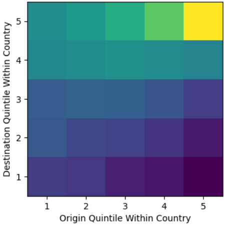


(b) India

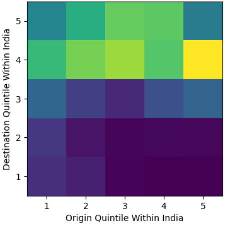
City Effect Transition Matrices



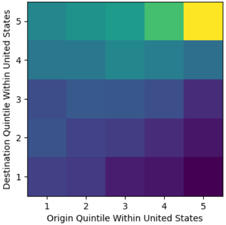
(a) Low Income Countries



(b) High Income Countries

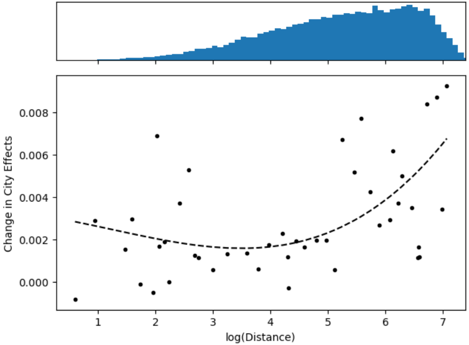


(c) India

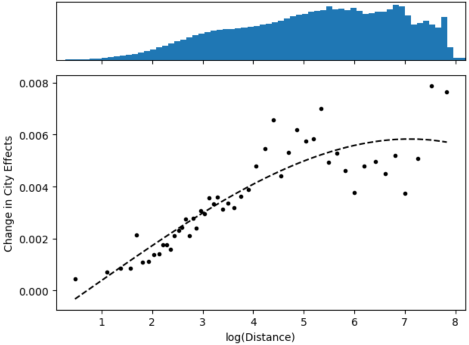


(d) United States

Move Distances

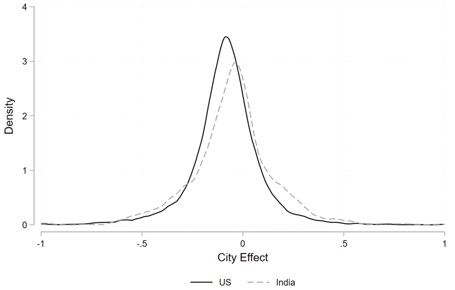


(a) Low Income Countries



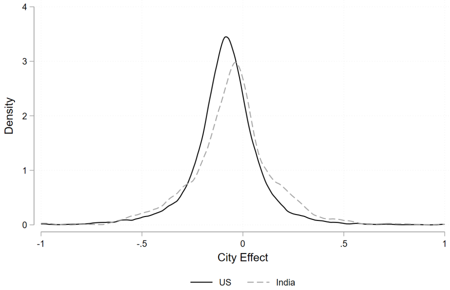
(b) High Income Countries

Distribution

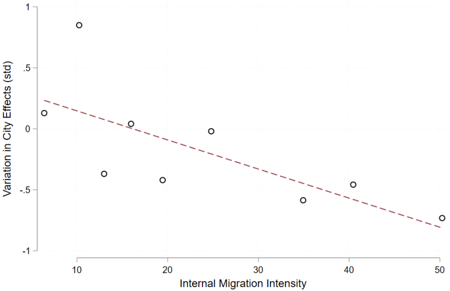


(a) City Effects Distribution

Distribution



(a) City Effects Distribution



(b) Migration Intensity and City Effect Variation

Reallocation

- What is the effect of reallocating workers in developing countries similar to developed countries?

Reallocation

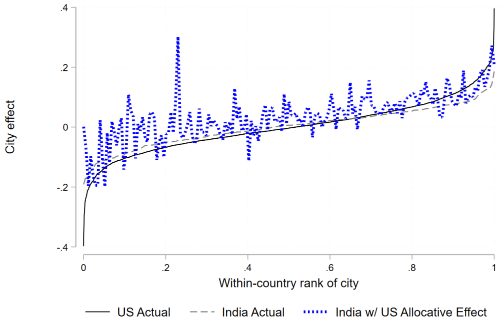
- What is the effect of reallocating workers in developing countries similar to developed countries?
- Perform quantification exercise moving workers in India to match US distribution

Firm Allocation

Move workers so that Olley-Pakes allocation component is the same for similarly ranked cities

Firm Allocation

Move workers so that Olley-Pakes allocation component is the same for similarly ranked cities



Firm Allocation

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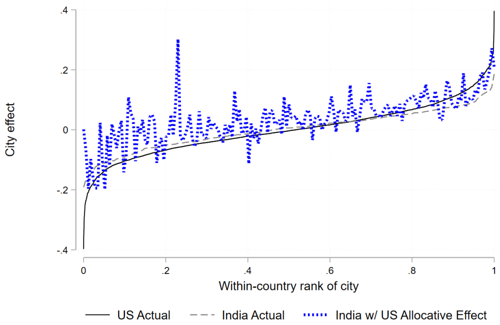

Average wages increase by **2.6%**

City Allocation

Move workers so population CDF across city effect rank is the same

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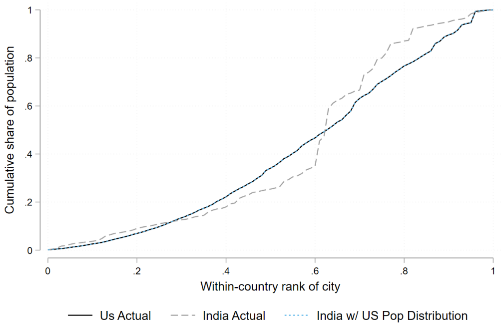
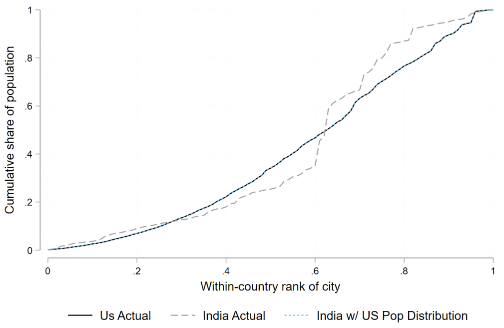
Move workers so population CDF across city effect rank is the same



City Allocation

Move workers so population CDF across city effect rank is the same



Average wages increase by **2.3%**

Both

- Limited crowding out from doing both

Both

- Limited crowding out from doing both
- Reallocation both within and across cities $\Longrightarrow$ Average wages increase by **4.3%**

Punchline

- City effects are important for explaining wage differences between cities
  - Within a Country: Explain 45-73% of wage variation
  - Between Countries: Explain 93% of wage variation

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- People move to cities where they make more
  - Internal Migrants: Move to higher effect cities
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  - Especially in developed countries

- Developed countries have a more efficient allocation of workers than developing countries
  - Both across firms within cities and across cities within a country
  - Worker reallocation in developing countries leads to significant potential wage gains

Thanks!

References I

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Pritchett, Lant. 2017. "Lant Pritchett on Poverty, Growth, and Experiments." Edited by EconLib.

Example LinkedIn Profile

Experience

Tobin Pre-Doctoral Fellow
Yale University · Full-time
Aug 2020 - Jun 2021 · 11 mos
New Haven, Connecticut, United States

Research fellow under Professor Rohini Pande

Research Associate
NERA Economic Consulting
Jul 2019 - Jul 2020 · 1 yr 1 mo
Greater New York City Area

Research Assistant
Department of Economics, UC Berkeley
May 2018 - May 2019 · 1 yr 1 mo
Berkeley, California

Evaluated the effects of unconditional direct cash transfers using data from a randomized control trial in Kenya (working with Professor Edward Miguel)

Undergraduate Student Instructor
University of California, Berkeley
Jan 2018 - May 2019 · 1 yr 5 mos

Teaching Assistant for an intermediate Data Science course (Data Science 100)

Software Engineering Intern
NVIDIA
May 2017 - Aug 2017 · 4 mos
Santa Clara, CA

Built tools to uncover performance bottlenecks in CUDA compiler and applications

Example Bad LinkedIn Profile

Experience

Research Assistant
Yale University
Jun 2019 - Present · 5 yrs
New Haven, Connecticut

Supplemental Instructor
Macalester College
Aug 2018 - May 2019 · 10 mos
Greater Minneapolis-St. Paul Area

Farm Hand
Easy Bean Farm
May 2018 - Sep 2018 · 5 mos
Greater Minneapolis-St. Paul Area

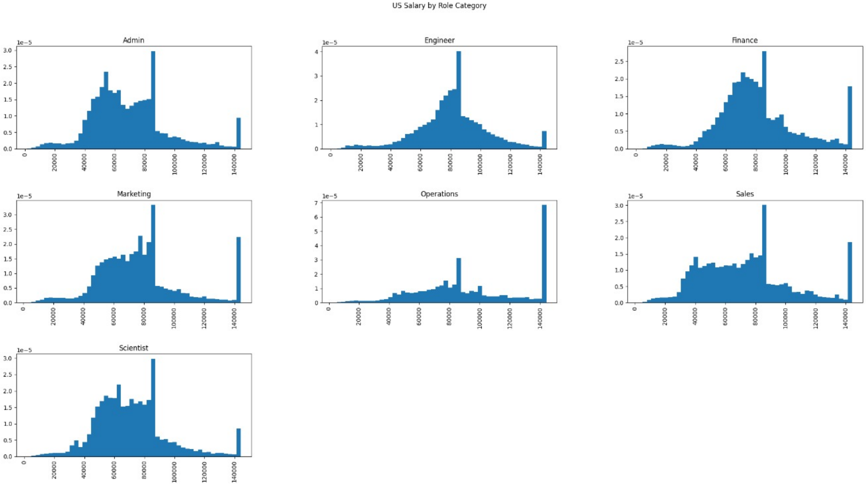
Macalester College
2 yrs 10 mos
Greater Minneapolis-St. Paul Area

- **Preceptor**
  Jan 2018 - May 2018 · 5 mos
- **Studeny Recyler**
  Aug 2015 - May 2018 · 2 yrs 10 mos

  - Responsible for maintaining clean living area in dorms
  - Ensures classrooms are orderly before each academic day
  - Practices sustainable cleaning methods

Back

Salary by Occupation (United States)



Back

How Different Are Movers? (Full Sample)

	Moved Firms	**Moved Cities**	**Moved Countries**	**Not in Dataset**
Salary	43,415.65	51,043.42	47,830.56	48,420.13
	(33,002.43)	(32,289.17)	(32,677.85)	(35,987.82)
NAICS Wage	51,848.30	52,026.82	52,275.66	47,883.93
	(9,604.69)	(9,058.45)	(8,803.39)	(12,982.51)
ONET Wage	48,589.38	48,074.86	50,897.55	49,356.41
	(13,172.00)	(12,567.75)	(13,431.65)	(15,439.86)
Seniority	2.48	2.39	2.63	2.67
	(1.41)	(1.41)	(1.45)	(1.61)
Num. Users	5,241,672	3,638,898	783,360	193,900,336

Notes: Standard deviations in parentheses.

How Different Are Movers? (United States)

	Moved Firms	Moved Cities	Moved Countries	Not in Dataset
Salary	63,753.10	64,052.72		63,831.08
	(36,280.31)	(32,930.04)		(39,277.46)
NAICS Wage	64,218.43	65,085.95		59,351.19
	(16,105.24)	(15,536.17)		(19,103.08)
ONET Wage	63,290.77	64,821.54		64,154.50
	(23,966.32)	(23,522.72)		(26,599.89)
Seniority	2.43	2.38		2.64
	(1.50)	(1.47)		(1.65)
Num. Users	1,644,316	1,708,471		66,721,565

Notes: Standard deviations in parentheses.

How Different Are Movers? (India)

	Moved Firms	Moved Cities	Moved Countries	Not in Dataset
Salary	10,482.96	10,518.35		10,722.45
	(3,254.26)	(3,445.25)		(4,939.91)
NAICS Wage	10,641.67	10,757.72		10,238.83
	(1,508.29)	(1,420.27)		(2,050.60)
ONET Wage	10,482.93	10,636.35		10,806.14
	(1,872.67)	(1,981.41)		(2,632.39)
Seniority	2.62	2.58		2.77
	(1.18)	(1.23)		(1.45)
Num. Users	751,519	306,936		11,958,280

Notes: Standard deviations in parentheses.

▸ Back

Share Formulas

Share of wage differences explained by city effects:

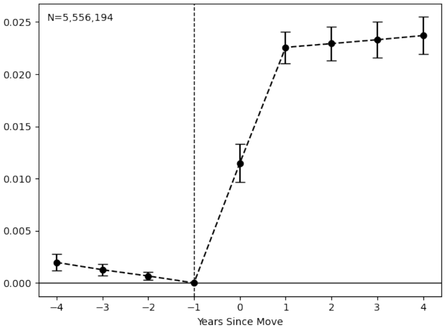
$$S(R, R') \equiv \frac{\Gamma_R - \Gamma_{R'}}{\bar{y}_R - \bar{y}_{R'}}$$

Share of variance in wages due to city effects:

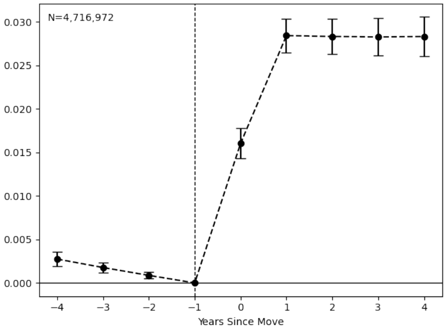
$$\Omega \equiv \frac{\text{Cov}\left(\Gamma_j, \bar{y}_j\right)}{\text{Var}\left(\bar{y}_j\right)}$$

▸ Back

Industry Score (Avg. log salary within NAICS code)



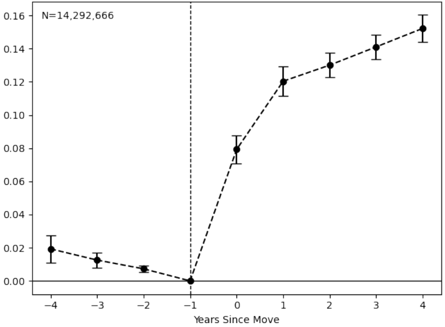
(a) All Moves



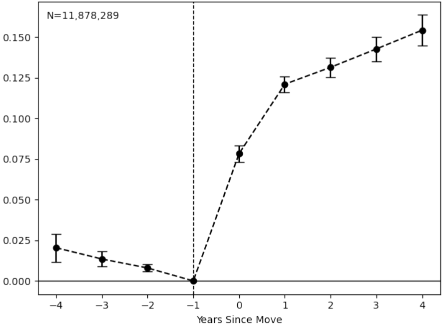
(b) Internal Moves

Back

Occupation Score (Avg. log salary within O*NET code)



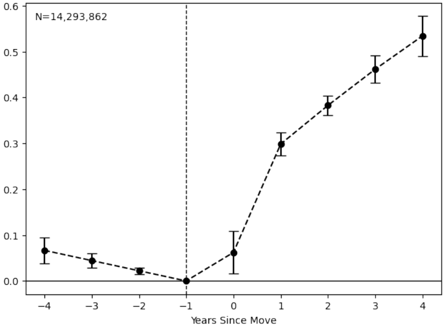
(a) All Moves



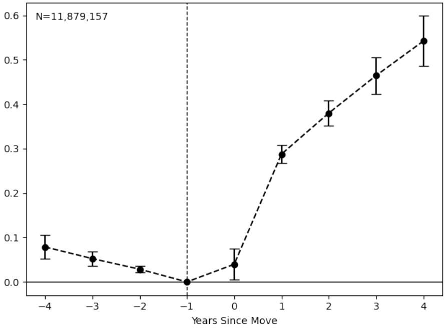
(b) Internal Moves

▸ Back

Seniority (1-5)



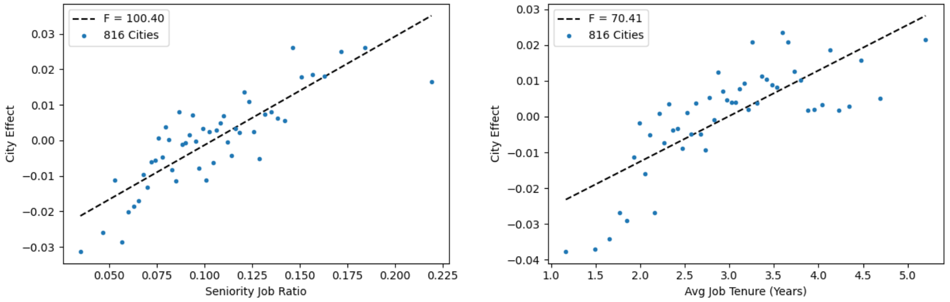
(a) All Moves



(b) Internal Moves

Back

Seniority

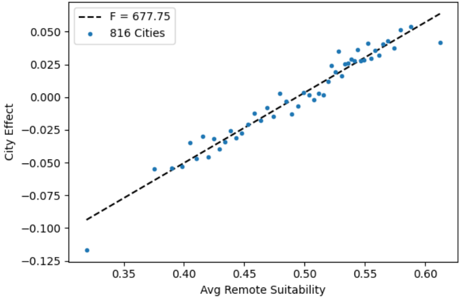


(a) Seniority Ratio

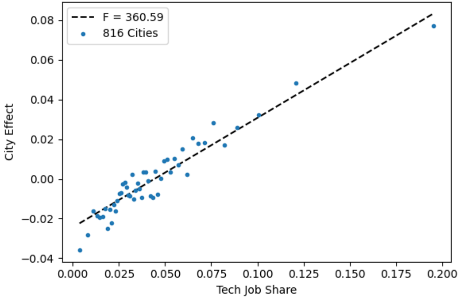
(b) Avg. Job Tenure

Back

Modern Firms



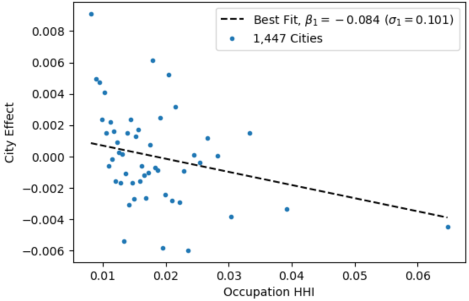
(a) Remote Suitability



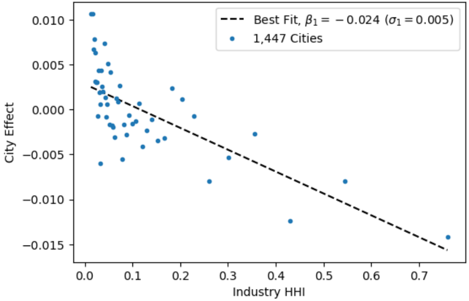
(b) Tech Jobs

Back

Industrial Diversity



(a) Occupational Diversity



(b) Industrial Diversity

Back