Skills, Distortions, and the Labor Market Outcomes of Immigrants Across Space

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Roadmap

Introduction

Motivation

- Income inequality is a growing concern
  - 40% of it is attributed to spatial inequality (Young, 2013)
- Spatial inequality:
  - Unequal distribution of resources and opportunities across different geographic areas
  - Key component $\rightarrow$ spatial earnings inequality:
    - The earnings gap b/w big and small cities
    - Higher and more persistent in the US than in other countries (Bauluz et al.,2023)
- U.S. immigration is a topic of lively debate
  - Immigrants represent about 15 % of the US population. Concerns related to:
    - Immigrants' performance in the labor market $\rightarrow$ earnings gap with natives
    - Relationship between immigration and spatial earnings inequality

Research Questions

What is the geography of immigrants' labor market outcomes in the US?

How does it tie to earnings gaps with natives and spatial earnings inequality?

How does immigration policy affect these outcomes?

Immigrants in the US and Spatial Earnings Inequality

- US immigrants earn 15% less than natives (Amo-Agyei et al., 2020)
  - Cross-country differences in education quality (Schoellman, 2012)
  - Lack of host-country-specific skills and undergo economic assimilation (Albert et al., 2022)
  - Labor market barriers (Birinci et al., 2024)

- Immigrants' performance in labor markets relates to:
  - Occupational choices:
    - Immigrants and natives specialize in different tasks (Peri and Sparber, 2009)
  - Location choices:
    - Immigrants live more in big and expensive cities than natives (Albert and Monras, 2022)

- Higher earnings in larger cities:
  - Skills sorting (Diamond, 2016)
  - Premium for working in cognitive occupations (Atalay et al., 2023)

What I Do

- Using US microdata, I document 3 facts:
  - The earnings gap b/w immigrants and natives is larger in big cities
  - No city-size earnings premia only for immigrants from low-income countries
  - Workers from high-income countries work more in cognitive jobs, especially in big cities
- I interpret this evidence with a spatial equilibrium model:
  - Cities differ in technology and housing supply
  - Workers differ in human capital and tastes for cities and occupations
  - Immigrants face labor market distortions:
    - Specific to locations, occupations, and observable characteristics
    - Wedges on the marginal product of labor
- I use the model to:
  - Study the role of human capital, tastes, and distortions to:
    - Explain the earnings gap b/w immigrants and natives vs spatial earnings inequality
  - Evaluate immigration policies' effects on earnings gap among workers and b/w cities

Preview of the Findings: Counterfactual Scenarios

- Counterfactual exercises reveal
  1. A trade-off in reducing the earnings gap among workers vs increasing spatial earnings inequality
     - No differences in human capital $\rightarrow$ earnings gap b/w immigrants and natives -19.9% vs spatial earnings inequality +1.1%
     - No differences in tastes $\rightarrow$ earnings gap b/w immigrants and natives -6.2% vs spatial earnings inequality +3%
     - Removing wedges on earnings $\rightarrow$ earnings gap b/w immigrants and natives -9.3%, no changes in spatial earnings inequality
- Mechanism $\rightarrow$ workers reallocation across cities and occupations:
  - Changes in skills prices $\rightarrow$ competition effect
  - Changes in average productivity $\rightarrow$ skills effect

Preview of the Findings: Changes in Immigration Policy

- Policy simulations suggest that
  - For an inflow of immigrants w/o college:
    - Earnings gap b/w immigrants and natives +2.6%, but spatial earnings inequality -0.3%
  - For an inflow of immigrants with college:
    - Earnings gap b/w immigrants and natives -6% and spatial earnings inequality -0.1%
- Mechanism $\rightarrow$ sorting of newcomers across cities and occupations
  - For inflow of immigrants w/o college:
    - Drop in skills prices and average productivity, especially in non-cognitive occupations
  - For an inflow of immigrants with college:
    - Average productivity rises and no impact on skill prices in cognitive occupations

Literature

Data & Stylised Facts

Data

- 2010 American Community Survey (ACS) sample from IPUMS:
  - Immigrants: foreign-born workers, first-generation
  - Hourly earnings
  - US cities: Metropolitan Statistical Areas (MSA)
  - Sample: male workers, 18-64 y.o., employed and work for wages
- O*NET:
  - Tasks intensity as in Acemoglu & Autor (2011)
- World Bank:
  - Countries GDP per capita 2017 USD
    - Low-income $\rightarrow$ GDP pc $<$ \$30,000
    - High-income $\rightarrow$ GDP pc $\geq$ \$30,000

Stylised Facts

- **Fact 1**
  - The earnings gap b/w immigrants and natives is larger in big cities
    - Natives $\rightarrow$ doubling the city size increases hourly earnings by 3.6%
    - Immigrants $\rightarrow$ no significant change in earnings b/w small and big cities Fact 1
- **Fact 2**
  - No city-size earnings premia only for immigrants from low-income countries
    - High-income $\rightarrow$ doubling the city size increases hourly earnings by 3.9% Fact 2
- **Fact 3**
  - Workers from high-income countries work more in cognitive jobs, especially in big cities. Doubling the city size:
    - The share of natives in cognitive jobs +1pp,
    - The share of immigrants from high-income countries in cognitive jobs +1.5pp,
    - The share of immigrants from low-income countries does not change Fact 3

From the Data to the Model

- Data shows:
  - Earnings gap increases with city size for immigrants from low-income countries
  - Workers from high-income countries work in cognitive occupations in big cities

- A spatial equilibrium model to:
  - Quantify how different factors affect job choices in U.S. cities b/w immigrants and natives
  - Quantify the consequences on spatial earnings inequality of inflows of new immigrants

- The model has three building blocks:
  - Differences in technology across cities (Atalay et al. (2023), Eeckhout et al. (2023), Giannone (2023))
  - Workers' heterogeneity in skills and tastes for where to work and live (Peri and Sparber (2009), Albert & Monras (2022))
  - Labor market distortions (Hsieh et al. (2019))

Model

Model Set Up

- Static economy
- Cities and production:
  - $j \in \{1, ..., J\}$ cities
  - Representative firm in city j produces Y_j
  - CES technology in two occupations $o \in \{M, D\}$
  - City-specific productivity bias θ_j in D
  - Housing supply H_j
- Workers:
  - Continuum of workers $i \in [0, 1]$
  - Each worker i belongs to a group $g = (k, e, x), k \in \mathcal{K}$, $e \in \mathcal{E}$, $x \in \mathcal{X}$
  - Each group has a measure ϕ_g such that $\sum_g \phi_g = 1$
  - Human capital endowment $\boldsymbol{s} = (s_M, s_D)$
  - City-occupation amenities z_{jog}
  - I.i.d. taste shocks over cities-occupations jo: $\varepsilon_{jo} \sim \text{Gumbel}(0, 1)$

The Problem of the Firm

- A firm in city j solves:

$$\max Y_j = \left[M_j^{\frac{\sigma-1}{\sigma}} + (\theta_j D_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - r_{jD} D_j - r_{jM} M_j$$

  where:

  - σ is the elasticity of substitution between the two inputs
  - r_{jo} is the city-occupation-specific skills price

- The city-occupation-specific skills price ratio is:

$$\frac{r_{jD}}{r_{jM}} = \left(\frac{D_j}{M_j}\right)^{-\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)}$$

The Earnings of the Worker

- Earnings in city j and occupation o for a worker in group g are given by:

$$w_{jog} = r_{jo} s_{og} \tau_{jog}$$

- τ_{jog} is a city-occupation-group-specific earnings compensation wedge:
  - $\tau_{jog} > 1 \rightarrow$ "reward" on earnings
  - $\tau_{jog} < 1 \rightarrow$ "penalty" on earnings

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The Problem of the Worker and Demands for Goods

- Given their city-occupation choice, a worker i from group g solves:

$$\max_{c_{jog}, h_{jog}} \quad U_{jog} = c_{jog}^{(1-\alpha)} h_{jog}^{\alpha} z_{jog} \exp\{\varepsilon_{jo}\}$$
$$\text{s.t.} \quad c_{jog} + p_j h_{jog} \leq w_{jog}$$

  where

  - c consumption good, h housing good, α expenditure share in the housing good

- Demands for goods are:

$$c_{jog}^{\star} = (1-\alpha)\, w_{jog}$$
$$h_{jog}^{\star} = \alpha \frac{w_{jog}}{p_j}$$

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Indirect Utility and Choice Equation

- Indirect utility from living in city j and working in occupation o is:

$$V_{jog} = \gamma p_j^{-\alpha} w_{jog} z_{jog} \exp\{\varepsilon_{jo}\}$$

where $\gamma = (1-\alpha)^{(1-\alpha)} \alpha^{\alpha}$

- The share of workers from group g choosing a city j and an occupation o is:

$$\pi_{jog} = \frac{\gamma p_j^{-\alpha} w_{jog} z_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} \gamma p_{j'}^{-\alpha} w_{j'o'g} z_{j'o'g} \tau_{1j'o'g}}$$

$$= \frac{\gamma p_j^{-\alpha} r_{jo} s_{og} \tau_{jog} z_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} \gamma p_{j'}^{-\alpha} r_{j'o'} s_{o'g'} \tau_{j'o'g'} z_{j'o'g} \tau_{1j'o'g}}$$

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Housing Market

- The housing market is competitive
- The housing supply is governed by:

$$p_j = \left(\frac{H_j}{T_j}\right)^{\frac{1}{\zeta_j}}$$

where:

- H_j is total demand for housing
- T_j is land
- ζ_j is the elasticity of the housing supply

Endogenous housing supply

Spatial Equilibrium

- A spatial equilibrium is a set of skills prices $\{r^{\star}_{jo}\}_{j\in\mathcal{J},o\in\mathcal{O}}$, housing prices $\{p^{\star}_{j}\}_{j\in\mathcal{J}}$, an allocation of workers across locations and occupations $\{\pi^{\star}_{jog}\}_{j\in\mathcal{J},o\in\mathcal{O}}$, such that:
  - The share of workers from group g in a city-occupation pair jo is:

$$\pi^{\star}_{jog} = \frac{\gamma p_j^{\star\,-\alpha} r^{\star}_{jo} s_{og}\tau_{jog} z_{jog}}{\sum_{j'\in\mathcal{J}}\sum_{o'\in\mathcal{O}} \gamma p_{j'}^{\star\,-\alpha} r^{\star}_{j'o'} s_{o'g'}\tau_{j'o'g'} z_{j'o'g'}}$$

  - Labor supply satisfies:

$$M^{\star}_j = \sum_g \pi^{\star}_{jMg} s_{Mg}\phi_g, \quad D^{\star}_j = \sum_g \pi^{\star}_{jDg} s_{Dg}\phi_g$$

  - Labor markets clear for each city-occupation pair, that is $\forall j \in \mathcal{J}$:

$$r^{\star}_{jM} = \frac{\left[M_j^{\star\,\frac{\sigma-1}{\sigma}} + (\theta_j D^{\star}_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}}{M_j^{\star\,\frac{1}{\sigma}}}, \quad r^{\star}_{jD} = \frac{\left[M_j^{\star\,\frac{\sigma-1}{\sigma}} + (\theta_j D^{\star}_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}}{D_j^{\star\,\frac{1}{\sigma}}}\theta_j^{(1-\frac{1}{\sigma})}$$

  - The housing market clear in each city, that is $\forall j \in \mathcal{J}$:

$$p^{\star}_j = \left[\frac{\alpha}{T_j}\sum_o\sum_g \pi^{\star}_{jog}\phi_g r^{\star}_{jo} s_{og}\tau_{jog}\right]^{\frac{1}{\zeta_j-1}}$$

Model Identification and Calibration

From the Model to the Data: Assumptions

- Identifying assumptions:
  - Native workers are not subject to labor market distortions
  - $z_{jog} = 1, \forall g$ in the smallest city and non-cognitive occupation
- Other assumptions:
  - ζ_j, T_j do not vary across city
  - ϕ_g is given
  - $\tau_{jog} = \tau_{jok}$, i.e. wedges vary only by origin, location, and occupation
- I calibrate the model on:
  - 2 cities $\rightarrow \quad \{\text{Small City}, \text{Big City}\}$
  - 3 countries of origin $\rightarrow \quad \{\text{Natives}, \text{Low-Income}, \text{High-Income}\}$
  - 2 education groups $\rightarrow \quad \{\text{No College}, \text{College}\}$
  - 3 experience groups $\rightarrow \quad \{0-14, 15-29, 30+\}$

From the Model to the Data: Internally Calibrated Parameters & Identification

- Vector of 6 parameters externally calibrated Externally calibrated parameters
- Vector of 100 parameters calibrated using the Method of Simulated Moments

Parameters Calibrated Using MSM

	Description	N. Parameters	Value
θ_j	City productivity bias	2	Bias
s_{og}	Human capital	36	Human capital
τ_{jok}	Wedge on earnings	8	Wedge on earnings
z_{jog}	Amenities	54	Amenities

Targeted Moments

Moment	N. Moments
Avg. natives earnings in city j and cognitive occupation	2
Avg. earnings in occupation o, $\forall g, o$	36
Avg. earnings for country of origin k in city j, occupation o, $\forall k \in \{\text{Low}, \text{High}\}, j, o$	8
Share of workers in group g in city j and occupation o	54

Model Fit: Earnings | Model Fit: Shares | Model Fit: Granular HC | Model Fit: Granular Earnings | Model Fit: Granular Shares

Counterfactual Exercises

The Model as a Laboratory

- I use the model to study the role of human capital, amenities and wedges on:
  - Earnings gap between natives and immigrants $\overline{w}^{\text{Gap}}_{\text{Workers}}$
  - Earnings gap between cities $\overline{w}^{\text{Gap}}_{\text{Cities}}$ Gaps definitions

- For all immigrants, keeping fixed the other parameters, I remove:
  - Experiment 1 $\rightarrow$ differences in human capital with natives
  - Experiment 2 $\rightarrow$ differences in amenities with natives
  - Experiment 3 $\rightarrow$ wedges on earnings
  - Experiment 4 $\rightarrow$ differences in amenities and wedges
  - Experiment 5 $\rightarrow$ differences in human capital, amenities and wedges

The Earnings Gaps Under the 5 Counterfactuals

	Baseline	Counterfactuals				
		Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_{okex} = s_{oUSex}$	-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$	-	-	x	-	x	x
$\tau_{jok} = 1$	-	-	-	x	x	x
$\overline{w}^{\text{Gap}}_{\text{Workers}}$	1	0.811	0.938	0.907	0.813	0.710
$\overline{w}^{\text{Gap}}_{\text{Cities}}$	1	1.011	1.030	0.999	1.025	1.023

- No differences in human capital:
  - Earnings gap -19.9% vs spatial earnings inequality +1.1%
- No differences in amenities:
  - Earnings gap -6.2% vs spatial earnings inequality +3%
- No wedges on earnings:
  - Earnings gap -9.3% vs spatial earnings inequality -0.1%

City-size premia | Aggregate output and housing prices

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	Baseline	Counterfactuals				
		Same Human Capital As Natives (1)	Same Amenities As Natives (2)	No Wedges On Earnings (3)	Same Amenities As Natives & No Wedge On Earnings (4)	Full (5)
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Mechanism: Workers' Reallocation across Cities

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$\tau_{jok} = 1$	-	-	-	x	x	x
		Share Of Workers In The Big City				
Natives	82.0	-0.2	-0.4	-0.1	-0.5	-0.4
High-Income	82.8	-0.6	-1.5	0.5	-1.0	-1.1
Low-Income	90.0	-0.1	-12.3	1.2	-9.5	-9.6

- Big-to-small cities reallocation:
    - No differences in human capital $\rightarrow$ workers from all countries
    - No differences in amenities $\rightarrow$ massive for low-income
- Small-to-big cities reallocation:
    - No wedges on earnings $\rightarrow$ larger effect for low-income

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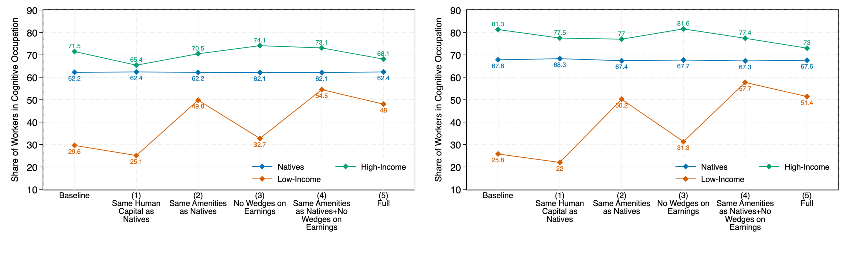
Mechanism: Workers' Reallocation across Occupations



Small City Big City

- No differences in human capital → immigrants in cognitive occupation ↓ in both cities
- No differences in amenities → low-income in cognitive occupation ↑ in both cities
- No wedges on earnings → immigrants in cognitive occupation ↑ in both cities

Mechanism: Competition Effect vs. Skills Effect

		Baseline	Counterfactuals				
			Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
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Parameters							
$s_{okex} = s_{oUSex}$		-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$		-	-	x	-	x	x
$\tau_{jok} = 1$		-	-	-	x	x	x
				Small City			
Non-Cognitive	Competition	1	0.989	1.003	1.002	1.007	0.993
	Skills	1	1.040	0.983	1.005	0.993	1.041
Cognitive	Competition	1	1.004	0.999	0.999	0.998	1.002
	Skills	1	0.999	0.981	1.000	0.981	0.989
				Big City			
Non-Cognitive	Competition	1	0.978	1.018	1.004	1.023	1.008
	Skills	1	1.089	1.028	1.003	1.033	1.084
Cognitive	Competition	1	1.006	0.995	0.999	0.994	0.998
	Skills	1	1.001	0.990	0.998	0.986	0.992

- No differences in human capital $\rightarrow$ productivity $\uparrow$ in non-cognitive occupation in all cities
- No differences in amenities $\rightarrow$ productivity $\uparrow$ in non-cognitive occupations in the big city
- No wedges on earnings $\rightarrow$ no large changes in productivity in all cities

Mechanism: Competition Effect vs. Skills Effect

		Baseline	Counterfactuals				
			Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
			(1)	(2)	(3)	(4)	(5)
Parameters							
$s_{okex} = s_{oUSex}$		-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$		-	-	x	-	x	x
$\tau_{jok} = 1$		-	-	-	x	x	x
			Small City				
Non-Cognitive	Competition	1	0.989	1.003	1.002	1.007	0.993
	Skills	1	1.040	0.983	1.005	0.993	1.041
Cognitive	Competition	1	1.004	0.999	0.999	0.998	1.002
	Skills	1	0.999	0.981	1.000	0.981	0.989
			Big City				
Non-Cognitive	Competition	1	0.978	1.018	1.004	1.023	1.008
	Skills	1	1.089	1.028	1.003	1.033	1.084
Cognitive	Competition	1	1.006	0.995	0.999	0.994	0.998
	Skills	1	1.001	0.990	0.998	0.986	0.992

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Mechanism: Competition Effect vs. Skills Effect

		Baseline	Counterfactuals				
			Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
			(1)	(2)	(3)	(4)	(5)
Parameters							
$s_{okex} = s_{oUSex}$		-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$		-	-	x	-	x	x
$\tau_{jok} = 1$		-	-	-	x	x	x
				Small City			
Non-Cognitive	Competition	1	0.989	1.003	1.002	1.007	0.993
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Mechanism: Competition Effect vs. Skills Effect

		Baseline	Counterfactuals				
			Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
			(1)	(2)	(3)	(4)	(5)
Parameters							
$s_{okex} = s_{oUSex}$		-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$		-	-	x	-	x	x
$\tau_{jok} = 1$		-	-	-	x	x	x
				Small City			
Non-Cognitive	Competition	1	0.989	1.003	1.002	1.007	0.993
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	Skills	1	0.999	0.981	1.000	0.981	0.989
				Big City			
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Policy Exercise

Immigration Policy

- General equilibrium responses after an inflow of immigrants:
  - Policy 1: inflow of immigrants with no college education
  - Policy 2: inflow of immigrants with college education
- Overall employment increases by 1 percentage point
- The estimated amenities parameters for immigrants are:

Education	Small City: Non-Cognitive Occupation (1)	Small City: Cognitive Occupation (2)	Big City: Non-Cognitive Occupation (3)	Big City: Cognitive Occupation (4)
No College	1.0	0.4	7.3	2.1
	(0.0)	(0.3)	(4.4)	(0.8)
College	1.0	1.4	5.4	9.7
	(0.0)	(1.0)	(3.0)	(6.3)

Allocations

Immigration Policy

- General equilibrium responses after an inflow of immigrants:
  - Policy 1: inflow of immigrants with no college education
  - Policy 2: inflow of immigrants with college education
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Allocations

Immigration Policy

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	Small City		Big City	
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No College	1.0	0.4	7.3	2.1
	(0.0)	(0.3)	(4.4)	(0.8)
College	1.0	1.4	5.4	9.7
	(0.0)	(1.0)	(3.0)	(6.3)

Allocations

Immigration Policy Evaluation

	Baseline	Policies	
		Inflow No College (1)	Inflow College (2)
$\overline{w}^{\text{Gap}}_{\text{Workers}}$	1	1.026	0.941
$\overline{w}^{\text{Gap}}_{\text{Cities}}$	1	0.997	0.999

- Inflow of immigrants with no college education:
  - Earnings gap b/w immigrants and natives +2.6%, but spatial earnings inequality -0.3%
    - Competition and skills effect larger in big cities than in small cities
- Inflow of immigrants with college education:
  - Earnings gap b/w immigrants and natives -5.9%, and spatial earnings inequality -0.1%
    - In all cities, positive skills effect, while competition effect is negligible

Human capital estimates Competition vs. Skills Effect

Conclusion

Conclusion

What is the geography of immigrants' labor market outcomes in the US?

- Earnings gap with natives grows with city size only for immigrants from low-income countries
  - More likely to work in non-cognitive occupations and live in big cities

How does it tie to earnings gaps with natives and spatial earnings inequality?

- Trade-off: Closing the immigrant-native earnings gap vs widening spatial earnings inequality
- Quantitatively important role for heterogeneity in amenities and labor market distortions

How does immigration policy affect these outcomes?

- Effects on earnings gap b/w immigrants and natives depends on who enters the country
- Spatial earnings inequality reduces regardless of who enters the country

Future work → housing policy and a new paper including monopsony power

THANK YOU!

Contribution to the Literature

- Immigration and inequality: Card (2009), Peri (2016), Gould (2019), Advani et al. (2022), Dustmann et al. (2023), Amior and Stuhler (2023), Lebow (2024)
  New empirical fact to explain earnings inequality: spatial distribution of occupational choices differ by origins

- Structural models to study economic outcomes related to immigration: Llull (2018), Lessem (2018), Burstein et al. (2020), Piyapromdee (2021), Albert et al. (2022), Adda et al. (2023)
  Highly-dimensional spatial equilibrium model to explain earnings inequality: heterogeneity in amenities and labor market distortions quantitatively important dimensions, other than human capital

- Misallocation of production factors: Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Gopinath et al. (2017), Bryan and Morten (2019), Hsieh et al. (2019), Guner and Ruggieri (2023), Birinci et al. (2024)
  Introducing city-occupation-origin distortions: removing them reduces earnings inequality among workers without large output gains

Preview

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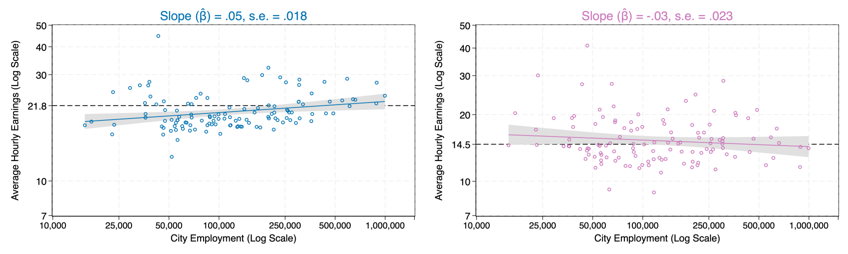
Preview

City-Size Earnings Premia: Natives vs Immigrants

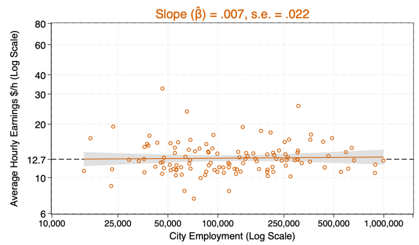


Natives Immigrants

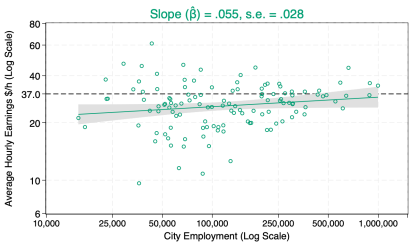
- The earnings gap b/w immigrants and natives is larger in big cities
  - Natives → doubling the city size increases hourly earnings by 3.6%
  - Immigrants → no significant change in earnings b/w small and big cities

Robustness 1 Male | Robustness 1 Male Conditional | Robustness Female 1 | Robustness 1 Female Conditional | Stylised Facts

City-Size Earnings Premium by Country of Origin



Low-income



High-income

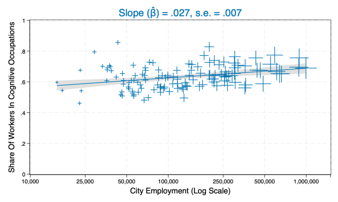
- No city-size earnings premia only for immigrants from low-income countries
  - High-income → doubling the city size increases hourly earnings by 3.9%

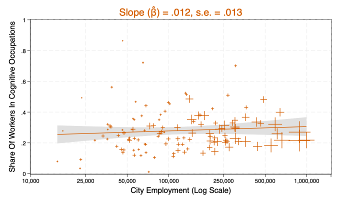
Robustness 2 Male | Robustness 2 Male Conditional | Robustness 2 Female | Robustness 2 Female Conditional

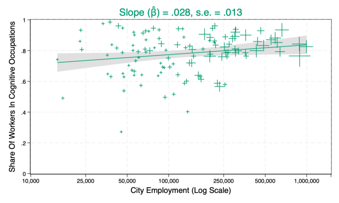
Table Natives vs Low-High Income | Stylised Facts

Spatial Distribution of Workers into Cognitive Occupations and Cities

Natives







Low-Income High-Income

- High-income country workers choose more cognitive jobs, especially in large cities. Doubling the city size:
  - The share of natives in cognitive jobs +1pp
  - The share of immigrants from high-income countries in cognitive jobs +1.5pp
  - The share of immigrants from low-income countries does not change

Fact 3 Table

Stylised Facts

Robustness Checks Fact 1

Fully interacted model with an immigrant dummy:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)	Log Hourly Earnings (6)
Log City Employment	0.068	0.039	0.046	0.049	0.042	0.042
	(0.013)	(0.008)	(0.008)	(0.008)	(0.01)	(0.007)
Imm#Log City Employment	−0.117	−0.060	−0.070	−0.074	−0.056	−0.051
	(0.016)	(0.009)	(0.012)	(0.014)	(0.01)	(0.008)
Immigrants	1.050	0.655	0.785	1.633	1.076	0.709
	(0.203)	(0.119)	(0.162)	(0.216)	(0.155)	(0.142)
Constant	1.950	1.705	0.639	−0.646	1.720	1.720
	(0.155)	(0.095)	(0.102)	(0.105)	(0.096)	(0.096)
N. Obs	619,576	619,576	619,576	619,576	619,576	619,576
Adj.R2	0.04	0.26	0.36	0.35	0.47	0.47
Years of School FE	✗	✓	✓	✗	✓	✓
Linear Years of School	✗	✗	✗	✓	✗	✗
Experience FE	✗	✗	✓	✗	✓	✓
Cubic Experience	✗	✗	✗	✓	✗	✗
Occupation FE	✗	✗	✗	✗	✓	✓
Origin FE	✗	✗	✗	✗	✗	✓

Fact 1 Plots

Robustness Checks Fact 1: Conditional Regressions

Fully interacted model with an immigrant dummy:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	No College Education	**College Education**	**0-14 Experience**	**15-29 Experience**	**30+ Experience**
	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Log City Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.010)
Immigrants#Log City Employment	−0.058	−0.103	−0.068	−0.089	−0.084
	(0.013)	(0.025)	(0.013)	(0.015)	(0.017)
Immigrants	0.525	1.493	0.650	0.715	0.662
	(0.162)	(0.316)	(0.16)	(0.182)	(0.207)
Constant	1.777	1.840	1.500	1.852	1.950
	(0.09)	(0.17)	(0.143)	(0.144)	(0.124)
N. Obs	248,852	370,724	189,288	251,364	178,924
Adj.R2	0.14	0.08	0.19	0.23	0.17
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 1: Female Workers

Fully interacted model with an immigrant dummy:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	Log Hourly Earnings (1)	**Log Hourly Earnings** (2)	**Log Hourly Earnings** (3)	**Log Hourly Earnings** (4)	**Log Hourly Earnings** (5)	**Log Hourly Earnings** (6)
Log City Employment	0.073	0.045	0.05	0.051	0.044	0.044
	(0.017)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)
Imm#Log City Employment	−0.088	−0.048	−0.054	−0.052	−0.051	−0.048
	(0.015)	(0.011)	(0.013)	(0.014)	(0.012)	(0.01)
Immigrants	0.694	0.503	0.582	1.498	0.615	0.562
	(0.185)	(0.132)	(0.157)	(0.184)	(0.207)	(0.183)
Constant	1.670	1.438	0.587	−0.614	1.786	1.786
	(0.210)	(0.138)	(0.164)	(0.165)	(0.158)	(0.158)
N. Obs	519,891	519,891	519,891	519,891	519,891	519,891
Adj.R2	0.04	0.23	0.30	0.29	0.44	0.44
Years of School FE	✗	✓	✓	✗	✓	✓
Linear Years of School	✗	✗	✗	✓	✗	✗
Experience FE	✗	✗	✓	✗	✓	✓
Cubic Experience	✗	✗	✗	✓	✗	✗
Occupation FE	✗	✗	✗	✗	✓	✓
Origin FE	✗	✗	✗	✗	✗	✓

Fact 1 Plots

Robustness Checks Fact 1: Female Workers Conditional Regressions

Fully interacted model with an immigrant dummy:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	No College Education	**College Education**	**0-14 Experience**	**15-29 Experience**	**30+ Experience**
	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Log City Employment	0.040	0.074	0.059	0.067	0.060
	(0.010)	(0.020)	(0.016)	(0.016)	(0.015)
Imm#Log City Employment	−0.060	−0.050	−0.056	−0.064	−0.076
	(0.018)	(0.019)	(0.022)	(0.017)	(0.017)
Immigrants	0.576	0.610	0.523	0.431	0.593
	(0.217)	(0.239)	(0.283)	(0.201)	(0.210)
Constant	1.533	1.675	1.296	1.508	1.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	188,642	331,249	164,887	200,182	154,822
Adj.R2	0.10	0.04	0.17	0.19	0.16
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 2

Fully interacted model with dummies for the country of origin:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Log Employment	0.068	0.039	0.046	0.049	0.042
	(0.013)	(0.008)	(0.008)	(0.008)	(0.007)
Low-Income#Log Employment	−0.107	−0.059	−0.070	−0.074	−0.057
	(0.016)	(0.01)	(0.013)	(0.015)	(0.01)
High-Income#Log Employment	−0.009	0.013	0.016	0.018	0.007
	(0.025)	(0.017)	(0.017)	(0.018)	(0.013)
Low-Income	0.850	0.636	0.794	1.810	0.808
	(0.193)	(0.126)	(0.171)	(0.226)	(0.206)
High-Income	0.613	0.361	0.121	−0.271	0.325
	(0.31)	(0.262)	(0.266)	(0.335)	(0.229)
Constant	1.950	1.705	0.639	−0.646	1.720
	(0.155)	(0.095)	(0.102)	(0.105)	(0.096)
N. Obs	619,576	619,576	619,576	619,576	619,576
Adj.R2	0.05	0.09	0.37	0.36	0.47
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Fact 2 Plots

Robustness Checks Fact 2: Conditional Regressions

Fully interacted model with dummies for the country of origin:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	No College Education	**College Education**	**0-14 Experience**	**15-29 Experience**	**30+ Experience**
	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Log Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.01)
Low-Income#Log Employment	−0.055	−0.108	−0.079	−0.089	−0.077
	(0.012)	(0.029)	(0.017)	(0.016)	(0.015)
High-Income#Log Employment	−0.001	0.008	0.028	−0.004	0.029
	(0.025)	(0.025)	(0.04)	(0.021)	(0.034)
Low-Income	0.475	1.443	0.777	0.692	0.549
	(0.155)	(0.346)	(0.219)	(0.2)	(0.19)
High-Income	0.497	0.397	0.124	0.259	−0.226
	(0.350)	(0.319)	(0.535)	(0.278)	(0.419)
Constant	01.777	1.840	1.500	1.852	1.950
	(0.09)	(0.17)	(0.143)	(0.144)	(0.124)
N. Obs	248,852	370,724	189,288	251,364	178,924
Adj.R2	0.14	0.09	0.19	0.24	0.18
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 2 Plots

Robustness Checks Fact 2: Female Workers

Fully interacted model with dummies for the country of origin:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Log Employment	0.073	0.045	0.05	0.051	0.044
	(0.017)	(0.011)	(0.013)	(0.013)	(0.012)
Low-Income#Log Employment	−0.083	−0.044	−0.051	−0.049	−0.051
	(0.015)	(0.011)	(0.013)	(0.014)	(0.013)
High-Income#Log Employment	−0.020	−0.027	−0.023	−0.023	−0.023
	(0.031)	(0.025)	(0.025)	(0.027)	(0.019)
Low-Income	0.584	0.452	0.543	1.468	0.337
	(0.178)	(0.13)	(0.156)	(0.182)	(0.228)
High-Income	0.371	0.487	0.344	0.534	0.476
	(0.387)	(0.321)	(0.344)	(0.503)	(0.325)
Constant	1.670	1.438	0.587	−0.614	1.786
	(0.210)	(0.138)	(0.164)	(0.165)	(0.158)
N. Obs	519,891	519,891	519,891	519,891	519,891
Adj.R2	0.04	0.14	0.30	0.30	0.44
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Fact 2 Plots

Robustness Checks Fact 2: Female Workers Conditional Regressions

Fully interacted model with dummies for the country of origin:

$$\ln w_i = \alpha + \beta \ln \text{Employment}_{j(i)} + X_i + \varepsilon_i$$

	No College Education	**College Education**	**0-14 Experience**	**15-29 Experience**	**30+ Experience**
	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Log Employment	0.040	0.074	0.059	0.067	0.060
	(0.01)	(0.02)	(0.016)	(0.016)	(0.015)
Low-Income#Log Employment	−0.056	−0.044	−0.058	−0.063	−0.069
	(0.018)	(0.019)	(0.026)	(0.016)	(0.017)
High-Income#Log Employment	−0.021	−0.017	−0.059	0.040	−0.083
	(0.029)	(0.04)	(0.054)	(0.037)	(0.043)
Low-Income	0.515	0.445	0.530	0.409	0.491
	(0.216)	(0.235)	(0.328)	(0.199)	(0.201)
High-Income	0.542	0.537	1.022	−0.436	0.966
	(0.389)	(0.511)	(0.704)	(0.459)	(0.540)
Constant	1.533	01.675	1.296	1.508	1.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	188,642	331,249	164,887	200,182	154,822
Adj.R2	0.10	0.04	0.18	0.19	0.16
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 2 Plots

Hourly Earnings: Big vs Small Cities

	Small City (Pop. $<$ 500,000)	Big City (Pop. $\geq$ 500,000)	City-Size Gap
Natives	21.0	23.8	+2.8
High-Income	33.2	39.6	+6.4
Low-Income	13.3	11.9	-1.4

Fact 2 Plots

Workers Distributions across Cities and Occupations

		Small City (Pop. $<$ 500,000)	Big City (Pop. $\geq$ 500,000)	Δ
Natives	% Cognitive	63.9	68.8	4.9
	% Total	17.7	82.3	64.6
High-Income	% Cognitive	71.6	80.4	8.9
	% Total	19.3	80.7	61.3
Low-Income	% Cognitive	27.5	24.7	-2.8
	% Total	10.7	89.3	78.7

- Workers from high-income countries work more in cognitive jobs in big cities
- Workers from low-income countries are more likely to live in big cities relative to all other workers

Fact 3 Plots

Endogenous Housing Supply

- The production function for housing is given by:

$$H_j = f(Y_j, T_j) = \omega_j Y_j^{\iota_j} T_j^{1-\iota_j}$$

where $\omega_j = \iota_j^{-\iota_j}$ is a constant, and $(1 - \iota_j)$ is the weight of land in the production of housing.

- The (absentee) landlord solves:

$$\max_{Y_j} \quad p_j \left(\omega_j Y_j^{\iota_j} T_j^{1-\iota_j} \right) - Y_j$$

- Solving FOC and rearranging:

$$Y_j = (p_j \omega_j \iota_j)^{\frac{1}{1-\iota}} \; T_j$$

- Plug FOC into the production function to get the housing supply in a city j:

$$p_j = \left(\frac{H_j}{T_j} \right)^{\frac{1}{\zeta_j}}$$

Externally Calibrated Parameters

Parameters From The Literature Or Assumed

Description	Symbol	Value	Source
Elasticity of substitution	σ	3	Hsieh et al. (2019)
Housing supply elasticity	ζ	1.54	Saiz (2010)
Share of expenditure in housing	α	0.32	Albouy (2008)
Share of group g in the economy	ϕ		ACS 2010
Small & Big City Land	T	1	Assumed

Identification

Estimated City Productivity Bias In Cognitive Occupations

	Small City (1)	Big City (2)
Productivity Bias In Cognitive Occupations	1.3	1.5

Parameters

Estimated Human Capital

Workers Origins	Non-Cognitive Occupation (1)	Cognitive Occupation (2)	Overall (3)
Natives	7.0 (1.3)	15.2 (5.6)	11.1 (5.8)
High-Income	7.1 (0.9)	22.5 (6.0)	14.8 (8.9)
Low-Income	4.6 (0.7)	11.6 (4.4)	8.1 (4.7)

Parameters

Estimated Wedges on Earnings

Workers Origins	Small City: Non-Cognitive Occupation (1)	Small City: Cognitive Occupation (2)	Big City: Non-Cognitive Occupation (3)	Big City: Cognitive Occupation (4)
High-Income	1.3	1.1	1.2	1.1
Low-Income	1.2	0.9	1.0	0.7

Parameters

Estimated Amenities

Workers Origins	Small City		Big City	
	Non-Cognitive Occupation (1)	Cognitive Occupation (2)	Non-Cognitive Occupation (3)	Cognitive Occupation (4)
	Amenities			
Natives	1.0 (0.0)	1.3 (0.8)	3.9 (0.2)	6.4 (4.5)
High-Income	1.0 (0.0)	1.3 (1.1)	3.2 (1.4)	7.1 (7.7)
Low-Income	1.0 (0.0)	0.5 (0.4)	9.5 (2.2)	4.7 (3.6)

Parameters

Model Fit: Earnings

	Small City (Pop. $<$ 500,000)		Big City (Pop. $\geq$ 500,000)		Δ	
	Data (1)	Model (2)	Data (3)	Model (4)	Data (5)	Model (6)
Natives	21.0	20.6	23.8	23.6	+2.8	+3.0
High-Income	33.2	33.3	39.6	40.0	+6.4	+6.7
Low-Income	13.3	13.7	11.9	12.1	-1.4	-1.6

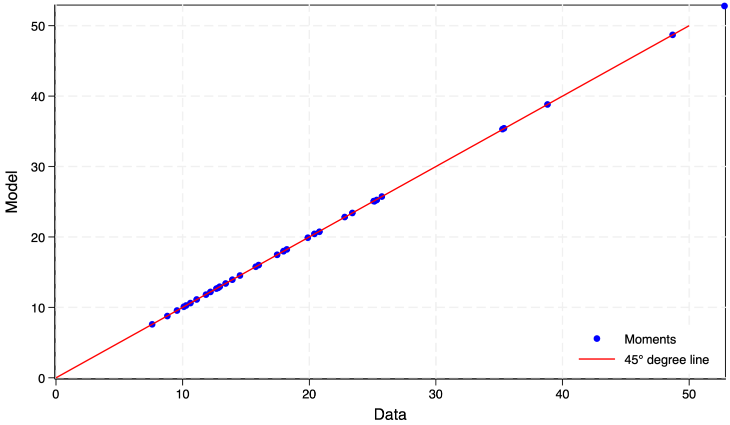
Parameters

Model Fit: Shares

		Small City (Pop. $<$ 500,000)		Big City (Pop. $\geq$ 500,000)		Δ	
		Data (1)	Model (2)	Data (3)	Model (4)	Data (5)	Model (6)
Natives	Cognitive Occ.	63.9	62.2	68.8	67.8	4.9	5.6
	Employment	17.7	18.0	82.3	82.0	64.6	64.1
High-Income	Cognitive Occ.	71.6	71.5	80.4	81.3	8.9	9.8
	Employment	19.3	17.2	80.7	82.8	61.3	65.6
Low-Income	Cognitive Occ.	27.5	29.6	24.7	25.8	-2.8	-3.8
	Employment	10.7	10.0	89.3	90.0	78.7	80.0

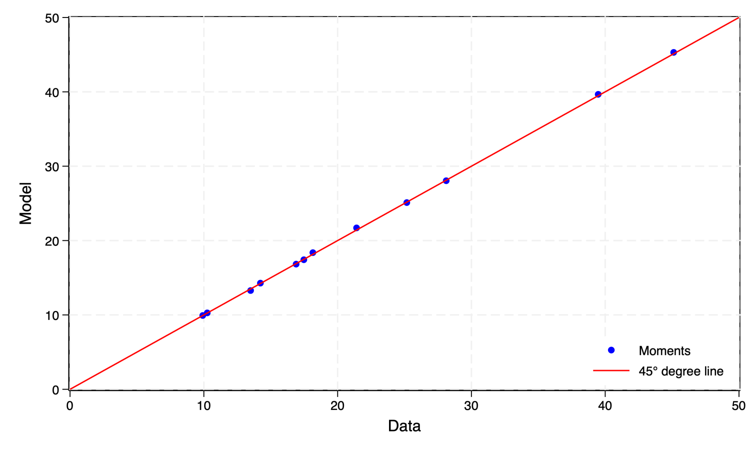
Parameters

Model Fit: Granular Human Capital



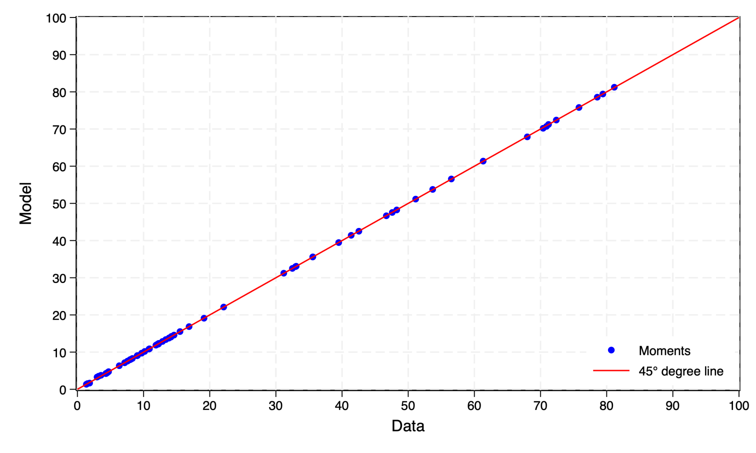
Parameters

Model Fit: Granular Earnings



Parameters

Model Fit: Granular Shares



Parameters

Real Output pc & Housing Prices Under The 5 Counterfactuals

- I measure the earnings gap between natives and immigrants as the ratio of the average natives' and immigrants' earnings:

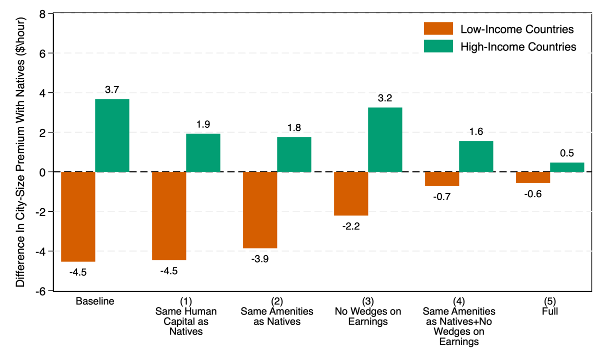
$$\overline{w}^{\text{Gap}}_{\text{Workers}} = \frac{\overline{w}_{\text{US}}}{\overline{w}_{\text{Imm}}} = \frac{\sum_j \sum_o \sum_e \sum_x \pi_{joUSex} \phi_{USex} w_{joUSex}}{\sum_j \sum_o \sum_{k \neq \text{US}} \sum_e \sum_x \pi_{jokex} \phi_{kex} w_{jokex}}$$

- Similarly, I define spatial earnings inequality as the ratio of average earnings in the big city and in the small city:

$$\overline{w}^{\text{Gap}}_{\text{Cities}} = \frac{\overline{w}_{\text{Big}}}{\overline{w}_{\text{Small}}} = \frac{\sum_o \sum_k \sum_e \sum_x \pi_{\text{Big}okex} \phi_{kex} w_{\text{Big}okex}}{\sum_o \sum_k \sum_e \sum_x \pi_{\text{Small}okex} \phi_{kex} w_{\text{Small}okex}}$$

Main result

What Determines the Differences in City-Size Earnings Premia?



Differences in city-size earnings premium:

- Human capital → no changes for low-income, -48.6% high-income
- Wedges on labor supply → +13.3% low-income, -51.3% high-income
- Wedges on earnings → +51.1% low-income, -13.5% high-income
- Both wedges → +84.4% low-income, -56.7% high-income

Main result

Real Output pc & Housing Prices Under The 5 Counterfactuals

	Baseline	Counterfactuals				
		Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_{okex} = s_{oUSex}$	-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$	-	-	x	-	x	x
$\tau_{jok} = 1$	-	-	-	x	x	x
			Housing Prices			
Big-Small City Ratio	1	1.010	1.026	1.008	1.034	1.031
			Real Output Per Capita			
US	1	1.018	1.007	1.002	1.009	1.023

- No differences in human capital:
  - Output gains larger than spatial increase in housing prices
- No differences in amenities or no wedges on earnings:
  - Output gains less than spatial increase in housing prices

Main result

Real Output pc & Housing Prices Under The 5 Counterfactuals

	Baseline	Counterfactuals				
		Same Human Capital As Natives (1)	Same Amenities As Natives (2)	No Wedges On Earnings (3)	Same Amenities As Natives & No Wedge On Earnings (4)	Full (5)
Parameters						
$s_{okex} = s_{oUSex}$	-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$	-	-	x	-	x	x
$\tau_{jok} = 1$	-	-	-	x	x	x
			Housing Prices			
Big-Small City Ratio	1	1.010	1.026	1.008	1.034	1.031
			Real Output Per Capita			
US	1	1.018	1.007	1.002	1.009	1.023

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- No differences in amenities or no wedges on earnings:
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Main result

Real Output pc & Housing Prices Under The 5 Counterfactuals

	Baseline	Counterfactuals				
		Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_{okex} = s_{oUSex}$	-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$	-	-	x	-	x	x
$\tau_{jok} = 1$	-	-	-	x	x	x
			Housing Prices			
Big-Small City Ratio	1	1.010	1.026	1.008	1.034	1.031
			Real Output Per Capita			
US	1	1.018	1.007	1.002	1.009	1.023

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- No differences in amenities or no wedges on earnings:
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Main result

Real Output pc & Housing Prices Under The 5 Counterfactuals

	Baseline	Counterfactuals				
		Same Human Capital As Natives (1)	Same Amenities As Natives (2)	No Wedges On Earnings (3)	Same Amenities As Natives & No Wedge On Earnings (4)	Full (5)
Parameters						
$s_{okex} = s_{oUSex}$	-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$	-	-	x	-	x	x
$\tau_{jok} = 1$	-	-	-	x	x	x
			Housing Prices			
Big-Small City Ratio	1	1.010	1.026	1.008	1.034	1.031
			Real Output Per Capita			
US	1	1.018	1.007	1.002	1.009	1.023

- No differences in human capital:
  - Output gains larger than spatial increase in housing prices
- No differences in amenities or no wedges on earnings:
  - Output gains less than spatial increase in housing prices

Main result

Human Capital Estimates

Education	Occupation	Low-Income (1)	High-Income (2)	All Immigrants (3)
No College	Non-Cognitive	4.3	6.5	4.3
		(0.5)	(0.5)	(0.5)
	Cognitive	9.4	13.6	9.9
		(1.1)	(0.4)	(1.5)
College	Non-Cognitive	5.5	7.3	5.7
		(0.5)	(1.0)	(0.6)
	Cognitive	18.8	25.8	20.7
		(1.8)	(2.5)	(3.7)

Policy results

Human Capital Estimates

Education	Occupation	Low-Income (1)	High-Income (2)	All Immigrants (3)
No College	Non-Cognitive	4.3 (0.5)	6.5 (0.5)	4.3 (0.5)
	Cognitive	9.4 (1.1)	13.6 (0.4)	9.9 (1.5)
College	Non-Cognitive	5.5 (0.5)	7.3 (1.0)	5.7 (0.6)
	Cognitive	18.8 (1.8)	25.8 (2.5)	20.7 (3.7)

Policy results

Human Capital Estimates

Education	Occupation	Low-Income (1)	High-Income (2)	All Immigrants (3)
No College	Non-Cognitive	4.3	6.5	4.3
		(0.5)	(0.5)	(0.5)
	Cognitive	9.4	13.6	9.9
		(1.1)	(0.4)	(1.5)
College	Non-Cognitive	5.5	7.3	5.7
		(0.5)	(1.0)	(0.6)
	Cognitive	18.8	25.8	20.7
		(1.8)	(2.5)	(3.7)

Policy results

Immigration Policy Evaluation: Cities' Allocations

	Baseline	Policies	
		Inflow No College (1)	Inflow College (2)
		Employment Share	
Big City	82.8	+0.1	+0.1
		Cognitive Occupation Share	
Small City	3.8	+0.2	+0.8
Big City	5.4	+0.2	+1.1

Policy: Competition vs. Skills Effects

		Baseline	Policies	
			Inflow No College (1)	Inflow College (2)
			Small City	
Non-Cognitive	Competition	1	0.999	1.001
	Skills	1	0.996	0.999
Cognitive	Competition	1	1.000	1.000
	Skills	1	0.999	1.002
			Big City	
Non-Cognitive	Competition	1	0.997	1.001
	Skills	1	0.993	0.999
Cognitive	Competition	1	1.001	1.000
	Skills	1	0.999	1.003

Policy: Competition vs. Skills Effects

		Baseline	Policies	
			Inflow No College (1)	Inflow College (2)
			Small City	
Non-Cognitive	Competition	1	0.999	1.001
	Skills	1	0.996	0.999
Cognitive	Competition	1	1.000	1.000
	Skills	1	0.999	1.002
			Big City	
Non-Cognitive	Competition	1	0.997	1.001
	Skills	1	0.993	0.999
Cognitive	Competition	1	1.001	1.000
	Skills	1	0.999	1.003

Policy: Competition vs. Skills Effects

		Baseline	Policies	
			Inflow No College (1)	Inflow College (2)
			Small City	
Non-Cognitive	Competition	1	0.999	1.001
	Skills	1	0.996	0.999
Cognitive	Competition	1	1.000	1.000
	Skills	1	0.999	1.002
			Big City	
Non-Cognitive	Competition	1	0.997	1.001
	Skills	1	0.993	0.999
Cognitive	Competition	1	1.001	1.000
	Skills	1	0.999	1.003