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

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Introduction

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- **Motivation**: There is a lively debate about US immigration.
  Immigrants are key contributors to the economy (jobs, businesses, taxes, expenditures), but **earn 30% less** than natives.
  This earnings gap:
  - Deters the attraction of talent
  - Affects labor market efficiency and inequality

- **Existing evidence**: US immigrants and natives mainly **differ in**:
  i. **Job choices** → Human capital (Lagakos et al., 2018), task specialization (Peri and Sparber, 2009), labor market barriers (Birinci et al., 2024)
  ii. **Residential choices** → Preferences for locations (Albert and Monras, 2022)

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Research Questions

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

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

How does immigration policy affect these outcomes?

This paper

- Documents **3 stylised facts:**
  i. The **earnings gap** b/w immigrants and natives is **larger in big cities**
  ii. No city-size earnings premia only for immigrants from **low-income countries**
  iii. Workers from **high-income countries** work more in **cognitive jobs**, especially in big cities

- Interprets these facts with a **spatial GE model** including:
  - Workers' location-occupation choices depending on **human capital**, **amenities**, and local labor market **wedges**
  - Cross-city heterogeneity: technology and housing supply

- Quantifies the role **these factors** influence workers' allocations and earnings gaps
  - No differences in **human capital** or **amenities** $\longrightarrow$ earnings gap among workers $\downarrow$, but across space $\uparrow$
  - Removing **wedges** $\longrightarrow$ earnings gap $\downarrow$ both among workers and across space

- Studies the **consequences of new immigration policies** on these outcomes
  - **Earnings gap across space** $\downarrow$ independent of who enter the country

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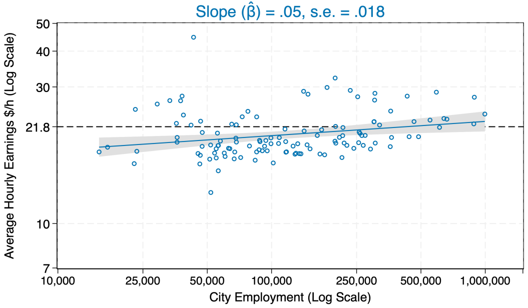
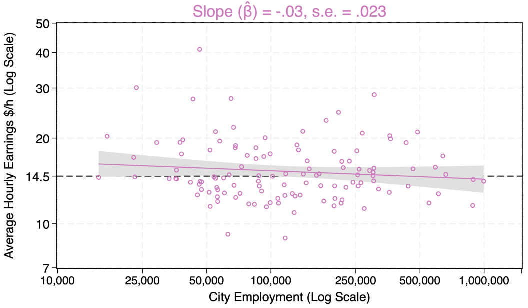
Stylised Facts

The Earnings Gap b/w Immigrants and Natives is Larger in Big Cities



Natives

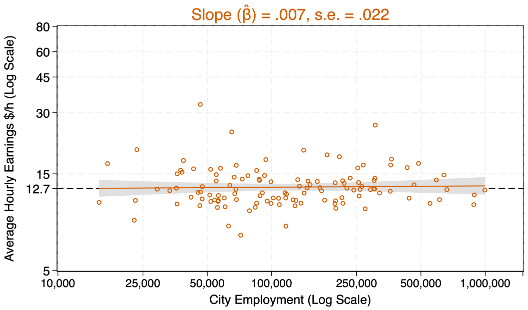


Immigrants

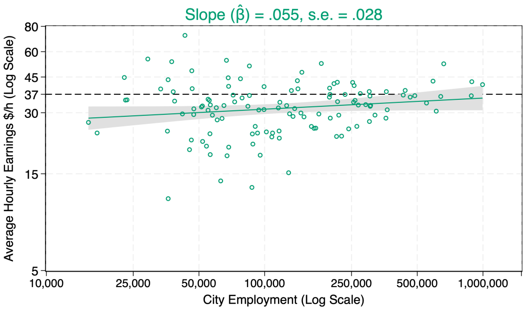
- Natives: doubling the city size $\longrightarrow$ hourly earnings +3.6%
- Immigrants: doubling the city size $\longrightarrow$ hourly earnings $\approx$ constant

Data | Robustness 1 Male | Robustness 1 Male CP | Robustness 1 Male Conditional | Robustness 1 Male Conditional CP | Robustness Female 1 | Robustness Female 1 CP | Robustness 1 Female Conditional | Robustness 1 Female Conditional CP

No City-Size Earnings Premia only for Immigrants from Low-Income Countries



Low-Income



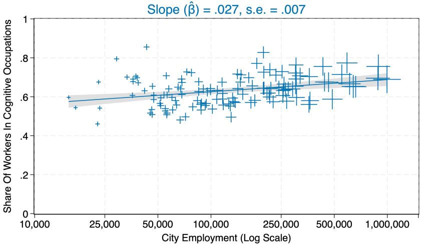
High-Income

- High-Income: doubling the city size → hourly earnings +3.9%

Robustness 2 Male | Robustness 2 Male CP | Robustness 2 Male Conditional | Robustness 2 Male Conditional CP | Robustness 2 Female | Robustness 2 Female CP | Robustness 2 Female Conditional | Robustness 2 Female Conditional CP | Table Natives vs Low-High Income

High-Income Countries Workers Work More in Cognitive Jobs, Especially in Large Cities

Natives



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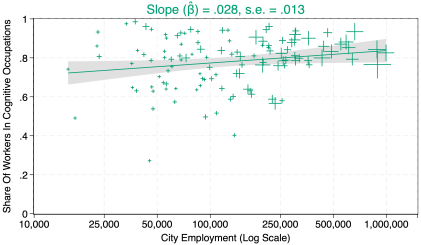

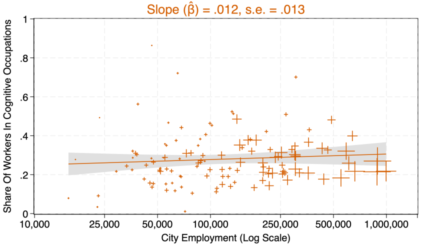

Low-Income

Fact 3 Table

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 the determinants of job choices b/w immigrants and natives accounting for spatial sorting
  - Study the consequences of inflows of new immigrants on earnings inequality
- **The model has three building blocks:**
  - Workers' heterogeneity in skills and tastes for where to work and live (Schoellman (2012), Lagakos et al. (2018), Albert & Monras (2022))
  - Local labor market distortions (Hsieh et al. (2019), Birinci et al. (2024))
  - Differences in technology across cities (Atalay et al. (2023), Eeckhout et al. (2024), Giannone (2023))

The Model

Environment

- **Static economy:** cities (local labor markets) and agents (workers)
- **Cities, production and housing:**
  - $j \in \{1, \dots, J\}$ cities
  - Firm in city j produces Y_j with CES technology using human capital in two occupations $o \in \{M, D\}$
  - City-specific productivity bias θ_j in cognitive occupations D
  - Absentee landlords own land T_j and produce housing H_j
- **Workers:**
  - Continuum of workers $i \in [0, 1]$
  - Each worker i is endowed with human capital $\mathbf{s} = (s_M, s_D)$ and belongs to a group $g = (k, e, x)$
  - Each group has a measure ϕ_g s.t. $\sum_g \phi_g = 1$
  - Cobb-Douglas utility function in consumption and housing goods

$$U_{jog} = c_{jog}^{(1-\alpha)} h_{jog}^{\alpha} \mathbf{z_{jog}} \exp\{\varepsilon_{jo}\}$$

$\varepsilon_{jo} \sim$ Gumbel$(0, 1)$ i.i.d. taste shock, city-occupation amenities z_{jog}, α expenditure share in housing

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Firms', Workers', Landlords' Problems, and Choice Equation

- **Each firm**
  - Sets skills prices r_{jo} to max profits and min costs Firm problem
- **A worker $i \in g$**
  - Earns: $w_{jog} = r_{jo} s_{og} \tau_{jog}$
    - τ_{jog} is a group-specific local labor market compensation wedge
  - Given their city-occupation choice, max utility subject to her budget constraint (earnings) Worker problem Indirect utility
  - The share of workers from group g choosing a city j and an occupation o is:

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

- **Absentee landlords**
  - Housing supply is governed by: $p_j = \left(\frac{H_j}{T_j}\right)^{\frac{1}{\zeta_j}}$, H_j is the housing demand, T_j is land, ζ_j is housing supply elasticity Housing supply

Spatial Eq.

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Model Identification and Calibration

From the Model to the Data: Assumptions and Identification

- **Identifying assumptions:**
  i. Native workers are not subject to labor market distortions
  ii. $\tau_{jog} = \tau_{jok}$, i.e. wedges vary only by origin, location, and occupation

- **Other assumptions:**
  - ζ_j, T_j do not vary across city
  - ϕ_g is given

- **Dimensionality reduction:**
  - 2 cities $\rightarrow$ {Small City, Big City}
  - 3 countries of origin $\rightarrow$ {Natives, Low-Income, High-Income}
  - 2 education groups $\rightarrow$ {No College, College}
  - 3 experience groups $\rightarrow$ $\{0-14, 15-29, 30+\}$

- **Parameters:**
  - 6 externally calibrated Externally calibrated parameters
  - 100 calibrated using the MSM Identification and internal calibration

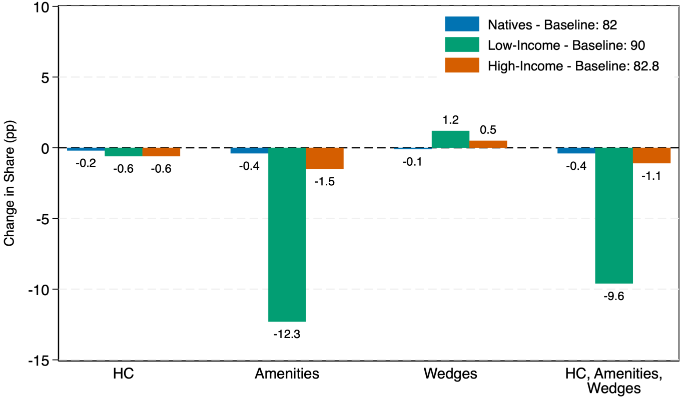
Counterfactual Exercises

The Model as a Laboratory

- **Quantification:** study how **human capital**, **amenities**, and **wedges** affect:
  - Workers' allocations
  - The earnings gap b/w natives and immigrants $\overline{w}^{\text{Gap}}_{\text{Workers}}$
  - The earnings gap b/w big and small cities $\overline{w}^{\text{Gap}}_{\text{Cities}}$ Gaps definitions

- **Counterfacutals:** for all immigrants
  - Keeping fixed the other parameters, remove:
    1. Differences in **human capital** with natives
    2. Differences in **amenities** with natives
    3. **Wedges** on earnings
  - Remove:
    4. Differences in **human capital** and **amenities** with natives, and **wedges**

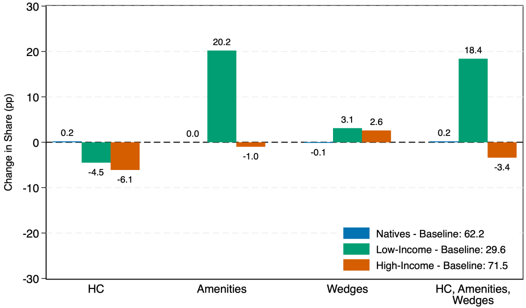
Workers' Reallocation across Space



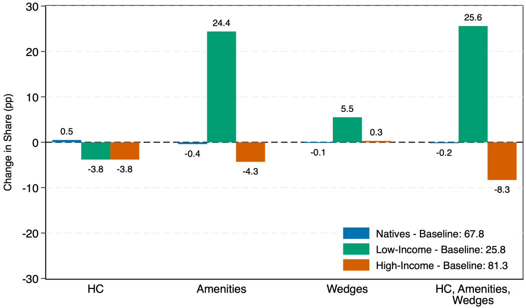
- **Human capital** & **Amenities**: big-to-small cities reallocation, larger for all immigrants
- **Wedges**: immigrants small-to-big cities reallocation, larger for low-income immigrants

Table

Workers’ Reallocation into Cognitive Occupations: Small and Big Cities



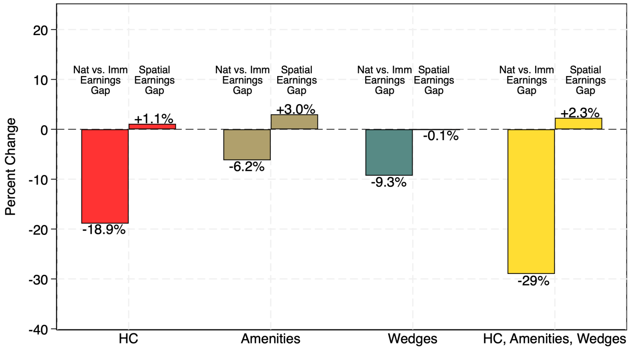
Small City



Big City

- **Human capital**: immigrants from any country in cognitive occupations ↓ in both cities
- **Amenities**: immigrants from low-income countries in cognitive occupations ↑ in both cities
- **Wedges**: immigrants in cognitive occupations ↑ in both cities

The Earnings Gaps: Human Capital vs Amenities vs Wedges



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- **Amenities:** nat-imm earnings gap **-6.2%** vs spatial earnings gap **+3%**
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- **All:**
  - Nat-Imm. earnings gap → mostly explained by differences in **human capital**
  - Spatial earnings gap → mostly explained by differences in **amenities**

Table | City-size premia | Agg. output and housing prices | Competition and skills effects

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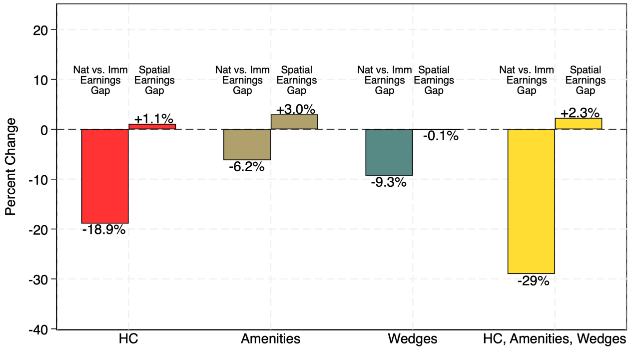

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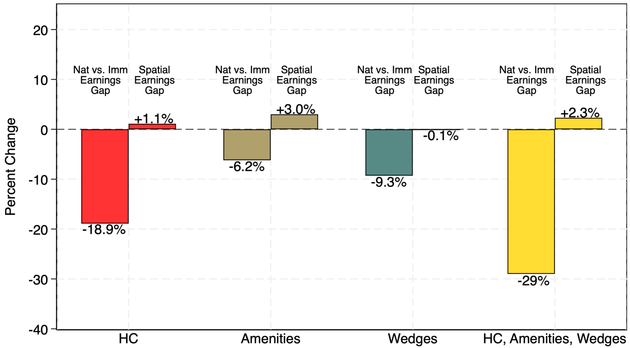

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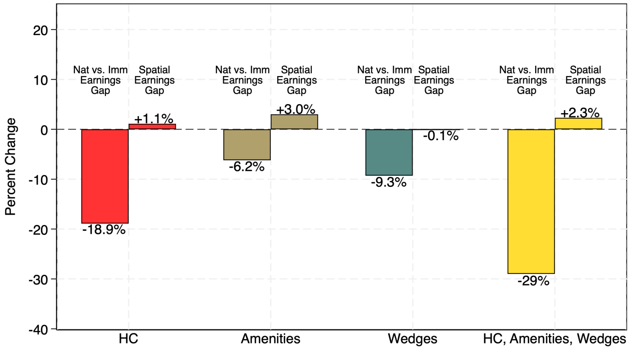

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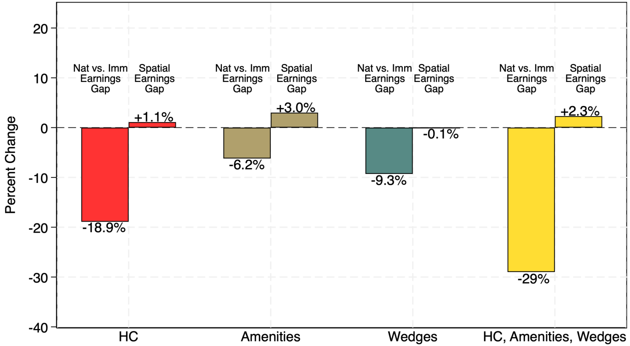

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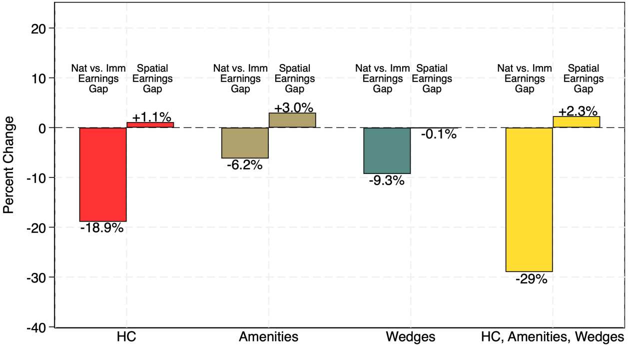

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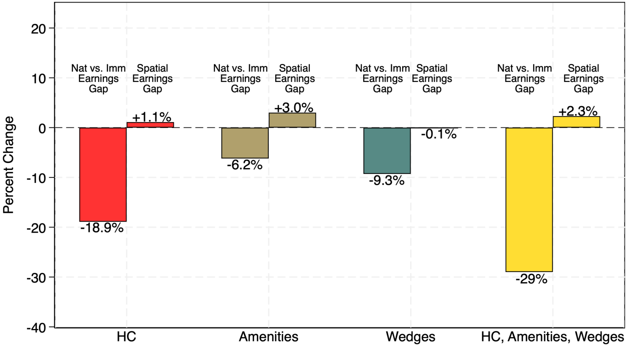

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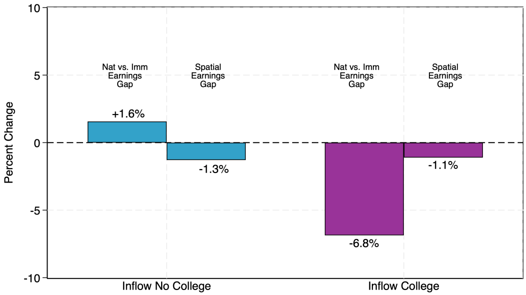
Policy Exercises

Immigration Policy: Earnings Gaps

- GE responses after an inflow of immigrants (overall employment +1pp):
  - **Policy 1:** inflow of immigrants with no college education
  - **Policy 2:** inflow of immigrants with college education



- Inflow of immigrants with **no college education**:
  - Nat-imm earnings gap **+1.6%** vs spatial earnings gap **-1.3%**
- Inflow of immigrants with **college education**:
  - Nat-imm earnings gap **-6.8%** vs spatial earnings gap **-1.1%**

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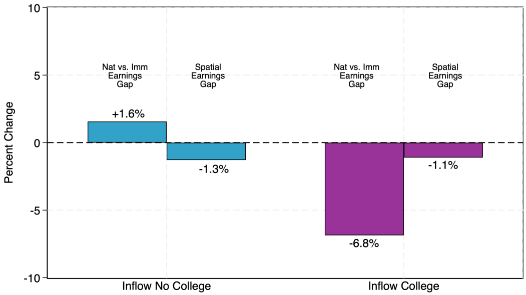

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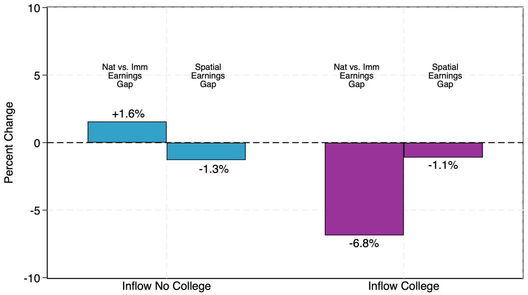
  - Nat-imm earnings gap **+1.6%** vs spatial earnings gap **-1.3%**
- Inflow of immigrants with **college education**:
  - Nat-imm earnings gap **-6.8%** vs spatial earnings gap **-1.1%**

Immigration Policy: Earnings Gaps

- GE responses after an inflow of immigrants (overall employment +1pp):
  - **Policy 1:** inflow of immigrants with no college education
  - **Policy 2:** inflow of immigrants with college education



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Amenities estimates | Human capital estimates | City allocations | Occ allocations | Competition vs. Skills Effect | Housing prices & Real Output pc

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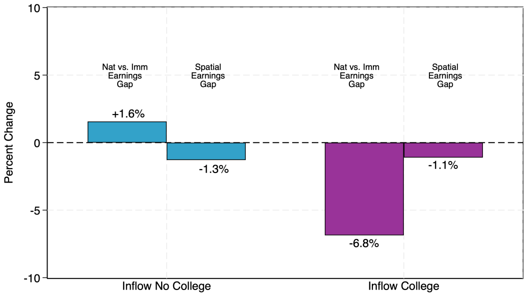

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Spatial Earnings Inequality ↓

Amenities estimates | Human capital estimates | City allocations | Occ allocations | Competition vs. Skills Effect | Housing prices & Real Output pc

Conclusion

Conclusion

- **Empirical evidence**:
  1. The earnings gap between immigrants and natives is larger in big cities:
     - Country of origin and occupational sorting across space are relevant factors

- **Spatial GE framework with occupational choices**:
  i. No differences in **human capital** or **amenities** b/w immigrants and natives → **Inequality trade-off**
  ii. No origin-specific local labor market **wedges** → **No inequality trade-off**
     - Improved allocation of all workers into occupations across space

- **Immigration policy based on education**
  1. Immigrants helps to **reduce spatial earnings inequality** regardless of their educational background

Thank you!

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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 fact: spatial distribution of occupational choices differ by origins

- **Structural models to study economic outcomes related to immigration**: Peri and Sparber (2009), Ottaviano and Peri (2012), Llull (2018), Lessem (2018), Burstein et al. (2020), Piyapromdee (2021), Albert et al. (2022), Adda et al. (2023)
  Rich heterogeneity in spatial GE to study inequality outcomes

- **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)
  Introduce origin-specific local labor market distortions

Fact 1 Plots

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Fact 1 Plots

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

Robustness Checks Fact 1

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

	Log Hourly Earnings (1)	**Log Hourly Earnings** (2)	**Log Hourly Earnings** (3)	**Log Hourly Earnings** (4)	**Log Hourly Earnings** (5)
			Immigrants		
Log City Employment	−0.049	−0.021	−0.024	−0.025	−0.014
	(0.021)	(0.011)	(0.012)	(0.014)	(0.012)
Constant	3.000	2.360	1.825	0.987	2.990
	(0.256)	(0.136)	(0.160)	(0.198)	(0.195)
N. Obs	56,999	56,999	56,999	56,999	56,999
Adj.R2	0.00	0.27	0.28	0.23	0.41
			Natives		
Log City Employment	0.068	0.039	0.046	0.049	0.042
	(0.013)	(0.008)	(0.008)	(0.008)	(0.007)
Constant	1.950	1.705	0.639	−0.646	1.720
	(0.155)	(0.095)	(0.102)	(0.105)	(0.096)
N. Obs	562,577	562,577	562,577	562,577	562,577
Adj.R2	0.01	0.23	0.35	0.34	0.45
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓
Origin FE	✗	✗	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 1 City Prices

	Log Hourly Earnings (1)	**Log Hourly Earnings** (2)	**Log Hourly Earnings** (3)	**Log Hourly Earnings** (4)	**Log Hourly Earnings** (5)
			Immigrants		
Log City Employment	−0.152	−0.126	−0.128	−0.130	−0.115
	(0.052)	(0.051)	(0.051)	(0.055)	(0.043)
Constant	−2.325	−2.922	−3.697	−4.287	−2.577
	(0.627)	(0.621)	(0.653)	(0.688)	(0.559)
N. Obs	56,999	56,999	56,999	56,999	56,999
Adj.R2	0.03	0.25	0.26	0.21	0.4
			Natives		
Log City Employment	−0.052	−0.079	−0.072	−0.069	−0.073
	(0.026)	(0.029)	(0.026)	(0.026)	(0.024)
Constant	−3.057	−3.332	−4.429	−5.572	−3.418
	(0.306)	(0.334)	(0.295)	(0.301)	(0.270)
N. Obs	562,577	562,577	562,577	562,577	562,577
Adj.R2	0.01	0.20	0.32	0.31	0.42
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

	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)
			Immigrants		
Log City Employment	−0.026	−0.030	−0.015	−0.031	−0.026
	(0.014)	(0.024)	(0.013)	(0.015)	(0.016)
Constant	2.302	3.333	2.151	2.567	2.612
	(0.176)	(0.310)	(0.168)	(0.189)	(0.195)
N. Obs	38,747	18,252	6,181	30,139	20,679
Adj.R2	0.03	0.01	0.36	0.23	0.12
			Natives		
Log City Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.010)
Constant	1.777	1.840	1.500	1.852	1.950
	(0.090)	(0.170)	(0.143)	(0.144)	(0.124)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.13	0.08	0.17	0.16	0.12
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 1: Conditional Regressions City Prices

	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)
			Immigrants		
Log City Employment	−0.137	−0.116	−0.133	−0.135	−0.124
	(0.049)	(0.059)	(0.05)	(0.051)	(0.052)
Constant	−2.911	−2.219	−2.966	−2.732	−2.802
	(0.593)	(0.726)	(0.609)	(0.621)	(0.633)
N. Obs	38,747	18,252	6,181	30,139	20,679
Adj.R2	0.06	0.03	0.34	0.23	0.12
			Natives		
Log City Employment	−0.087	−0.047	−0.073	−0.056	−0.055
	(0.026)	(0.024)	(0.026)	(0.024)	(0.025)
Constant	−3.246	−3.204	−3.414	−3.199	−3.112
	(0.313)	(0.285)	(0.307)	(0.281)	(0.291)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.14	0.09	0.15	0.14	0.10
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 1: Female Workers

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
			Immigrants		
Log City Employment	−0.015	−0.003	−0.004	0.000	−0.007
	(0.018)	(0.012)	(0.012)	(0.011)	(0.012)
Constant	2.363	1.941	1.689	0.884	2.861
	(0.222)	(0.149)	(0.186)	(0.169)	(0.263)
N. Obs	40,794	40,794	40,794	40,794	40,794
Adj.R2	0.00	0.22	0.22	0.19	0.38
			Natives		
Log City Employment	0.073	0.045	0.050	0.051	0.044
	(0.017)	(0.011)	(0.013)	(0.013)	(0.012)
Constant	1.670	1.438	0.587	−0.614	1.786
	(0.210)	(0.138)	(0.164)	(0.165)	(0.158)
N. Obs	479,097	479,097	479,097	479,097	479,097
Adj.R2	0.01	0.21	0.29	0.28	0.42
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 City Prices

	Log Hourly Earnings (1)	**Log Hourly Earnings** (2)	**Log Hourly Earnings** (3)	**Log Hourly Earnings** (4)	**Log Hourly Earnings** (5)
			Immigrants		
Log City Employment	−0.121	−0.110	−0.110	−0.106	−0.109
	(0.044)	(0.045)	(0.046)	(0.049)	(0.042)
Constant	−2.978	−3.369	−3.665	−4.466	−2.523
	(0.533)	(0.555)	(0.585)	(0.559)	(0.586)
N. Obs	40,794	40,794	40,794	40,794	40,794
Adj.R2	0.02	0.21	0.21	0.17	0.36
			Natives		
Log City Employment	−0.053	−0.078	−0.072	−0.072	−0.077
	(0.024)	(0.029)	(0.026)	(0.026)	(0.025)
Constant	−3.286	−3.547	−4.435	−5.491	−3.322
	(0.292)	(0.340)	(0.297)	(0.308)	(0.287)
N. Obs	479,097	479,097	479,097	479,097	479,097
Adj.R2	0.00	0.17	0.26	0.25	0.39
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

	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)
			Immigrants		
Log City Employment	−0.020	0.025	0.003	0.003	−0.016
	(0.017)	(0.018)	(0.018)	(0.017)	(0.016)
Constant	2.109	2.285	1.819	1.939	2.261
	(0.202)	(0.252)	(0.229)	(0.203)	(0.201)
N. Obs	26,646	14,148	2,835	20,619	17,340
Adj.R2	0.01	0.00	0.24	0.17	0.13
			Natives		
Log City Employment	0.040	0.074	0.059	0.067	0.060
	(0.010)	(0.020)	(0.016)	(0.016)	(0.015)
Constant	01.533	01.675	01.296	01.508	01.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.08	0.04	0.17	0.14	0.11
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 1: Female Workers Conditional Regressions City Prices

	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)
			Immigrants		
Log City Employment	−0.131	−0.070	−0.119	−0.103	−0.119
	(0.044)	(0.049)	(0.057)	(0.044)	(0.045)
Constant	−3.145	−3.191	−3.297	−3.386	−3.134
	(0.533)	(0.575)	(0.705)	(0.532)	(0.547)
N. Obs	26,646	14,148	2,835	20,619	17,340
Adj.R2	0.04	0.01	0.23	0.17	0.14
			Natives		
Log City Employment	−0.08	−0.053	−0.076	−0.052	−0.058
	(0.027)	(0.024)	(0.028)	(0.023)	(0.023)
Constant	−3.488	−3.294	−3.538	−3.511	−3.357
	(0.319)	(0.286)	(0.339)	(0.271)	(0.279)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.09	0.04	0.14	0.12	0.09
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 1 Plots

Robustness Checks Fact 2

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
			Low-Income		
Log Employment	−0.039	−0.020	−0.024	−0.025	−0.016
	(0.018)	(0.012)	(0.012)	(0.014)	(0.011)
Constant	2.800	2.341	1.803	1.164	2.681
	(0.229)	(0.139)	(0.165)	(0.207)	(0.217)
N. Obs	51,470	51,470	51,470	51,470	51,470
Adj.R2	0.00	0.14	0.23	0.18	0.34
			High-Income		
Log Employment	0.059	0.052	0.063	0.067	0.048
	(0.027)	(0.020)	(0.020)	(0.022)	(0.016)
Constant	2.564	2.066	1.049	−0.917	2.127
	(0.346)	(0.289)	(0.321)	(0.355)	(0.378)
N. Obs	5,529	5,529	5,529	5,529	5,529
Adj.R2	0.00	0.29	0.24	0.2	0.38
			Natives		
Log Employment	0.068	0.039	0.046	0.049	0.042
	(0.013)	(0.008)	(0.008)	(0.008)	(0.007)
Constant	1.950	1.705	0.639	−0.646	1.720
	(0.155)	(0.095)	(0.102)	(0.105)	(0.096)
N. Obs	562,577	562,577	562,577	562,577	562,577
Adj.R2	0.01	0.09	0.35	0.34	0.45
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Fact 2 Plots

Robustness Checks Fact 2 City Prices

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
			Low-Income		
Log Employment	−0.143	−0.125	−0.128	−0.129	−0.116
	(0.053)	(0.052)	(0.053)	(0.056)	(0.044)
Constant	−2.522	−2.939	−3.797	−4.106	−2.981
	(0.641)	(0.635)	(0.733)	(0.699)	(0.671)
N. Obs	51,470	51,470	51,470	51,470	51,470
Adj.R2	0.03	0.64	0.21	0.16	0.34
			High-Income		
Log Employment	−0.044	−0.050	−0.038	−0.035	−0.048
	(0.059)	(0.05)	(0.046)	(0.047)	(0.040)
Constant	−2.773	−3.386	−4.592	−6.366	−3.421
	(0.710)	(0.564)	(0.635)	(0.675)	(0.682)
N. Obs	5,529	5,529	5,529	5,529	5,529
Adj.R2	0.00	0.56	0.23	0.19	0.37
			Natives		
Log Employment	−0.052	−0.079	−0.072	−0.069	−0.073
	(0.026)	(0.029)	(0.026)	(0.026)	(0.024)
Constant	−3.057	−3.332	−4.429	−5.572	−3.418
	(0.306)	(0.334)	(0.295)	(0.301)	(0.270)
N. Obs	562,577	562,577	562,577	562,577	562,577
Adj.R2	0.00	0.33	0.32	0.31	0.42
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Fact 2 Plots

Robustness Checks Fact 2: Conditional Regressions

	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)
			Low-Income		
Log City Employment	−0.023	−0.035	−0.025	−0.030	−0.019
	(0.014)	(0.025)	(0.013)	(0.016)	(0.014)
Constant	02.251	03.283	02.277	02.544	02.499
	(0.170)	(0.317)	(0.173)	(0.198)	(0.173)
N. Obs	37,308	14,162	5,568	27,059	18,843
Adj.R2	0.03	0.01	0.3	0.17	0.08
			High-Income		
Log City Employment	0.030	0.081	0.082	0.054	0.087
	(0.026)	(0.032)	(0.046)	(0.025)	(0.037)
Constant	2.274	2.237	1.625	2.111	1.724
	(0.353)	(0.406)	(0.597)	(0.327)	(0.459)
N. Obs	1,439	4,090	613	3,080	1,836
Adj.R2	0.00	0.03	0.10	0.17	0.17
			Natives		
Log City Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.01)
Constant	1.777	1.840	1.500	1.852	1.950
	(0.090)	(0.170)	(0.143)	(0.144)	(0.124)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.13	0.08	0.17	0.16	0.12
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 2 Plots

Robustness Checks Fact 2: Conditional Regressions City Prices

	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)
			Low-Income		
Log City Employment	−0.133	−0.117	−0.141	−0.135	−0.117
	(0.050)	(0.065)	(0.056)	(0.054)	(0.051)
Constant	−2.967	−2.288	−2.870	−2.744	−2.921
	(0.603)	(0.771)	(0.683)	(0.652)	(0.621)
N. Obs	37,308	14,162	5,568	27,059	18,843
Adj.R2	0.06	0.03	0.30	0.17	0.09
			High-Income		
Log City Employment	−0.106	−0.009	−0.058	−0.043	−0.009
	(0.068)	(0.041)	(0.043)	(0.046)	(0.057)
Constant	−2.643	−3.321	−3.254	−3.313	−3.739
	(0.849)	(0.514)	(0.557)	(0.529)	(0.685)
N. Obs	1,439	4,090	613	3,080	1,836
Adj.R2	0.02	0.03	0.08	0.17	0.18
			Natives		
Log City Employment	−0.087	−0.047	−0.073	−0.056	−0.055
	(0.026)	(0.024)	(0.026)	(0.024)	(0.025)
Constant	−3.246	−3.204	−3.414	−3.199	0 − 3.112
	(0.313)	(0.285)	(0.307)	(0.281)	(0.291)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.14	0.09	0.15	0.14	0.1
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 2 Plots

Robustness Checks Fact 2: Female Workers

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
			Low-Income		
Log Employment	−0.009	0.001	−0.001	0.003	−0.007
	(0.017)	(0.012)	(0.012)	(0.011)	(0.012)
Constant	2.253	1.890	1.644	0.853	2.577
	(0.214)	(0.148)	(0.190)	(0.169)	(0.312)
N. Obs	37,531	37,531	37,531	37,531	37,531
Adj.R2	0.00	0.15	0.20	0.17	0.35
			High-Income		
Log Employment	0.053	0.018	0.027	0.028	0.021
	(0.032)	(0.027)	(0.028)	(0.029)	(0.025)
Constant	2.040	1.925	0.556	−0.080	1.496
	(0.406)	(0.343)	(0.543)	(0.534)	(0.665)
N. Obs	3,263	3,263	3,263	3,263	3,263
Adj.R2	0.00	0.34	0.22	0.19	0.40
			Natives		
Log Employment	0.073	0.045	0.050	0.051	0.044
	(0.017)	(0.011)	(0.013)	(0.013)	(0.012)
Constant	1.670	1.438	0.587	−0.614	1.786
	(0.21)	(0.138)	(0.164)	(0.165)	(0.158)
N. Obs	479,097	479,097	479,097	479,097	479,097
Adj.R2	0.01	0.14	0.29	0.28	0.42
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Fact 2 Plots

Robustness Checks Fact 2: Female Workers City Prices

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
			Low-Income		
Log Employment	−0.114	−0.105	−0.106	−0.102	−0.108
	(0.044)	(0.046)	(0.046)	(0.049)	(0.043)
Constant	−3.11	−3.439	−3.727	−4.509	−2.893
	(0.536)	(0.558)	(0.589)	(0.565)	(0.594)
N. Obs	37,531	37,531	37,531	37,531	37,531
Adj.R2	0.02	0.56	0.19	0.15	0.33
			High-Income		
Log Employment	−0.065	−0.096	−0.086	−0.087	−0.085
	(0.055)	(0.048)	(0.044)	(0.047)	(0.034)
Constant	−3.116	−3.345	−4.507	−5.364	−3.536
	(0.666)	(0.577)	(0.694)	(0.594)	(0.65)
N. Obs	3,263	3,263	3,263	3,263	3,263
Adj.R2	0.01	0.58	0.21	0.18	0.40
			Natives		
Log Employment	−0.053	−0.078	−0.072	−0.072	−0.077
	(0.024)	(0.029)	(0.026)	(0.026)	(0.025)
Constant	−3.286	−3.547	−4.435	−5.491	−3.322
	(0.292)	(0.340)	(0.297)	(0.308)	(0.287)
N. Obs	479,097	479,097	479,097	479,097	479,097
Adj.R2	0.00	0.34	0.26	0.25	0.39
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

	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)
			Low-Income		
Log City Employment	−0.016	0.031	0.001	0.004	−0.009
	(0.016)	(0.018)	(0.020)	(0.016)	(0.016)
Constant	2.048	2.12	1.826	1.917	2.160
	(0.201)	(0.247)	(0.252)	(0.194)	(0.199)
N. Obs	25,450	12,081	2,520	18,995	16,016
Adj.R2	0.01	00	0.2	0.15	0.12
			High-Income		
Log City Employment	0.019	0.057	0.000	0.107	−0.023
	(0.030)	(0.045)	(0.055)	(0.04)	(0.042)
Constant	2.076	2.213	2.318	1.072	2.634
	(0.406)	(0.572)	(0.719)	(0.502)	(0.536)
N. Obs	1,196	2,067	315	1,624	1,324
Adj.R2	0.00	0.01	0.13	0.13	0.13
			Natives		
Log City Employment	0.040	0.074	0.059	0.067	0.060
	(0.010)	(0.020)	(0.016)	(0.016)	(0.015)
Constant	1.533	1.675	1.296	1.508	1.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.08	0.04	0.17	0.14	0.11
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Fact 2 Plots

Robustness Checks Fact 2: Female Workers Conditional Regressions City Prices

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Low-Income		
Log City Employment	−0.126	−0.061	−0.119	−0.101	−0.110
	(0.044)	(0.050)	(0.061)	(0.045)	(0.044)
Constant	−3.222	−3.386	−3.309	−3.417	−3.270
	(0.542)	(0.576)	(0.746)	(0.546)	(0.540)
N. Obs	25,450	12,081	2,520	18,995	16,016
Adj.R2	0.04	0.01	0.20	0.15	0.12
			High-Income		
Log City Employment	−0.120	−0.045	−0.136	−0.004	−0.142
	(0.055)	(0.051)	(0.073)	(0.053)	(0.056)
Constant	−2.880	−3.204	−2.675	−4.191	−2.522
	(0.670)	(0.634)	(0.912)	(0.649)	(0.681)
N. Obs	1,196	2,067	315	1,624	1,324
Adj.R2	0.03	0.00	0.15	0.11	0.17
			Natives		
Log City Employment	−0.080	−0.053	−0.076	−0.052	−0.058
	(0.027)	(0.024)	(0.028)	(0.023)	(0.023)
Constant	−3.488	−3.294	−3.538	−3.511	−3.357
	(0.319)	(0.286)	(0.339)	(0.271)	(0.279)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.09	0.04	0.14	0.12	0.09
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

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:

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

Model in a Nutshell

The Problem of the Worker and Demands for Goods

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

$$\max_{c_{jog}, h_{jog}} \quad U_{jog} = c_{jog}^{(1-\alpha)} h_{jog}^{\alpha} \mathbf{z_{jog}} \exp\{\varepsilon_{jo}\}$$

$$\text{s.t.} \quad c_{jog} + p_j h_{jog} \leq w_{jog}$$

  where

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

- Demands for goods are:

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

$$h_{jog}^{\star} = \alpha \frac{w_{jog}}{p_j}$$

Model in a Nutshell

Indirect Utility and Choice Equation

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

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

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

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

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

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

Model in a Nutshell

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:

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

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

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

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:

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

  - Labor supply satisfies:

$$M^\star_j = \sum_g \pi^\star_{jMg} \mathbf{s_{Mg}} \phi_g, \quad D^\star_j = \sum_g \pi^\star_{jDg} \mathbf{s_{Dg}} \phi_g$$

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

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

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

$$p^\star_j = \left[\frac{\alpha}{T_j} \sum_o \sum_g \pi^\star_{jog} \phi_g r^\star_{jo} \mathbf{s_{og}} \tau_{\mathbf{jog}}\right]^{\frac{1}{\varsigma_j - 1}}$$

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

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 | Identification

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		Big City	
	Non-Cognitive Occupation (1)	Cognitive Occupation (2)	Non-Cognitive Occupation (3)	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: Non-Cognitive Occupation (1)	Small City: Cognitive Occupation (2)	Big City: Non-Cognitive Occupation (3)	Big City: 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

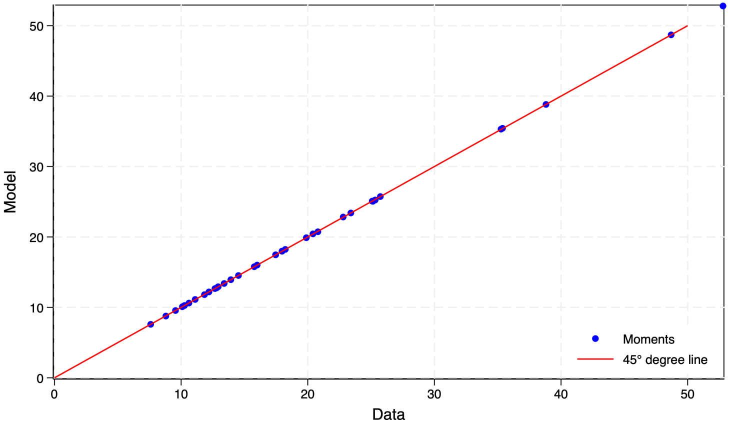
Parameters

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

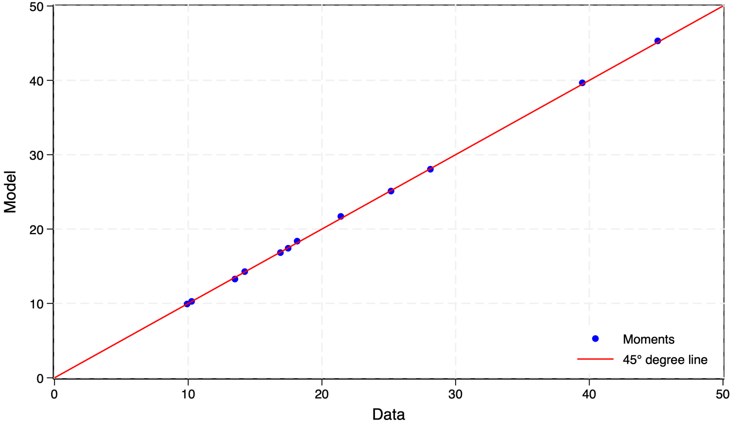
Parameters

Model Fit: Granular Human Capital



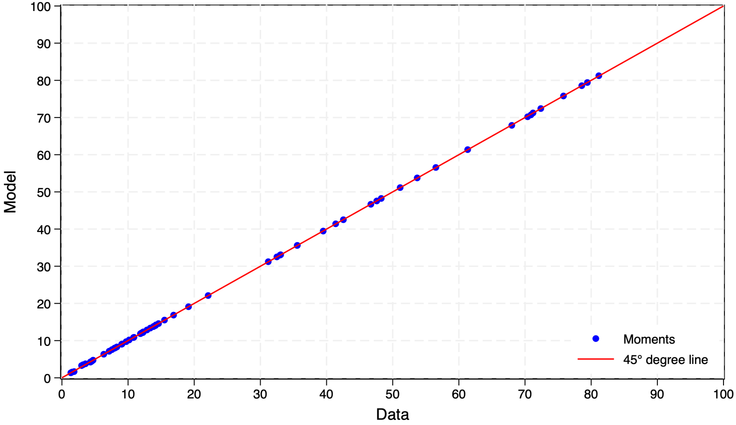
Parameters

Model Fit: Granular Earnings



Parameters

Model Fit: Granular Shares



Parameters

Wage Gaps: Equations

- The earnings gap between natives and immigrants is:

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

- The earnings gap b/w the big and small city (spatial earnings inequality) is:

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

Main result

The Earnings Gaps: Human Capital vs Amenities vs Wedges

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges 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
$\overline{w}^{Gap}_{Workers}$	1	**0.811**	**0.938**	**0.907**	0.813	0.710
$\overline{w}^{Gap}_{Cities}$	1	**1.011**	**1.030**	**0.999**	1.025	1.023

Main result

The Earnings Gaps: Human Capital vs Amenities vs Wedges

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges 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

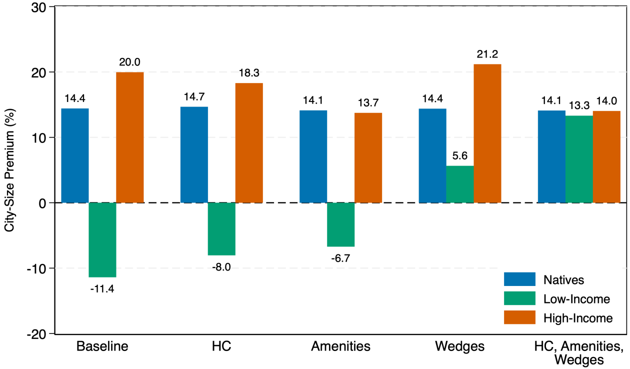
Main result

The Earnings Gaps: Human Capital vs Amenities vs Wedges

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges 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

Main result

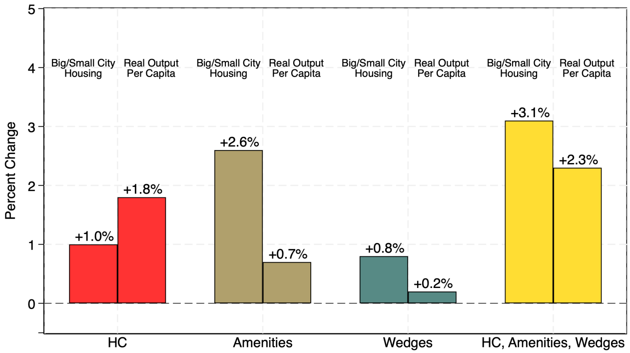
What Determines the Relationship b/w Earnings and City-Size?



- **Human capital** & **Wedges**: more important for immigrants from low-income countries
- **Amenities**: more important for immigrants from high-income countries

Main result

Housing Prices & Real Output pc: Human Capital vs Amenities vs Wedges



- **Human capital:** spatial housing prices gap **+1.0%** vs real output pc **+1.8%**
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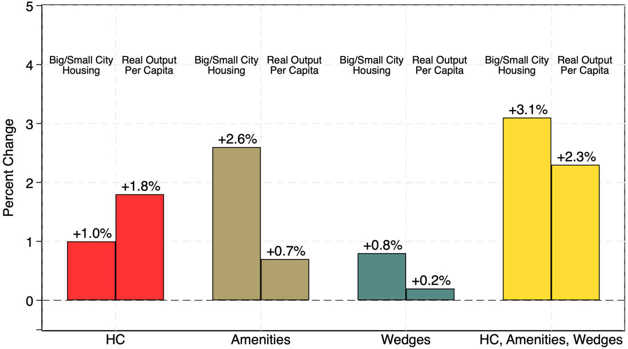
- **Wedges:** spatial housing prices gap **+0.8%** vs real output pc **+0.2%**
- **All:**
  - Spatial housing price gap → mostly explained by differences in **amenities**
  - Real output per pc → mostly explained by differences in **human capital**

Table Main result

Housing Prices & Real Output pc: Human Capital vs Amenities vs Wedges



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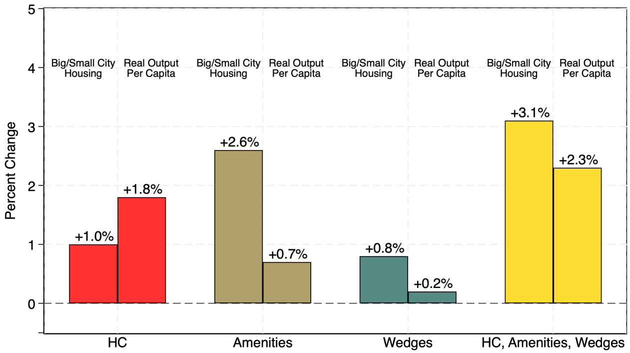

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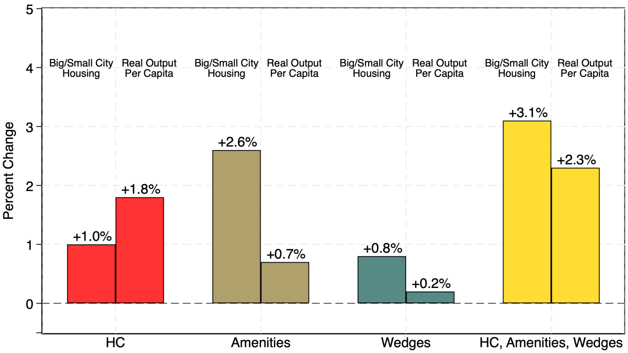

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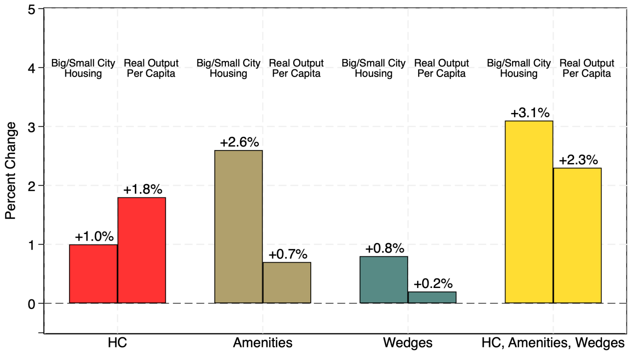

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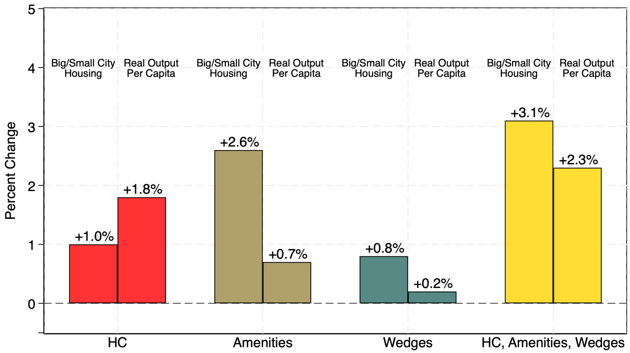

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Table Main result

Real Output pc & Housing Prices: Human Capital vs Amenities vs Wedges

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges 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

Plot

Real Output pc & Housing Prices: Human Capital vs Amenities vs Wedges

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges On Earnings	Full
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Big-Small City Ratio	1	**1.010**	**1.026**	**1.008**	1.034	1.031
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Plot

Real Output pc & Housing Prices: Human Capital vs Amenities vs Wedges

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges On Earnings	Full
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			Real Output Per Capita			
US	1	**1.018**	**1.007**	**1.002**	1.009	1.023

Plot

Mechanism: Workers' Reallocation across Cities

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges 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
		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

Main result

Mechanism: Workers' Reallocation across Cities

	Baseline	Counterfactuals				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges On Earnings	Full
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_{okex} = s_{oUSex}$	-	**x**	**-**	**-**	-	x
$z_{jokex} = z_{joUSex}$	-	**-**	**x**	**-**	x	x
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		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_{okex} = s_{oUSex}$	-	**x**	**-**	**-**	-	x
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Main result

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 Wedges 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

- **Human capital**: productivity ↑ in non-cognitive occupation in all cities
- **Amenities**: productivity ↑ in non-cognitive occupations in the big city
- **Wedges**: no large changes in productivity/wages in all cities Main result

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 Wedges On Earnings	Full	
		(1)	(2)	(3)	(4)	(5)	
Parameters							
$s_{okex} = s_{oUSex}$	-	**x**	-	-	-	x	
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	Baseline	Counterfactuals					
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	Same Amenities As Natives & No Wedges 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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- **Amenities**: productivity ↑ in non-cognitive occupations in the big city
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Amenities Estimates: Immigrants

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

Policy results

Amenities Estimates: Immigrants

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)

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)

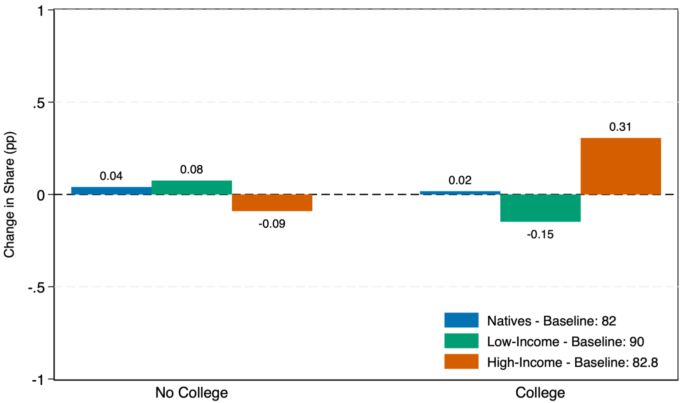
Policy results

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)

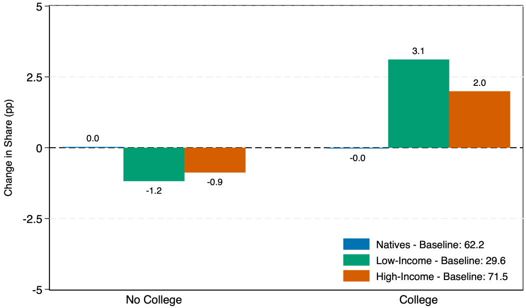
Policy results

Policy: Workers' Allocations across Cities

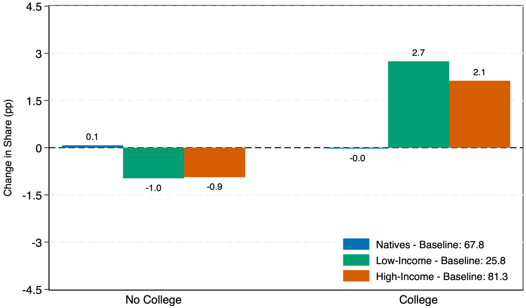


- **No college education**: Natives and immigrants from low-income countries in the big city ↑
- **College education**: Natives and immigrants from high-income countries in the big city ↑
- All in all: Immigration attracts natives to big cities

Policy: Workers' Allocations into the Cognitive Occupation



Small City



Big City

- In both cities:
  - **No college education**: Natives in cognitive occupations ↑, while immigrants ↓
  - **College education**: Natives in cognitive occupations ↓, while immigrants ↑

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

- **No college education**: in all cities, competition and skills effects larger in non-cognitive occupations
- **College education**: in all cities and occupations, positive competition effect Policy

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
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	Skills	1	0.999	1.003

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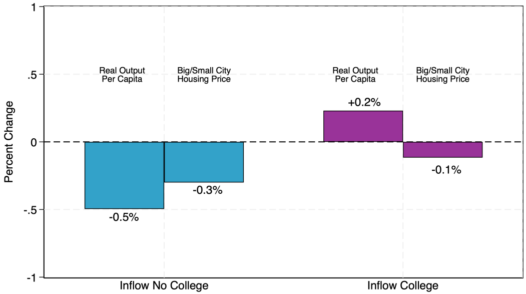
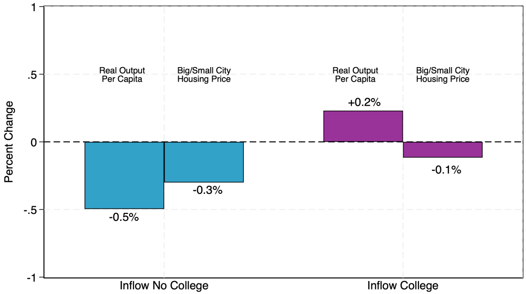
Immigration Policy: Real Output pc & Housing Prices Gap



- Inflow of immigrants with **no college education**:
  - Real output per capita **-0.5%** vs housing prices gap **-0.3%**
- Inflow of immigrants with **college education**:
  - Real output per capita **+0.2%** vs housing prices gap **-0.1%**

Policy Slide

Immigration Policy: Real Output pc & Housing Prices Gap



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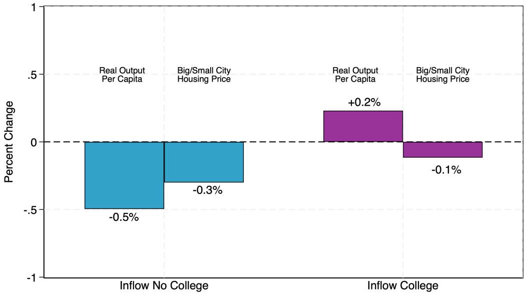
Policy Slide

Immigration Policy: Real Output pc & Housing Prices Gap



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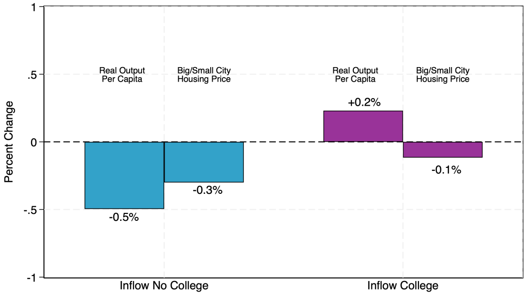
Policy Slide

Immigration Policy: Real Output pc & Housing Prices Gap



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Policy Slide