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

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Introduction

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- **Motivation**: Immigration is central to economic and political debates in the U.S.
  - The U.S. receives more immigrants than any other country
  - Immigrants are crucial to sustaining U.S. productivity and the labor force (Peri, 2016)
  - But, they earn -on average- **14% less** than natives (BLS, 2023) → **Why?**

- **Existing explanations**: US immigrants and natives mainly **differ in**:
  1. **Human capital** → Schoellman (2012), Lagakos et al. (2018)
  2. **Tasks specialization** → Peri and Sparber (2009)
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The Role of Space and Research Questions

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- **The role of space**:
  - **Immigrants** $\longrightarrow$ more likely than natives to live in large and expensive cities (Albert and Monras, 2022)
  - **Big cities** $\longrightarrow$ higher wages due to stronger demand for skilled labor (Eeckhout et al., 2024)
- **Unexplored**: The role of worker-location interactions in shaping labor market outcomes
- **Questions**:
  i. *How do worker and location characteristics interact to shape the immigrant-native earnings gap?*
  ii. *What are the implications for spatial earnings inequality?*
  iii. *How do selective immigration policies shape the immigrant-native earnings gap and spatial earnings inequality?*

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- Documents **3 stylised facts** using data from the American Community Survey:
  i. The **earnings gap** between immigrants and natives is **larger in big cities**
  ii. Only for immigrants from **low-income countries**, earnings do not increase with city size
  iii. Natives and immigrants from **high-income countries** are more likely to be employed in **cognitive jobs** in big cities

- Interprets these facts with a **spatial GE model** including two-sided heterogeneity:
  - Workers: origins, **human capital**, preferences for **amenities**, and local labor market **wedges**
  - Cities: technology and housing supply

- Quantifies how **these factors** influence earnings gaps through cross-city-occupations allocation
  - 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 **selective immigration policies** on these outcomes
  - **Earnings gap across space $\downarrow$** independent of who enter the country

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- **Stylised facts**:
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        - **Natives**: doubling the city-size $\Longrightarrow$ hourly earnings +3.6%
        - **Immigrants**: doubling the city-size $\Longrightarrow$ no significant change in earnings Fact 1

    ii. No significant change in earnings across cities only for immigrants from low-income countries
        - **High-Income Countries**: doubling the city-size $\Longrightarrow$ hourly earnings +3.9% Fact 2

    iii. Natives and immigrants from high-income countries work more in cognitive jobs, especially in big cities
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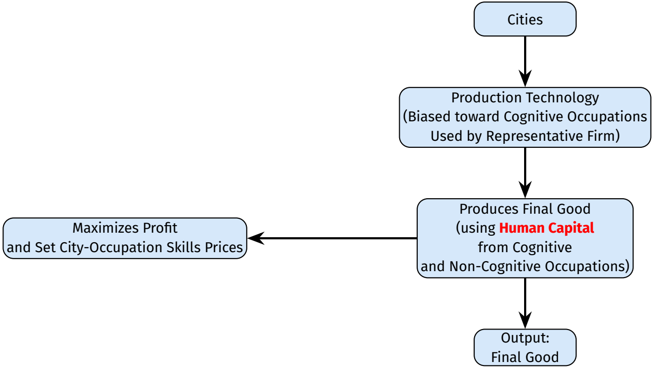
- **A spatial equilibrium model to:**
  - Quantify the factors shaping workers' occupational allocation across space
  - Study how they influence the immigrant-native earnings gap and spatial earnings inequality
  - Study the consequences of inflows of new immigrants on earnings inequality
- **The model 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))

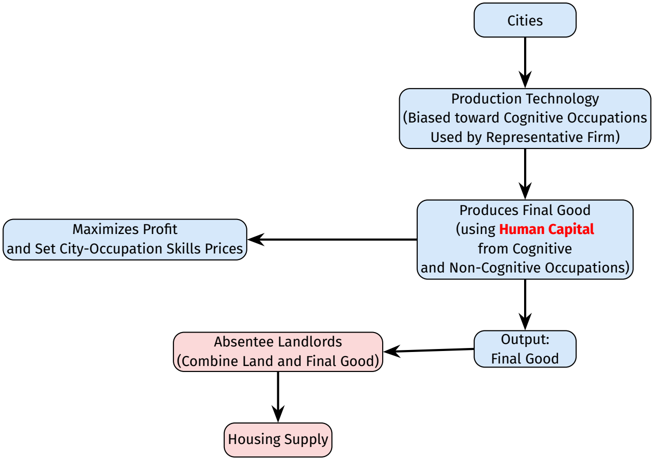
The Model

The Model



Cities
Production Technology
(Biased toward Cognitive Occupations
Used by Representative Firm)
Produces Final Good
(using **Human Capital**
from Cognitive
and Non-Cognitive Occupations)
Maximizes Profit
and Set City-Occupation Skills Prices
Output:
Final Good

The Model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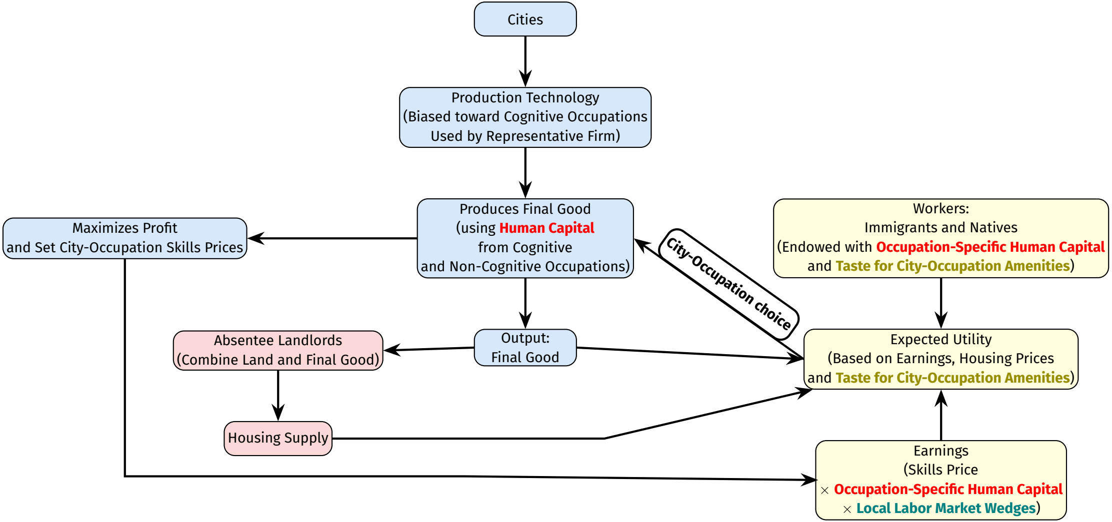
Absentee Landlords
(Combine Land and Final Good)
Housing Supply

The Model



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(Biased toward Cognitive Occupations
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Produces Final Good
(using Human Capital
from Cognitive
and Non-Cognitive Occupations)
Maximizes Profit
and Set City-Occupation Skills Prices
City-Occupation choice
Workers:
Immigrants and Natives
(Endowed with Occupation-Specific Human Capital
and Taste for City-Occupation Amenities)
Absentee Landlords
(Combine Land and Final Good)
Output:
Final Good
Expected Utility
(Based on Earnings, Housing Prices
and Taste for City-Occupation Amenities)
Housing Supply
Earnings
(Skills Price
× Occupation-Specific Human Capital
× Local Labor Market Wedges)

Workers Occupational Allocation across Space

- A worker's with characteristics g chooses a city-occupation pair jo based on maximum expected utility

- The share of workers with characteristics g choosing a city-occupation pair jo is given by:

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

Environment Model Identification

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Environment Model Identification

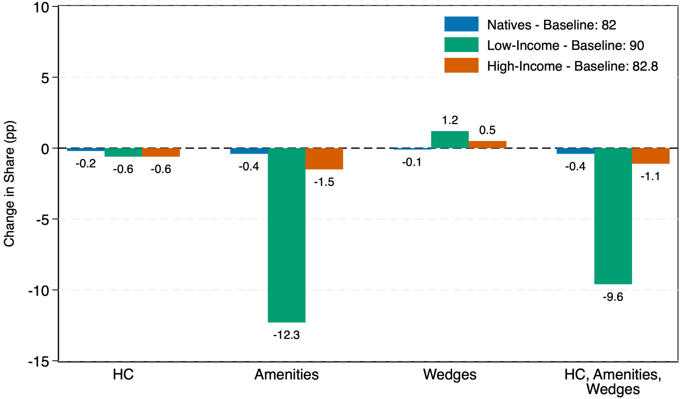
Counterfactual Analysis

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:
    i. Differences in **human capital** with natives
    ii. Differences in **amenities** with natives
    iii. **Wedges** on earnings
  - Remove together:
    iv. Differences in **human capital** and **amenities** with natives, and **wedges**

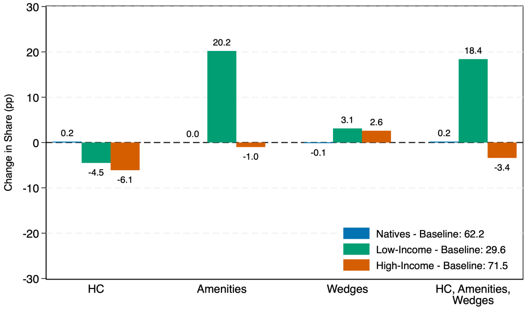
Workers' Reallocation across Space



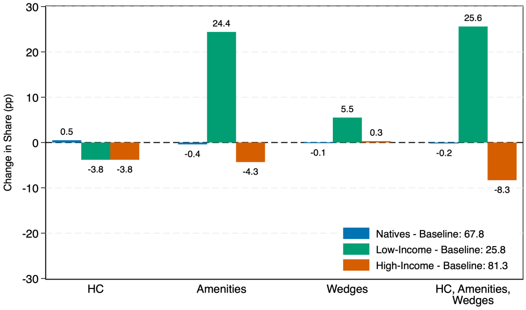
- **Human capital** & **Amenities**: big-to-small cities reallocation, larger for all immigrants
- **Wedges**: immigrants small-to-big cities reallocation, larger for low-income immigrants

Table

Workers' Reallocation into Cognitive Occupations: Small and Big Cities



Small City



Big City

- **Human capital**: immigrants 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

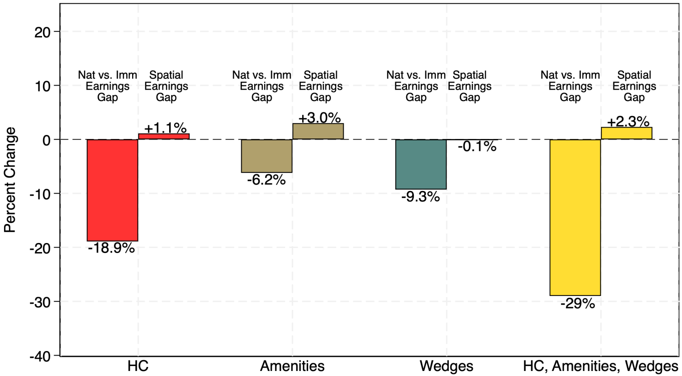


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Table | City-size premia | Agg. output and housing prices | Competition and skills effects

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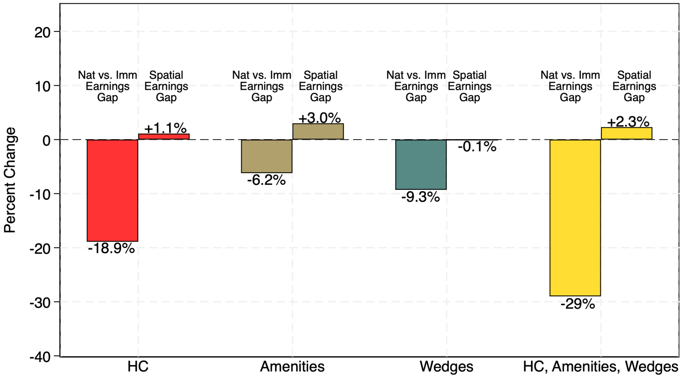

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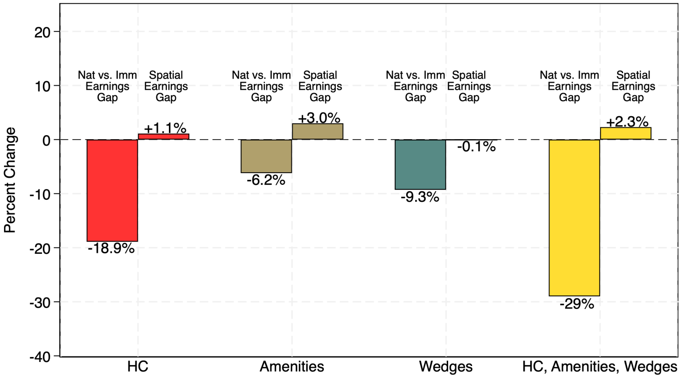

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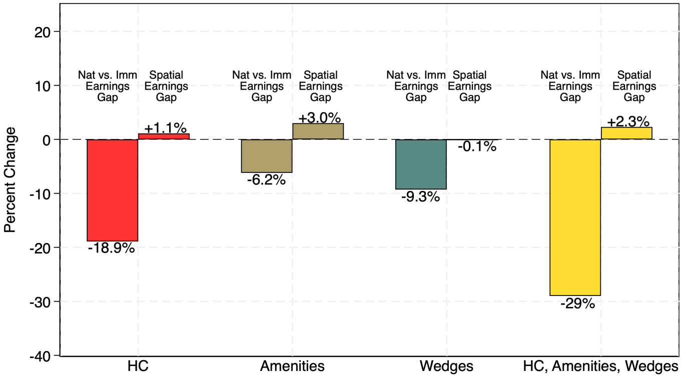

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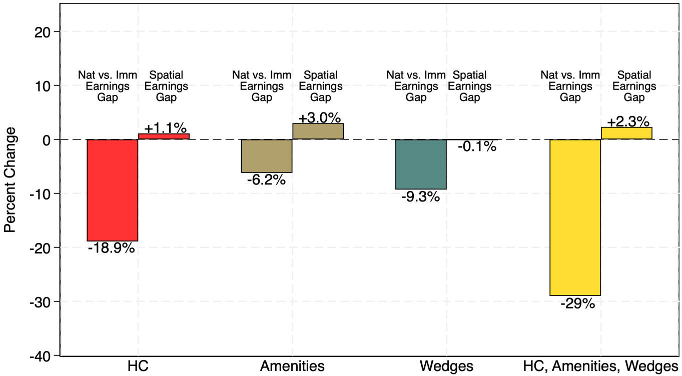

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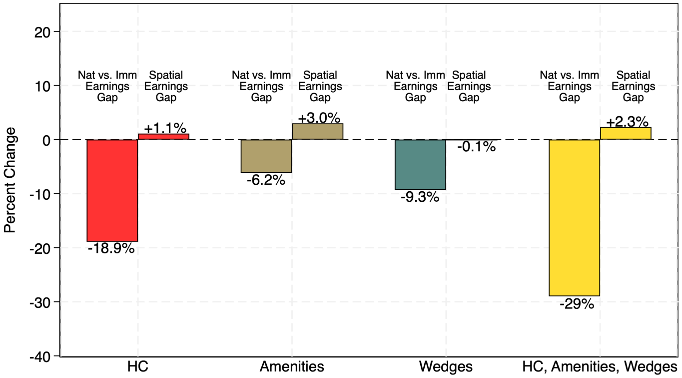

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Policy Exercises

The Earnings Gaps: Selective Immigration Policy

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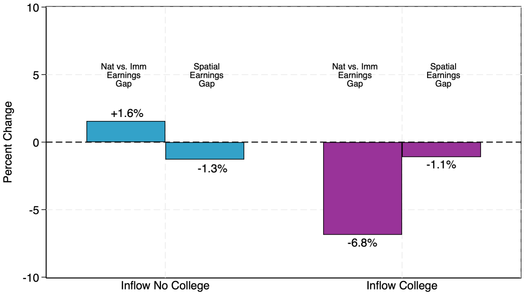

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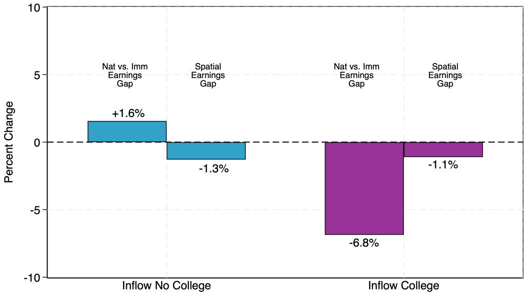

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Amenities estimates | Human capital estimates | City allocations | Occ allocations | Competition vs. Skills Effect | Housing prices & Real Output pc

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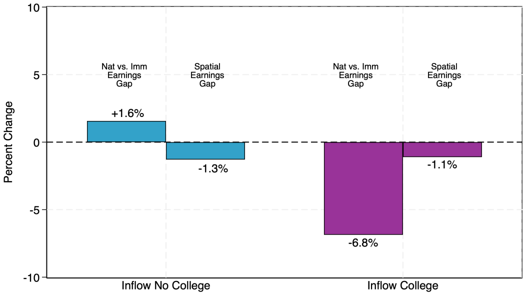

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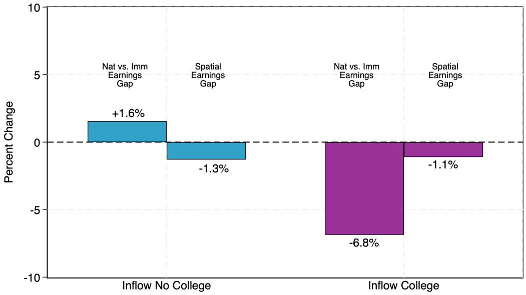

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Spatial Earnings Inequality ↓

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Conclusion

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- **I study the drivers of workers' occupational allocation across space and their impact on immigrant-native earnings gap**

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

- **Spatial GE framework with occupational choices**:
  i. No immigrant-native differences in **human capital** or **amenities** $\longrightarrow$ **Earnings inequality trade-off**
     - Immigrant-natives earnings gap $\downarrow$, but big-small city earnings gap $\uparrow$
  ii. No origin-specific local labor market **wedges** $\longrightarrow$ **No earnings inequality trade-off**
     - Improved allocation of all workers into occupations across space

- **Immigration policy based on education**:
  i. Immigrants helps to **reduce earnings inequality across space** 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

Summary

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

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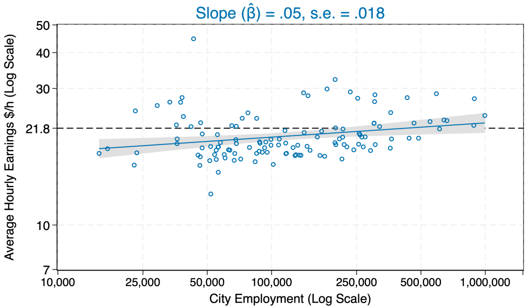
Summary

Data

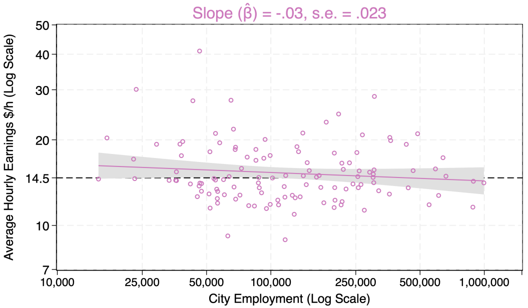
- 2010 American Community Survey (ACS) sample from IPUMS:
  - Immigrants: foreign-born workers, first-generation
  - Hourly earnings
  - US cities: Metropolitan Statistical Areas (MSA)
  - Sample: male workers, 18-64 y.o., employed and work for wages
- O*NET:
  - Tasks intensity as in Acemoglu & Autor (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

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



Natives

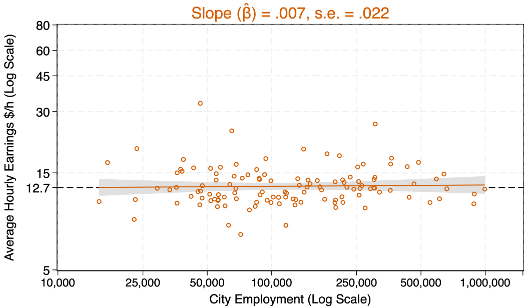


Immigrants

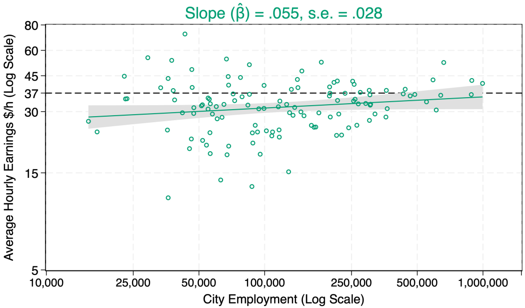
- **Natives**: doubling the city size → hourly earnings +3.6%
- **Immigrants**: doubling the city size → hourly earnings ≈ constant

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 | Stylised Facts

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



Low-Income



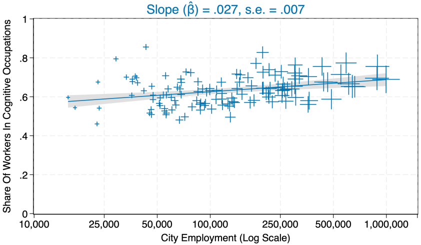
High-Income

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

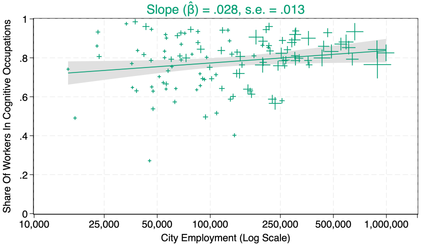
Robustness 2 Male | Robustness 2 Male CP | Robustness 2 Male Conditional | Robustness 2 Male Conditional CP | Robustness 2 Female | Robustness 2 Female CP
Robustness 2 Female Conditional | Robustness 2 Female Conditional CP | Table Natives vs Low-High Income | Stylised Facts

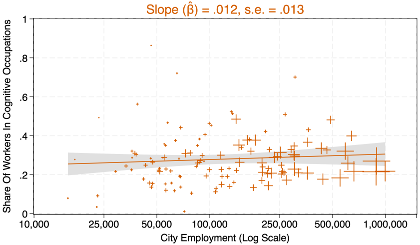
High-Income Countries Workers Work More in Cognitive Jobs, Especially in Large Cities

Natives



High-Income





Low-Income

Fact 3 Table
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	✗	✗	✗	✗	✓

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	✗	✗	✗	✗	✓

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	✗	✗	✗	✗	✓

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 (0.044)	−0.110 (0.045)	−0.110 (0.046)	−0.106 (0.049)	−0.109 (0.042)
Constant	−2.978 (0.533)	−3.369 (0.555)	−3.665 (0.585)	−4.466 (0.559)	−2.523 (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 (0.024)	−0.078 (0.029)	−0.072 (0.026)	−0.072 (0.026)	−0.077 (0.025)
Constant	−3.286 (0.292)	−3.547 (0.340)	−4.435 (0.297)	−5.491 (0.308)	−3.322 (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	✗	✗	✗	✗	✓

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	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(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	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(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 (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (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

Environment

- **Static economy:** cities (local labor markets) and agents (workers)
- **Cities, production and housing:**
  - $j \in \{1, \ldots, J\}$ 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

Allocation Equation

Environment

- **Static economy:** cities (local labor markets) and agents (workers)
- **Cities, production and housing:**
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Allocation Equation

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

Allocation Equation

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 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. Allocation Equation

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

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- **A worker $i \in g$**
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  - The share of workers from group g choosing a city j and an occupation o is:

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

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

- **Absentee landlords**
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Spatial Eq. Allocation Equation

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 $\forall j \in \mathcal{J}$:

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

Model

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 location, occupation, and origin
- **Other assumptions:**
  - ζ_j, T_j do not vary across city
  - ϕ_g is given
- **Dimensionality reduction:**
  - 2 cities $\rightarrow$ $\{\text{Small City}, \text{Big City}\}$
  - 3 countries of origin $\rightarrow$ $\{\text{Natives}, \text{Low-Income}, \text{High-Income}\}$
  - 2 education groups $\rightarrow$ $\{\text{No College}, \text{College}\}$
  - 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

Allocation Equation

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

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

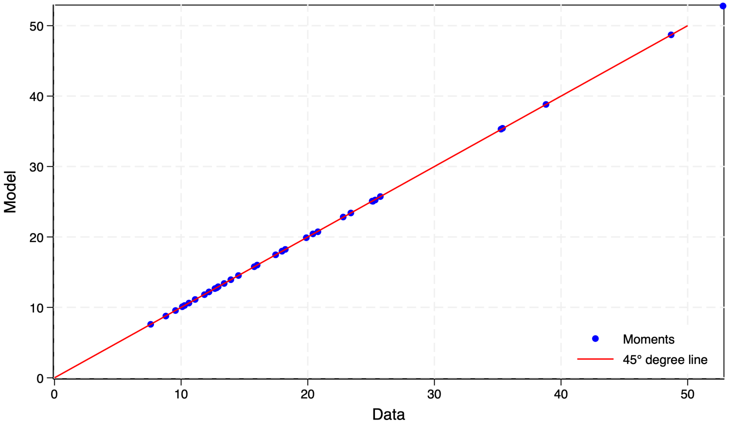
Parameters

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

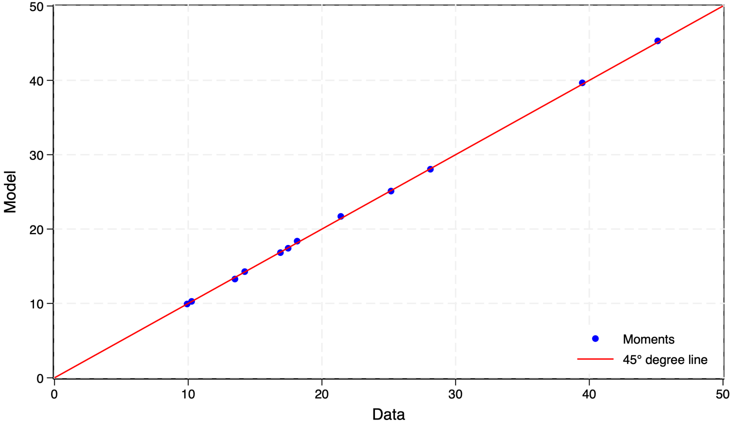
Parameters

Model Fit: Granular Human Capital



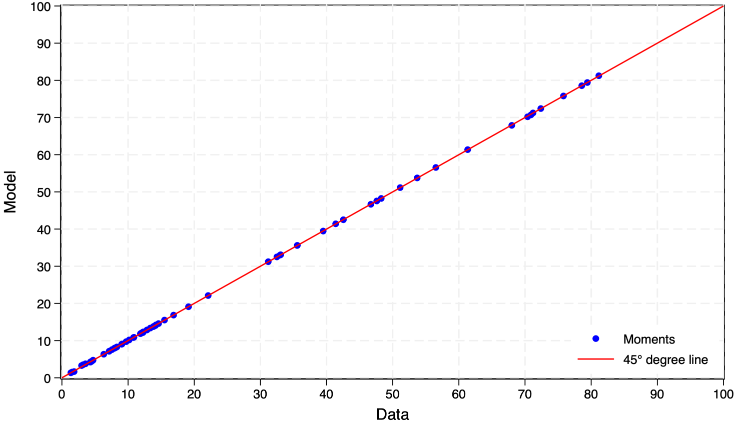
Parameters

Model Fit: Granular Earnings



Parameters

Model Fit: Granular Shares



Parameters

Wage Gaps: Equations

- The earnings gap between natives and immigrants is:

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

- 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
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$s_{okex} = s_{oUSex}$	-	**x**	**-**	**-**	-	x
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Main result

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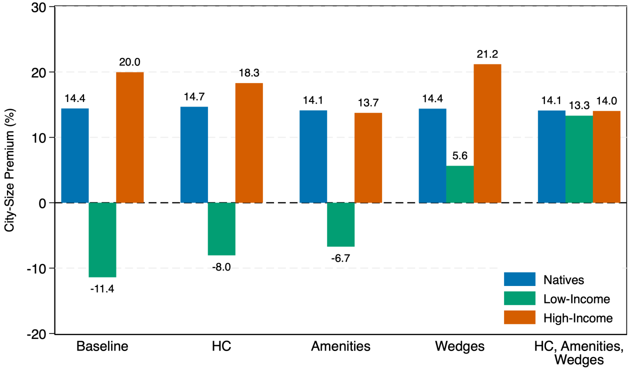
Main result

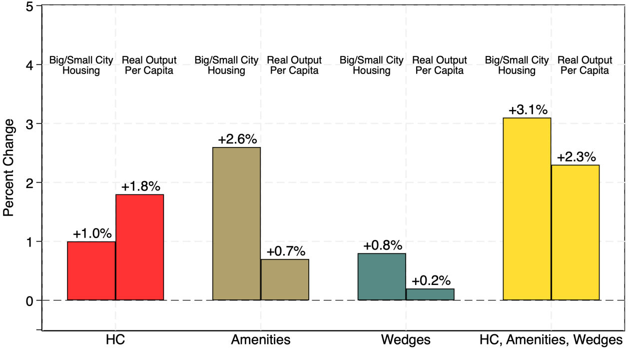
What Determines the Relationship b/w Earnings and City-Size?



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

Main result

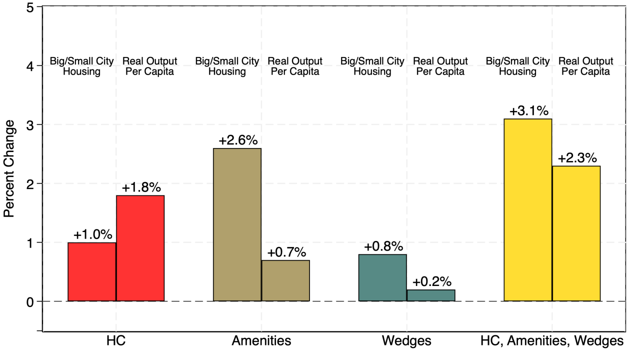
Housing Prices & Real Output pc: Human Capital vs Amenities vs Wedges



- **Human capital:** spatial housing prices gap **+1.0%** vs real output pc **+1.8%**
- **Amenities:** spatial housing prices gap **+2.6%** vs real output pc **+0.7%**
- **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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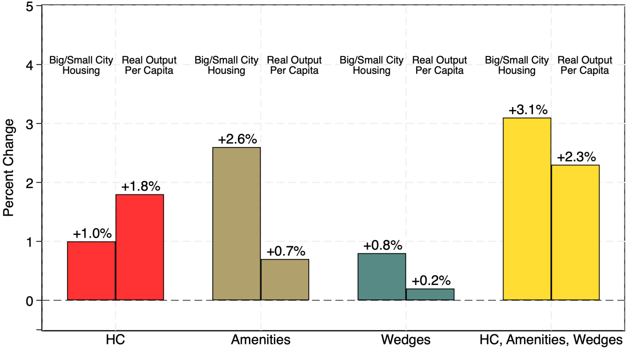
Housing Prices & Real Output pc: Human Capital vs Amenities vs Wedges



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

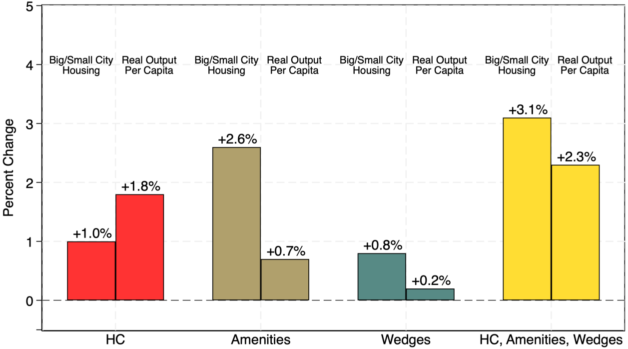

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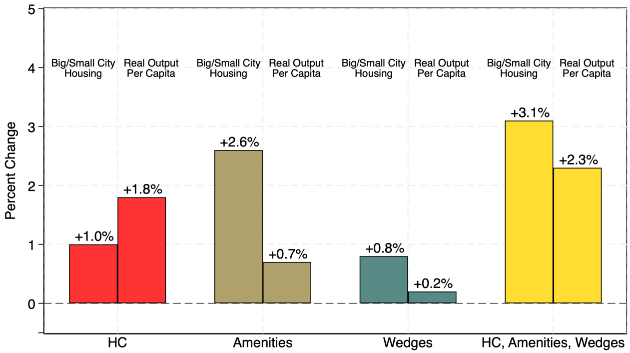
Table Main result

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



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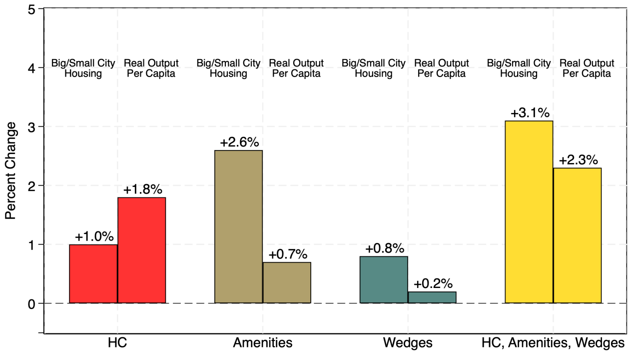

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Table Main result

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
		(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
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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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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

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
$\tau_{jok} = 1$	-	**-**	**-**	**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
$\tau_{jok} = 1$	-	**-**	**-**	**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: 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
$z_{jokex} = z_{joUSex}$		-	-	**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
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	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
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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 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
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- **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

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

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	0.4	**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)

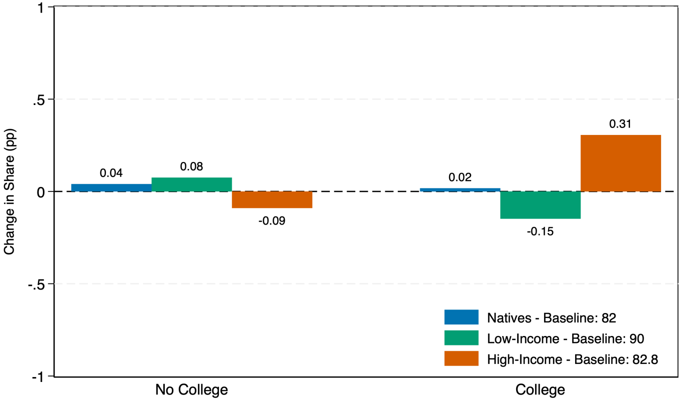
Policy results

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)

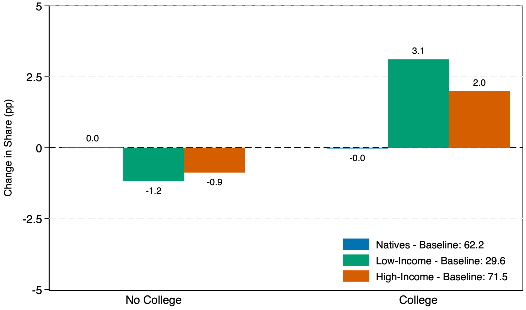
Policy results

Policy: Workers' Allocations across Cities

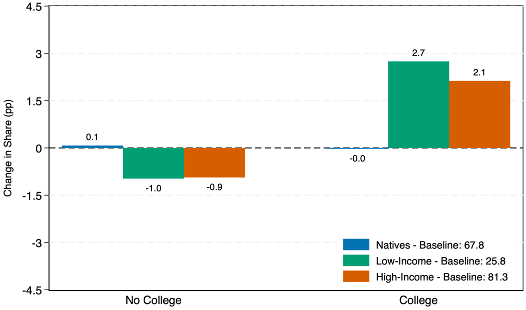


- **No college education**: Natives and immigrants from low-income countries in the big city ↑
- **College education**: Natives and immigrants from high-income countries in the big city ↑
- All in all: Immigration attracts natives to big cities

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

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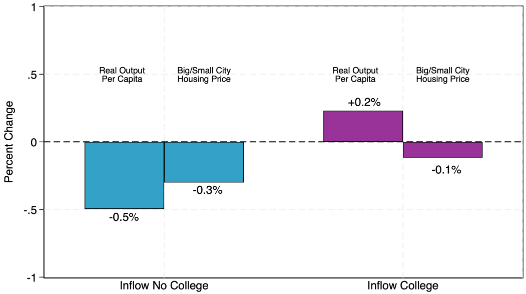
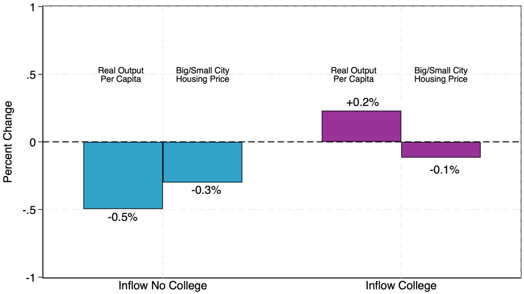
Immigration Policy: Real Output pc & Housing Prices Gap



- 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

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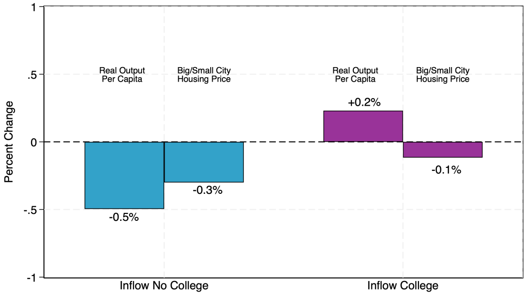

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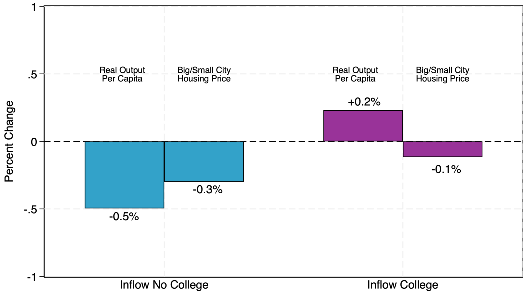
Policy Slide

Immigration Policy: Real Output pc & Housing Prices Gap



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Policy Slide