Human Capital, Amenities, and Distortions: The Immigrant Earnings Gap across Space*

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Abstract

I document that the city-size earnings premium is smaller for immigrants than for natives, driven by low-income-country immigrants who sort less into cognitive occupations in larger cities. I interpret these facts through a spatial equilibrium model with heterogeneous human capital, amenities, and local earnings wedges, which are the main quantitative channels behind the immigrant-native gap in the city-size earnings premium. Making immigrants equivalent to natives closes 62 percent of the immigrant-native earnings gap but widens the spatial earnings gap by 20 percent. Expanding college immigration narrows the immigrant-native earnings gap without widening the spatial earnings gap.

Keywords: Immigrant Earnings Gap, City-Size Earnings Premium, Spatial Equilibrium, Occupational Sorting, Human Capital

JEL Classification: F22, J24, J31, J61, R13

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Foreign-born workers represent 19.2 percent of the U.S. civilian labor force (Bureau of Labor Statistics, 2025) and contribute substantially to innovation, entrepreneurship, and economic growth (Hunt and Gauthier-Loiselle, 2010; Peri, 2016; Azoulay et al., 2022). Yet immigrants continue to earn less than native-born workers on average. A large literature attributes the immigrant-native earnings gap to differences in the human capital immigrants bring to the labor market and to labor market barriers that they face in the country of arrival.[1]

In this paper, I study how space shapes the immigrant-native earnings gap. Immigrants are disproportionately concentrated in large, high-productivity cities (Albert and Monras, 2022). Because large cities disproportionately reward cognitive-intensive labor (Atalay, Sotelo and Tannenbaum, 2022; Eeckhout, Hedtrich and Pinheiro, 2026), this concentration might be expected to narrow the immigrant-native earnings gap. Instead, immigrants benefit less from large cities than natives do. Using data from the American Community Survey (ACS) for 2010–2019, I show that the city-size earnings gradient is half as large for immigrants as for natives. This average masks substantial heterogeneity by origin: the gradient is larger for immigrants from high-income countries than for natives, but much smaller for immigrants from low-income countries. Consistent with this pattern, low-income-country immigrants are less likely than natives and immigrants from high-income countries to sort into cognitive occupations as city size rises. These facts suggest that the aggregate immigrant-native earnings gap has an important spatial component and raise a central question: which channels account for the immigrant-native gap in city-size earnings gradient, and how do those channels shape the relationship between the aggregate immigrant-native earnings gap and the earnings gap between large and small cities?

To answer this question, I develop and estimate a quantitative spatial equilibrium model in which workers choose both a city and an occupation. Cities differ in the extent to which they reward cognitive-intensive labor, with larger cities favoring cognitive occupations, and in housing costs. All workers trade off earnings and amenities across city-occupation pairs. For natives, city and occupation choices are governed by common city-occupation returns, human capital, and amenity preferences. Immigrants face the same environment, but differ from natives along three margins that vary by country of origin: the occupation-specific human capital they bring to the U.S. labor market, the amenity value they attach to particular city-occupation pairs, and the local earnings wedges they face relative to natives. The three margins are observationally intertwined in repeated cross-sectional data, and their separate identification requires a structural framework.

Since human capital, amenity valuations, and earnings wedges vary by country of origin, they shape city-occupation sorting in distinct ways. Human capital determines workers' comparative advantage across occupations and varies with education and experience (Schoellman, 2010; Caunedo, Keller and Shin, 2021; Martellini, Schoellman and Sockin, 2024). Amenity valuations capture the non-pecuniary value that workers of different origins assign to city-occupation pairs, shaped by forces such as ethnic networks and cultural ties (Munshi, 2003). Earnings wedges capture the resid-

[1] Lagakos et al. (2018) document that workers from poor countries exhibit experience-wage profiles that are, on average, half as steep as those in rich countries. Schoellman (2012) shows that immigrants from high-income economies earn higher returns to education than immigrants from low-income economies. Oreopoulos (2011) shows, using an experiment on responses to job postings, that immigrants admitted under Canada's point system face hiring discrimination based on their name and country of origin. Dostie et al. (2021) document that employer wage-setting policies contribute to the earnings gap between immigrants and natives in Canada.

ual gap between what immigrants earn and what observationally equivalent natives would earn at the competitive wage, and vary across city-occupation pairs, absorbing barriers such as discrimination, licensing restrictions, and informational frictions (Hsieh et al., 2019; Birinci, Leibovici and See, 2024). Together, these channels generate heterogeneous patterns of sorting across cities and occupations that determine the immigrant-native earnings gap across space.

I estimate the model by the simulated method of moments using the pooled ACS 2010–2019. Each channel is identified from a distinct set of moments: human capital from occupation-specific earnings by education, experience, and origin group; amenity valuations from workers' shares across city-occupation pairs by education, experience, and origin group; and earnings wedges from the gap between immigrant and native earnings within the same city-occupation cell, corrected for human capital differences. The estimates reveal that low-income-country immigrants face a reversal in local earnings wedges across city types: they earn above the native benchmark in small cities but below it in large cities, especially in cognitive occupations. This pattern directly dampens their returns to city size. By contrast, amenity valuations pull these immigrants toward large cities and occupations with denser same-origin networks, generating spatial concentration despite lower labor market returns. Consistent with this interpretation, estimated amenity valuations are positively correlated with the 2010 share of same-origin workers in each city-occupation cell, especially for immigrants from low-income countries.

Counterfactual decompositions show that the three channels matter in different ways. Differences in local earnings wedges account for most of the immigrant-native gap in returns to city size for low-income-country immigrants. Human capital is the single largest driver of the aggregate immigrant-native earnings gap, but leaves the spatial earnings gap largely unchanged, because it scales earnings within occupations without altering location choices. Heterogeneous amenity valuations are the dominant force behind spatial sorting: equalizing them between immigrants and natives induces large reallocations of low-income-country immigrants across cities and occupations, narrows the aggregate immigrant-native earnings gap, and widens the spatial earnings gap. Taken together, these results reveal a structural trade-off: the same channels that reduce the earnings gap between immigrants and natives can increase the earnings gap across space. Removing all three sources of heterogeneity closes 61.8 percent of the aggregate immigrant-native earnings gap[2] but widens the spatial earnings gap by 20.2 percent.

Motivated by this trade-off, I evaluate two immigration expansion policies calibrated to increase immigrant employment by one percentage point: one through college-educated immigrants and one through non-college-educated immigrants. Although the main empirical heterogeneity in the paper is by country of origin, education provides a natural policy margin because it shifts immigrant inflows along a dimension that directly affects comparative advantage and occupational sorting.[3] Expanding college immigration shifts the inflow toward immigrants with stronger comparative advantage in cognitive jobs, narrowing the immigrant-native earnings gap while leaving the spa-

[2]The remaining 38.2 percent reflects differences in the size of each origin group, which are held fixed across counterfactuals.

[3]Recently, there has been an increasing interest in assessing the effect of selective U.S. immigration policies. See, among others, Peri, Shih and Sparber (2015), Mayda et al. (2018), and Mahajan et al. (2024).

tial earnings gap essentially unchanged. Expanding non-college immigration instead increases the weight of immigrants who sort less into high-return cognitive jobs, widening the immigrant-native earnings gap while slightly compressing the spatial earnings gap. These policy experiments show that the distributional effects of immigration expansion depend on the skill composition of the inflow, as different policies generate different trade-offs between the immigrant-native earnings gap and the earnings gap between large and small cities.

This paper makes two main contributions. First, it is the first paper to document a smaller city-size earnings gradient for immigrants than natives, with the gap varying by country of origin. It further shows that these differences are closely linked to differential sorting into cognitive occupations across space. The structural decomposition shows that the gap in city-size earnings premia goes beyond human capital differences: equalizing human capital across groups leaves most of the gap intact, with amenity valuations and local earnings wedges accounting for the bulk of the difference. Second, the paper develops a quantitative spatial equilibrium framework that links immigrant sorting across cities and occupations to earnings inequality both between workers and across places. The framework reveals a structural trade-off: removing the differences in human capital, amenity valuations, and earnings wedges that generate immigrants' earnings disadvantage substantially closes the aggregate immigrant-native earnings gap but widens the earnings gap between large and small cities. College immigration expansion narrows the immigrant-native earnings gap without widening the spatial earnings gap, while structural interventions that remove amenity differences or earnings wedges between immigrants and natives generate larger increases in spatial earnings inequality.

Relation to the Literature This paper contributes to several strands of the literature.

First, this paper relates to the literature studying the relationship between immigration and labor market inequality (Card, 2009; Advani et al., 2022; Dustmann, Kastis and Preston, 2023; Amior and Stuhler, 2024; Lebow, 2024). I contribute to this literature by documenting two novel facts: that the immigrant-native earnings gap varies across space and origin groups, and that these differences are linked to differential occupational sorting across cities. Existing work in this strand focuses on the aggregate effects of immigration on the wage distribution of natives, abstracting from the spatial dimension of immigrants' labor market outcomes. I show that accounting for space reveals a new dimension of immigrant earnings disadvantage: low-income-country immigrants fail to earn a city-size premium despite concentrating in large cities.

Second, this paper contributes to the literature on structural models that study the labor market consequences of immigration (Borjas, 2003; Peri and Sparber, 2009; Ottaviano and Peri, 2012; Lessem, 2018; Monras, 2020; Burstein et al., 2020; Piyapromdee, 2021; Albert, Glitz and Llull, 2021; Albert and Monras, 2022; Adda, Dustmann and Görlach, 2022). Relative to this literature, I introduce three origin-specific margins within a quantitative spatial equilibrium framework: occupation-specific human capital, amenity valuations for city-occupation pairs, and local earnings wedges. This framework allows me to quantify how these channels shape both the immigrant-native earnings gap and the spatial earnings gap, and to uncover a trade-off between the two.

Third, this paper relates to the literature on city-size earnings premia, worker sorting across cities, and spatial earnings inequality (Glaeser and Mare, 2001; Baum-Snow and Pavan, 2012; Eeckhout, Pinheiro and Schmidheiny, 2014; Diamond, 2016; Baum-Snow, Freedman and Pavan, 2018; Eeckhout, Hedtrich and Pinheiro, 2026). This literature documents that high-skill workers sort into large cities and earn higher returns there, but it has not examined how these patterns differ between immigrants and natives or what drives such differences. Panel-based approaches identify heterogeneity in city-size returns while flexibly controlling for sorting on unobservables (De La Roca and Puga, 2017). Recent work using structural general equilibrium models shows that two-sided worker-firm sorting amplifies spatial earnings inequality and has distinct implications for place-based policies (Oh, 2025; Hong, 2026). I contribute by providing the first quantitative decomposition of immigrant-native gaps in city-size earnings premia, showing that amenity valuations and local earnings wedges dominate human capital as drivers, and that both channels operate through differential occupational sorting across space.

The rest of the paper is organized as follows. In section I., I describe the sources of data and present the stylized facts about immigrants' labor market outcomes across space. In section II., I introduce the spatial equilibrium model. In section III., I describe the estimation procedure. In section IV., I present the estimation results and the counterfactual exercises. In section V., I describe the immigration policy exercises and discuss the results from them. In section VI., I summarise the findings and discuss ideas for future research.

I. Data and Motivating Facts

This section describes the data sources used to document the three stylized facts and to estimate the structural parameters of the spatial equilibrium model. I construct a dataset on worker and city characteristics drawing from three main sources: the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2025), the World Bank Development Indicators (World Bank, 2025), and the Occupational Information Network (O*NET) Database (National Center for O*NET Development, 2021).

IPUMS Data. The main data source is the Integrated Public Use Microdata Series (IPUMS), a database containing samples of the American population. I select 1 percent pooled cross-sectional samples from the American Community Survey (ACS) between 2010 and 2019, an annual demographic survey that collects information about individuals living in the United States. For all individuals in the sample, the ACS provides country of birth and citizenship status. I combine this information to define immigrants as foreign-born workers who are either naturalized citizens or non-citizens, excluding individuals born abroad to American parents.[4] The ACS also contains individual demographic characteristics — such as age, gender, and educational attainment — which I use to compute each worker's potential labor market experience and to assign workers to the

[4]For the definition of this variable and others, see Appendix A.

college/no-college category. The survey further reports labor market outcomes including annual earnings, employment status, number of weeks and hours worked, and occupation.[5] I use the information on annual earnings, number of weeks, and hours worked to compute hourly earnings. Finally, the dataset includes information on the Metropolitan Statistical Area (MSA) in which an individual resides, which I use to identify U.S. cities.[6].

World-Bank Development Indicators. I collect data on countries' GDP per capita from the World Bank Development Indicators, O*NET Database, a country-level database covering a broad set of economic development measures. Specifically, I use GDP per capita at PPP in constant 2021 international U.S. dollars to divide immigrant workers into two groups: those originating from high-income countries (HIC), defined as countries with GDP per capita greater or equal than 40,000, and those from low-income countries (LIC), defined as countries with GDP per capita below 40,000.

Occupational Information Network (O*NET) Database. I collect data on the task content of occupations from the Occupational Information Network (O*NET) Database, which provides descriptors for the various requirements to perform an occupation, including knowledge, skills, abilities, work activities, work context, work styles, and work values. Occupations in O*NET are classified using the Standard Occupational Classification (SOC) system. Following Acemoglu and Autor (2011), I construct a task intensity measure for each occupation and use it to assign occupations to either a cognitive or non-cognitive category.[7]

Sample Selection. I construct the analysis sample by merging data from IPUMS, the World Bank Development Indicators, O*NET Database, and the O*NET Database. The sample consists of prime-age workers (25–54) who are in the labor force, work for wages, report positive wage and salary income, worked at least one week in the previous year, and do not work in the armed forces or in the public sector. I further exclude individuals living in group quarters and those enrolled in school at the time of the interview. Following De La Roca and Puga (2017), I also drop individuals employed in farming, forestry, and fishing occupations, since — even if they reside in urban areas — their workplace may be located in rural areas. The main analysis focuses on male workers.[8] I restrict the immigrant sample to first-generation immigrants, defined as foreign-born individuals who migrated to the United States after the age of 18 and therefore plausibly received no education from a U.S. institution. Since the ACS does not provide information on the country where individuals received their education, I follow Schoellman (2012) and use information on year of arrival, age, and years of completed schooling to exclude immigrants who likely studied in the United States.[9] The earnings

[5] Wages are top-coded. To address this, I follow the procedure in Albert, Glitz and Llull (2021).

[6] Measuring cities through MSAs is common practice in the urban economics literature (see Moretti (2013), among others), as their definition sits at the intersection of geographical boundaries, demographic information, and economic activity. Specifically, the U.S. Office of Management and Budget (OMB) defines an MSA as one or more contiguous counties containing an urbanized area with a population of at least 50,000 individuals.

[7] More details on the construction of the task measures, task categories, and the criterion used to assign occupations to the cognitive/non-cognitive category can be found in Appendix A.

[8] Due to changes in female labor force participation rates over the sample period, I restrict the main analysis to male workers. I report results for the female sample in Appendix B.

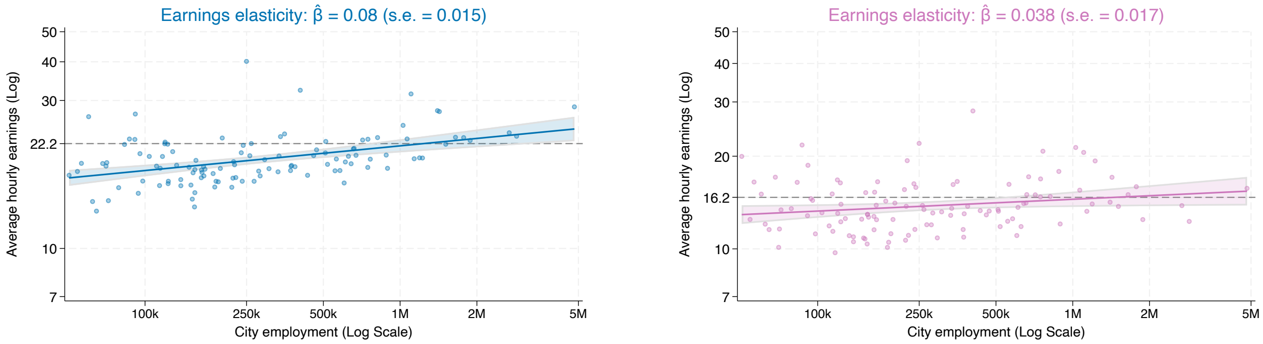
[9] See Appendix A for details on the selection of immigrants.

of immigrants I retain in the sample thus net out any returns to U.S. education and U.S.-specific human capital acquisition. I then drop individuals residing in areas not identifiable as an MSA and retain only MSAs in which I consistently observe immigrants from each country-of-origin group (LIC and HIC) across the sample years 2010–2019. I proxy city size by the employment stock and classify cities into two categories: small (employment stock below 750,000) and large (employment stock of 750,000 or above). The final sample covers workers from 120 countries of origin (including the United States) and 115 MSAs. I report summary statistics for the main socio-demographic characteristics of workers and cities in Appendix A.

I.A. Empirical Evidence

Fact 1: The City-Size Earnings Gradient Is Half as Large for Immigrants as for Natives. Figure 1 documents how average hourly earnings differ across US cities of varying size for native and immigrant workers.

Figure 1: City-size earnings gradient



(a) Natives

(b) Immigrants

Notes: This figure shows the relationship between the natural logarithm of average hourly earnings of male workers aged 25–54 in each Metropolitan Statistical Area (MSA) and the natural logarithm of the employment stock of that MSA. Each dot represents the natural logarithm of average hourly earnings in a given MSA. At the top of the figure, I report the estimated coefficient and its heteroscedasticity-robust standard error for the slope of this relationship, obtained by regressing the natural logarithm of average hourly earnings on the natural logarithm of city employment stock. The shaded area in each panel represents the 95 percent confidence interval. Earnings are deflated by the 1999 CPI Index provided by IPUMS. Individual sample weights are used in all calculations. Source: ACS 2010-2019, World Bank Development Indicators, O*NET Database, and author's calculations.

Panel 1a shows that native workers earn approximately \$22 per hour on average, with earnings rising with city size. A linear regression of log hourly earnings on log city employment yields a statistically significant elasticity of 0.08, implying that doubling city size is associated with an increase in native earnings of approximately 5.7 percent.[10]

Panel 1b shows that immigrant workers earn approximately \$16 per hour on average—about \$6 per hour less than natives—and exhibit greater dispersion around the mean. In contrast to natives, the estimated earnings elasticity for immigrants is 0.038, half the size of that for native workers,

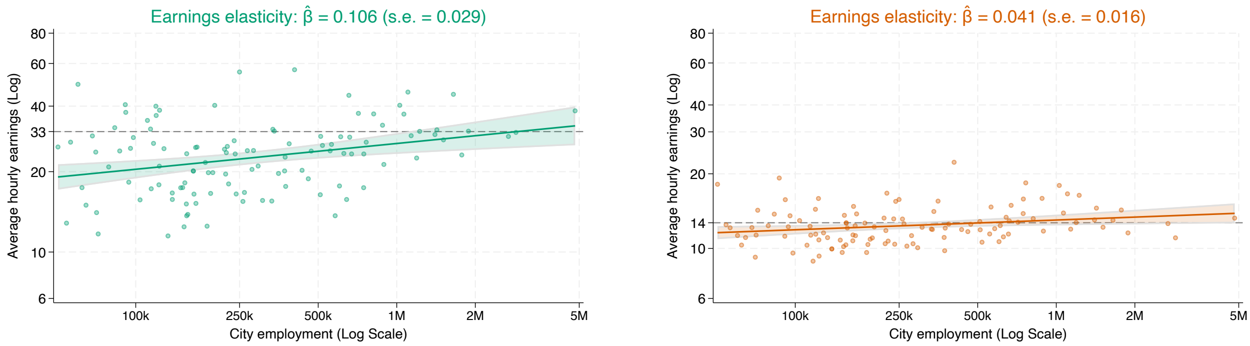
[10]The derivation for the earnings change associated with a given change in city size can be found in Appendix III.C..

and statistically significant at the 5 percent level. As an example, a native worker in Chicago, IL earns approximately 13.7 percent more than a native in Gainesville, FL—the smallest city in the sample—while the corresponding figure for immigrants is about 6.3 percent.

Taken together, these patterns imply that the earnings gap between native and immigrant workers widens as city size increases.[11]

Fact 2: The City-Size Earnings Gradient among Immigrants Varies by Country of Origin. Does the city-size earnings gradient depend on the country of origin? To answer this question, I split the sample of immigrants into immigrants from high-income countries (HIC-GDP per capita at least \$40,000) and from low-income countries (LIC-GDP per capita less than \$40,000), and I plot the relationship between hourly earnings and the size of US cities in Figure 2.

Figure 2: City-size earnings gradient



(a) High-Income Countries (b) Low-Income Countries

Notes: This figure shows the relationship between the natural logarithm of average hourly earnings of male workers aged 25–54 in each Metropolitan Statistical Area (MSA) and the natural logarithm of the employment stock of that MSA for high-income countries immigrants (HIC GDP pc $\geq \$40,000$, Panel a) and low-income countries immigrants (LIC-GDP pc $< \$40,000$, Panel b). Each dot corresponds to the natural logarithm of the average hourly earnings in a Metropolitan Statistical Area. At the top of the figure, I report the estimated coefficient and its heteroscedasticity-robust standard error for the slope of this relationship, obtained by regressing the natural logarithm of average hourly earnings on the natural logarithm of city employment stock. The shaded area in each panel represents the 95 percent confidence interval. Earnings are deflated by the 1999 CPI Index provided by IPUMS. Individual sample weights are used in all calculations. Source: ACS 2010-2019, World Bank Development Indicators, O*NET Database, and author's calculations.

Overall, there are substantial differences in hourly earnings even among immigrants. The average hourly earnings of HIC immigrants are about two and a half times as high as those of LIC immigrants. In addition, the hourly earnings of HIC immigrants are more dispersed around the mean compared to the earnings of LIC immigrants. Both groups exhibit a positive city-size earnings gradient, but the gradient is significantly larger for HIC immigrants. The estimated earnings elasticity to city size is 0.106 for HIC immigrants and 0.041 for LIC immigrants, both significant at 1 percent. In other words, doubling the city population leads to a 7.6 percent increase in the average hourly earnings of an HIC immigrant, compared to a 2.9 percent increase for a LIC immigrant.

[11] Appendix II.A. reports Fact 1 for female workers. While the magnitude of the coefficients is not the same, Figure 9 shows that the earnings gap between immigrants and natives increases in city size also for female immigrants.

Hence, while all immigrants benefit from locating in larger cities, the gains are more than twice as large for immigrants from high-income countries.

To gain further insight, I report average hourly earnings by worker origin and city size in Table 1 shows the average earnings in small and big cities and the city-size gap for all groups of workers. In small cities, the hourly earnings of natives are \$19.8 per hour and rise to \$24.2 per hour in big cities, a gap of \$4.3 per hour (roughly 22 percent). HIC immigrants earn more on average than all other workers, both in small and big cities, and receive a city-size premium even larger than that of natives (+\$8.5 vs. +\$4.3 per hour). By contrast, the earnings of LIC immigrants are virtually unchanged across city sizes (+\$0.2 per hour).

Table 1: Hourly Earnings: Big vs Small Cities

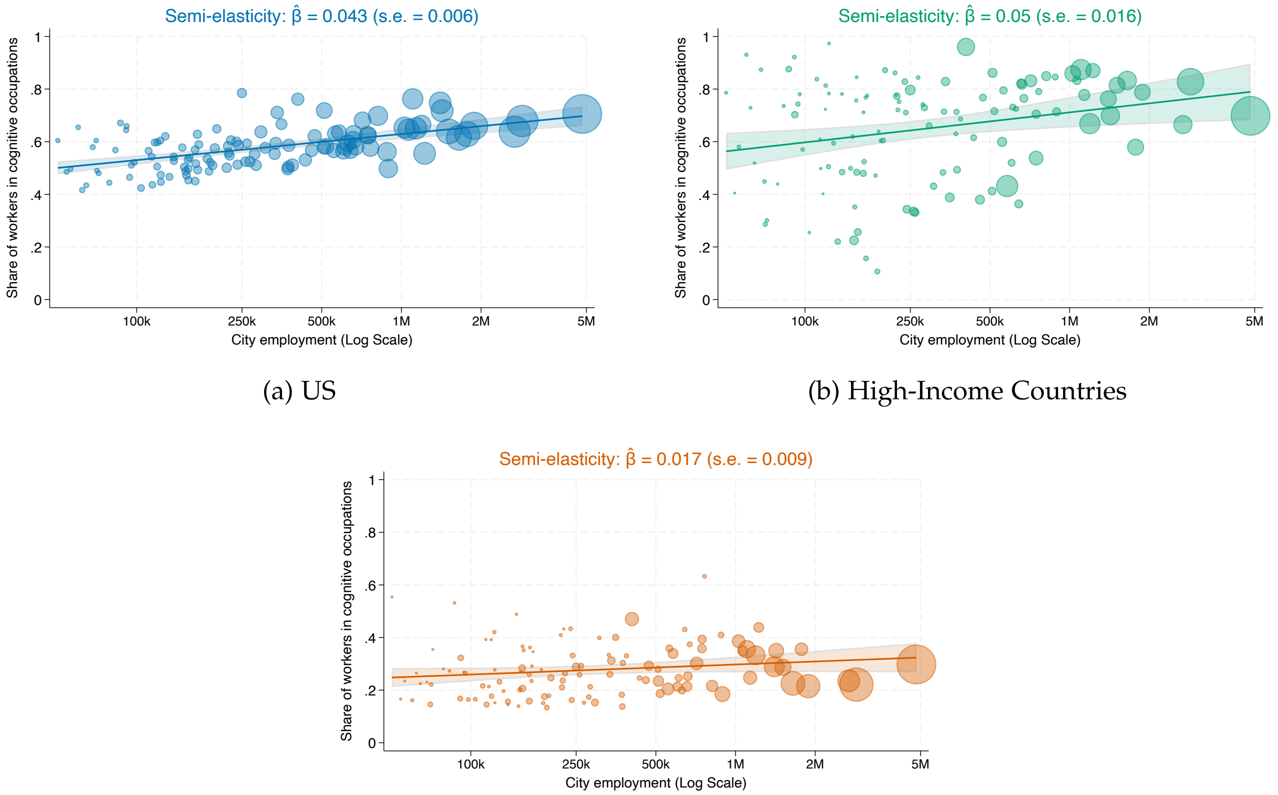
	Small Cities (Pop. $<$ 750,000)	Big Cities (Pop. $\geq$ 750,000)	Gap
Natives	19.8	24.2	+4.3
High-Income Countries	27.5	36.0	+8.5
Low-Income Countries	14.1	14.3	+0.2

Notes: This table reports average hourly earnings (USD/hour) in the average small city (city employment stock $< 750,000$) and average big city (city employment stock $\geq 750,000$), as well as the city-size earnings gap (average earnings in big cities minus average earnings in small cities) for natives, immigrants from high-income countries (GDP per capita $\geq 40,000$), and immigrants from low-income countries (GDP per capita $< 40,000$). Average earnings are calculated from a sample of male workers aged 25–54 who report being employed. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are applied in all calculations. Source: ACS 2010-2019, World Bank Development Indicators, O*NET Database, and author's calculations.

All things considered, Fact 2 suggests the existence of spatial differences in earnings not only between natives and immigrants but also among immigrants.

Fact 3: US Natives And Immigrants From Rich Countries Work More In Cognitive Occupations. A natural question is whether the heterogeneity in earnings premia reflects differences in how workers from different origins sort across occupations as city size increases. Figure 3 shows the relationship between the share of workers in cognitive occupations and city size for natives (panel a), HIC immigrants (panel b), and LIC immigrants (panel c). Both natives and HIC immigrants work substantially more in cognitive occupations compared to LIC immigrants. Furthermore, the propensity to work in cognitive occupations increases significantly with city size for both natives and HIC immigrants, with semi-elasticities of 0.043 and 0.050, respectively. By contrast, LIC immigrants not only have a much lower baseline propensity to work in cognitive occupations, but their sorting into these occupations across city sizes is weak (semi-elasticity of 0.017) and only significant at 10%.

Figure 3: Sorting into Cognitive Occupations across Cities



(a) US

(b) High-Income Countries

(c) Low-Income Countries

Notes: This figure shows the relationship between the share of male workers in cognitive occupations in each metropolitan statistical area and the natural logarithm of the employment stock of each metropolitan statistical area for native workers (panel a), immigrants from high-income countries (GDP pc $\geq \$40,000$, panel b), immigrants from low-income countries (GDP pc $< \$40,000$, panel c). Each marker corresponds to the share of workers who work in a cognitive occupation in a Metropolitan Statistical Area. The size of the marker indicates, for each origin group, the share of workers living in the corresponding Metropolitan Statistical Area. At the top of the figures, I report the estimated coefficient and the corresponding standard error robust to heteroscedasticity for the slope of this relationship obtained by regressing the share of workers in a cognitive occupation in each city on the log of the city's employment stock. The area in each panel represents the estimated confidence intervals at the 5 percent significance level. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are used in the calculations. Source: ACS 2010-2019, World Bank Development Indicators, O*NET Database, and author's calculation.

To illustrate these patterns more precisely, Table 2 reports the share of workers in cognitive occupations and their spatial distribution across small and big cities for all three groups. HIC immigrants have the highest share of workers in cognitive occupations both in small and big cities (61.7% and 75.5% respectively), followed by natives (58.3% and 65.6%). Moving from small to big cities, the share of HIC immigrants working in cognitive occupations increases by 13.9 percentage points, nearly twice the increase observed for natives (7.3 percentage points).

By contrast, the share of LIC immigrants in cognitive occupations is virtually unchanged across city sizes (27.0% vs 27.4%, a difference of just 0.4 percentage points), consistent with the weak semi-elasticity documented in Figure 3. Despite receiving little occupational upgrade from city size, LIC immigrants are the most spatially concentrated in big cities: 71.2% of them work in big cities, compared to 61.5% of HIC immigrants and 53.4% of natives.

Overall, these patterns suggest that occupational sorting across cities is a mechanism behind the heterogeneous city-size earnings premia documented in Fact 2.

Table 2: Shares of workers in cognitive occupations: small vs big cities

		Small Cities (Pop. $<$ 750,000)	Big Cities (Pop. $\geq$ 750,000)	Δ
Natives	% Cognitive	58.3	65.6	+7.3
	% Total	46.6	53.4	+6.7
High-Income Countries	% Cognitive	61.7	75.5	+13.9
	% Total	38.5	61.5	+23.0
Low-Income Countries	% Cognitive	27.0	27.4	+0.4
	% Total	28.8	71.2	+42.3

Notes: This table reports the share of workers who work in a cognitive occupation (% cognitive) and the spatial distribution (% total) of workers between the representative small and big city expressed in percentage terms for natives, immigrants from high-income countries (GDP per capita $\geq 40,000$), and immigrants from low-income countries (GDP per capita $< 40,000$). For each outcome, Column (3) reports the difference in the shares between the big and small cities expressed in percentage points. The shares are calculated from a sample of male workers reporting to be employed. Individual sample weights are used in the calculations. Source: ACS 2010-2019, World Bank Development Indicators, O*NET Database, and author's calculation.

Summary. In this section I document three stylized facts about workers' earnings and occupational sorting across cities: (i) the city-size earnings gradient is twice as large for natives as for immigrants; (ii) among immigrants, the city-size earnings gradient is largest for HIC immigrants and smallest for LIC immigrants; (iii) natives and HIC immigrants are significantly more likely to work in cognitive occupations as city size increases, while the occupational composition of LIC immigrants remains unchanged, despite LIC immigrants being the most spatially concentrated in large cities. Appendix B presents robustness checks for these facts. I show that the facts are consistent also for female workers and robust to the inclusion of a wide set of controls. Furthermore, following Moretti (2013), in Appendix III.B. I provide additional evidence that the documented earnings differences across cities do not disappear when earnings are deflated by local living costs.

In the next section, I build a general equilibrium spatial model that accounts for workers' heterogeneity in human capital and tastes for city-occupation pairs to study the determinants of these patterns in the data.

II. A Quantitative General Equilibrium Spatial Model

The three stylized facts document that workers of different origins differ sharply in how their earnings and occupational composition respond to city size. To understand the mechanisms driving these patterns and to conduct counterfactual experiments, I build a quantitative spatial general equilibrium model with heterogeneous cities and workers. The model has three key ingredients: (i) a production technology that values cognitive skills and whose cognitive bias varies across cities; (ii) workers who differ in human capital and in their idiosyncratic preferences over city–occupation pairs; and (iii) labor-market distortions that vary across city–occupation pairs by countries of origin.

II.A. Model Setup

Environment. Consider a static economy with $j \in \{1, \ldots, J\}$ cities and a unit continuum of prime-age workers $i \in [0, 1]$, corresponding to the workforce analyzed in Section 1. Workers are organized into groups $g = (k, e, x)$, where $k \in \mathcal{K}$ denotes country of origin, $e \in \mathcal{E}$ educational attainment, and $x \in \mathcal{X}$ potential labor-market experience. Each group g has an exogenous workforce share $\phi_g > 0$, with $\sum_g \phi_g = 1$, taken as given by all agents in the model.[12] In each city, a representative firm produces a homogeneous, tradable consumption good by combining labor in two occupations: *cognitive* ($o = c$) and *non-cognitive* ($o = n$). Workers are fully mobile across cities and occupations. The labor market is perfectly competitive. A competitive housing market operates in each city; land T_j is owned by absentee landlords.[13]

Notation. Throughout the model, I use subscripts to denote the city–occupation pair jo that a worker *chooses*, and function arguments to denote the group characteristics that a worker *has*. For instance, $w_{jo}(g)$ denotes the earnings obtained by a worker from group g who chooses city j and occupation o, while r_{jo} — which carries no group argument — denotes the competitive wage per efficiency unit, common to all workers in that city–occupation cell. Where a variable depends only on the country-of-origin component of g, I write $k = k(g) \in \mathcal{K}$ as the argument; for example, $\tau_{jo}(k)$ is the earnings wedge that depends on city, occupation, and country of origin but not on education or experience.

Production Technology. The representative firm in city j combines efficiency units of cognitive labor L_{jc} and non-cognitive labor L_{jn} using a CES production function:

$$Y_j = \left[L_{jn}^{\frac{\sigma-1}{\sigma}} + \left(\theta_j \, L_{jc}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{II.1}$$

[12] Treating $\{\phi_g\}$ as exogenous is consistent with the static framework: workers choose *where* to locate within the US, but the total mass of each origin–education–experience group in the US workforce is taken as fixed. Counterfactuals that alter the skill composition of immigrants change the values of $\{\phi_g\}$ directly; the equilibrium is then recomputed holding all other structural parameters constant.

[13] The absentee-landlord assumption allows for avoiding the accrual of rental income to workers. This assumption is standard in quantitative spatial models (see, e.g., Eeckhout, Pinheiro and Schmidheiny, 2014). It also implies that housing expenditure represents a pure cost to workers rather than a transfer within the economy.

where $\sigma > 0$ is the (city-invariant) elasticity of substitution between occupations and $\theta_j > 0$ is a city-specific *cognitive productivity bias*. The bias θ_j shifts the firm's demand for cognitive labor: when $\sigma > 1$ (gross substitutes), a higher θ_j raises the relative price of cognitive skills, amplifying the city-size earnings premium for cognitive workers; when $\sigma < 1$ (gross complements), the effect is reversed. Variation in θ_j across cities is the primary supply-side mechanism generating the heterogeneous city-size earnings premia documented in Facts 1 and 2.[14]

Human Capital. Each worker from group g is endowed with occupation-specific human capital $s_o(g)$, where $s_c(g)$ and $s_n(g)$ denote the efficiency units supplied when choosing a cognitive or non-cognitive occupation, respectively. Human capital depends on group characteristics but not on the city chosen, so all within-group earnings differences across cities are driven by wages, distortions, and amenities rather than by human capital accumulation.

Worker Preferences. Worker i from group g who chooses city j and occupation $o \in \{c, n\}$ derives utility from consumption c and housing h:

$$U^i_{jo}(g) = c^{1-\alpha}\, h^{\alpha}\, \exp\{z_{jo}(g) + \varepsilon^i_{jo}\} \tag{II.2}$$

where $\alpha \in (0,1)$ is the housing expenditure share, $z_{jo}(g)$ is the mean log-amenity that group g assigns to pair jo, varying across the full group $g = (k, e, x)$, and ε^i_{jo} is an idiosyncratic taste draw that is i.i.d. across workers and pairs, following a Type-I Extreme Value (Gumbel) distribution with location zero and scale one.[15][16] Workers within the same group g share identical preferences over consumption and housing and the same mean log-amenity $z_{jo}(g)$; they differ only in their idiosyncratic draw ε^i_{jo}, which generates within-group heterogeneity in location–occupation choices.

The budget constraint for worker i from group g choosing pair jo is:

$$c + p_j\, h \le w_{jo}(g) \tag{II.3}$$

where p_j is the city-specific housing price (the consumption good is the numeraire) and $w_{jo}(g)$ are earnings. The optimal demands are therefore $c^* = (1-\alpha)\, w_{jo}(g)$ and $h^* = \alpha\, w_{jo}(g)/p_j$, identical for

[14] This assumption deviates from Ottaviano and Peri (2012), who estimate an elasticity of substitution between immigrant and native workers of around 20, implying imperfect substitutability even conditional on education and experience. In my framework, group-specific labor market wedges absorb residual earnings gaps between immigrants and natives within occupation-city cells, partially accounting for this channel.

[15] The unit-scale normalization is without loss of generality: the degree of sorting across alternatives is governed by the dispersion of systematic utility differences, not by the scale of the taste shock. The Gumbel assumption delivers closed-form multinomial-logit shares for city–occupation pairs (Eq. II.12).

[16] The model allows for joint city-occupation taste shocks $\varepsilon_{jo}(g)$ rather than imposing separability between city preferences $\varepsilon_j(g)$ and occupation preferences $\varepsilon_o(g)$. This choice is motivated by two considerations. First, there is evidence that the attractiveness of a city depends on the occupation, see Papageorgiou (2022). Second, a separable structure would impose the restriction that the amenity-driven component of occupational sorting is identical across city types for each origin group. The cost of the joint structure, by contrast, is that the amenity parameters $z_{jo}(g)$ are identified as residuals conditional on wages, human capital, and wedges, and therefore absorb any misspecification in these components. This implies that the amenity estimates should be interpreted as a composite of preferences and any unmodeled heterogeneity in the city-occupation attractiveness for each origin group.

all workers within group g at pair jo. Substituting into (II.2) yields the individual indirect utility:

(II.4)
$$V^i_{jo}(g) = \gamma\, p_j^{-\alpha}\, w_{jo}(g)\, \exp\{z_{jo}(g) + \varepsilon^i_{jo}\}$$

where $\gamma \equiv (1-\alpha)^{1-\alpha}\alpha^{\alpha}$ is a constant. Worker i chooses the city–occupation pair that delivers the highest $V^i_{jo}(g)$. I define the *systematic* component of indirect utility — the part common to all workers in group g at pair jo — as:

(II.5)
$$\Omega_{jo}(g) \equiv \gamma\, p_j^{-\alpha}\, w_{jo}(g)\, \exp\{z_{jo}(g)\}$$

so that $V^i_{jo}(g) = \Omega_{jo}(g)\, \exp\{\varepsilon^i_{jo}\}$.

Earnings and Local Labor Market Distortions. Conditional on choosing city j and occupation o, a worker from group g supplies human capital $s_o(g)$ inelastically. Earnings are:

(II.6)
$$w_{jo}(g) = r_{jo}\, s_o(g)\, \big(1 + \tau_{jo}(k)\big)$$

where r_{jo} is the competitive wage per efficiency unit — common to all workers in city j and occupation o — and $\big(1 + \tau_{jo}(k)\big)$ is a wedge that depends on the city–occupation pair and the worker's country of origin $k = k(g)$, with $\tau_{jo}(k) \in (-1, \infty)$. Earnings therefore vary across groups within a city–occupation cell through two channels: differences in human capital $s_o(g)$ and differences in the country-of-origin wedge $\tau_{jo}(k)$. A wedge $\tau_{jo}(k) < 0$ acts as a tax, reducing the earnings of workers from country k below the competitive benchmark $r_{jo}\, s_o(g)$; a wedge $\tau_{jo}(k) > 0$ acts as a subsidy. The wedge $\tau_{jo}(k)$ absorbs any factor — discrimination, informational frictions, occupational licensing, or network barriers — that drives a gap between the earnings of workers from country k and what a worker with the same human capital would earn at the competitive wage.

Housing Technology. Absentee landlords in city j combine land T_j with the final good Y_j to produce the housing good:

(II.7)
$$H_j = \omega_j\, Y_j^{\iota_j}\, T_j^{1-\iota_j}$$

where $\iota_j \in (0, 1)$ is the expenditure share of the final good in housing production and $\omega_j = \iota_j^{-\iota_j}$ is a city-specific normalizing constant.

II.B. Model Solution and Spatial Equilibrium

Firm's Problem and Labor Demand. The representative firm in city j solves:

(II.8)
$$\max_{L_{jc}, L_{jn}} \left[L_{jn}^{\frac{\sigma-1}{\sigma}} + \left(\theta_j L_{jc}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} - r_{jc}\, L_{jc} - r_{jn}\, L_{jn}$$

The first-order conditions equate wages per efficiency unit to marginal products:

$$r_{jn} = \left(\frac{Y_j}{L_{jn}}\right)^{1/\sigma} \tag{II.9}$$

$$r_{jc} = \left(\frac{Y_j}{L_{jc}}\right)^{1/\sigma} \theta_j^{1-1/\sigma} \tag{II.10}$$

Taking the ratio of (II.10) and (II.9) gives the relative price of cognitive skills:

$$\frac{r_{jc}}{r_{jn}} = \left(\frac{L_{jc}}{L_{jn}}\right)^{-1/\sigma} \theta_j^{1-1/\sigma} \tag{II.11}$$

The relative price of cognitive labor decreases in the cognitive–non-cognitive employment ratio (diminishing returns) and increases in θ_j whenever $\sigma > 1$: when the two inputs are gross substitutes, a city with a higher cognitive productivity bias attracts more cognitive workers *and* pays them a higher relative wage, reinforcing spatial earnings inequality.

Worker Location and Occupation Choice. Given the Gumbel assumption on ε^i_{jo}, the share of group g workers at city–occupation pair jo takes the multinomial-logit form:

$$\pi_{jo}(g) = \frac{\Omega_{jo}(g)}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \{c,n\}} \Omega_{j'o'}(g)} \tag{II.12}$$

where, substituting (II.6) into (II.5):

$$\Omega_{jo}(g) = \gamma\, p_j^{-\alpha}\, r_{jo}\, s_o(g)\, \big(1 + \tau_{jo}(k)\big)\, \exp\{z_{jo}(g)\} \tag{II.13}$$

The denominator of (II.12) sums $\Omega_{j'o'}(g)$ over all possible city–occupation choices while holding group g fixed — making it transparent that the choice probabilities are computed for a given worker type across all available alternatives. Note that $\pi_{jo}(g)$ is a *conditional* probability: it sums to one over all pairs jo for a fixed group g, i.e. $\sum_j \sum_o \pi_{jo}(g) = 1$. The *unconditional* share of the total workforce located at pair jo from group g is therefore $\pi_{jo}(g)\, \phi_g$, which is the product that appears in all aggregation expressions below.

Equation (II.12) formalizes the key mechanisms of the model. Cross-group differences in spatial and occupational sorting arise from three sources: differences in human capital $s_o(g)$, labor-market distortions $\tau_{jo}(k)$, and mean log-amenities $z_{jo}(g)$. Crucially, because $\tau_{jo}(k)$ varies across both cities and occupations, two workers from different countries of origin but with identical human capital face different effective returns to locating in large cities and to working in cognitive occupations — generating heterogeneous sorting patterns and city-size earnings premia across origin groups even in the absence of any human capital differences. At the same time, $z_{jo}(g)$ varying at the full group level $g = (k, e, x)$ captures the additional fact that college-educated and non-college workers from the same country may sort differently across cities even after accounting for wages and distortions.

Average City Earnings. Average hourly earnings in city j — required for the housing-price equation derived below — are:

$$\bar{w}_j \equiv \frac{\sum_o \sum_g \pi_{jo}(g)\, \phi_g\, w_{jo}(g)}{\sum_o \sum_g \pi_{jo}(g)\, \phi_g} \tag{II.14}$$

where $w_{jo}(g) = r_{jo}\, s_o(g)\,(1+\tau_{jo}(k))$ as in (II.6), and the denominator $n_j \equiv \sum_o \sum_g \pi_{jo}(g)\, \phi_g$ is the share of the total workforce located in city j.

Housing Market. Solving the landlords' profit-maximization problem and imposing housing-market clearing ($H_j = \alpha\, \bar{w}_j / p_j$) yields the equilibrium housing price:

$$p_j = \left(\frac{\alpha\, \bar{w}_j L_j}{T_j}\right)^{\frac{1}{1+\zeta_j}} \tag{II.15}$$

where $\zeta_j \equiv \frac{\iota_j}{1-\iota_j}$ is the city-specific housing supply elasticity and $\bar{w}_j$ is defined in (II.14).[17] Cities with inelastic housing supply (low ζ_j) translate worker inflows into larger price increases, dampening the real-earnings gains from locating in productive cities.

Labor Supply. The efficiency units of labor supplied to occupation $o \in \{c, n\}$ in city j aggregate over all groups:

$$L_{jn} = \sum_g \pi_{jn}(g)\, s_n(g)\, \phi_g \tag{II.16}$$

$$L_{jc} = \sum_g \pi_{jc}(g)\, s_c(g)\, \phi_g \tag{II.17}$$

Spatial Equilibrium. A spatial equilibrium is a set of skill prices $\{r^*_{jo}\}_{j,o}$, housing prices $\{p^*_j\}_j$, and worker distributions $\{\pi^*_{jo}(g)\}_{j,o,g}$ such that the following four conditions hold simultaneously.

1. **Worker optimality.** The share of group g workers at city–occupation pair jo satisfies:

$$\pi^*_{jo}(g) = \frac{\Omega^*_{jo}(g)}{\sum_{j'} \sum_{o'} \Omega^*_{j'o'}(g)}, \qquad \Omega^*_{jo}(g) = \gamma\, p_j^{*\,-\alpha}\, r^*_{jo}\, s_o(g)\, \big(1+\tau_{jo}(k)\big)\, \exp\{z_{jo}(g)\} \tag{II.18}$$

2. **Labor supply.** Efficiency units of labor at each city–occupation pair aggregate as in (II.16)–(II.17):

$$L^*_{jn} = \sum_g \pi^*_{jn}(g)\, s_n(g)\, \phi_g \tag{II.19}$$

$$L^*_{jc} = \sum_g \pi^*_{jc}(g)\, s_c(g)\, \phi_g \tag{II.20}$$

[17] See the Appendix IV.A. for the derivation.

3. **Labor-market clearing.** In each city j, wages per efficiency unit equal marginal products:

$$r^*_{jn} = \left[\left(L^*_{jn}\right)^{\frac{\sigma-1}{\sigma}} + \left(\theta_j\, L^*_{jc}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} \left(L^*_{jn}\right)^{-\frac{1}{\sigma}} \tag{II.21}$$

$$r^*_{jc} = \left[\left(L^*_{jn}\right)^{\frac{\sigma-1}{\sigma}} + \left(\theta_j\, L^*_{jc}\right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} \left(L^*_{jc}\right)^{-\frac{1}{\sigma}} \theta_j^{1-\frac{1}{\sigma}} \tag{II.22}$$

4. **Housing-market clearing.** The equilibrium housing price satisfies:

$$p^*_j = \left(\frac{\alpha \sum_o \sum_g \pi^*_{jo}(g)\, \phi_g\, w^*_{jo}(g)}{T_j} \right)^{\frac{1}{1+\zeta_j}} \tag{II.23}$$

III. Bringing The Model To The Data

In this section, I discuss the identifying assumptions, describe the externally calibrated parameters, present the identification and estimates of the internally estimated parameters, and briefly discuss the model fit.

III.A. Dimensionality Reduction and Identifying Assumptions

The model describes the US economy as populated by workers from different origins who choose where to live and which occupation to perform. I calibrate the model to replicate the stylized facts presented in Table 1 and Table 2 in Section I.. I represent the US economy as one small city and one big city, $j \in \{S, B\}$, where workers can perform either a cognitive occupation ($o = c$) or a non-cognitive occupation ($o = n$). Workers differ in their group characteristics $g = (k, e, x)$: country of origin $k \in$ {US, LIC, HIC}, educational attainment $e \in$ {no college, college}, and potential labor-market experience $x \in$ {0–14, 15–29, 30+}. Under this discretization, 18 groups of workers choose among 4 city–occupation alternatives: (S, n), (S, c), (B, n), and (B, c).

I impose one normalization and one identifying assumption, summarized in Table 3.

Table 3: Normalizations and identifying assumptions

Description	Parameter	Determination	Value
Mean log-amenity	$z_{Sn}(k, \text{no college}, 0\text{–}14)$	Normalization	0
Earnings wedges for native workers	$\tau_{jo}(k_{\text{US}})$	Assumption	0

Notes: The table reports one normalization and one identifying assumption required to bring the model to the data.

First, I normalize the mean log-amenity in the small city and non-cognitive occupation to zero for the baseline education–experience group within each country of origin:

$$z_{Sn}(g) = 0 \qquad \text{for } g = (k, \text{no college}, 0\text{–}14), \quad \forall\, k. \tag{III.1}$$

Since $z_{jo}(g)$ enters the indirect utility additively in logs, setting $z_{Sn}(g) = 0$ for the baseline group is equivalent to normalizing the amenity level to one, and it implies $\exp\{z_{Sn}(g)\} = 1$ for these workers. All remaining amenity parameters are therefore identified as log-deviations from this baseline: within each origin group k, they measure the additional amenity value that workers with different education or experience levels, or in different city–occupation pairs, assign to each alternative relative to the no-college, 0–14 experience worker choosing (S, n).

Second, I assume that native workers are not subject to any local labor-market wedge:

$$\tau_{jo}(k_{\mathrm{US}}) = 0 \qquad \forall\, j,\, o. \tag{III.2}$$

Under this assumption, the estimated wedges $\tau_{jo}(k)$ for $k \in \{\mathrm{LIC}, \mathrm{HIC}\}$ measure the earnings gap between immigrants and observationally equivalent native workers — those with the same education and experience — that cannot be attributed to differences in human capital. I also assume that the wedge varies across cities and occupations only through the country-of-origin component of g, so that $\tau_{jo}(k)$ does not depend on e or x within an origin group.

III.B. Externally Calibrated Parameters

Overall, the model features 121 structural parameters, net of the assumptions and normalizations, which I split into two groups. Six parameters capture macroeconomic features of the US economy and are calibrated directly from the literature or from the ACS 2010. The remaining 115 parameters govern the earnings and allocation of workers across cities and occupations and are estimated internally using the simulated method of moments (SMM).

Table 4: Externally calibrated parameters

Description	Symbol (1)	Value (2)	Source (3)
Elasticity of substitution	σ	3	Hsieh et al. (2019)
Housing supply elasticity	ζ	1.54	Saiz (2010)
Housing expenditure share	α	0.32	Albouy (2008)
Workforce share of group g	ϕ_g		ACS 2010
Land supply (both cities)	T_j	1	Assumed

Notes: The table reports the set of externally calibrated parameters used to internally estimate the model.

Table 4 describes the externally calibrated parameters. I set the elasticity of substitution between cognitive and non-cognitive labor $\sigma = 3$, following Hsieh et al. (2019). For the housing supply elasticity I use $\zeta = 1.54$, estimated by Saiz (2010), and I set the housing expenditure share $\alpha = 0.32$ following Albouy (2008). I compute the workforce share ϕ_g of each group $g = (k, e, x)$ directly from the ACS 2010, obtaining the exogenous distribution of workers across origin–education–experience cells. Finally, I normalize land supply to $T_j = 1$ in both cities.[18]

III.C. Internally Estimated Parameters

The remaining 115 structural parameters govern the allocation of workers across cities and occupations. They can be organized into four groups: (i) 2 parameters for the city-specific cognitive productivity bias θ_j; (ii) 36 parameters for the occupation-specific human capital $s_o(g)$; (iii) 8 parameters for the city–occupation–origin earnings wedges $\tau_{jo}(k)$; and (iv) 69 parameters for the city–occupation amenities $z_{jo}(g)$. I estimate all four groups jointly using the SMM.[19] Each group of parameters is identified by a set of data moments, as I describe in turn below.

Identification and Estimates of the City Productivity Bias. I identify the city-specific cognitive productivity bias θ_j from the average earnings of native workers in cognitive occupations in each city. Since natives face no wedge ($\tau_{jo}(k_{\text{US}}) = 0$), their earnings $w_{jo}(g) = r_{jo}\, s_o(g)$ reflect only the competitive wage per efficiency unit and their human capital. Conditional on human capital, cross-city variation in the earnings of native cognitive workers therefore pins down the variation in r_{jc} across cities, which — through the firm's first-order condition (II.10) — identifies θ_j.

Table 5 reports the estimated values. Both cities exhibit a productivity bias toward cognitive occupations, and the bias is larger in the big city ($\theta_B = 3.07$) than in the small city ($\theta_S = 2.51$), an increase of approximately 22 percent. This finding is consistent with Eeckhout, Hedtrich and Pinheiro (2026), who show that an uneven spatial diffusion of technology drives labor market polarization and spatial wage inequality.

Table 5: Estimated cognitive productivity bias

	Small City	Big City
	(1)	(2)
Cognitive productivity bias θ_j	2.51	3.07

Notes: Point estimates of θ_j obtained via SMM. The bias measures the city-specific productivity advantage of cognitive labor in the CES production function (II.1).

Identification and Estimates of Workers' Human Capital. The model includes 36 human capital parameters $s_o(g)$, one for each occupation–group combination. I identify these parameters by tar-

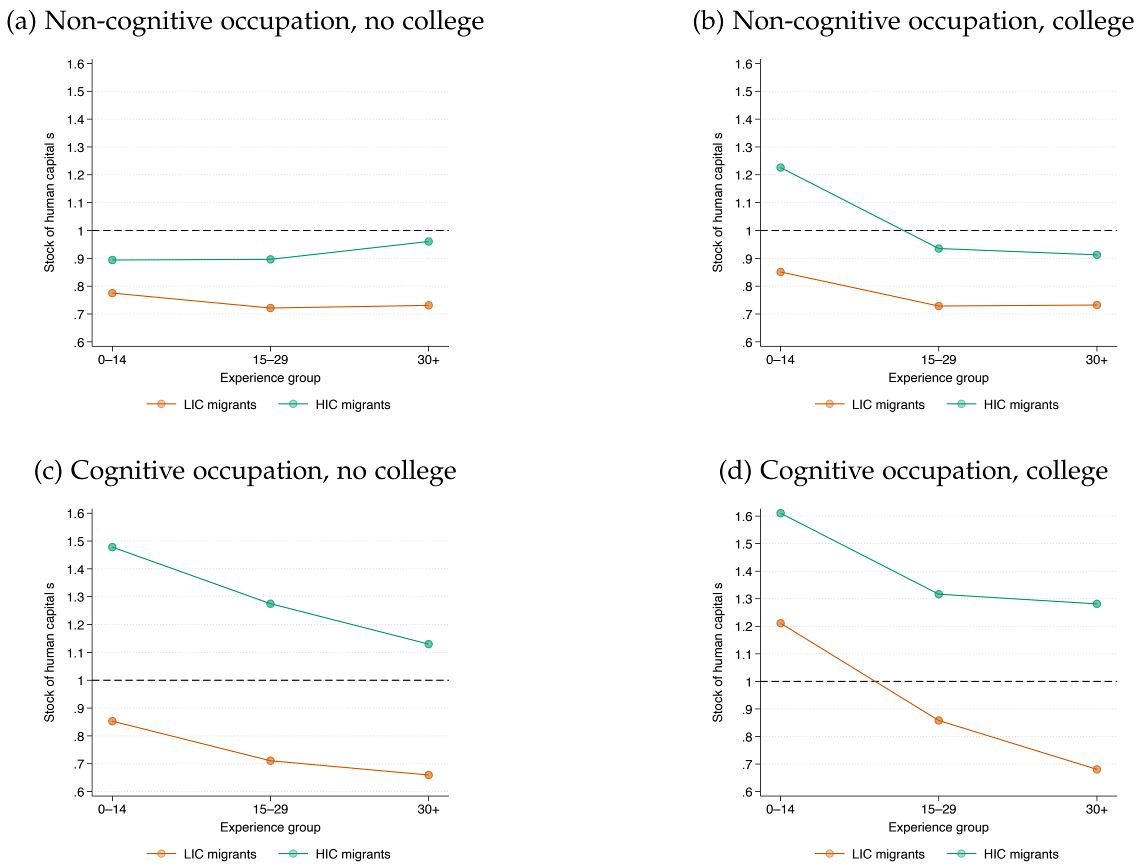
[18] I verify robustness to alternative values of the externally calibrated parameters, including σ, ζ, and T. The estimation results are qualitatively unchanged.

[19] See McFadden (1989).

geting the average occupation-specific earnings of workers in each group $g = (k, e, x)$, conditional on country of origin, education, and experience. Specifically, for native workers — who face no wedge — the earnings equation $w_{jo}(g) = r_{jo}\, s_o(g)$ implies that, conditional on the estimated r_{jo}, the human capital $s_o(g)$ is directly pinned down by the group's average earnings in occupation o. For immigrant workers, human capital is identified jointly with the wedges, as described below.

Figure 4 presents the estimated human capital of LIC and HIC immigrants relative to natives — that is, $s_o(k, e, x)/s_o(\mathrm{US}, e, x)$ —, where the dashed line at one marks parity with natives. The figure reveals several patterns. First, in non-cognitive occupations (top row), the human capital gaps are moderate and the cross-sectional experience gradient is flat. Among no-college workers (Panel a), both LIC and HIC immigrants are below the native benchmark, with LIC immigrants showing a stable deficit of about 20 percent across all experience groups and HIC immigrants closer to parity. Among college workers in non-cognitive occupations (Panel b), HIC immigrants are close to or slightly above the native benchmark throughout, while LIC immigrants remain below it by roughly 25 percent with little variation across experience groups.

Figure 4: Estimated human capital relative to natives



Notes: Each panel plots the estimated human capital of LIC (orange) and HIC (teal) immigrants relative to the native worker with the same education and experience, i.e. $s_o(k, e, x)/s_o(\mathrm{US}, e, x)$. The dashed line at one indicates parity with natives. Top row: non-cognitive occupation ($o = n$); bottom row: cognitive occupation ($o = c$). Left column: no-college workers; right column: college workers.

Second, in cognitive occupations (bottom row), the gaps are larger, and the cross-sectional experience gradient is more pronounced. Among no-college workers (Panel c), HIC immigrants are above the native benchmark at all experience levels but decline steadily with experience, while LIC immigrants are consistently below the line with a deficit that widens from around 15 percent at low experience, to around 35 percent at 30 or more years. The pattern is most striking among college workers in cognitive occupations (Panel d): HIC immigrants start well above the native benchmark at low experience, but converge toward it as experience increases; LIC college immigrants, by contrast, start near parity but fall progressively below the line, reaching a deficit of around 30 percent at the highest experience group.

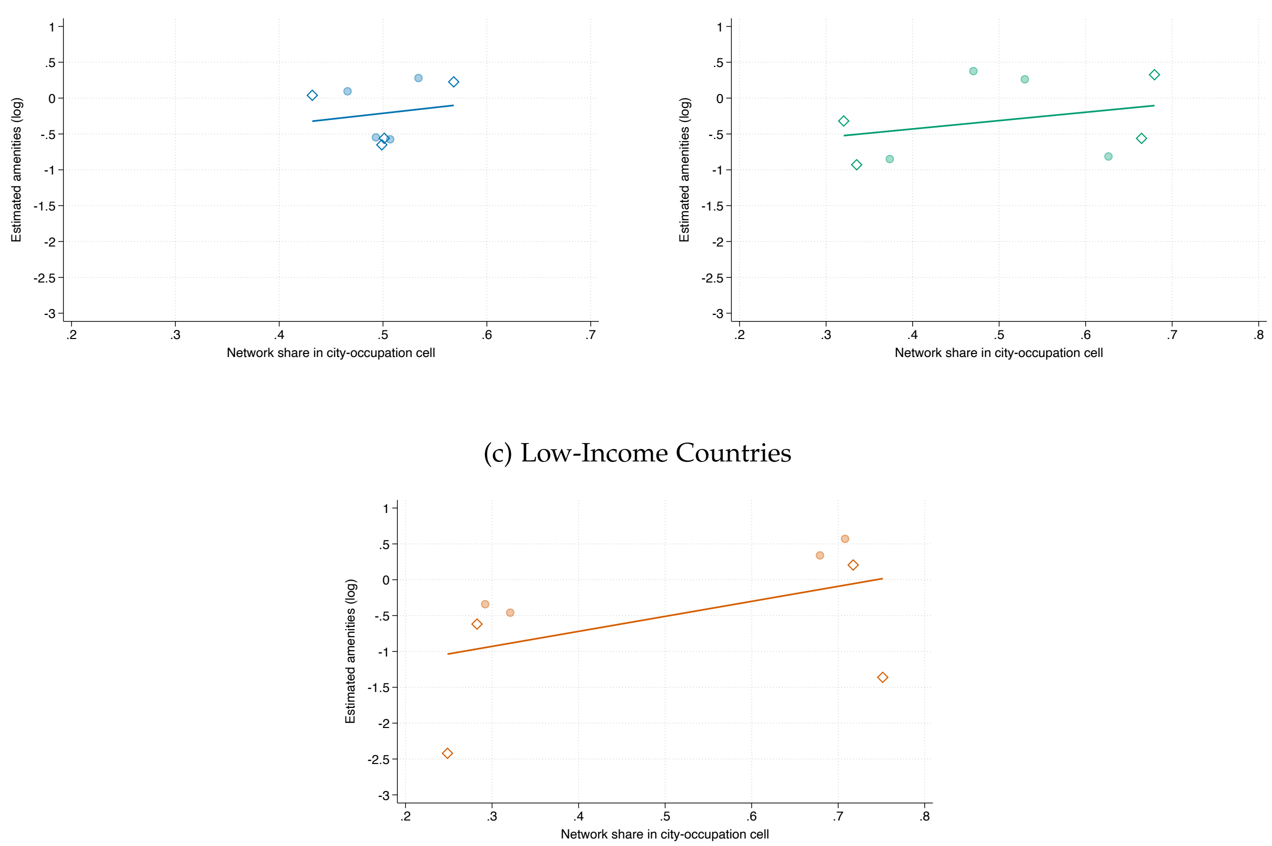
Taken together, the estimates indicate that the human capital deficit of LIC immigrants is largest in cognitive occupations and grow with labor-market experience, consistent with the hypothesis that immigrants from low-income countries face a steeper depreciation of their human capital when working outside their country-specific occupational structure. This pattern is consistent with the evidence in Caunedo, Keller and Shin (2021), who show that countries with lower GDP per capita employ relatively more workers in occupations with high routine content and fewer in occupations intensive in non-routine cognitive tasks. Moreover, even within the same occupation, jobs in developing countries involve more routine and fewer non-routine tasks than in developed countries. As a result, workers from LICs accumulate human capital in task environments that differ systematically from those characterizing the U.S. occupational structure, potentially reducing the transferability of their previously acquired skills to cognitive-intensive jobs in U.S. cities.

Identification and Estimates of City–Occupation Amenities. The remaining 23 preference for amenity parameters per origin group — after imposing the normalization (III.1) — yields a total of 69 amenity parameters $z_{jo}(g)$. I identify these parameters from the observed shares of workers $\pi_{jo}(g)$ in each city–occupation cell for each group g. Conditional on wages, wedges, and housing prices, the amenity parameters absorb any residual variation in location–occupation choices that is not explained by earnings. As such, they capture a broad range of non-pecuniary factors that make a given city–occupation pair attractive to workers of a given origin, including local amenities, social ties, and occupational networks.

To shed light on what drives the estimated preference for amenities, Figure 5 plots the estimated $z_{jo}(g)$, averaged across education and experience groups, against the share of same-origin workers in the same city–occupation cell in 2010 — a measure of the density of city–occupation specific networks. For immigrant groups, this measure proxies for the strength of ethnic enclaves in each city–occupation cell; for natives, it captures the density of local occupational networks. This exercise serves as a validation of the amenity estimates: if $z_{jo}(g)$ were absorbing unmodeled earnings components rather than genuine location–occupation preferences, one would not expect a systematic relationship with network density, which is predetermined relative to the estimation sample.

Figure 5: Estimated amenities and city–occupation networks

(a) Natives (b) High-Income Countries (c) Low-Income Countries



Notes: Each panel plots the estimated log-amenity $z_{jo}(g)$, averaged across education and experience groups within each city–occupation cell, against the share of same-origin workers (men and women) in that cell in 2010. Circles correspond to non-cognitive occupations; diamonds to cognitive occupations. Both small and big cities are included in each panel. The solid line is a linear fit.

Figure 5 reveals a positive association between estimated amenities and network density in all three groups, consistent with city–occupation specific networks being an important component of the non-pecuniary value that workers assign to each alternative. The strength of this association, however, differs markedly across groups. For natives (Panel a) and HIC immigrants (Panel b), the positive slope is moderate and amenity values vary substantially within cells with similar network densities, suggesting that networks are one factor among several shaping their location–occupation choices. For LIC immigrants (Panel c), the association is steeper than for either of the other two groups, consistent with co-ethnic networks being the dominant component of their amenity valuations. This pattern aligns with a large literature documenting that LIC immigrants disproportionately rely on ethnic networks for job finding and residential sorting (Munshi, 2003).

Identification and Estimates of the Earnings Wedges. The model includes 8 wedge parameters $\tau_{jo}(k)$ for $k \in \{\text{LIC}, \text{HIC}\}$, $j \in \{S, B\}$, and $o \in \{c, n\}$. Since $\tau_{jo}(k)$ varies across cities and occupations but not across education and experience groups within an origin, it is identified from the average earnings of immigrants from origin k in city j and occupation o relative to the average earnings of native workers in the same city–occupation cell. Specifically, averaging the earnings equation (II.6) over education and experience groups within origin k, and using assumption (III.2) to substitute $r_{jo} = \bar{w}_{jo}(\text{US}) \,/\, \bar{s}_o(\text{US})$, yields:

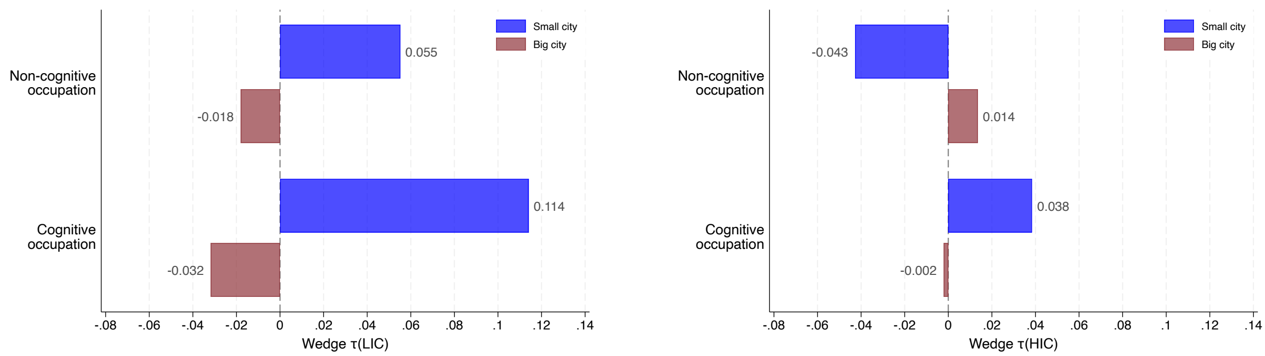
$$1 + \tau_{jo}(k) \;=\; \frac{\bar{w}_{jo}(k)}{\bar{w}_{jo}(\text{US})} \cdot \frac{\bar{s}_o(\text{US})}{\bar{s}_o(k)} \tag{III.3}$$

where $\bar{w}_{jo}(k)$ and $\bar{s}_o(k)$ denote average earnings and average human capital of origin group k in cell jo, and $\bar{w}_{jo}(\text{US})$ and $\bar{s}_o(\text{US})$ denote the corresponding native averages. The wedge is therefore the immigrant-to-native average earnings ratio in the same city–occupation cell, corrected for differences in average human capital between the two groups. A positive wedge indicates that immigrants earn more than natives with the same average human capital would earn at the competitive wage in that cell; a negative wedge indicates the opposite. [20] I target the average earnings of immigrants from each origin group k in each city–occupation cell jo as the identifying moments.

Figure 6 reports the estimated wedges for LIC and HIC immigrants across city–occupation pairs: a bar extending to the right indicates a positive wedge (earnings above the competitive benchmark); a bar extending to the left indicates a negative wedge. Several patterns emerge from the estimated wedges. For LIC immigrants (Panel a), the wedges differ sharply across occupations and cities. In non-cognitive occupations, LIC immigrants earn above the competitive benchmark in the small city ($\tau_{Sn} = 0.055$) but below it in the big city ($\tau_{Bn} = -0.018$), indicating that their relative earnings position deteriorates as city size increases.

Figure 6: Estimated earnings wedges $\tau_{jo}(k)$

(a) Low-Income Countries (b) High-Income Countries



Notes: Each panel shows the average estimated wedge $\tau_{jo}(k)$ for LIC (left) and HIC (right) immigrants in each city–occupation cell. Blue bars denote the small city; red bars denote the big city. A positive value indicates earnings above the competitive benchmark; a negative value indicates earnings below it. Native workers are the base group with $\tau_{jo}(\text{US}) = 0$ for all j, o.

[20] By construction, $\tau_{jo}(k)$ is orthogonal to human capital differences: the human capital ratio $\bar{s}_o(\text{US})/\bar{s}_o(k)$ in equation (III.3) fully absorbs productivity differences between immigrants and natives, so the wedge captures only the residual earnings gap.

In cognitive occupations, the pattern is even more striking: LIC immigrants have a large positive wedge in the small city ($\tau_{Sc} = 0.114$) but a negative wedge in the big city ($\tau_{Bc} = -0.032$). The reversal from a large positive wedge in the small city to a negative wedge in the big city is consistent with the stylized fact that LIC immigrants do not benefit from moving to larger cities in the same way as natives: even though big cities offer higher competitive wages for cognitive workers, LIC immigrants earn below the competitive benchmark in this cell, dampening their city-size earnings premium.

The pattern for HIC immigrants (Panel b) is qualitatively and quantitatively different. In non-cognitive occupations, HIC immigrants earn below the competitive benchmark in the small city ($\tau_{Sn} = -0.043$) but above it in the big city ($\tau_{Bn} = 0.014$), so their relative earnings position improves with city size in this occupation. In cognitive occupations, HIC immigrants have a positive wedge in the small city ($\tau_{Sc} = 0.038$) and are essentially at the competitive benchmark in the big city ($\tau_{Bc} = -0.002$). Overall, the wedges for HIC immigrants are small in magnitude and do not display the sharp reversal observed for LIC immigrants, consistent with the near-native city-size earnings premium documented for this group in Section I..

Model Fit The model is exactly identified, using 115 empirical moments from the pooled ACS 2010–2019 to estimate 115 structural parameters. I provide additional information on the model fit in Appendix IV.B..

IV. Counterfactual Analysis

In this section, I use the general equilibrium spatial model to study the role of human capital, amenities, and labor market distortions in determining earnings inequality between immigrants and natives, and how this outcome relates to spatial earnings inequality. I proceed through five counterfactual scenarios. In the first, I assign all immigrants the same occupation-specific human capital as comparable natives. In the second, I remove differences in how immigrants and natives value amenities, so that immigrants value working in a city and occupation as much as natives with the same education and experience. In the third, I remove labor market distortions faced by immigrants. The fourth combines the second and third scenarios, so that immigrants and natives only differ in productivity and their observed distribution across education and experience groups. The fifth and final scenario combines all three, leaving only differences due to the observed distribution across education and experience groups.

The City-Size Earnings Premium for Immigrants. For each origin group k, I compute average earnings in city j as:

$$\overline{w}_{k,j} = \frac{\sum_{o} \sum_{g:\,k(g)=k} \pi_{j,o}(g)\, \phi_g\, w_{j,o}(g)}{\sum_{o} \sum_{g:\,k(g)=k} \pi_{j,o}(g)\, \phi_g} \tag{IV.1}$$

where $w_{j,o}(g) = r_{jo}\, s_o(g)\, (1 + \tau_{jo}(k))$ as in equation (II.6), and the denominator is the total workforce share of group k in city j. I then define the city-size earnings premium for origin group k as:

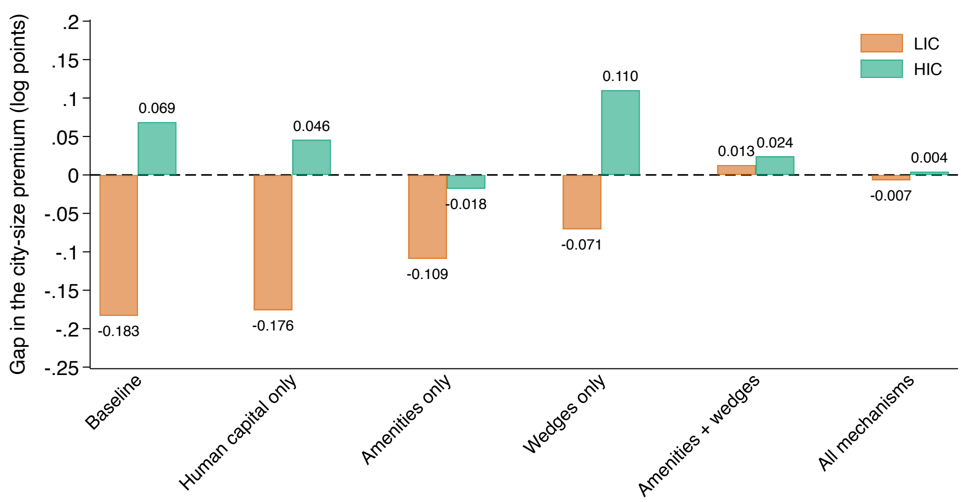
$$\overline{w}_k^{\text{Premium}} = \ln \overline{w}_{k,\text{Big}} - \ln \overline{w}_{k,\text{Small}} \tag{IV.2}$$

and the gap in city-size earnings premia between immigrants from country k and natives as:

$$\overline{w}_k^{\Delta\text{Premium}} = \overline{w}_k^{\text{Premium}} - \overline{w}_{\text{US}}^{\text{Premium}} \tag{IV.3}$$

Figure 7 shows how the gap in city-size earnings premia between immigrants and natives changes across counterfactuals. In the baseline economy, $\overline{w}_k^{\Delta\text{Premium}}$ is $+0.068$ log points for HIC immigrants and -0.183 log points for LIC immigrants, as documented in the stylized facts: HIC immigrants benefit from working in big cities relative to natives, while LIC immigrants do not.

Figure 7: Gap in city-size earnings premia between immigrants and natives



Notes: The figure shows $\overline{w}_k^{\Delta\text{Premium}}$, the difference in city-size earnings premia between immigrants from low-income countries (orange) and natives, and between immigrants from high-income countries (green) and natives, under the baseline and five counterfactual scenarios. Values are expressed in log points.

The counterfactuals reveal a hierarchy of mechanisms. Human capital differences account for only a small share of the differential city-size premia: equalizing human capital narrows the gap by 0.007 log points for LIC and 0.022 log points for HIC immigrants, leaving most of the baseline gap intact for both groups. Amenity valuations, by contrast, are the dominant channel — and they operate in opposite directions for the two groups. Removing amenity differences narrows the LIC gap by 0.074 log points, while for HIC immigrants the gap not only closes but reverses sign, falling from $+0.068$ to -0.018 log points. This reversal reveals that amenity valuations currently push HIC immigrants toward cognitive occupations — particularly in large cities — more than natives, inflating their city-size premium beyond what their productivity alone would generate.

Labor market distortions reinforce this asymmetry. Removing wedges narrows the LIC gap substantially — from -0.183 to -0.071 log points — but simultaneously widens the HIC gap from $+0.068$ to $+0.110$ log points. Wedges therefore penalize LIC immigrants in large cities relative to small ones, while compressing the city-size earnings premium of HIC immigrants relative to natives.

When amenities and wedges are jointly removed (counterfactual 4), the gaps become positive and of $+0.013$ log points for LIC and $+0.024$ log points for HIC, confirming that these two channels together account for the majority of the differential city-size premia. The small residual gaps that remain when all three mechanisms are removed (counterfactual 5: -0.007 for LIC and $+0.004$ for HIC) reflect only the remaining differences in the distribution of workers across education and experience groups $\{\phi_g\}$. The model therefore accounts for nearly all of the observed heterogeneity in city-size earnings premia across origin groups, with amenity valuations and labor market distortions — rather than human capital — as the primary drivers, operating through different mechanisms for LIC and HIC immigrants.

The Role of Heterogeneity in Human Capital, Amenities, and Labor Market Distortions in Relocating Workers across Cities and Occupations. The changes in city-size earnings premia documented above are driven by reallocations of workers across city-occupation pairs. To understand the nature of these reallocations, I decompose them along two margins: changes in the marginal distribution of workers across cities, aggregating over occupations, and changes in occupational composition within each city type. Since workers choose city and occupation jointly in the model, these two margins are not independent — a reallocation from (Small, Non-cognitive) to (Big, Cognitive) contributes to both — but examining them separately helps isolate which dimension of the joint choice space is most affected by each mechanism. The counterfactuals reveal that these two margins respond to the same hierarchy of mechanisms — amenities dominate, wedges play a secondary role, and human capital is largely irrelevant for sorting — but the amenity channel operates differently for LIC and HIC immigrants, and differently across city types for HIC immigrants specifically.

Reallocation Across Cities. Table 6 reports the baseline share of each group residing in the big city and the change under each counterfactual. The main finding is that amenity valuations — not human capital or labor market distortions — account for nearly all of the disproportionate concentration of immigrants in large cities. Removing amenity differences alone moves LIC immigrants out of the big city by 23.72 percentage points and HIC immigrants by 8.64 percentage points, while natives barely move (-0.07 pp). By comparison, equalizing human capital generates little location effects for all groups (at most -0.71 pp for HIC immigrants), and removing wedges draws immigrants *toward* the big city — by 1.78 pp for LIC and 0.11 pp for HIC — because wedges currently penalize immigrants more in large cities than in small ones, making large cities relatively more attractive once distortions are removed. The combined and full counterfactuals (4 and 5) closely mirror the amenities-only scenario, confirming that the amenity channel dominates and that human capital and wedges contribute little to location sorting once amenities are accounted for.

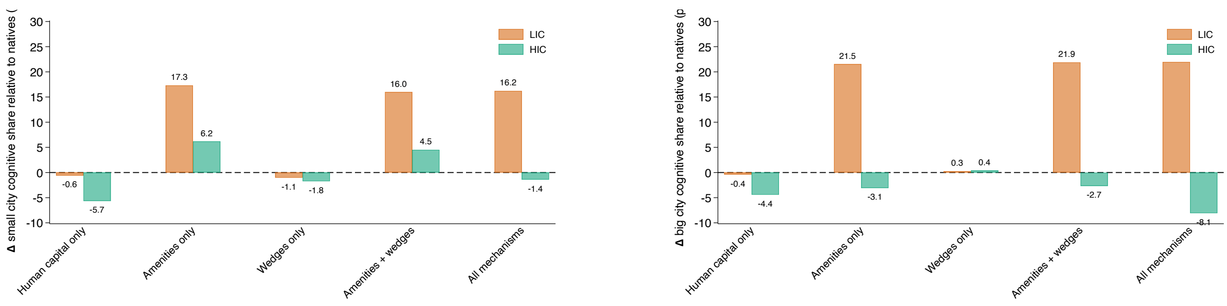
Table 6: Share of workers in the big city: baseline levels and changes (pp)

	Baseline	**Counterfactuals**				
		Same Human Capital As Natives	**Same Amenities As Natives**	**No Wedges On Earnings**	**Same Amenities & No Wedges**	**Full**
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_o(g) = s_o(g')$	-	x	-	-	-	x
$z_{jo}(g) = z_{jo}(g')$	-	-	x	-	x	x
$\tau_{jo}(k) = 0$	-	-	-	x	x	x
			Share of Workers in the Big City			
Natives	53.41	-0.09	-0.07	-0.03	-0.11	-0.10
LIC	71.17	-0.14	-23.72	$+1.78$	-21.20	-21.20
HIC	61.69	-0.71	-8.64	$+0.11$	-8.44	-8.69

Notes: The table reports the baseline share of each group residing in the big city (first column, expressed as a percentage) and the change in that share under each counterfactual scenario (Columns 1 to 5, expressed in percentage points). g' denotes a native worker with the same education e and experience x as immigrant group g.

Occupational Reallocation. Figure 8 shows the changes in the share of workers in cognitive occupations relative to natives in the small and big cities. The reallocation at the occupational margin tells a complementary but distinct story: amenities again dominate, but here they operate in opposite directions for LIC and HIC immigrants across city types, generating reallocations that partially offset each other in the aggregate.

Figure 8: Changes in cognitive occupation shares relative to natives



(a) Small Cities

(b) Big Cities

Notes: The figure shows the change in the share of LIC (orange) and HIC (green) immigrants in cognitive occupations relative to natives, in the small city (Panel a) and the big city (Panel b), under the five counterfactual scenarios. Changes are expressed in percentage points.

The main finding is that amenity valuations suppress LIC immigrants' entry into cognitive occupations across both city types, while their effect on HIC immigrants differs by city type. Removing amenity differences moves LIC immigrants strongly into cognitive occupations (+17.4 pp in small cities, +21.6 pp in large cities relative to natives). For HIC immigrants, the direction depends on the city: they move into cognitive occupations in small cities (+6.2 pp) but out of them in large cities (−3.1 pp). This city-type asymmetry among HIC immigrants reflects that amenity valuations currently push them disproportionately toward cognitive occupations in large cities — removing this tendency reduces their relative concentration there — whereas in small cities the effect runs in the opposite direction.

Wedges have little effect on occupational sorting — the cognitive shares of both groups change by at most 1.8 pp under counterfactual 3 — confirming that local labor market barriers operate primarily through the earnings-per-efficiency-unit channel rather than through occupational reallocation. Human capital equalization reduces HIC immigrants' cognitive share relative to natives (−5.7 pp in small cities, −4.5 pp in large cities) but leaves LIC immigrants essentially unaffected, reflecting the fact that HIC immigrants currently hold a human capital advantage over comparable natives in cognitive occupations that equalization removes.

The joint removal of amenities and wedges (counterfactual 4) closely mirrors the amenities-only scenario for LIC immigrants (+16.0 pp in small cities, +21.9 pp in large cities). For HIC immigrants, the pattern remains qualitatively similar to counterfactual 2 — into cognitive occupations in small cities (+4.5 pp) and out in large cities (−2.7 pp) — though the magnitudes differ, suggesting a modest complementarity between the two channels. When all three mechanisms are removed (counterfactual 5), the larger outflow of HIC immigrants from cognitive occupations in large cities (−8.1 pp relative to −2.7 pp in counterfactual 4) reflects the additional role of human capital equalization in reducing their concentration in cognitive jobs.

The Earnings Gap between Natives and Immigrants vs between Cities. Table 7 aggregates the reallocation patterns documented above into two summary statistics: the average log earnings gap between immigrants and natives, and the average log earnings gap between the big and small city. I measure the native-immigrant earnings gap as:

(IV.4)
$$\overline{w}^{\text{Gap}}_{\text{Workers}} = \ln \overline{w}_{\text{Imm}} - \ln \overline{w}_{\text{US}} = \ln \frac{\sum_j \sum_o \sum_{g \neq \text{US}} \pi_{j,o}(g)\, \phi_g\, w_{j,o}(g)}{\sum_j \sum_o \sum_{g \neq \text{US}} \pi_{j,o}(g)\, \phi_g} - \ln \frac{\sum_j \sum_o \sum_{g = \text{US}} \pi_{j,o}(g)\, \phi_g\, w_{j,o}(g)}{\sum_j \sum_o \sum_{g = \text{US}} \pi_{j,o}(g)\, \phi_g}$$

and spatial earnings inequality as:

(IV.5)
$$\overline{w}^{\text{Gap}}_{\text{Cities}} = \ln \overline{w}_{\text{Big}} - \ln \overline{w}_{\text{Small}} = \ln \frac{\sum_o \sum_g \pi_{\text{Big},o}(g)\, \phi_g\, w_{\text{Big},o}(g)}{\sum_o \sum_g \pi_{\text{Big},o}(g)\, \phi_g} - \ln \frac{\sum_o \sum_g \pi_{\text{Small},o}(g)\, \phi_g\, w_{\text{Small},o}(g)}{\sum_o \sum_g \pi_{\text{Small},o}(g)\, \phi_g}$$

where $w_{j,o}(g) = r_{jo}\, s_o(g)\, (1 + \tau_{jo}(k))$ as in equation (II.6).

Three findings stand out. First, human capital is the single largest individual driver of the aggregate native-immigrant earnings gap, closing almost half of the baseline gap of -0.317 log points when equalized (column 1). This result reflects a fundamental distinction between the determinants of earnings levels and the determinants of sorting: since human capital $s_o(g)$ scales earnings proportionally within each occupation regardless of city, its effect cancels in the log difference between cities and therefore leaves the marginal distribution of workers across city-occupation pairs largely unchanged. Human capital thus shapes how much immigrants earn, given where they are, but not where they choose to locate or which occupation they enter.

Second, amenities and wedges together account for a further 7.3 percent of the gap (column 4), but their individual contributions are modest and partially offsetting. Removing amenities alone closes 14.5 percent of the gap (column 2), while removing wedges alone leaves it essentially unchanged (-0.6 percent, column 3).[21] This near-zero aggregate effect does not imply, however, that wedges are unimportant at the local level: as shown in Figure 7, removing wedges narrows the city-size earnings premium gap for LIC immigrants substantially — from -0.183 to -0.071 log points — while simultaneously widening it for HIC immigrants from $+0.068$ to $+0.110$ log points, indicating that distortions generate large and economically significant effects on earnings at the origin-group level even when their aggregate effect is negligible. As established in Figure 7, the near-zero aggregate effect moreover masks large and opposite effects for LIC and HIC immigrants that cancel in the aggregate — a finding that underscores the importance of disaggregating by origin group when studying the earnings consequences of labor market distortions, and that implies targeted policies addressing wedges for specific origin groups could be effective even when aggregate analyses would suggest otherwise.

Third, even when all modeled differences are removed (column 5), a residual gap of -0.121 log points remains, accounting for 38 percent of the baseline. This residual is driven purely by the compositional distribution $\{\phi_g\}$: immigrants are on average less educated and less experienced than natives, and this observed heterogeneity alone explains more than a third of the aggregate earnings gap independently of any labor market mechanism.

A fourth and perhaps unexpected finding concerns the relationship between worker inequality and spatial inequality. Across all five counterfactuals, the big-small city earnings gap *widens* as the native-immigrant earnings gap narrows — there is a trade-off between the two. The mechanisms that generate immigrant earnings disadvantage are also mechanisms that currently compress spatial earnings inequality: immigrants' amenity valuations and the labor market distortions they face draw workers toward large cities and productive occupations, reducing the earnings gap between cities even as they widen the gap between immigrants and natives. Removing these mechanisms, therefore, simultaneously reduces immigrant earnings disadvantage and widens spatial inequality. The amenity channel generates the largest spatial widening ($+0.031$ log points, column 2), while

[21]The near-zero aggregate effect of wedges reflects the fact that $\tau_{jo}(k)$ enters earnings multiplicatively and its variation across city-occupation pairs is empirically small relative to the variation in $z_{jo}(g)$, so wedge removal generates limited reallocation across the joint choice set and its direct effect on earnings levels is largely offset by general equilibrium adjustments in rental rates r_{jo}.

wedges alone contribute the least (+0.005 log points, column 3), consistent with their primary role operating through the earnings-per-efficiency-unit channel rather than through location sorting.

Table 7: Changes in earnings inequality between workers and between cities

	Baseline	Counterfactuals				
		Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities & No Wedges	Full
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_o(g) = s_o(g')$	-	x	-	-	-	x
$z_{jo}(g) = z_{jo}(g')$	-	-	x	-	x	x
$\tau_{jo}(k) = 0$	-	-	-	x	x	x
Average Earnings Gap: Immigrants vs. Natives						
$\ln \bar{w}_{\text{Imm}} - \ln \bar{w}_{\text{US}}$	-0.317	-0.159	-0.271	-0.319	-0.294	-0.121
Δ from baseline	—	$+0.158$	$+0.046$	-0.002	$+0.023$	$+0.196$
% of baseline gap closed	—	49.8	14.5	-0.6	7.3	61.8
Spatial Earnings Gap: Big vs. Small City						
$\ln \bar{w}_{\text{Big}} - \ln \bar{w}_{\text{Small}}$	0.163	0.174	0.194	0.168	0.201	0.196
Δ from baseline	—	$+0.011$	$+0.031$	$+0.005$	$+0.038$	$+0.033$
% increase in baseline gap	—	6.7	19.0	3.1	23.3	20.2

Notes: The table reports the log difference in average earnings between immigrants and natives ($\ln \bar{w}_{\text{Imm}} - \ln \bar{w}_{\text{US}}$) and between the big and small city ($\ln \bar{w}_{\text{Big}} - \ln \bar{w}_{\text{Small}}$) in the baseline and under the five counterfactual scenarios (Columns 1 to 5). The Δ from baseline rows reports the change in the respective log gap relative to the baseline. For the native-immigrant gap, the % row reports the share of the baseline gap closed (positive values indicate narrowing). For the spatial gap, the % row reports the percentage increase in the baseline gap (positive values indicate widening). g' denotes a native worker with the same education e and experience x as immigrant group g.

V. Immigration Policy and the Worker-Spatial Earnings Gap Trade-Off

The counterfactual analysis in Section IV. establishes a trade-off between reducing worker inequality and exacerbating spatial inequality: removing all differences in human capital and structural barriers facing immigrants closes 61.8 percent of the immigrant-native earnings gap but widens the big-small city earnings gap by 20.2 percent. To quantify the severity of this trade-off and compare it across policy instruments, I define the trade-off rate as the change in the spatial earnings gap per unit change in the immigrant-native earnings gap, both measured in log points:

$$\mathcal{T} = \frac{\Delta(\ln \bar{w}_{\text{Big}} - \ln \bar{w}_{\text{Small}})}{\Delta(\ln \bar{w}_{\text{Imm}} - \ln \bar{w}_{\text{US}})} \tag{V.1}$$

A value of $\mathcal{T} > 0$ indicates that the two gaps move in the same direction; $\mathcal{T} \approx 0$ indicates they are effectively decoupled. Under the full structural counterfactual (counterfactual 5 in Table 7), $\mathcal{T} = 0.171$ — the benchmark against which I evaluate the following policy exercises.

Motivated by the open borders literature (Clemens, 2011; Kennan, 2013), I consider two large-scale immigration expansion policies calibrated to generate a one percentage point increase in total male employment aged 25–54. Achieving this requires a 28.3 percent expansion of the college immigrant workforce and an 11.2 percent expansion of the non-college immigrant workforce —

large shocks closer in spirit to an open borders scenario than to a marginal policy change.[22] Table 8 reports the results.

Panel A of Table 8 shows that the two policies have sharply different implications for the worker-spatial inequality trade-off. College immigration expansion narrows the immigrant-native earnings gap by 17.1 percent — from -0.317 to -0.263 log points — while leaving the spatial earnings gap essentially unchanged, with the big-small city gap moving by -0.2 percent of its baseline value. The implied trade-off rate of $\mathcal{T} = 0.005$ is negligible relative to the structural benchmark of 0.171. This reflects the sorting behavior of college immigrants, who enter cognitive occupations proportionally across both city types, generating balanced labor supply increases that leave the relative skill price across cities essentially unchanged. Non-college expansion generates the opposite pattern: it widens the immigrant-native earnings gap by 7.3 percent — from -0.317 to -0.340 log points — while narrowing the spatial earnings gap by 1.9 percent, from 0.163 to 0.160 log points. In this case $\mathcal{T} = 0.134$, but since the worker gap widens rather than narrows, this should not be interpreted as a spatial cost of closing the earnings gap — rather, it reflects that the two gaps move in the same direction, with non-college expansion simultaneously worsening worker inequality and compressing spatial inequality. The ordering

$$\underbrace{0.005}_{\text{College}} < \underbrace{0.134}_{\text{Non-college}} < \underbrace{0.171}_{\text{Structural}} \tag{V.2}$$

reveals that among instruments that narrow the immigrant-native earnings gap, the spatial cost depends critically on how that narrowing is achieved: college immigration expansion does so at essentially zero spatial cost, while structural interventions that remove amenity differences, distortions, or human capital gaps generate the highest spatial costs.

Panel B of Table 8 disaggregates by origin group and reveals a further asymmetry. The city-size earnings premium gap for LIC immigrants is essentially unchanged under both policies — moving by at most 0.002 log points from its baseline of -0.183 — while the HIC premium gap responds in opposite directions: college expansion narrows it from $+0.068$ to $+0.057$ log points while non-college expansion widens it from $+0.068$ to $+0.073$ log points. This asymmetry reflects the core finding of the paper: the lack of a spatial earnings premium for LIC immigrants is driven by amenity valuations and distortions that immigration policy does not engage with. HIC immigrants respond because college expansion intensifies competition in large-city cognitive occupations where they are concentrated; LIC immigrants are largely absent from these occupations and therefore unaffected.

Panel C confirms that neither policy generates meaningful changes in LIC immigrants' location choices — their big-city share moves by at most 0.1 percentage points under both policies — while HIC immigrants respond more substantially to the college expansion, increasing their big-city share by 0.6 percentage points. Cognitive occupation shares also respond asymmetrically: non-college expansion reduces the big-city cognitive share by 0.5 percentage points, reflecting the compositional effect of adding workers who sort predominantly into non-cognitive occupations, while college

[22] Both policies hold $z_{jo}(g)$, $\tau_{jo}(k)$, and $s_o(g)$ fixed, so that new entrants are drawn from the same population as existing immigrants of the same type, and the model is re-solved for the full general equilibrium.

Table 8: Immigration Policy and the Worker-Spatial Inequality Trade-Off

	Baseline	Immigration Expansion		Structural CF
		College Expansion	Non-College Expansion	
		(1)	(2)	
Panel A: Aggregate Earnings Gaps				
$\ln \bar{w}_{\text{Imm}} - \ln \bar{w}_{\text{US}}$	−0.317	−0.263	−0.340	—
Δ from baseline	—	0.054	−0.023	—
% of baseline gap closed	—	17.1%	−7.3%	—
$\ln \bar{w}_{\text{Big}} - \ln \bar{w}_{\text{Small}}$	0.163	0.163	0.160	—
Δ from baseline	—	0.000	−0.003	—
% of baseline gap closed	—	−0.2%	1.9%	—
Trade-off rate ($\mathcal{T}$)	—	0.005	0.134	0.171
Panel B: City-Size Earnings Premium Gaps				
$\bar{w}^{\Delta\text{Premium}}_{\text{Imm}}$	−0.174	−0.173	−0.175	—
Δ from baseline	—	0.001	−0.001	—
$\bar{w}^{\Delta\text{Premium}}_{\text{LIC}}$	−0.183	−0.185	−0.184	—
Δ from baseline	—	−0.002	−0.000	—
$\bar{w}^{\Delta\text{Premium}}_{\text{HIC}}$	0.068	0.057	0.073	—
Δ from baseline	—	−0.011	0.005	—
Panel C: Sorting Outcomes				
Cognitive share, big city (%)	60.3	60.4	59.9	—
Δ from baseline (pp)	—	0.1	−0.5	—
Cognitive share, small city (%)	56.1	56.2	55.9	—
Δ from baseline (pp)	—	0.1	−0.2	—
LIC big-city share (%)	71.2	71.1	71.2	—
Δ from baseline (pp)	—	−0.1	0.0	—
HIC big-city share (%)	61.7	62.3	61.4	—
Δ from baseline (pp)	—	0.6	−0.3	—

Notes: Both policies are calibrated to generate a one percentage point increase in total male employment aged 25–54. This requires a 28.3 percent increase in the college immigrant workforce (column 1) and a 11.2 percent increase in the non-college immigrant workforce (column 2). The trade-off rate $\mathcal{T}$ is defined in equation (V.1) and measures the change in the spatial earnings gap per unit change in the immigrant-native earnings gap, both in log points. The Structural CF column reports $\mathcal{T}$ from the full structural counterfactual (counterfactual 5 in Table 7) as the benchmark. The % of baseline gap closed rows report the percentage change in each gap relative to its baseline value: positive values indicate the gap narrows, negative values indicate the gap widens. The model is re-solved for the full general equilibrium after each policy shock. All monetary values are in log points unless otherwise indicated.

expansion leaves it essentially unchanged at 60.4 percent.

Taken together, the results deliver a unified message. College immigration expansion narrows the immigrant-native earnings gap at essentially zero spatial cost — but does so through a composition effect that leaves LIC immigrants' city-size premium gap unchanged at -0.183 log points. The spatial dimension of LIC immigrant earnings disadvantage is driven by amenity valuations and distortions that immigration policy, however large in scale, does not engage with.

VI. Conclusion

This paper documents a novel asymmetry in city-size earnings premia across immigrant groups and provides a quantitative account of its origins. While HIC immigrants earn a city-size premium that exceeds the native premium, LIC immigrants earn a premium less than half the size of the native premium. The model identifies the role of three channels: heterogeneity in human capital, city-occupation amenities, and local labor market distortions. While local labor market distortions are important for earnings gaps between immigrants and natives *within* cities, differences in amenity valuations across groups are the main driver of occupational sorting across space.

A key finding from the study is a trade-off between worker inequality and spatial inequality. Policies that reduce the immigrant–native earnings gap tend to widen the gap between large and small cities, with the reallocation of low-income-country immigrants as the central margin. This trade-off is quantitatively meaningful and survives two distinct policy experiments involving large-scale immigration expansions.

A key limitation of the analysis is the measurement of city-occupation amenities and distortions. In this paper, I treat amenity valuations as reduced-form objects that may partly capture local occupational networks, but I take their formation to be exogenous. Immigration policies themselves may affect amenity valuations through their effects on the concentration of same-origin workers across cities and occupations — a channel this paper abstracts from. Direct measures of local labor market distortions remain similarly limited. Endogenizing amenities and developing better measures of local labor market distortions are both important directions for future research, as they would allow for a more complete evaluation of immigration policies and clarify how location-specific factors interact with immigrant economic assimilation and non-competitive labor market structures, including monopsony.

Appendices

A Data Appendix

I.A. Variables definition

Immigrants. I define immigrants as foreign-born workers who are either naturalized citizens or non-citizens, excluding individuals born abroad to American parents. To obtain unbiased estimates of country-of-origin-specific human capital, I follow Schoellman (2012) and exclude immigrants who are likely to have received their education either entirely or partially in the US. I construct a measure of age at migration as *age - years in the US*, and combine this with years of schooling to drop immigrants who arrived in the US before completing their education abroad — specifically, those who arrived: before age 18 and report fewer than 12 years of schooling; before age 24 and report exactly 12 years of schooling; before age 27 and report between 13 and 15 years of schooling; before age 31 and report more than 15 years of schooling.

Low-Income And High-Income Countries. I define as low-income those countries whose GDP per capita at PPP in constant 2021 international U.S. dollars is less than $\$40,000$ and as high-income those countries whose GDP per capita is greater than or equal to $\$40,000$.

Years of Schooling, College, and No College. In the ACS, individuals are asked to report their educational attainment. I use the detailed version of the variable *EDUC* to impute years of schooling as follows: 4 years for "No schooling completed" through "Grade 4"; 7 years for "Grade 5, 6, 7, or 8"; 9 years for "Grade 9"; 10 years for "Grade 10"; 11 years for "Grade 11"; 12 years for "Grade 12"; 13 years for "1 year of college, no degree"; 14 years for "2 years of college, no degree"; 16 years for "Bachelor's degree"; 18 years for "Master's degree"; and 21 years for "Doctoral degree." Based on years of schooling, I construct a dummy variable distinguishing workers without a college education (years of schooling ≤ 12) from those with a college education (years of schooling > 12).

Potential Experience. I compute potential experience in the labor market as a worker's age minus years of schooling minus 6. I divide workers into three experience groups: 0–14 years, 15–29 years, and 30 or more years.

Hourly Earnings. I construct hourly earnings using the variables *INCWAGE*, *WKSWORK2*, and *UHRSWORK*. The first contains an individual's pre-tax wage and salary income from the previous year, the second provides the number of weeks worked in the previous year, and the third gives the usual hours worked per week. Since weeks worked are reported in intervals, I follow Albert, Glitz and Llull (2021) and impute weeks worked for each interval as: 7.4, 21.3, 33.1, 42.4, 48.2, and 51.9. To account for inflation, I convert hourly earnings to constant 1999 dollars using the CPI-U multiplier index available in IPUMS.

Task Intensity. I collect data from O*NET on work activities and work context importance scales. I follow Acemoglu and Autor (2011) and define the five macro-categories of occupation tasks with all their descriptors of tasks required by each occupation[23]:

- Non-routine cognitive analytical:
  - Analyzing data/information
  - Thinking creatively
  - Interpreting information for others
- Non-routine cognitive interpersonal:
  - Establishing and maintaining personal relationships
  - Guiding, directing, and motivating subordinates
  - Coaching/developing others
- Routine cognitive:
  - Importance of repeating the same tasks
  - Importance of being exact or accurate
  - Structured v. Unstructured work
- Routine manual:
  - Pace determined by speed of equipment
  - Controlling machines and processes
  - Spend time making repetitive motions
- Non-routine manual:
  - Operating vehicles, mechanized devices, or equipment
  - Spend time using hands to handle, control, or feel objects, tools, or controls
  - Manual dexterity
  - Spatial orientation

I standardize each measure to have a mean of zero and a standard deviation of one, and I aggregate the subcategories into the five macro-task categories by taking the summation of the constituent measures. I define the cognitive tasks category as the aggregation of non-routine cognitive analytical, non-routine cognitive interpersonal, and routine cognitive macro-categories. Similarly, I define the non-cognitive tasks category as the aggregation of routine manual and non-routine manual macro-categories. To aggregate the subcategories into the broader cognitive and non-cognitive categories, I compute the employment shares at the 3-digit SOC 2010 level.

[23] Differently from Acemoglu and Autor (2011), I do not consider the category "Offshorability".

Finally, I divide occupations into "Cognitive" and "Non-cognitive" as follows. For each of the 95 occupations, I measure the exposure to cognitive and non-cognitive tasks: if the exposure to the cognitive task is larger than the exposure to the non-cognitive tasks, then the occupation is classified as "Cognitive"; otherwise, it is classified as a "Non-cognitive" occupation.

Small And Big Cities. I classify cities as 'Small' or 'Big' based on their employment stock, where small cities have fewer than 750,000 workers and big cities have 750,000 or more.

I.B. Descriptive statistics

Table 9: List of the 10 biggest MSAs for ranked by employment stock

Metropolitan Statistical Area	Rank By Employment	Workers In Cognitive Occupations (%)	Immigrants (%)	Avg. Hourly Wage
New York-Newark-Jersey City, NY-NJ-PA	1	75.1	19.3	25.1
Los Angeles-Long Beach-Anaheim, CA	2	67.9	23.3	20.2
Chicago-Naperville-Elgin, IL-IN-WI	3	72.3	9.7	22.0
Dallas-Fort Worth-Arlington, TX	4	72.7	12.6	20.7
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	5	74.4	5.4	21.8
Houston-The Woodlands-Sugar Land, TX	6	68.3	16.8	21.2
Atlanta-Sandy Springs-Roswell, GA	7	73.9	8.5	20.7
Boston-Cambridge-Newton, MA-NH	8	78.7	10.1	26.1
Washington-Arlington-Alexandria, DC-VA-MD-WV	9	78.9	14.9	26.0
Detroit-Warren-Dearborn, MI	10	68.9	4.8	18.9
Miami-Fort Lauderdale-West Palm Beach, FL	11	73.9	21.6	19.0
Phoenix-Mesa-Scottsdale, AZ	12	73.9	8.0	19.1
San Francisco-Oakland-Hayward, CA	13	79.1	17.0	29.9
Minneapolis-St. Paul-Bloomington, MN-WI	14	72.2	4.0	21.0
Seattle-Tacoma-Bellevue, WA	15	73.1	9.1	23.7
Riverside-San Bernardino-Ontario, CA	16	60.0	14.7	16.7
St. Louis, MO-IL	17	69.0	2.2	18.7
Denver-Aurora-Lakewood, CO	18	77.1	6.4	22.1
Pittsburgh, PA	19	68.3	1.3	17.6
Baltimore-Columbia-Towson, MD	20	74.6	5.3	21.5

Notes: The table reports the share (expressed in percentages) of workers in cognitive occupations and immigrants, and the average hourly earnings for the 20 biggest cities in the sample ranked by employment stocks pooled for the years 2010-2019. Individual sample weights are used in the calculations.

Table 10: Descriptive statistics: men

Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Observations
	(1)	(2)	(3)	(4)	(5)
Native	17.3	14.1	18.8	–	1,248,634
	(25.3)	(2.3)	(9.3)	–	
Immigrant	11.8	11.2	26.2	12.7	132,349
	(18.3)	(3.8)	(7.6)	(7.7)	
LIC	11.0	10.9	26.4	12.9	117,950
	(16.7)	(3.8)	(7.6)	(7.6)	
HIC	18.7	13.8	24.2	10.7	14,399
	(28.4)	(3.1)	(7.6)	(7.6)	

Notes: The table reports the descriptive statistics for natives, immigrants, and the pool of immigrants from high- and low-income countries. The reported statistics are average hourly earnings, average years of schooling, average years of potential experience in the labor market (age - years of schooling - 6), average years spent in the US, and the number of observations in the sample for male workers pooled for the years 2010-2019. Individual sample weights are used in the calculations.

Table 11: Descriptive statistics: women

Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Observations
	(1)	(2)	(3)	(4)	(5)
Native	22.2	13.9	19.0	–	1,509,139
	(32.7)	(2.4)	(9.1)	(–)	
Immigrant	16.2	11.0	25.1	12.2	180,915
	(28.1)	(4.1)	(7.9)	(8.0)	
LIC	14.2	10.6	25.4	12.6	157,722
	(24.4)	(4.0)	(7.9)	(7.9)	
HIC	32.8	14.4	22.9	9.0	23,193
	(46.1)	(3.4)	(7.4)	(7.2)	

Notes: The table reports the descriptive statistics for natives, immigrants, and the pool of immigrants from high- and low-income countries. The reported statistics are average hourly earnings, average years of schooling, average years of potential experience in the labor market (age - years of schooling - 6), average years spent in the US, and the number of observations in the sample for female workers pooled for the years 2010-2019. Individual sample weights are used in the calculations.

Table 12: Descriptive statistics for low-income countries

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
South Africa	33.2	14.5	23.3	9.5	856
	(31.9)	(2.6)	(6.5)	(6.6)	
India	27.8	15.6	20.1	7.3	16,583
	(37.8)	(3.0)	(7.6)	(6.4)	
Croatia	23.3	12.7	26.7	13.3	264
	(140.8)	(2.6)	(6.7)	(6.2)	
Zimbabwe	22.1	14.0	24.8	10.6	164
	(25.3)	(2.4)	(6.0)	(5.8)	
Argentina	22.0	13.4	24.3	11.4	1,430
	(31.7)	(3.3)	(6.9)	(6.5)	
Greece	21.6	13.7	24.6	11.5	304
	(25.4)	(3.8)	(8.5)	(9.2)	
Russian Federation	21.5	15.2	24.6	11.4	2,017
	(20.7)	(3.1)	(6.9)	(6.7)	
Byelorussia	20.4	14.6	24.8	11.4	456
	(21.5)	(3.0)	(7.1)	(6.8)	
Romania	20.3	14.0	25.2	12.0	1,279
	(23.7)	(2.9)	(6.8)	(6.6)	
Tanzania	20.0	13.6	25.8	11.0	110
	(21.0)	(3.3)	(7.2)	(6.4)	
Turkey	19.9	13.9	23.4	10.5	759
	(21.5)	(3.5)	(7.7)	(7.5)	
Latvia	19.7	14.3	23.8	10.9	82
	(16.5)	(2.8)	(7.9)	(6.8)	
Malaysia	19.7	13.0	25.3	11.7	569
	(19.2)	(3.8)	(8.0)	(8.0)	
Hungary	19.6	14.0	22.8	10.1	291
	(18.3)	(3.1)	(7.2)	(7.0)	
Slovakia	18.9	13.8	23.2	11.7	144
	(13.6)	(3.0)	(7.5)	(7.0)	
Iran	18.5	14.2	24.2	9.7	1,876
	(19.9)	(3.2)	(7.6)	(6.8)	
Brazil	18.4	12.9	22.9	9.0	3,684
	(26.4)	(3.4)	(7.7)	(6.7)	

Table 12 – Continued

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
Chile	18.3	13.5	25.9	11.8	587
	(22.0)	(2.8)	(7.2)	(7.4)	
Lebanon	18.1	12.7	26.7	12.4	578
	(20.2)	(3.7)	(7.5)	(7.3)	
Pakistan	18.0	13.5	24.9	10.7	2,139
	(56.5)	(3.7)	(7.5)	(7.1)	
Ukraine	17.9	14.2	24.9	11.2	2,245
	(31.5)	(2.9)	(7.0)	(6.6)	
Sri Lanka	17.7	13.9	24.4	10.2	469
	(16.4)	(2.9)	(7.1)	(6.5)	
Barbados	17.4	12.3	28.5	14.9	191
	(19.5)	(2.0)	(6.5)	(7.6)	
Bulgaria	17.1	14.7	24.0	10.4	747
	(14.7)	(2.8)	(6.3)	(5.8)	
Algeria	17.1	13.8	22.5	9.5	270
	(18.8)	(3.6)	(7.4)	(6.9)	
Kazakhstan	17.0	14.4	24.1	10.0	181
	(15.1)	(3.0)	(7.9)	(6.8)	
Poland	16.8	12.8	27.3	14.2	2,478
	(17.3)	(2.7)	(6.9)	(7.1)	
Azerbaijan	16.5	15.0	24.1	10.0	139
	(13.9)	(2.6)	(7.3)	(6.6)	
Nigeria	16.5	14.3	23.5	9.1	2,108
	(18.1)	(2.7)	(6.8)	(6.2)	
Uganda	16.3	13.8	23.5	9.2	167
	(18.6)	(2.9)	(7.3)	(6.3)	
Moldavia	16.0	13.7	23.7	9.4	274
	(16.8)	(2.6)	(6.8)	(6.0)	
Dominica	15.9	11.4	26.2	11.5	228
	(32.7)	(3.2)	(7.5)	(7.6)	
Armenia	15.9	14.1	25.4	11.5	440
	(16.6)	(2.9)	(7.0)	(6.8)	
Indonesia	15.8	13.7	25.0	11.4	719
	(19.2)	(2.9)	(6.5)	(6.4)	

Table 12 – Continued

Country of Origin	Avg. Hourly Earnings (1)	Avg. Years of Schooling (2)	Avg. Experience (3)	Avg. Years in the US (4)	Obs. (5)
Macedonia	15.7	11.9	25.9	11.3	190
	(13.2)	(3.3)	(7.9)	(8.2)	
China	15.6	12.2	26.2	11.0	17,239
	(21.0)	(4.4)	(7.8)	(7.2)	
Egypt	15.6	14.3	22.6	8.0	1,242
	(20.4)	(2.7)	(7.0)	(6.1)	
Philippines	15.5	14.1	25.1	10.5	14,414
	(17.4)	(2.5)	(6.6)	(6.8)	
Syria	15.5	12.3	25.0	9.7	461
	(31.8)	(3.4)	(7.5)	(7.2)	
Kenya	15.5	13.6	23.4	9.2	737
	(12.7)	(2.4)	(6.9)	(5.9)	
Jordan	15.5	13.4	22.7	9.1	299
	(19.6)	(2.9)	(7.4)	(7.5)	
Albania	15.5	12.7	26.0	10.7	1,034
	(66.1)	(2.5)	(6.9)	(6.3)	
Trinidad and Tobago	15.4	12.3	27.7	13.9	1,405
	(21.6)	(2.3)	(6.4)	(6.8)	
Fiji	15.1	12.1	27.2	12.4	416
	(18.0)	(2.5)	(7.3)	(7.8)	
Cameroon	14.8	13.7	21.9	8.0	424
	(12.2)	(3.4)	(6.8)	(5.3)	
Bolivia	14.5	12.4	25.9	12.5	598
	(28.6)	(3.2)	(7.2)	(6.8)	
Morocco	14.4	12.7	23.1	9.7	796
	(16.9)	(3.2)	(7.0)	(6.1)	
Antigua	14.3	12.1	26.8	12.8	103
	(11.8)	(2.1)	(6.5)	(8.4)	
Paraguay	14.2	12.2	25.5	12.3	104
	(15.0)	(2.9)	(7.9)	(8.1)	
Republic of Georgia	14.1	14.8	24.7	9.0	153
	(10.8)	(3.1)	(6.6)	(5.5)	
Ghana	14.0	12.7	24.7	10.1	1,739
	(19.4)	(2.9)	(7.3)	(6.0)	

Table 12 – Continued

Country of Origin	Avg. Hourly Earnings (1)	Avg. Years of Schooling (2)	Avg. Experience (3)	Avg. Years in the US (4)	Obs. (5)
Costa Rica	13.9	11.2	26.2	12.4	560
	(16.7)	(3.4)	(7.4)	(7.3)	
Bosnia	13.9	12.0	28.0	14.6	1,460
	(12.1)	(2.3)	(5.7)	(4.5)	
Uruguay	13.7	12.0	25.5	12.0	467
	(15.0)	(2.5)	(6.7)	(5.5)	
Bangladesh	13.7	13.1	24.2	9.6	1,970
	(40.1)	(3.7)	(7.6)	(7.0)	
Colombia	13.7	12.8	26.3	11.7	5,684
	(20.3)	(3.1)	(7.1)	(7.3)	
Laos	13.4	8.8	31.0	17.9	863
	(24.8)	(4.2)	(7.6)	(8.5)	
Senegal	13.4	11.6	26.0	12.1	233
	(11.5)	(3.7)	(7.0)	(6.7)	
Guyana	13.3	11.5	28.1	12.7	2,283
	(12.6)	(2.8)	(6.8)	(7.5)	
Iraq	13.2	12.1	23.3	7.8	1,432
	(19.1)	(3.6)	(7.5)	(6.6)	
Sierra Leone	13.2	12.3	25.7	12.1	328
	(14.2)	(2.8)	(7.1)	(6.9)	
Uzbekistan	13.2	13.6	22.8	8.2	577
	(11.2)	(3.3)	(6.9)	(5.5)	
Panama	13.0	12.7	26.8	13.9	414
	(14.8)	(2.7)	(7.1)	(7.7)	
Jamaica	12.7	12.1	26.6	11.7	4,728
	(14.7)	(2.2)	(7.1)	(7.4)	
Tonga	12.7	11.3	27.4	13.4	79
	(8.4)	(3.1)	(8.0)	(10.3)	
Afghanistan	12.7	11.9	21.2	8.1	513
	(15.8)	(3.3)	(8.4)	(7.5)	
Belize/British Honduras	12.6	11.8	26.5	12.8	232
	(20.0)	(3.1)	(7.7)	(7.7)	
Bahamas	12.5	12.9	24.4	10.0	151
	(7.9)	(2.0)	(7.4)	(7.4)	

Table 12 – Continued

Country of Origin	Avg. Hourly Earnings (1)	Avg. Years of Schooling (2)	Avg. Experience (3)	Avg. Years in the US (4)	Obs. (5)
St. Lucia	12.4	11.7	26.6	12.0	176
	(7.4)	(2.4)	(7.1)	(7.3)	
Nepal	12.3	13.0	21.9	7.3	1,072
	(13.2)	(3.7)	(7.2)	(5.2)	
Peru	12.3	12.7	26.5	12.3	3,847
	(17.6)	(2.7)	(6.5)	(6.7)	
Thailand	12.1	12.0	25.0	10.4	1,118
	(17.2)	(4.2)	(7.6)	(7.1)	
Grenada	12.1	12.0	27.9	14.6	193
	(7.7)	(2.0)	(6.5)	(8.3)	
Cape Verde	11.9	9.5	27.7	11.8	398
	(9.2)	(3.5)	(8.8)	(7.9)	
Cambodia	11.8	9.4	28.8	15.1	1,153
	(12.1)	(4.1)	(8.8)	(9.3)	
Liberia	11.6	12.1	24.7	9.6	558
	(9.3)	(3.0)	(7.2)	(6.3)	
Ethiopia	11.5	12.5	22.9	9.4	2,365
	(13.5)	(2.5)	(7.0)	(6.2)	
Myanmar	11.5	9.1	23.9	6.5	1,397
	(35.6)	(4.3)	(8.2)	(4.9)	
Ecuador	11.3	10.2	25.9	13.0	4,352
	(12.7)	(3.4)	(7.3)	(7.1)	
Haiti	11.2	11.6	26.2	12.0	5,169
	(16.6)	(2.7)	(7.2)	(7.3)	
Sudan	11.0	12.4	23.6	9.9	322
	(10.4)	(3.5)	(7.5)	(6.5)	
Vietnam	10.8	10.2	28.7	13.5	11,795
	(12.0)	(3.6)	(7.5)	(8.2)	
Nicaragua	10.4	10.6	26.8	14.0	1,761
	(11.6)	(3.3)	(7.6)	(8.1)	
Dominican Republic	10.4	10.9	26.5	11.7	8,841
	(13.1)	(3.1)	(7.8)	(8.0)	
Mexico	10.2	8.8	26.8	15.1	90,967
	(19.4)	(3.0)	(7.8)	(7.9)	

Table 12 – Continued

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
Micronesia	10.0	11.4	22.5	8.8	207
	(9.2)	(2.3)	(7.6)	(5.9)	
El Salvador	10.0	8.4	26.7	14.4	15,282
	(12.8)	(3.2)	(8.2)	(8.1)	
Guinea	9.9	11.0	25.6	10.9	148
	(5.9)	(3.7)	(7.1)	(6.0)	
Guatemala	9.8	7.9	25.1	12.4	9,395
	(13.7)	(3.2)	(8.1)	(7.6)	
Honduras	9.7	8.6	24.5	11.7	6,400
	(14.5)	(3.0)	(7.6)	(7.0)	
Somalia	9.4	9.7	24.6	10.4	600
	(7.7)	(3.8)	(8.3)	(6.5)	

Notes: The table reports the sample of countries classified as low-income countries (GDP per capita $< 40,000$ US$). The reported statistics are average hourly earnings, average years of schooling, average years of potential experience in the labor market (age - years of schooling - 6), average years spent in the US, and the number of observations in the sample pooled for the years 2010-2019. Individual sample weights are used in the calculations.

Table 13: Descriptive statistics for high-income countries (GDP pc $\geq 40,000$)

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
France	50.3	16.5	20.4	7.2	1,428
	(103.8)	(2.9)	(7.0)	(6.4)	
Switzerland	48.3	15.9	22.0	9.4	252
	(54.0)	(2.8)	(7.0)	(7.0)	
Finland	45.8	16.4	20.3	6.9	155
	(54.3)	(2.7)	(6.6)	(6.3)	
Netherlands	43.9	16.2	22.5	8.3	528
	(39.1)	(2.8)	(7.0)	(6.5)	
Denmark	43.8	15.5	22.1	7.7	220
	(50.0)	(2.9)	(7.3)	(7.0)	
Norway	43.8	16.0	21.2	7.6	110
	(31.7)	(3.1)	(8.2)	(7.3)	
Austria	42.6	15.6	21.6	9.0	154
	(44.8)	(3.5)	(7.2)	(6.9)	
Sweden	42.3	15.7	21.4	7.6	383
	(35.8)	(3.0)	(7.3)	(6.3)	
United Kingdom	40.4	15.0	24.0	9.7	5,234
	(44.5)	(2.8)	(7.0)	(7.0)	
Australia	39.3	15.1	21.1	7.1	954
	(37.9)	(2.7)	(6.9)	(6.3)	
New Zealand	35.9	14.5	23.2	9.6	262
	(34.5)	(2.7)	(7.2)	(7.2)	
Belgium	35.8	15.9	21.7	8.1	223
	(31.4)	(3.0)	(7.5)	(7.0)	
Canada	35.8	14.9	23.8	9.7	4,194
	(42.2)	(2.6)	(7.0)	(6.8)	
Germany	34.7	15.4	22.9	9.8	2,499
	(54.6)	(3.3)	(7.4)	(7.4)	
Spain	32.5	15.8	20.1	6.8	710
	(35.8)	(3.3)	(7.4)	(6.9)	
Singapore	32.4	15.4	22.2	8.9	192
	(29.1)	(2.8)	(7.9)	(7.4)	
Ireland	31.4	13.9	23.4	11.2	862
	(32.1)	(2.7)	(7.4)	(8.0)	

Table 13 – Continued

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
Japan	29.4	15.3	21.9	7.2	2,987
	(31.5)	(2.7)	(7.0)	(6.8)	
Israel	29.4	14.8	21.4	9.5	846
	(26.7)	(3.1)	(7.3)	(7.4)	
Italy	28.3	14.4	23.2	10.0	1,236
	(26.9)	(3.6)	(7.9)	(7.9)	
Saudi Arabia	26.4	14.3	19.8	5.3	95
	(30.3)	(2.9)	(7.3)	(5.5)	
Czech Republic	21.0	13.6	22.7	10.8	173
	(21.5)	(3.0)	(6.8)	(6.4)	
South Korea	20.5	14.6	24.9	10.9	4,857
	(38.1)	(3.0)	(7.0)	(7.0)	
Kuwait	19.4	13.7	22.6	9.3	131
	(24.9)	(2.8)	(7.0)	(7.3)	
Hong Kong	19.3	12.8	28.5	14.0	1,076
	(22.6)	(3.6)	(7.7)	(8.3)	
Portugal	18.7	9.7	29.6	16.6	811
	(16.8)	(4.0)	(8.7)	(9.4)	
Lithuania	16.5	14.3	24.5	10.3	247
	(15.7)	(2.6)	(6.8)	(5.6)	
Puerto Rico	12.4	12.2	23.2	9.5	6,773
	(16.3)	(2.8)	(7.8)	(7.6)	

Notes: The table reports the sample of countries classified as low-income countries (GDP per capita $\geq 40,000$ US$). The reported statistics are average hourly earnings, average years of schooling, average years of potential experience in the labor market (age - years of schooling - 6), average years spent in the US, and the number of observations in the sample pooled for the years 2010-2019. Individual sample weights are used in the calculations.

Table 14: List of cognitive occupations

Occupation (SOC 3-dig)	Avg. Hourly Earnings	Share Of Immigrant Workers (%)	Number of Workers
Lawyers, Judges, and Related Workers	48.9	1.2	3,149,760
Top Executives	39.9	5.5	6,750,261
Air Transportation Workers	34.6	3.4	1,113,451
Mathematical Science Occupations	31.9	3.8	4,870,399
Advertising, Marketing, Promotions, Public Relations, and Sales Managers	31.5	5.2	629,681
Physical Scientists	30.8	5.4	11,925,592
Health Diagnosing and Treating Practitioners	30.4	7.2	6,405,476
Engineers	30.4	5.3	11,099,642
Operations Specialties Managers	30.0	12.0	972,130
Life Scientists	29.8	2.9	6,694,898
Financial Specialists	29.0	3.5	10,841,298
Computer Occupations	28.7	9.4	14,235,431
Sales Representatives, Services	28.0	15.1	466,332
Social Scientists and Related Workers	26.9	3.9	289,565
Other Management Occupations	26.8	5.9	21,178,342
Architects, Surveyors, and Cartographers	26.4	3.6	5,523,197
Sales Representatives, Wholesale and Manufacturing	25.2	5.3	739,883
Business Operations Specialists	24.8	3.7	13,255,617
Media and Communication Workers	24.1	3.7	2,096,352
Entertainers and Performers, Sports and Related Workers	24.0	4.9	3,205,614
Other Sales and Related Workers	23.9	4.8	1,432,499
Other Healthcare Practitioners and Technical Occupations	21.0	3.8	213,432
Postsecondary Teachers	21.0	5.6	3,205,605
Supervisors of Construction and Extraction Workers	20.6	9.7	2,046,153
Art and Design Workers	20.5	8.9	883,263
Supervisors of Installation, Maintenance, and Repair Workers	19.9	5.4	727,221
Drafters, Engineering Technicians, and Mapping Technicians	19.7	3.3	761,062
Media and Communication Equipment Workers	19.5	4.9	14,013,743
Supervisors of Sales Workers	19.3	2.0	1,894,901
Legal Support Workers	19.1	5.9	1,894,396
Supervisors of Production Workers	19.0	7.5	671,570
Life, Physical, and Social Science Technicians	18.9	3.3	41,372
Law Enforcement Workers	18.6	3.4	70,778
Fire Fighting and Prevention Workers	18.5	8.9	2,567,751
Supervisors of Protective Service Workers	17.9	4.0	3,910,589
Supervisors of Office and Administrative Support Workers	17.9	3.1	195,392
Librarians, Curators, and Archivists	17.0	3.8	129,570
Religious Workers	17.0	5.0	1,267,068
Other Teachers and Instructors	16.6	10.4	20,839
Counselors, Social Workers, and Other Community and Social Service Specialists	16.5	5.5	6,624,406
Health Technologists and Technicians	16.4	3.4	1,814,016
Funeral Service Workers	16.3	1.5	115,478
Supervisors of Transportation and Material Moving Workers	16.1	3.9	294,523
Occupational Therapy and Physical Therapist Assistants and Aides	15.5	6.1	774,417
Secretaries and Administrative Assistants	14.6	4.3	7,173,910
Financial Clerks	14.4	3.5	6,980,156
Supervisors of Personal Care and Service Workers	14.3	4.5	3,564,698
Preschool, Primary, Secondary, and Special Education School Teachers	14.2	7.4	410,819
Other Office and Administrative Support Workers	14.1	4.7	7,376,781
Supervisors of Building and Grounds Cleaning and Maintenance Workers	13.3	5.0	14,642,821
Information and Record Clerks	13.1	17.8	478,787
Other Protective Service Workers	12.9	7.1	3,124,344
Tour and Travel Guides	12.5	11.6	14,834,840
Other Healthcare Support Occupations	11.9	6.7	3,941,792
Retail Sales Workers	11.9	14.4	64,579
Baggage Porters, Bellhops, and Concierges	11.4	15.3	318,905
Other Education, Training, and Library Occupations	11.3	8.7	836,217
Supervisors of Food Preparation and Serving Workers	10.9	19.4	3,141,822
Nursing, Psychiatric, and Home Health Aides	10.4	23.3	5,122,429
Other Personal Care and Service Workers	10.2	17.7	4,092,665

Notes: The table reports the list of occupations categorized as "cognitive" and the share (expressed in percentages) of immigrant workers in these occupations. Individual sample weights are used in the calculations.

Table 15: List of non-cognitive occupations

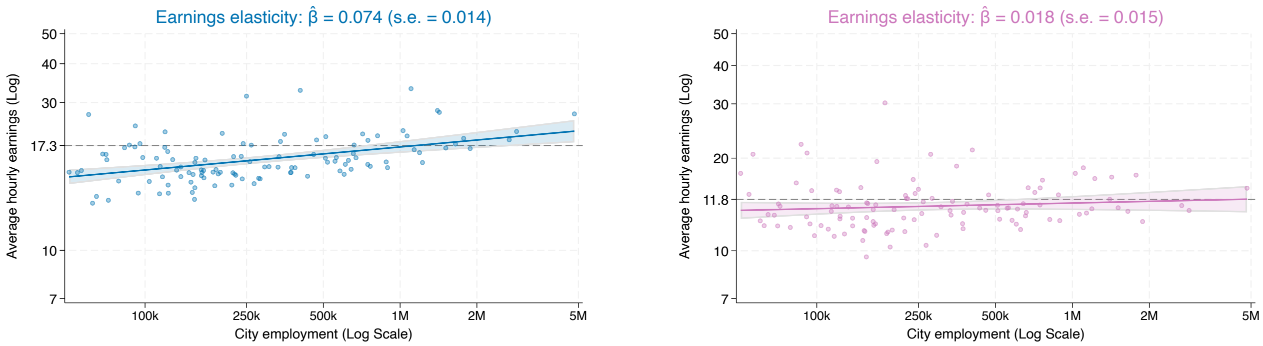
Occupation (SOC 3-dig)	Avg. Hourly Earnings	Share Of Immigrant Workers (%)	Number of Workers
Plant and System Operators	21.8	5.5	569,868
Water Transportation Workers	21.4	4.4	152,691
Rail Transportation Workers	19.9	1.7	316,887
Other Construction and Related Workers	18.5	14.5	548,716
Extraction Workers	17.7	8.8	315,611
Electrical and Electronic Equipment Mechanics, Installers, and Repairers	17.1	6.1	1,724,191
Other Installation, Maintenance, and Repair Occupations	16.6	10.1	5,907,123
Construction Trades Workers	15.1	30.7	17,014,271
Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	15.0	12.2	4,960,687
Metal Workers and Plastic Workers	14.1	18.1	4,663,080
Printing Workers	13.9	4.0	191,001
Other Production Occupations	13.2	12.1	780,389
Motor Vehicle Operators	13.2	21.5	8,292,245
Communications Equipment Operators	13.1	14.8	11,268,325
Assemblers and Fabricators	12.6	14.7	679,131
Material Recording, Scheduling, Dispatching, and Distributing Workers	12.5	23.6	3,227,760
Woodworkers	12.3	10.7	8,382,093
Entertainment Attendants and Related Workers	11.7	19.9	722,247
Other Transportation Workers	11.6	22.2	294,920
Material Moving Workers	11.5	37.3	127,509
Helpers, Construction Trades	11.2	19.8	11,861,115
Food Processing Workers	10.7	31.8	1,894,560
Personal Appearance Workers	10.2	13.0	8,079,804
Building Cleaning and Pest Control Workers	10.2	28.6	3,004,133
Food and Beverage Serving Workers	9.5	43.4	8,475,437
Textile, Apparel, and Furnishings Workers	9.0	55.3	1,485,624
Cooks and Food Preparation Workers	8.5	39.0	7,459,385
Other Food Preparation and Serving Related Workers	8.2	40.2	1,599,298

Notes: The table reports the list of occupations categorised as "non-cognitive" and the share (expressed in percentages) of immigrant workers in these occupations pooled for the years 2010-2019. Individual sample weights are used in the calculations.

B Additional figures

II.A. Robustness checks: female workers

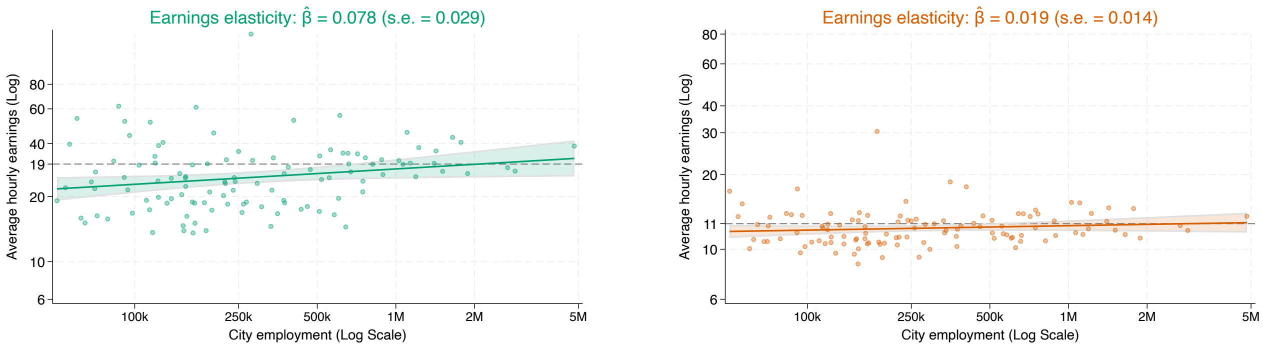
Figure 9: Fact 1 female workers



(a) Natives (b) Immigrants

Notes: This figure shows the relationship between the natural logarithm of average hourly earnings of female workers aged 25–54 in each Metropolitan Statistical Area (MSA) and the natural logarithm of the employment stock of that MSA. Each dot represents the natural logarithm of average hourly earnings in a given MSA. At the top of the figure, I report the estimated coefficient and its heteroscedasticity-robust standard error for the slope of this relationship, obtained by regressing the natural logarithm of average hourly earnings on the natural logarithm of city employment stock. The shaded area in each panel represents the 95 percent confidence interval. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are used in the calculations Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

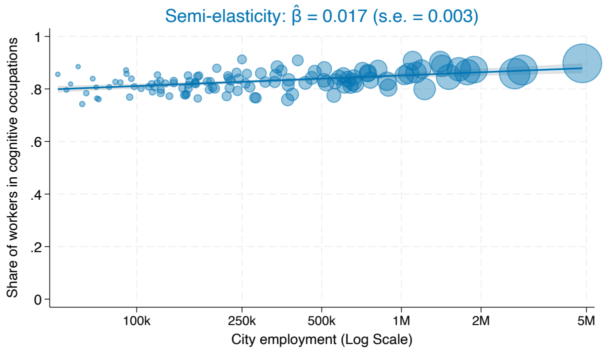
Figure 10: Fact 2 female workers



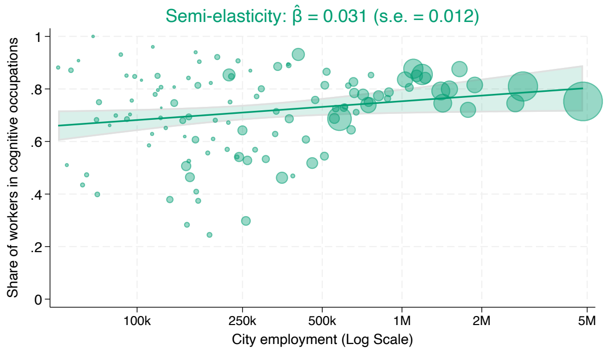
(a) Low-Income (b) High-Income

Notes: This table reports average hourly earnings (USD/hour) in the average small city (city employment stock $<$ $750,000$) and average big city (city employment stock $\geq 750,000$), as well as the city-size earnings gap (average earnings in big cities minus average earnings in small cities) for natives, immigrants from high-income countries (GDP per capita $\geq 40,000$), and immigrants from low-income countries (GDP per capita $< 40,000$). Average earnings are calculated from a sample of female workers aged 25–54 who report being employed. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are applied in all calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

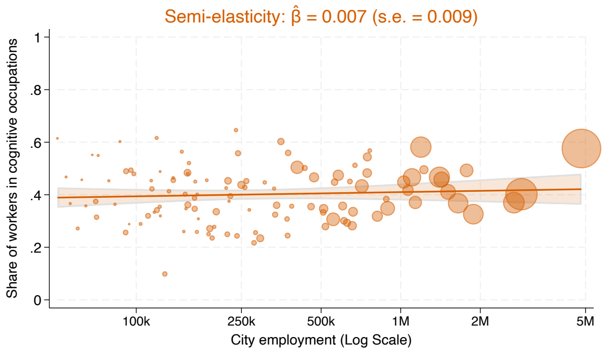
Figure 11: Fact 3 female workers



(a) US



(b) High-Income Countries



(c) Low-Income Countries

Notes: This figure shows the relationship between the share of female workers in cognitive occupations in each metropolitan statistical area and the natural logarithm of the employment stock of each metropolitan statistical area for native workers, immigrants from low-income countries (GDP pc $< \$40,000$, Panel a) and immigrants from high-income countries (GDP pc $< \$40,000$, Panel b). Each marker corresponds to the share of workers who work in a cognitive occupation in a Metropolitan Statistical Area. The size of the marker indicates, for each origin group, the share of female workers living in the corresponding Metropolitan Statistical Area. At the top of the figures, I report the estimated coefficient and the corresponding standard error robust to heteroscedasticity for the slope of this relationship obtained by regressing the share of workers in a cognitive occupation in each city on the log of the city's employment stock. The area in each panel represents the estimated confidence intervals at the 5 percent significance level. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

C Additional tables

III.A. Robustness Checks Fact 1: Regressions

Table 16: Regressions for fact 1 and fact 2: male workers

	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
	Panel A: Immigrants vs. Natives				
Log City Employment	0.085	0.085	0.063	0.068	0.058
	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)
Imm#Log City Employment	−0.098	−0.098	−0.066	−0.071	−0.065
	(0.014)	(0.014)	(0.009)	(0.010)	(0.009)
Immigrants	0.979	0.975	0.635	0.888	0.841
	(0.203)	(0.202)	(0.13)	(0.146)	(0.140)
Constant	1.645	1.645	1.629	1.324	1.324
	(0.154)	(0.154)	(0.142)	(0.144)	(0.139)
N. Obs	1,690,054	1,690,054	1,690,054	1,690,054	1,690,054
Adj.R2	0.04	0.04	0.16	0.19	0.25
	Panel B: Low-Income Countries and High-Income Countries vs. Natives				
Log City Employment	0.085	0.085	0.063	0.068	0.058
	(0.012)	(0.012)	(0.011)	(0.011)	(0.01)
LIC#Log City Employment	−0.100	−0.100	−0.071	−0.076	−0.070
	(0.013)	(0.013)	(0.01)	(0.011)	(0.01)
HIC#Log City Employment	0.020	0.020	0.013	0.009	−0.003
	(0.033)	(0.033)	(0.022)	(0.022)	(0.019)
LIC	0.938	0.934	0.687	0.955	0.921
	(0.181)	(0.180)	(0.140)	(0.153)	(0.152)
HIC	−0.023	−0.028	−0.170	−0.027	−0.004
	(0.489)	(0.489)	(0.312)	(0.315)	(0.270)
Constant	1.645	1.645	1.629	1.324	1.324
	(0.154)	(0.154)	(0.142)	(0.144)	(0.139)
N. Obs	1,690,054	1,690,054	1,690,054	1,690,054	1,690,054
Adj.R2	0.05	0.05	0.16	0.20	0.25
Year FE		✓	✓	✓	✓
College FE			✓	✓	✓
Experience FE				✓	✓
Cognitive occupation FE					✓

Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment (column 1) controlling for year fixed effects (column 2), college fixed effects (column 3), experience class (0-14, 15-29, 30+) fixed effects (column 4) and cognitive occupations FE (column 5). All fixed effects, apart from time effects, are interacted with a dummy for immigrants (panel A) or for country of origin (panel B). The model is estimated by pooling observations for male workers who are US-born and foreign-born. Results are based on a sample of male workers aged 25-54 who report being employed. LIC immigrants come from a country with a GDP per capita below $40,000 at 2021 PPP, and HIC immigrants come from a country with a GDP per capita greater than or equal to $40,000 at 2021 PPP. Standard errors are clustered at the MSA level. Native workers are the base group. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

Table 17: Regressions for fact 3: male workers

	Cognitive Occupation Dummy (1)	Cognitive Occupation Dummy (2)	Cognitive Occupation Dummy (3)	Cognitive Occupation Dummy (4)
	Panel A: Immigrants vs. Natives			
Log City Employment	0.044	0.044	0.026	0.026
	(0.004)	(0.004)	(0.003)	(0.003)
Imm#Log City Employment	−0.044	−0.044	−0.018	−0.017
	(0.009)	(0.009)	(0.004)	(0.004)
Immigrants	0.296	0.294	0.042	0.102
	(0.122)	(0.122)	(0.057)	(0.055)
Constant	0.018	0.018	0.004	0.000
	(0.055)	(0.055)	(0.041)	(0.042)
N. Obs	1,690,054	1,690,054	1,690,054	1,690,054
Adj.R2	0.05	0.05	0.24	0.24
	Panel B: Low-Income Countries and High-Income Countries vs. Natives			
Log City Employment	0.044	0.044	0.026	0.026
	(0.004)	(0.004)	(0.003)	(0.003)
LIC#Log City Employment	−0.042	−0.042	−0.017	−0.017
	(0.008)	(0.008)	(0.004)	(0.004)
HIC#Log City Employment	0.003	0.003	0.005	0.006
	(0.022)	(0.022)	(0.012)	(0.011)
LIC	0.226	0.225	0.022	0.087
	(0.115)	(0.115)	(0.057)	(0.057)
HIC	0.025	0.023	−0.054	−0.034
	(0.306)	(0.306)	(0.155)	(0.160)
Constant	0.018	0.018	0.004	0.000
	(0.055)	(0.055)	(0.041)	(0.042)
N. Obs	1,690,054	1,690,054	1,690,054	1,690,054
Adj.R2	0.06	0.06	0.24	0.24
Year FE		✓	✓	✓
College FE			✓	✓
Experience FE				✓

Notes: This table reports the estimated coefficients from regressing a dummy variable for cognitive occupations on the natural logarithm of cities' employment (column 1) controlling for year fixed effects (column 2), college fixed effects (column 3), and experience class (0-14, 15-29, 30+) fixed effects (column 4). All fixed effects, apart from time effects, are interacted with a dummy for immigrants (panel A) or for country of origin (panel B). The model is estimated by pooling observations for male workers who are US-born and foreign-born. Results are based on a sample of male workers aged 25-54 who report being employed. LIC immigrants come from a country with a GDP per capita below $40,000 at 2021 PPP, and HIC immigrants come from a country with a GDP per capita greater than or equal to $40,000 at 2021 PPP. Standard errors are clustered at the MSA level. Native workers are the base group. Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

Table 18: Regressions for fact 1 and fact 2: female workers

	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
	Panel A: Immigrants vs. Natives				
Log City Employment	0.087	0.087	0.071	0.075	0.069
	(0.011)	(0.011)	(0.01)	(0.01)	(0.009)
Imm#Log City Employment	−0.074	−0.074	−0.056	−0.059	−0.065
	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)
Immigrants	0.592	0.586	0.498	0.666	0.89
	(0.133)	(0.132)	(0.104)	(0.114)	(0.124)
Constant	1.397	1.397	1.299	1.121	0.939
	(0.145)	(0.146)	(0.131)	(0.135)	(0.129)
N. Obs	1,380,983	1,380,983	1,380,983	1,380,983	1,380,983
Adj.R2	0.05	0.05	0.14	0.16	0.19
	Panel B: Low-Income Countries and High-Income Countries vs. Natives				
Log City Employment	0.087	0.087	0.071	0.075	0.069
	(0.011)	(0.011)	(0.010)	(0.010)	(0.009)
LIC#Log City Employment	−0.077	−0.076	−0.060	−0.063	−0.069
	(0.01)	(0.01)	(0.008)	(0.008)	(0.009)
HIC#Log City Employment	0.016	0.017	0.016	0.014	0.004
	(0.017)	(0.017)	(0.015)	(0.015)	(0.015)
LIC	0.585	0.580	0.539	0.697	0.941
	(0.134)	(0.133)	(0.107)	(0.116)	(0.129)
HIC	−0.269	−0.283	−0.276	−0.130	−0.024
	(0.253)	(0.254)	(0.214)	(0.233)	(0.222)
Constant	1.397	1.397	1.299	1.121	0.939
	(0.145)	(0.146)	(0.131)	(0.135)	(0.129)
N. Obs	1,380,983	1,380,983	1,380,983	1,380,983	1,380,983
Adj.R2	0.05	0.05	0.15	0.16	0.19
Year FE		✓	✓	✓	✓
College FE			✓	✓	✓
Experience FE				✓	✓
Cognitive occupation FE					✓

Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment (column 1) controlling for year fixed effects (column 2), college fixed effects (column 3), experience class (0-14, 15-29, 30+) fixed effects (column 4) and cognitive occupations FE (column 5). All fixed effects, apart from time effects, are interacted with a dummy for immigrants (panel A) or for country of origin (panel B). The model is estimated by pooling observations for female workers who are US-born and foreign-born. Results are based on a sample of male workers aged 25-54 who report being employed. LIC immigrants come from a country with a GDP per capita below $40,000 at 2021 PPP, and HIC immigrants come from a country with a GDP per capita greater than or equal to $40,000 at 2021 PPP. Standard errors are clustered at the MSA level. Native workers are the base group. Earnings are deflated using the 1999 CPI provided by IPUMS. Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

Table 19: Regressions for fact 3: female workers

	Cognitive Occupation Dummy	Cognitive Occupation Dummy	Cognitive Occupation Dummy	Cognitive Occupation Dummy
	(1)	(2)	(3)	(4)
	Panel A: Immigrants vs. Natives			
Log City Employment	0.022	0.022	0.015	0.016
	(0.002)	(0.002)	(0.002)	(0.002)
Imm#Log City Employment	0.013	0.013	0.021	0.021
	(0.017)	(0.017)	(0.016)	(0.015)
Immigrants	−0.568	−0.567	−0.688	−0.626
	(0.224)	(0.224)	(0.199)	(0.201)
Constant	0.552	0.552	0.513	0.494
	(0.031)	(0.031)	(0.027)	(0.027)
N. Obs	1,380,983	1,380,983	1,380,983	1,380,983
Adj.R2	0.09	0.09	0.17	0.17
	Panel B: Low-Income Countries and High-Income Countries vs. Natives			
Log City Employment	0.022	0.022	0.015	0.016
	(0.002)	(0.002)	(0.002)	(0.002)
LIC#Log City Employment	0.018	0.018	0.025	0.025
	(0.019)	(0.019)	(0.017)	(0.017)
HIC#Log City Employment	0.019	0.019	0.016	0.016
	(0.016)	(0.016)	(0.012)	(0.012)
LIC	−0.677	−0.676	−0.766	−0.708
	(0.248)	(0.249)	(0.224)	(0.227)
HIC	−0.365	−0.365	−0.375	−0.336
	(0.216)	(0.216)	(0.161)	(0.168)
Constant	0.552	0.552	0.513	0.494
	(0.031)	(0.031)	(0.027)	(0.027)
N. Obs	1,380,983	1,380,983	1,380,983	1,380,983
Adj.R2	0.10	0.10	0.17	0.17
Year FE		✓	✓	✓
College FE			✓	✓
Experience FE				✓

Notes: This table reports the estimated coefficients from regressing a dummy variable for cognitive occupations on the natural logarithm of cities' employment (column 1) controlling for year fixed effects (column 2), college fixed effects (column 3), and experience class (0-14, 15-29, 30+) fixed effects (column 4). All fixed effects, apart from time effects, are interacted with a dummy for immigrants (panel A) or for country of origin (panel B). The model is estimated by pooling observations for male workers who are US-born and foreign-born. Results are based on a sample of female workers aged 25-54 who report being employed. LIC immigrants come from a country with a GDP per capita below $40,000 at 2021 PPP, and HIC immigrants come from a country with a GDP per capita greater than or equal to $40,000 at 2021 PPP. Standard errors are clustered at the MSA level. Native workers are the base group. Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

III.B. Robustness Checks With Living Costs

In this section, I present the robustness checks for the stylised facts 1 and 2 using workers' earnings deflated by a local prices built on the Local CPI 1 index from Moretti (2013). This measure represents the average local prices as the average rent and utilities (such as water, gas, electricity) and fuels (such as coal, oil, wood, kerosene). I compute the local price index from a subsample of native workers who report paying a positive rent and live in a unit with either two or three rooms.

Table 20: Regressions for fact 1 and fact 2 using avg. city prices as deflator: male workers

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
	Immigrants vs. Natives				
Log City Employment	0.034	0.034	0.013	0.018	0.008
	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)
Imm#Log City Employment	−0.096	−0.095	−0.064	−0.069	−0.063
	(0.011)	(0.011)	(0.007)	(0.007)	(0.007)
Immigrants	0.926	0.905	0.571	0.829	0.783
	(0.158)	(0.155)	(0.092)	(0.108)	(0.110)
Constant	2.608	2.609	2.594	2.283	2.283
	(0.124)	(0.126)	(0.118)	(0.102)	(0.104)
N. Obs	1,690,054	1,690,054	1,690,054	1,690,054	1,690,054
Adj.R2	0.04	0.04	0.15	0.20	0.24
	Low-Income Countries and High-Income Countries vs. Natives				
Log City Employment	0.034	0.034	0.013	0.018	0.008
	(0.01)	(0.01)	(0.009)	(0.008)	(0.008)
LIC#Log City Employment	−0.099	−0.097	−0.069	−0.074	−0.068
	(0.011)	(0.011)	(0.008)	(0.009)	(0.009)
HIC#Log City Employment	0.022	0.024	0.017	0.013	0.001
	(0.029)	(0.029)	(0.017)	(0.017)	(0.016)
LIC	0.888	0.869	0.625	0.900	0.867
	(0.150)	(0.147)	(0.118)	(0.130)	(0.134)
HIC	−0.088	−0.115	−0.254	−0.111	−0.088
	(0.425)	(0.425)	(0.254)	(0.254)	(0.216)
Constant	2.608	2.609	2.594	2.283	2.283
	(0.124)	(0.126)	(0.118)	(0.102)	(0.104)
N. Obs	1,690,054	1,690,054	1,690,054	1,690,054	1,690,054
Adj.R2	0.05	0.05	0.16	0.20	0.25
Year FE		✓	✓	✓	✓
College FE			✓	✓	✓
Experience FE				✓	✓
Cognitive occupation FE					✓

Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment (column 1) controlling for year fixed effects (column 2), college fixed effects (column 3), experience class (0-14, 15-29, 30+) fixed effects (column 4) and cognitive occupations FE (column 5). All fixed effects, apart from time effects, are interacted with a dummy for immigrants (panel A) or for country of origin (panel B). The model is estimated by pooling observations for male workers who are US-born and foreign-born. Results are based on a sample of male workers aged 25-54 who report being employed. LIC immigrants come from a country with a GDP per capita below $40,000 at 2021 PPP, and HIC immigrants come from a country with a GDP per capita greater than or equal to $40,000 at 2021 PPP. Standard errors are clustered at the MSA level. Native workers are the base group. Earnings are deflated using a local CPI index constructed using the methodology described in Moretti (2013). Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

Table 21: Regressions for fact 1 and fact 2 using avg. city prices as deflator: female workers

	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
	Panel A: Immigrants vs. Natives				
Log City Employment	0.036	0.036	0.020	0.024	0.018
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Imm#Log City Employment	−0.072	−0.07	−0.053	−0.057	−0.062
	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)
Immigrants	0.530	0.510	0.422	0.596	0.815
	(0.109)	(0.106)	(0.083)	(0.09)	(0.096)
Constant	2.371	2.372	2.275	2.092	1.913
	(0.079)	(0.081)	(0.073)	(0.063)	(0.061)
N. Obs	1,380,983	1,380,983	1,380,983	1,380,983	1,380,983
Adj.R2	0.04	0.05	0.15	0.16	0.19
	Panel B: Low-Income Countries and High-Income Countries vs. Natives				
Log City Employment	0.036	0.036	0.02	0.024	0.018
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
LIC#Log City Employment	−0.074	−0.073	−0.057	−0.06	−0.066
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
HIC#Log City Employment	0.014	0.017	0.016	0.014	0.004
	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)
LIC	0.516	0.499	0.458	0.623	0.86
	(0.112)	(0.109)	(0.088)	(0.094)	(0.105)
HIC	−0.275	−0.318	−0.312	−0.167	−0.064
	(0.216)	(0.219)	(0.194)	(0.207)	(0.212)
Constant	2.371	2.372	2.275	2.092	1.913
	(0.079)	(0.081)	(0.073)	(0.063)	(0.061)
N. Obs	1,380,983	1,380,983	1,380,983	1,380,983	1,380,983
Adj.R2	0.05	0.05	0.15	0.16	0.19
Year FE		✓	✓	✓	✓
College FE			✓	✓	✓
Experience FE				✓	✓
Cognitive occupation FE					✓

Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment (column 1) controlling for year fixed effects (column 2), college fixed effects (column 3), experience class (0-14, 15-29, 30+) fixed effects (column 4) and cognitive occupations FE (column 5). All fixed effects, apart from time effects, are interacted with a dummy for immigrants (panel A) or for country of origin (panel B). The model is estimated by pooling observations for female workers who are US-born and foreign-born. Results are based on a sample of male workers aged 25-54 who report being employed. LIC immigrants come from a country with a GDP per capita below $40,000 at 2021 PPP, and HIC immigrants come from a country with a GDP per capita greater than or equal to $40,000 at 2021 PPP. Standard errors are clustered at the MSA level. Native workers are the base group. Earnings are deflated using a local CPI index constructed using the methodology described in Moretti (2013). Individual sample weights are used in the calculations. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

III.C. Additional derivation of the change in hourly earnings across space

Here, I derive the interpretation for the elasticity of average hourly earnings to city-size. The econometric model to estimate the elasticity of the average hourly earnings to city-size (measured as total population) for a worker from group $k \in \{\text{Native}, \text{Immigrants}\}$ is:

$$\ln(\bar{w}_j^k) = \alpha + \beta \ln(\text{Population}_j) + \nu_j \tag{C1}$$

Take two cities j, j' such that

$$\text{Population}_j = \bar{q}\text{Population}_{j'} \tag{C2}$$

where $\bar{q} \geq 1$ is a constant. Then, the difference in log-earnings between the two cities is:

$$\ln(\bar{w}_j^k) - \ln(\bar{w}_{j'}^k) = \beta \left[\ln(\bar{q}\text{Population}_{j'}) - \ln(\text{Population}_{j'})\right] \tag{C3}$$

$$\ln\left(\frac{\bar{w}_j^k}{\bar{w}_{j'}^k}\right) = \beta \left[\ln \bar{q} + \ln\left(\frac{\text{Population}_{j'}}{\text{Population}_{j'}}\right)\right] \tag{C4}$$

$$= \beta \ln \bar{q} \tag{C5}$$

Applying the exponential function and subtracting 1 from to both sides of the equation, I obtain:

$$\frac{\bar{w}_j^k}{\bar{w}_{j'}^k} - 1 = \bar{q}^\beta - 1 \tag{C6}$$

Thus, increasing the city-size $\bar{q}$ times, generates a change in the average wage of:

$$\Delta\bar{w}\% = (\bar{q}^\beta - 1) \times 100 \tag{C7}$$

D Model derivations and fit

IV.A. Housing Market Derivation

Each worker of from group g spends share α of earnings on housing, yielding individual demand $h^* = \alpha w_{jo}(g)/p_j$. Aggregating over all worker types in city j, total housing demand is

$$H_j^d = \frac{\alpha}{p_j} \sum_o \sum_g \pi_{jo}(g)\, \phi_g\, w_{jo}(g) = \frac{\alpha\, \bar{w}_j\, L_j}{p_j}, \tag{D1}$$

where $\bar{w}_j \equiv \sum_{o,g} \pi_{jo}(g)\phi_g w_{jo}(g)/L_j$ is average earnings in city j and $L_j = \sum_{o,g} \pi_{jo}(g)\phi_g$ is city population.

On the supply side, the absentee landlord in city j maximises profits by choosing the quantity of the final good Y_j to combine with the fixed land endowment T_j:

$$\max_{Y_j} \quad p_j \left(\omega_j\, Y_j^{\iota_j}\, T_j^{1-\iota_j}\right) - Y_j. \tag{D2}$$

The first-order condition gives

$$Y_j = \left(p_j\, \omega_j\, \iota_j\right)^{\frac{1}{1-\iota_j}}\, T_j. \tag{D3}$$

Substituting back into (II.7) and using the normalisation $\omega_j = \iota_j^{-\iota_j}$ (which causes all ι_j-dependent prefactors to cancel) yields the housing supply curve:

$$p_j = \left(\frac{H_j}{T_j}\right)^{\frac{1}{\zeta_j}}, \qquad \zeta_j \equiv \frac{\iota_j}{1-\iota_j}, \tag{D4}$$

where ζ_j is the city-specific housing supply elasticity.

Imposing market clearing $H_j^d = H_j^s \equiv H_j$ and solving for p_j:

$$p_j = \left(\frac{\alpha\, \bar{w}_j\, L_j}{p_j\, T_j}\right)^{\frac{1}{\zeta_j}} \implies p_j^{1+\frac{1}{\zeta_j}} = \left(\frac{\alpha\, \bar{w}_j\, L_j}{T_j}\right)^{\frac{1}{\zeta_j}} \implies p_j^{\frac{1+\zeta_j}{\zeta_j}} = \left(\frac{\alpha\, \bar{w}_j\, L_j}{T_j}\right)^{\frac{1}{\zeta_j}}, \tag{D5}$$

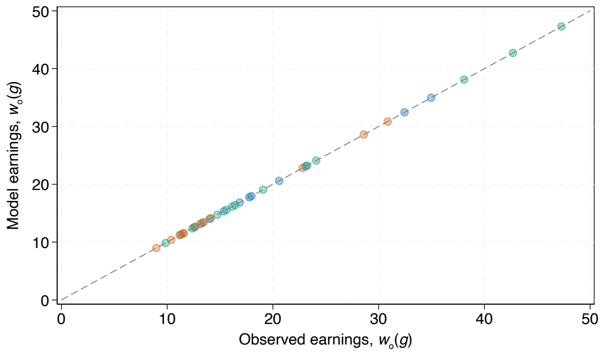
which gives the equilibrium housing price:

$$p_j = \left(\frac{\alpha\, \bar{w}_j\, L_j}{T_j}\right)^{\frac{1}{1+\zeta_j}}. \tag{D6}$$

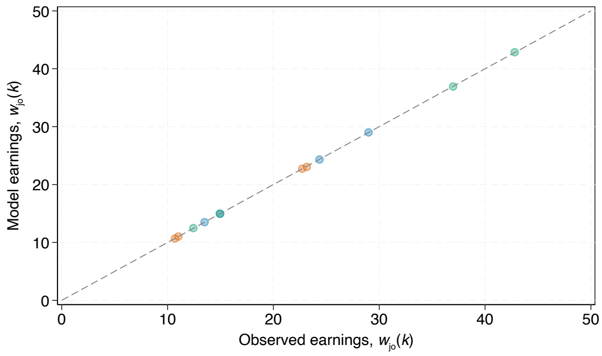
Cities with inelastic housing supply (low ζ_j) translate worker inflows into larger housing price increases, dampening the real-earnings gains from locating in productive cities.

IV.B. Model fit

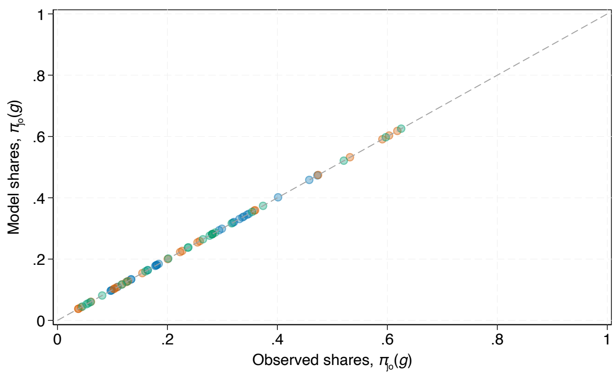
Figure 12 shows that model-generated moments closely match their empirical counterparts, lying near the 45-degree line.



(a) Avg. earnings by occupation and observable characteristics



(b) Avg. earnings city-occupation by country of origin



(c) Shares in city-occupation by observable characteristics

Figure 12: Model fit

Notes: Each panel plots model-generated moments against their data counterparts along the 45-degree line (dashed). Colors denote worker origin: blue = Natives, orange = Low-Income Countries (LIC), teal = High-Income Countries (HIC). Panel (a) shows occupation-specific earnings $w_o(g)$ by origin, education, and experience group (36 moments). Panel (b) shows average earnings $w_{jo}(k)$ by city, occupation, and origin group (12 moments). Panel (c) shows city–occupation shares $\pi_{jo}(g)$ by origin, education, and experience group (72 moments). Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

Table 22 compares model-generated and data earnings for natives and immigrants from each origin group in small and big cities. The model matches the data counterparts closely for all groups. The model also reproduces the direction of the city-size earnings gap for all groups, including the near-zero gap for LIC immigrants.

Table 22: Model fit: average hourly earnings by city and origin

	Small City		Big City		Δ	
	Data	Model	Data	Model	Data	Model
	(1)	(2)	(3)	(4)	(5)	(6)
Natives	19.8	19.8	24.2	24.2	+4.3	+4.4
HIC	27.5	27.6	36.0	36.0	+8.5	+8.5
LIC	14.1	14.0	14.3	14.2	0.2	0.2

Notes: Average hourly earnings ($/hour) in small and big cities for each origin group, comparing data moments to model-generated counterparts. Δ denotes the big-city minus small-city difference.Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

Table 23 shows the model fit for occupational sorting andspatial distribution. The model reproduces closely the share of workers in cognitive occupations and the share of workers located in big cities for all three origin groups.

Table 23: Model fit: occupational sorting and spatial distribution

		Small City		Big City		Δ	
		Data	Model	Data	Model	Data	Model
		(1)	(2)	(3)	(4)	(5)	(6)
Natives	% Cognitive	58.3	58.3	65.6	65.7	7.3	7.4
	% Total	46.6	46.6	53.4	53.4	6.7	6.8
HIC	% Cognitive	61.7	61.7	75.5	75.5	13.9	13.8
	% Total	38.5	38.3	61.5	61.7	23.0	23.4
LIC	% Cognitive	27.0	27.0	27.4	27.4	0.4	0.4
	% Total	28.8	28.8	71.2	71.2	42.3	42.3

Notes: % Cognitive is the share of workers in cognitive occupations within each city–origin cell. % Employment is the share of workers from each origin group located in each city. All entries are in percentage points; Δ denotes big-city minus small-city differences. Source: ACS 2010-1019, World Bank Development Indicators, O*NET Database, and author's calculations.

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