

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

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Abstract

Using US microdata, I document three stylized facts on immigrants' labor market outcomes across space. First, the city-size earnings premium is half as large for immigrants as for natives. Second, there is substantial heterogeneity by origin: immigrants from high-income countries earn a premium exceeding that of natives, while immigrants from low-income countries earn a substantially smaller premium. Third, as cities grow, natives and high-income country immigrants increasingly sort into cognitive occupations, while low-income country immigrants do not. To study these facts, I build a quantitative spatial general equilibrium model where technology favors cognitive skills, workers differ in human capital and tastes for cities and occupations, and immigrants face local labor market distortions. Full equalization of immigrants' human capital, preferences, and labor market conditions to native levels closes 61.8 percent of the immigrant-native earnings gap but widens earnings inequality across cities by 20.2 percent. College immigration expansion narrows the earnings gap at minimal spatial cost, while interventions targeting human capital, preferences, or labor market conditions do not.

Keywords: Immigrants, Human Capital, Inequality, Spatial Equilibrium

JEL Classification: J21, J31, J61, R13

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1 Introduction

The United States has more immigrants than any other country in the world. In 2024, foreign-born workers represented 19.2 percent of the U.S. civilian labor force¹, contributing substantially to innovation, entrepreneurship, and economic growth.² Despite their economic importance, immigrants consistently earn less than native-born workers—a gap that has persisted for decades. A large body of literature has identified human capital differences among workers from different countries³ and labor market barriers⁴ as its main sources, but standard explanations that account for these factors leave unexplained a substantial portion of the gap. Understanding what drives this persistent disadvantage matters not only for the economic integration of immigrants but also for assessing the broader consequences of immigration for labor market inequality in the United States.

A natural place to look for the missing piece is space. Immigrants are not randomly distributed across the United States — they concentrate disproportionately in large, high-productivity cities (Albert and Monras, 2022), where wages are higher precisely because these cities disproportionately reward cognitive-intensive labor (Eeckhout, Hedtrich and Pinheiro, 2026). If the mechanisms generating the immigrant-native earnings gap operated uniformly across space, this concentration would translate into similar city-size earnings premia for immigrants and natives alike. But there is no reason to expect this: immigrants differ from natives not only in human capital and labor market barriers, but also in the non-pecuniary value they assign to different locations and occupations — shaped by ethnic networks, cultural ties, and origin-country characteristics. These differences may interact with the labor market’s spatial structure in ways that amplify or dampen the earnings gains from locating in large cities, and may do so differently for immigrants of different origins. This paper asks: what determines how the city-size earnings premium varies across immigrant origin groups, and what are the implications for earnings inequality between workers and across space?

To study these questions, I use data from the American Community Survey (ACS) 2010–2019 and document three stylized facts for prime-age male workers. First, the city-size earnings premium is significantly smaller for immigrants than for natives: doubling the city-size is associated with a 5.7 percent increase in native earnings, but only a 2.8 percent increase in immigrants’ earnings. Second, this gap masks substantial heterogeneity by origin: doubling the city-size, immigrants from high-income countries (HIC) earn a premium of 7.3 percent — exceeding that of natives — while immigrants from low-income countries (LIC) earn a premium of just 2.0 percent. Third, LIC immigrants sort into cognitive occupations at a rate that is largely insensitive to city-size: their cognitive occupation share rises with a semi-elasticity of 1.7 percent, significant only at the 10 percent level, compared to 5.0 percent for high-income country immigrants and 4.3 percent for

¹See [of Labor Statistics](#) (BLS).

²See, for example, [Azoulay et al. \(2022\)](#), [Peri \(2016\)](#), [Hunt and Gauthier-Loiselle \(2010\)](#).

³[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 from education than do immigrants from low income economies.

⁴[Oreopoulos \(2011\)](#) shows that foreign experience is substantially penalized across a broad set of occupations. [Dostie et al. \(2021\)](#) document that employer-specific wage setting policies contribute to the earnings gap between immigrants and natives in Canada.

natives.

Motivated by these facts, I develop a quantitative spatial general equilibrium model with heterogeneous workers and cities. Cities differ in housing costs and in the degree to which they reward cognitive-intensive labor, with larger cities disproportionately favoring cognitive occupations. Workers of different origins differ across three dimensions: their occupation-specific human capital, their preferences for city-occupation pairs, and the local earnings wedges they face in local labor markets. These three channels jointly determine how workers of different origins sort across cities and occupations, and therefore how the city-size earnings premium varies across groups. Estimating the model allows me to disentangle their contributions to the immigrant-native earnings gap — both in the aggregate and across space — and to evaluate how immigration policies that alter the skill composition of immigrant inflows affect the trade-off between worker and spatial inequality.

Local earnings wedges, amenity valuations, and human capital each shape workers' joint choices of city and occupation through distinct mechanisms. Human capital determines workers' comparative advantage across occupations: immigrants from low-income countries accumulate human capital in task environments that differ systematically from those characterizing the US occupational structure (Caunedo, Keller and Shin, 2021). Amenity valuations capture the non-pecuniary value workers assign to city-occupation pairs, shaped by ethnic networks, cultural ties, and origin-country characteristics (Munshi, 2003): they influence where workers locate and which occupations they enter, independently of wages. Local earnings wedges capture the residual gap between what immigrants earn and what observationally equivalent natives would earn at the competitive wage — absorbing frictions such as discrimination, occupational licensing barriers, and informational asymmetries (Hsieh et al., 2019; Birinci, Leibovici and See, 2024). No single channel is sufficient on its own: human capital shapes the level of earnings but not necessarily where workers locate; amenities drive spatial concentration but operate independently of productivity; and wedges distort occupational choices without directly affecting preferences. Together, they provide a rich framework for understanding why workers of different origins make such different joint choices of city and occupation.

I structurally estimate the model using the simulated method of moments, matching moments on earnings and occupational shares from the ACS 2010–2019. Two identifying assumptions pin down the model: I normalize amenity parameters relative to a baseline city-occupation pair separately for each origin group, and I assume native workers face no earnings wedges, so that the estimated wedges — which vary across city-occupation pairs and countries of origin — measure the earnings gap relative to observationally equivalent natives that cannot be attributed to human capital differences. The estimates reveal that LIC immigrants face a sharp reversal in earnings wedges across city types — earning above the competitive benchmark in small cities but below it in large cities, particularly in cognitive occupations — which directly dampens their city-size earnings premium. Amenity valuations, by contrast, strongly pull LIC immigrants toward large cities and network-dense occupations, generating their disproportionate spatial concentration independently of wages.

To quantify the role of these channels, I conduct three counterfactual experiments in general

equilibrium, each isolating a single source of heterogeneity between immigrants and natives: human capital, amenity valuations, and earnings wedges. Human capital is the single largest driver of the aggregate immigrant-native earnings gap, closing 49.8 percent of it, but leaves spatial inequality largely unchanged — reflecting the fact that human capital scales earnings within occupations without altering where workers locate. Amenity valuations are the dominant channel for sorting: equalizing them generates large reallocations of LIC immigrants out of large cities and into cognitive occupations, closing 14.5 percent of the earnings gap while widening the big-small city earnings gap by 19.0 percent. Earnings wedges, by contrast, have a near-zero aggregate effect on the immigrant-native earnings gap, but this masks large and opposing effects across origin groups: removing wedges substantially narrows the city-size premium gap for LIC immigrants while simultaneously widening it for HIC immigrants, with the two effects cancelling in the aggregate. Together, removing all three sources of heterogeneity closes 61.8 percent of the immigrant-native earnings gap but widens the big-small city earnings gap by 20.2 percent — revealing a structural trade-off between worker inequality and spatial inequality that runs through all three channels.

Motivated by the trade-off uncovered by the counterfactual analysis, I evaluate two large-scale immigration expansion policies calibrated to generate a one percentage point increase in total employment: an expansion of the college immigrant workforce and an expansion of the non-college immigrant workforce. To compare their spatial costs, I define a trade-off rate as the change in the spatial earnings gap per unit change in the immigrant-native earnings gap. The two policies generate sharply different outcomes. College expansion narrows the immigrant-native earnings gap by 17.1 percent while leaving the spatial earnings gap essentially unchanged, implying a spatial cost near zero. Non-college expansion generates the opposite pattern: it widens the immigrant-native earnings gap by 7.3 percent while slightly narrowing the spatial gap. The spatial cost of closing the immigrant-native earnings gap therefore depends critically on the instrument used: college immigration expansion does so at essentially zero spatial cost, while structural interventions that remove amenity differences, distortions, or human capital gaps — whether simultaneously or individually — generate higher spatial costs.

This paper makes two main contributions. First, it provides new empirical evidence on how the immigrant-native earnings gap varies across space and across origin groups — evidence that, to the best of my knowledge, has not been systematically documented in previous research. Existing work on immigrant earnings abstracts from the spatial dimension, while the urban wage premium literature focuses on natives or treats immigrants as homogeneous. This paper is the first to show that differential occupational sorting across cities — rather than human capital differences alone (which explain the level of the gap but not its spatial dimension) — accounts for the heterogeneous city-size earnings premia across origin groups. Second, it develops a quantitative spatial general equilibrium framework to understand how immigration shapes earnings inequality both between workers and across space. The framework reveals a structural trade-off: the mechanisms that generate immigrants' earnings disadvantage — amenity valuations and labor market wedges — simultaneously compress earnings inequality between large and small cities, and the severity of this trade-off depends critically on the policy instrument used to address it.

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

Immigration and labor market inequality. 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 a novel set of facts on how the immigrant-native earnings gap varies across space and origin groups. 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: the failure of low-income country immigrants to earn a city-size premium despite concentrating in large cities, driven by their insensitivity to occupational upgrading across cities. This highlights the importance of jointly studying workers' occupational choices and their geographical nature to understand earnings inequality between immigrants and natives.

Structural models of immigration. This paper also contributes to the literature that uses structural models to 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 sources of earnings disparities within a spatial equilibrium framework: occupation-specific human capital, amenity valuations for city-occupation pairs, and local earnings wedges. No existing paper in this strand jointly models these three channels within a spatial general equilibrium, nor identifies the trade-off between worker inequality and spatial inequality that emerges when they are removed. The structural framework also allows me to evaluate how large-scale immigration expansion policies affect this trade-off — a quantitative exercise that reduced-form approaches cannot perform.

Spatial wage inequality. This paper relates to the literature on city-size wage premia and the sorting of workers across cities (Glaeser and Mare, 2001; Baum-Snow and Pavan, 2012; Eeckhout, Pinheiro and Schmidheiny, 2014; Diamond, 2016; Baum-Snow, Freedman and Pavan, 2018; De La Roca and Puga, 2017). A growing body of work documents that large cities disproportionately reward cognitive-intensive skills and that workers sort into cities based on their comparative advantage (Papageorgiou, 2022; Eeckhout, Hedtrich and Pinheiro, 2026). I contribute to this literature by showing that immigrants — despite concentrating in large cities — sort into occupations across cities very differently from natives, and that this differential sorting is driven primarily by amenity valuations rather than human capital or labor market frictions. To the best of my knowledge, this is the first paper to document and quantify the role of occupational sorting across cities in generating heterogeneous city-size earnings premia across immigrant origin groups.

Misallocation of labor. Finally, this paper contributes to the literature on the misallocation of production factors (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Gopinath et al., 2017; Hsieh et al., 2019; Bryan and Morten, 2019; Guner and Ruggieri, 2022). The closest paper to mine is Birinci, Leibovici and See (2024), which quantifies large output gains from eliminating labor market barriers

faced by immigrants in the US labor market. My framework extends this analysis by introducing a spatial and origin-based dimension to these barriers: wedges vary across city–occupation pairs and countries of origin, so their removal generates reallocation both across occupations and across cities. Crucially, the counterfactual analysis reveals that removing local labor market wedges has a near-zero aggregate effect on the immigrant-native earnings gap — because the large and opposing effects for LIC and HIC immigrants cancel in the aggregate — while generating only modest changes in spatial earnings inequality. This stands in contrast to amenity valuations, which are the dominant driver of both immigrant spatial concentration and the worker-spatial inequality trade-off.

The rest of the paper is organized as follows. In section 2, I describe the sources of data and present the stylized facts about immigrants’ labor market outcomes across space. In section 3, I introduce the spatial equilibrium model. In section 4, I describe the estimation procedure. In section 5, I present the estimation results and the counterfactual exercises to quantify the determinants of the earnings gaps between immigrants and natives and the effects on real gdp per capita and prices of removing sources of inequality among workers. In section 6, I show and discuss the results of the policy exercise. In section 7, I summarise the findings and discuss ideas for future research.

2 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 (WDI, World Bank, 2025), and the Occupational Information Network (O*NET) Database.

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.⁵ 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 college/no-college category. The survey further reports labor market outcomes including annual earnings, employment status, number of weeks and hours worked, and occupation.⁶ 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

⁵For the definition of this variable and others, see Appendix A.

⁶Wages are top-coded. To address this, I follow the procedure in Albert, Glitz and Lull (2021).

individual resides, which I use to identify U.S. cities.⁷

World-Bank Development Indicators. I collect data on countries' GDP per capita from the World Bank Development Indicators, 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.⁸

Sample Selection. I construct the analysis sample by merging data from IPUMS, the World Bank Development Indicators, 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.⁹ 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.¹⁰ The earnings 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 700,000) and large (employment

⁷Measuring 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.

⁸More 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.

⁹Due 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.

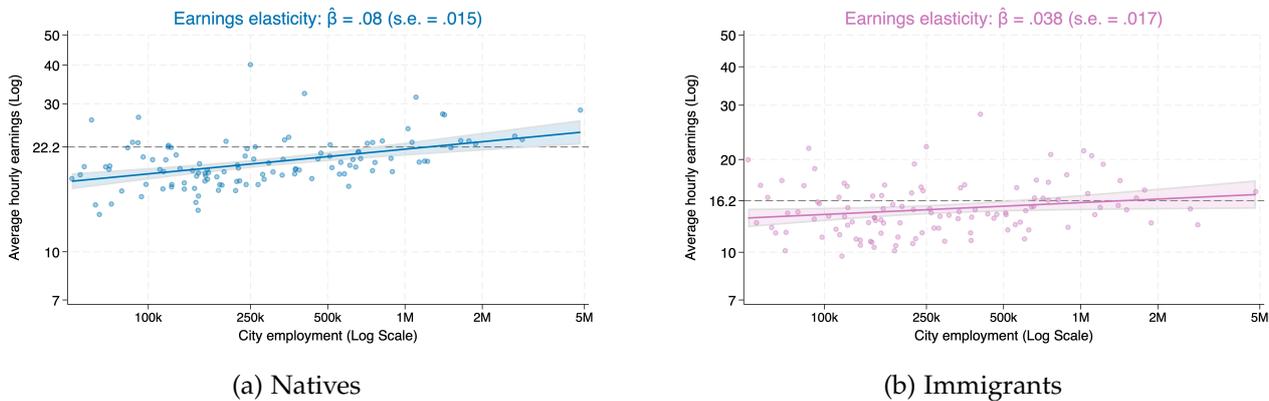
¹⁰See Appendix A for details on the selection of immigrants.

stock of 700,000 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 Table 10 and Table 9 in Appendix A.

2.1 Empirical Evidence

Fact 1: The City-Size Earnings Premium 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. 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 population 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.¹¹

Figure 1: Cities hourly earnings premia



Source: ACS, World Bank Development Database, and author’s calculations. 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.

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, 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.

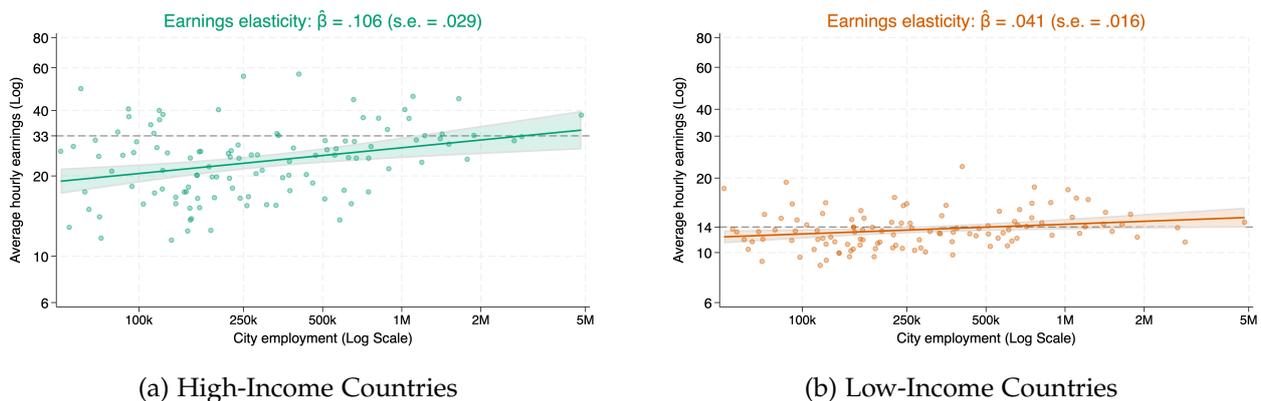
Taken together, these patterns imply that the earnings gap between native and immigrant workers widens as city size increases.¹²

¹¹The derivation for the earnings change associated with a given change in city size can be found in Appendix E.

¹²Appendix B.1 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.

Fact 2: The City-Size Earnings Premium among Immigrants Varies by Country of Origin. Does the city-size earnings premium 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. 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 receive a city-size earnings premium, but the premium 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 7.3 percent increase in the average hourly earnings of an HIC immigrant, compared to a 2.8 percent increase for a LIC immigrant. Hence, while all immigrants benefit from locating in larger cities, the gains are more than twice as large for immigrants from high-income countries.

Figure 2: Cities hourly earnings premia



Source: ACS, World Bank Development Database, and author's calculations. 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.

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. ≥ 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

Source: ACS, World Bank Development Indicators Database, and author’s calculations. 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 ≥ 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 ≥ 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.

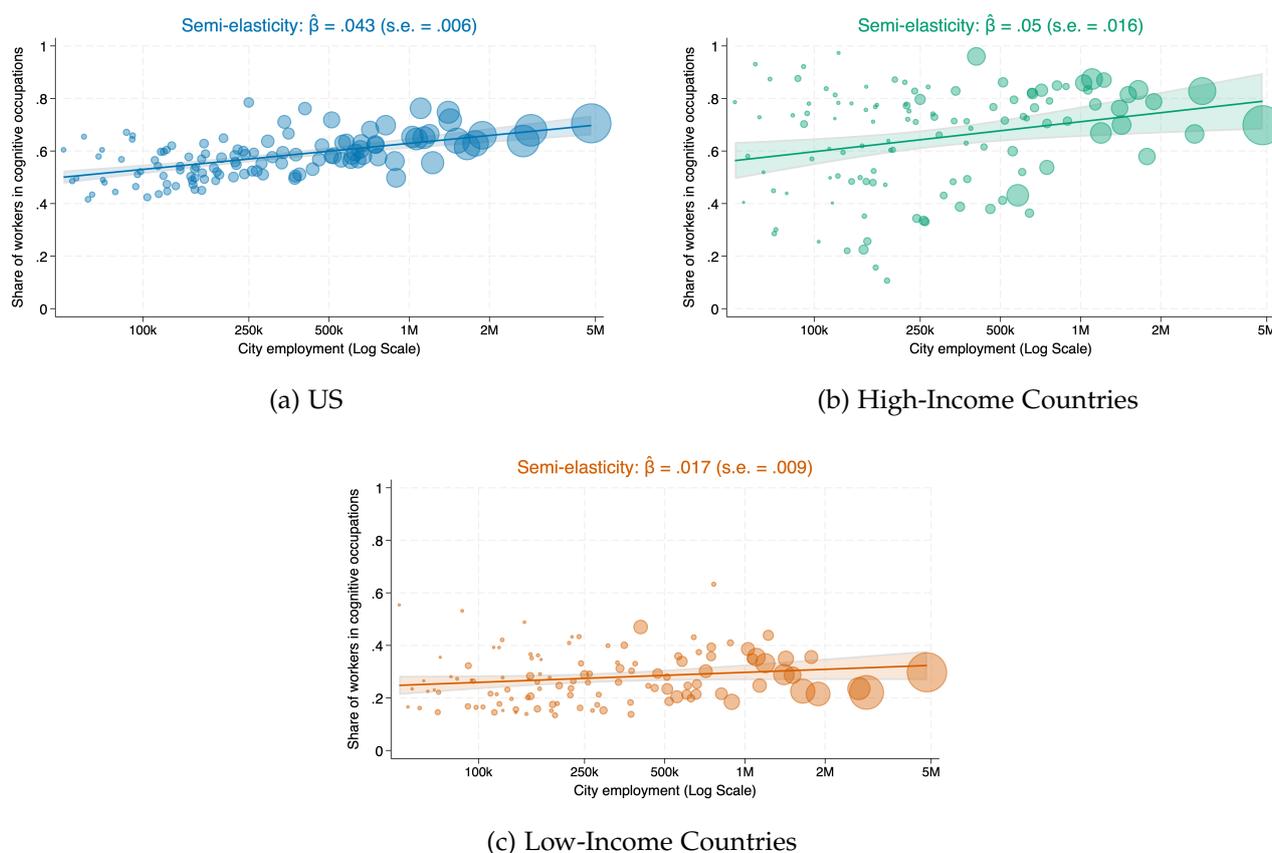
All things considered, Fact 2 suggests the existence of spatial differences in earnings not only between natives and immigrants but also among immigrants.

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, HIC immigrants, and LIC immigrants. 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 (Panels a and b), 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%.

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 13.8 percentage points, nearly twice the increase observed for natives (7.3 percentage points).

Figure 3: Sorting into Cognitive Occupations across Cities



Source: ACS, World Bank Development Database, and author's calculation. 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, immigrants from low-income countries (GDP pc < \$40,000, Panel a) and immigrants from high-income countries (GDP pc \geq \$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 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.

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. Notably, 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

Source: ACS, World Bank Development Database, and author’s calculation. 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.

Summary. In this section I documented three stylized facts about workers’ earnings and occupational sorting across cities: (i) the city-size earnings premium is larger for natives than immigrants; (ii) among immigrants, the city-size earnings is largest for HIC immigrants, and smallest for LIC immigrants; (iii) natives and HIC immigrants are significantly more likely to work in cognitive occupations, while the occupational composition of LIC immigrants remains unchanged, despite them being the most spatially concentrated in big 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 D 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 session, I build a general equilibrium spatial model that accounts for workers’ heterogeneity in human capital and tastes to understand the determinants of these patterns in the data.

3 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 and countries of origin.

3.1 Model Setup

Environment. Consider a static economy with $j \in \{1, \dots, J\}$ 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.¹³ 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. A competitive housing market operates in each city; land T_j is owned by absentee landlords who repatriate all rental income, so it does not accrue to workers.¹⁴

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:

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

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 2.¹⁵

¹³Treating $\{\phi_g\}$ 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.

¹⁴The absentee-landlord assumption is standard in quantitative spatial models (see, e.g., ?). It implies that housing expenditure represents a pure cost to workers rather than a transfer within the economy.

¹⁵This 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.

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 :

$$U_{jo}^i(g) = c^{1-\alpha} h^\alpha \exp\{z_{jo}(g) + \varepsilon_{jo}^i\} \quad (2)$$

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_{jo}^i 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.¹⁶¹⁷ 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_{jo}^i , which generates within-group heterogeneity in location–occupation choices.

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

$$c + p_j h \leq w_{jo}(g) \quad (3)$$

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

$$V_{jo}^i(g) = \gamma p_j^{-\alpha} w_{jo}(g) \exp\{z_{jo}(g) + \varepsilon_{jo}^i\} \quad (4)$$

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

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

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.

¹⁶The 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. 12).

¹⁷The 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.

so that $V_{jo}^i(g) = \Omega_{jo}(g) \exp\{\varepsilon_{jo}^i\}$.

Earnings and 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:

$$w_{jo}(g) = r_{jo} s_o(g) (1 + \tau_{jo}(k)) \quad (6)$$

where r_{jo} is the competitive wage per efficiency unit — common to all workers in city j and occupation o — and $(1 + \tau_{jo}(k))$ 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:

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

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. This specification implies a city-specific housing supply elasticity ζ_j , consistent with the well-documented heterogeneity in supply responsiveness across U.S. metropolitan areas (?).

3.2 Model Solution and Spatial Equilibrium

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

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

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

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

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

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

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

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_{jo}^i , the share of group g workers at city–occupation pair jo takes the multinomial-logit form:

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

where, substituting (6) into (5):

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

The denominator of (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 (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:

$$\bar{w}_j \equiv \frac{\sum_o \sum_g \pi_{jo}(g) \phi_g w_{jo}(g)}{\sum_o \sum_g \pi_{jo}(g) \phi_g} \quad (14)$$

where $w_{jo}(g) = r_{jo} s_o(g) (1 + \tau_{jo}(k))$ as in (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:

$$p_j = \left(\frac{\alpha \bar{w}_j}{T_j} \right)^{\frac{1}{1+\zeta_j}} \quad (15)$$

where ζ_j is the city-specific housing supply elasticity and \bar{w}_j is defined in (14). 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:

$$L_{jn} = \sum_g \pi_{jn}(g) s_n(g) \phi_g \quad (16)$$

$$L_{jc} = \sum_g \pi_{jc}(g) s_c(g) \phi_g \quad (17)$$

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:

$$\pi_{jo}^*(g) = \frac{\Omega_{jo}^*(g)}{\sum_{j'} \sum_{o'} \Omega_{j'o'}^*(g)}, \quad \Omega_{jo}^*(g) = \gamma p_j^{*-\alpha} r_{jo}^* s_o(g) (1 + \tau_{jo}(k)) \exp\{z_{jo}(g)\} \quad (18)$$

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

$$L_{jn}^* = \sum_g \pi_{jn}^*(g) s_n(g) \phi_g \quad (19)$$

$$L_{jc}^* = \sum_g \pi_{jc}^*(g) s_c(g) \phi_g \quad (20)$$

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

$$r_{jn}^* = \left[(L_{jn}^*)^{\frac{\sigma-1}{\sigma}} + (\theta_j L_{jc}^*)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} (L_{jn}^*)^{-\frac{1}{\sigma}} \quad (21)$$

$$r_{jc}^* = \left[(L_{jn}^*)^{\frac{\sigma-1}{\sigma}} + (\theta_j L_{jc}^*)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}} (L_{jc}^*)^{-\frac{1}{\sigma}} \theta_j^{1-\frac{1}{\sigma}} \quad (22)$$

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

$$p_j^* = \left(\frac{\alpha}{T_j} \cdot \frac{\sum_o \sum_g \pi_{jo}^*(g) \phi_g r_{jo}^* s_o(g) (1 + \tau_{jo}(k))}{\sum_o \sum_g \pi_{jo}^*(g) \phi_g} \right)^{\frac{1}{1+\zeta_j}} \quad (23)$$

4 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.

4.1 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 2. 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 $k \in \{\text{US, LIC, HIC}\}$, educational attainment $e \in \{\text{no college, college}\}$, and potential labor-market experience $x \in \{0\text{--}14, 15\text{--}29, 30+\}$. Under this discretization, 18 groups of workers choose among 4 city–occupation alternatives: (S, n) , (S, c) , (B, n) , and (B, c) .

I impose two identifying normalizations. 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:

$$z_{Sn}(g) = 0 \quad \text{for } g = (k, \text{no college}, 0\text{--}14), \quad \forall k. \quad (24)$$

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 labor-market distortion:

$$\tau_{jo}(k_{\text{US}}) = 0 \quad \forall j, o. \quad (25)$$

Under this assumption, the estimated wedges $\tau_{jo}(k)$ for $k \in \{\text{LIC, HIC}\}$ 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.

Table 3 summarizes the two normalizations.

Table 3: Normalizations and identifying assumptions

Description	Parameter	Determination	Value
Mean log-amenity: small city, non-cognitive occupation, no college, 0–14 experience (each origin k)	$z_{sn}(k, \text{no college, 0–14})$	Normalization	0
Earnings wedge for native workers	$\tau_{jo}(k_{US})$	Assumption	0

4.2 Externally Calibrated Parameters

Overall, the model features 106 structural parameters, 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 100 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 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

Table 4: Externally calibrated parameters

Description	Symbol	Value	Source
	(1)	(2)	(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

4.3 Internally Estimated Parameters

The remaining 100 structural parameters govern the allocation of workers across cities and occupations. They can be organized into four groups: (i) the city-specific cognitive productivity bias θ_j ; (ii) occupation-specific human capital $s_o(g)$; (iii) city–occupation–origin earnings wedges $\tau_{jo}(k)$; and (iv) city–occupation amenities $z_{jo}(g)$. I estimate all four groups jointly using the SMM.¹⁹ Each

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

¹⁹See [McFadden \(1989\)](#).

group of parameters is identified by a distinct 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 ($\tau_{jo}(k_{US}) = 0$), 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 (10) — identifies θ_j .

Table 5 reports the estimated values.

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 (1).

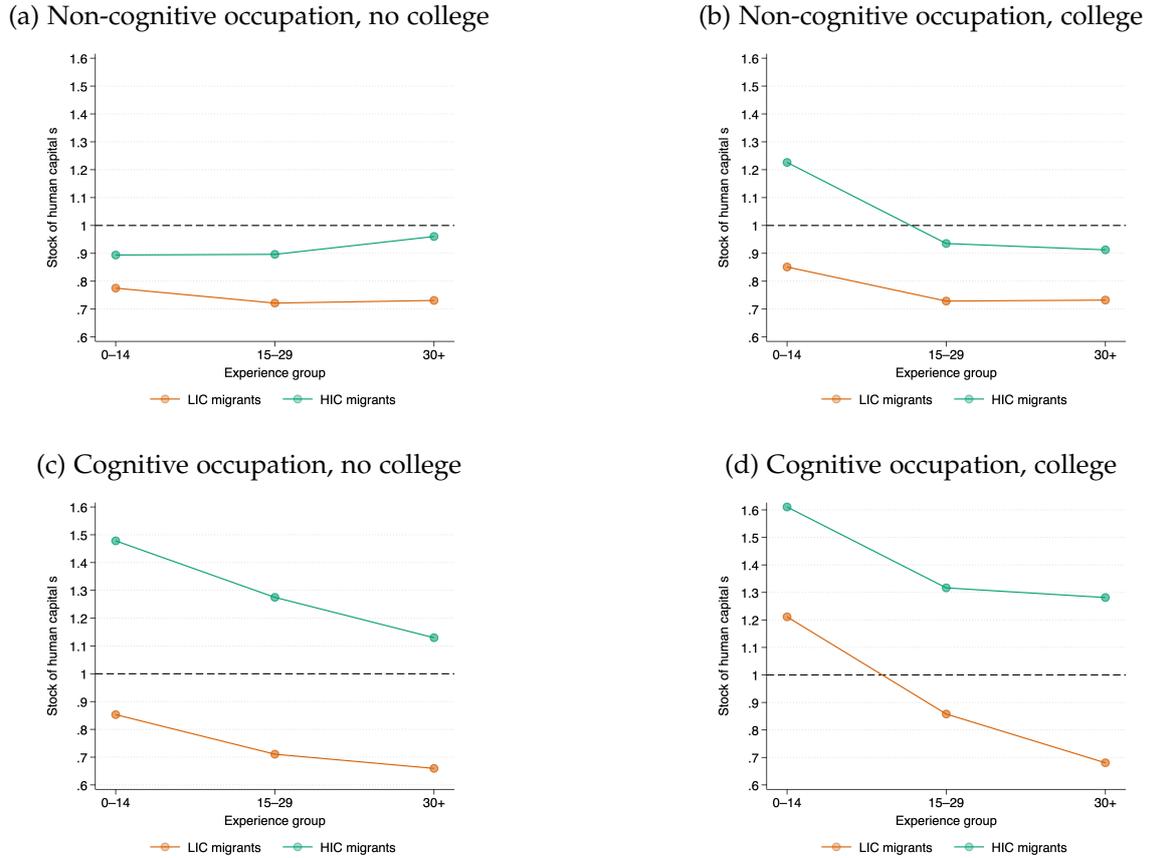
Both cities exhibit a productivity bias toward cognitive occupations, and the bias is larger in the big city ($\theta_B = 3.07$) than in the small city ($\theta_S = 2.51$), an increase of approximately 22 percent. This finding is consistent with [Eckhout, Hedtrich and Pinheiro \(2026\)](#), who show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

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 targeting 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, $s_o(k, e, x)/s_o(US, e, x)$ —, 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. $s_o(k, e, x)/s_o(\text{US}, e, x)$. 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 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 (6) over education and experience groups within origin k , and using assumption (25) to substitute $r_{jo} = \bar{w}_{jo}(\text{US}) / \bar{s}_o(\text{US})$, yields:

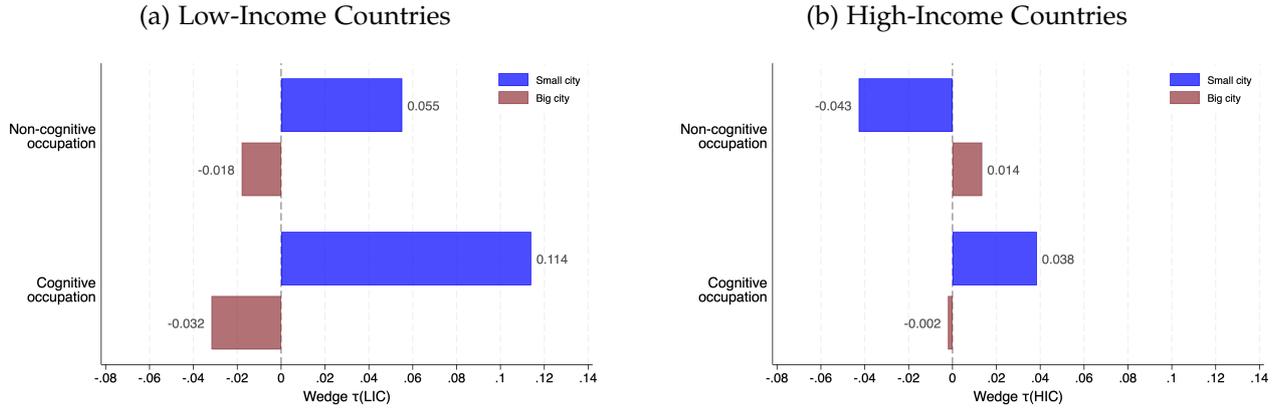
$$1 + \tau_{jo}(k) = \frac{\bar{w}_{jo}(k)}{\bar{w}_{jo}(\text{US})} \cdot \frac{\bar{s}_o(\text{US})}{\bar{s}_o(k)} \quad (26)$$

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 5 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. 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.

²⁰By 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 (26) fully absorbs productivity differences between immigrants and natives, so the wedge captures only the residual earnings gap.

Figure 5: Estimated earnings wedges $\tau_{jo}(k)$



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 .

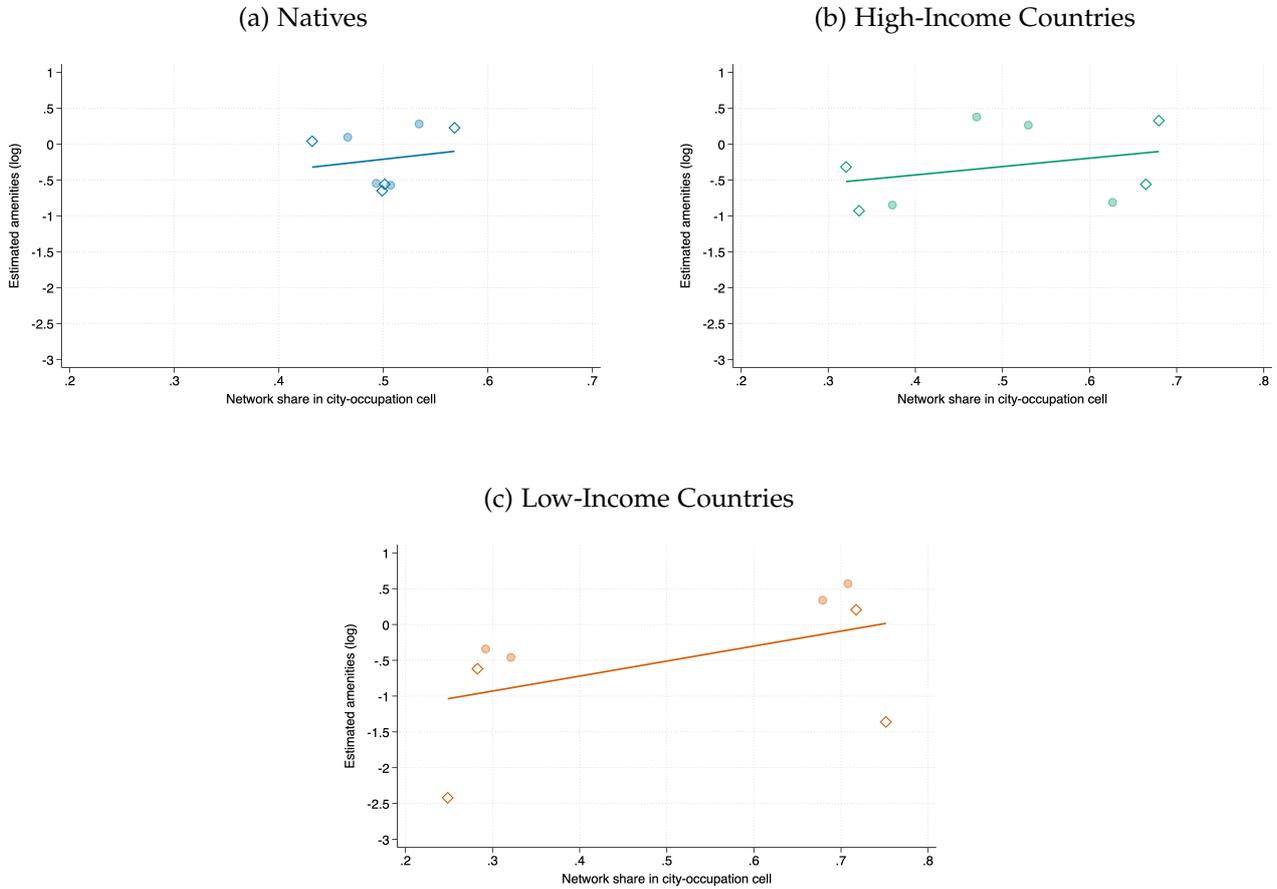
The pattern for HIC immigrants (Panel b) is qualitatively and quantitatively different. In non-cognitive occupations, HIC immigrants earn below the competitive benchmark in the small city ($\tau_{Sn} = -0.043$) but above it in the big city ($\tau_{Bn} = 0.014$), so their relative earnings position improves 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 2.

Identification and Estimates of City–Occupation Amenities. The remaining 23 preference for amenity parameters per origin group — after imposing the normalization (24) — 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 6 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 6: Estimated amenities and city–occupation networks



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 6 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).

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 the Appendix.

5 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. Figure 7 shows how the gap in city-size earnings premia between immigrants and natives changes across counterfactuals. For each origin group k , I first compute average earnings in city j as:

$$\bar{w}_{k,j} = \frac{\sum_o \sum_{g:k(g)=k} \pi_{j,o}(g) \phi_g w_{j,o}(g)}{\sum_o \sum_{g:k(g)=k} \pi_{j,o}(g) \phi_g} \quad (27)$$

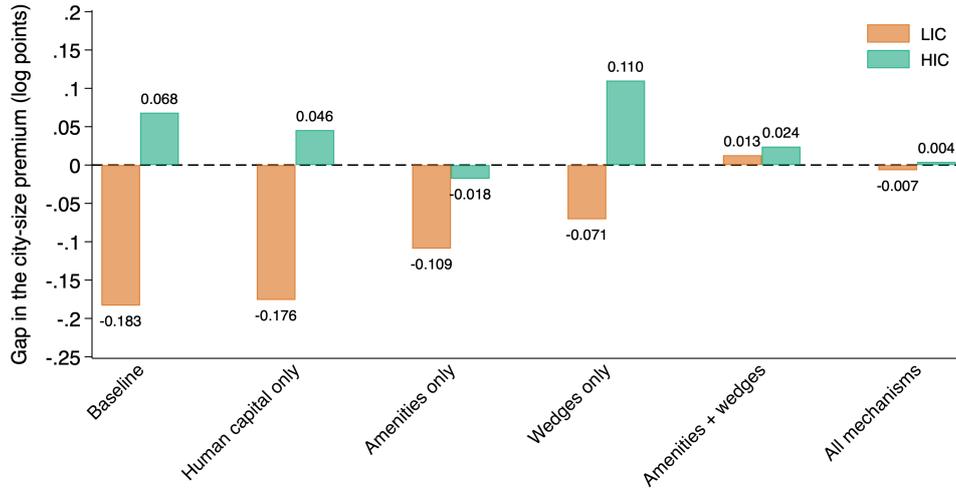
where $w_{j,o}(g) = r_{j,o} s_o(g) (1 + \tau_{j,o}(k))$ as in equation (6), and the denominator is the total workforce share of group k in city j . I then define the city-size earnings premium for origin group k as:

$$\bar{w}_k^{\text{Premium}} = \ln \bar{w}_{k,\text{Big}} - \ln \bar{w}_{k,\text{Small}} \quad (28)$$

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

$$\bar{w}_k^{\Delta \text{Premium}} = \bar{w}_k^{\text{Premium}} - \bar{w}_{\text{US}}^{\text{Premium}} \quad (29)$$

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



Notes: The figure shows $\bar{w}_k^{\Delta \text{Premium}}$, 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.

In the baseline economy, $\bar{w}_k^{\Delta \text{Premium}}$ 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.

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 narrow to -0.013 log points for LIC and +0.024 log points for HIC, confirming that these two channels together account for the overwhelming 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 mechanisms that

are fundamentally different 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.

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	
$\tau_{jo}(k) = 0$	-	-	-	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

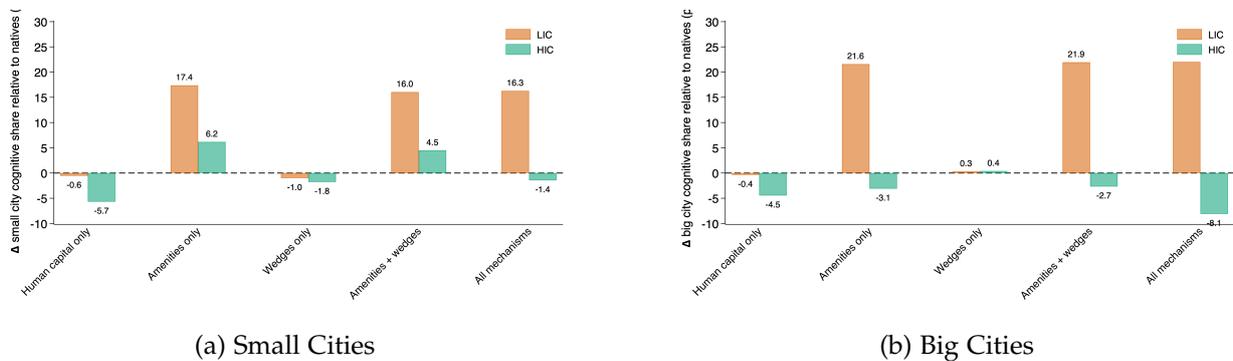
Notes: The table reports the baseline share of each group residing in the big city (first column, expressed as a percentage) and the change in that share under each counterfactual scenario (Columns 1 to 5, expressed in percentage points). g' denotes a native worker with the same education e and experience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

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.

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 sharply 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



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:

$$\bar{w}_{\text{Workers}}^{\text{Gap}} = \ln \bar{w}_{\text{US}} - \ln \bar{w}_{\text{Imm}} = \ln \frac{\sum_j \sum_o \sum_{g:k(g)=\text{US}} \pi_{j,o}(g) \phi_g w_{j,o}(g)}{\sum_j \sum_o \sum_{g:k(g)=\text{US}} \pi_{j,o}(g) \phi_g} - \ln \frac{\sum_j \sum_o \sum_{g:k(g) \neq \text{US}} \pi_{j,o}(g) \phi_g w_{j,o}(g)}{\sum_j \sum_o \sum_{g:k(g) \neq \text{US}} \pi_{j,o}(g) \phi_g} \quad (30)$$

and spatial earnings inequality as:

$$\bar{w}_{\text{Cities}}^{\text{Gap}} = \ln \bar{w}_{\text{Big}} - \ln \bar{w}_{\text{Small}} = \ln \frac{\sum_o \sum_g \pi_{\text{Big},o}(g) \phi_g w_{\text{Big},o}(g)}{\sum_o \sum_g \pi_{\text{Big},o}(g) \phi_g} - \ln \frac{\sum_o \sum_g \pi_{\text{Small},o}(g) \phi_g w_{\text{Small},o}(g)}{\sum_o \sum_g \pi_{\text{Small},o}(g) \phi_g} \quad (31)$$

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

²¹The near-zero aggregate effect of wedges reflects the fact that $\tau_{j,o}(k)$ enters earnings multiplicatively and its variation across city-occupation pairs is empirically small relative to the variation in $z_{j,o}(g)$, so wedge removal generates limited

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 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.

reallocation across the joint choice set and its direct effect on earnings levels is largely offset by general equilibrium adjustments in rental rates r_{j0} .

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

	Baseline		Counterfactuals			Full
		Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities & No Wedges	
	(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						
$\ln \bar{w}_{Imm} - \ln \bar{w}_{US}$	-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						
$\ln \bar{w}_{Big} - \ln \bar{w}_{Small}$	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 ($\ln \bar{w}_{Imm} - \ln \bar{w}_{US}$) and between the big and small city ($\ln \bar{w}_{Big} - \ln \bar{w}_{Small}$) 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 .

6 Immigration Policy and the Worker-Spatial Inequality Trade-Off

The counterfactual analysis in Section 5 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:

$$\mathcal{T} = \frac{\Delta(\ln \bar{w}_{Big} - \ln \bar{w}_{Small})}{\Delta(\ln \bar{w}_{Imm} - \ln \bar{w}_{US})} \quad (32)$$

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-

²²Both 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 (1)	Non-College Expansion (2)	
<i>Panel A: Aggregate Earnings Gaps</i>				
$\ln \bar{w}_{Imm} - \ln \bar{w}_{US}$	-0.317	-0.263	-0.340	—
Δ from baseline	—	0.054	-0.023	—
% of baseline gap closed	—	17.1%	-7.3%	—
$\ln \bar{w}_{Big} - \ln \bar{w}_{Small}$	0.163	0.163	0.160	—
Δ from baseline	—	0.000	-0.003	—
% of baseline gap closed	—	-0.2%	1.9%	—
<i>Trade-off rate (\mathcal{T})</i>	—	0.005	0.134	0.171
<i>Panel B: City-Size Earnings Premium Gaps</i>				
$\bar{w}_{Imm}^{\Delta Premium}$	-0.174	-0.173	-0.175	—
Δ from baseline	—	0.001	-0.001	—
$\bar{w}_{LIC}^{\Delta Premium}$	-0.183	-0.185	-0.184	—
Δ from baseline	—	-0.002	-0.000	—
$\bar{w}_{HIC}^{\Delta Premium}$	0.068	0.057	0.073	—
Δ from baseline	—	-0.011	0.005	—
<i>Panel C: Sorting Outcomes</i>				
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, the sample used throughout the analysis. 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 (32) 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.

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

$$\underbrace{0.005}_{\text{College}} < \underbrace{0.134}_{\text{Non-college}} < \underbrace{0.171}_{\text{Structural}} \quad (33)$$

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 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.

7 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 its size. 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. For the former, I provide evidence in line with the literature suggesting that amenity valuations may partly capture the existence of local occupational networks—a mechanism that shapes where immigrants locate and what occupations they enter. For the latter, direct measures of local labor market distortions remain limited. Measuring these distortions and networks carefully is an important direction for future research, as it would clarify how location-specific factors interact with immigrant economic assimilation and with non-competitive structures in local labor markets, including monopsony.

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Appendices

A Data Appendix

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 occupation²³:

- 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.

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.

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

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.

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 (25.3)	14.1 (2.3)	18.8 (9.3)	– –	1,248,634
Immigrant	11.8 (18.3)	11.2 (3.8)	26.2 (7.6)	12.7 (7.7)	132,349
LIC	11.0 (16.7)	10.9 (3.8)	26.4 (7.6)	12.9 (7.6)	117,950
HIC	18.7 (28.4)	13.8 (3.1)	24.2 (7.6)	10.7 (7.6)	14,399

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 (32.7)	13.9 (2.4)	19.0 (9.1)	– (–)	1,509,139
Immigrant	16.2 (28.1)	11.0 (4.1)	25.1 (7.9)	12.2 (8.0)	180,915
LIC	14.2 (24.4)	10.6 (4.0)	25.4 (7.9)	12.6 (7.9)	157,722
HIC	32.8 (46.1)	14.4 (3.4)	22.9 (7.4)	9.0 (7.2)	23,193

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

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

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

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

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

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)
Micronesia	10.0 (9.2)	11.4 (2.3)	22.5 (7.6)	8.8 (5.9)	207
El Salvador	10.0 (12.8)	8.4 (3.2)	26.7 (8.2)	14.4 (8.1)	15,282
Guinea	9.9 (5.9)	11.0 (3.7)	25.6 (7.1)	10.9 (6.0)	148
Guatemala	9.8 (13.7)	7.9 (3.2)	25.1 (8.1)	12.4 (7.6)	9,395
Honduras	9.7 (14.5)	8.6 (3.0)	24.5 (7.6)	11.7 (7.0)	6,400
Somalia	9.4 (7.7)	9.7 (3.8)	24.6 (8.3)	10.4 (6.5)	600

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

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

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

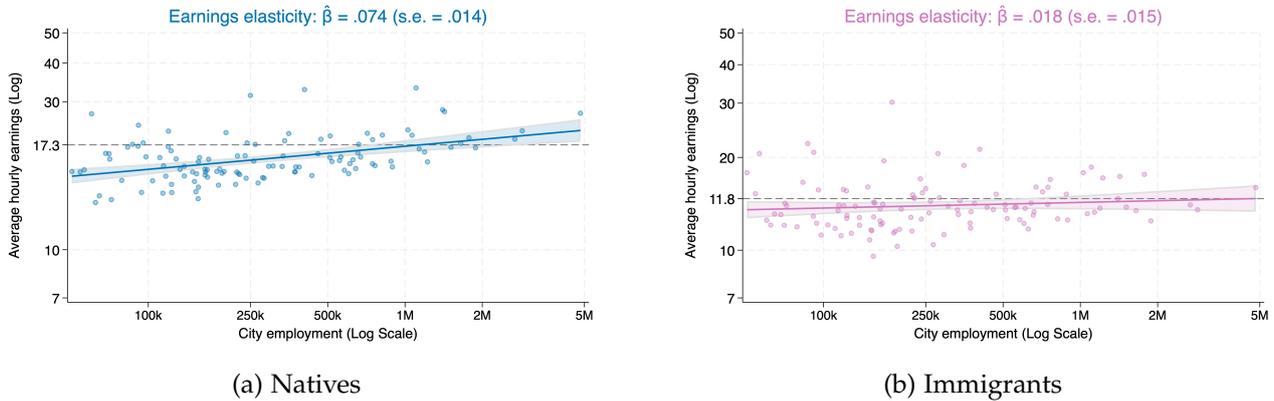
Occupation (SOC 3-dig)	Avg. Hourly Earnings	Share Of Immigrant Workers (%)	Number of Workers
Plant and System Operators	21.8	5.5	569,868
Water Transportation Workers	21.4	4.4	152,691
Rail Transportation Workers	19.9	1.7	316,887
Other Construction and Related Workers	18.5	14.5	548,716
Extraction Workers	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 Figures

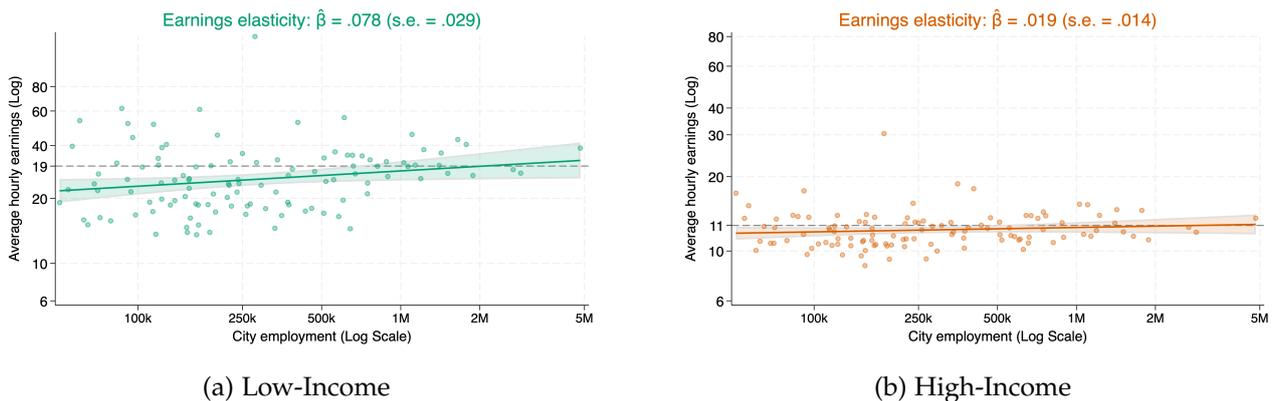
B.1 Robustness checks: female workers

Figure 9: Fact 1 for female workers



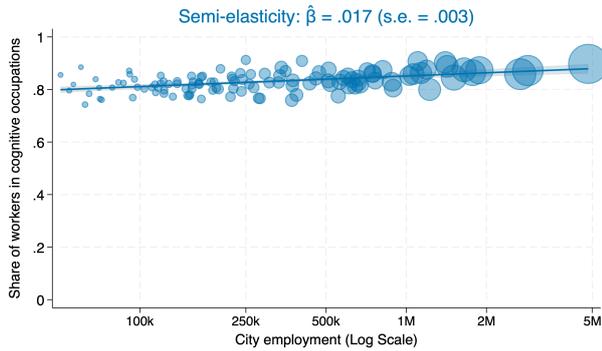
Source: ACS, World Bank Development Database, and author's calculations. Notes: This figure shows the relationship between the natural logarithm of average hourly earnings of female workers aged 25–54 in each Metropolitan Statistical Area (MSA) and the natural logarithm of the employment stock of that 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.

Figure 10: Fact 2 female workers

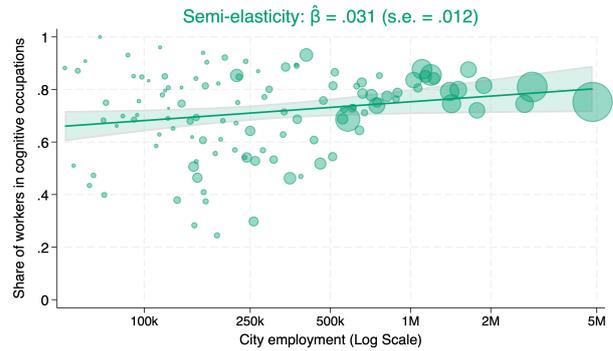


Source: ACS, World Bank Development Indicators Database, and author's calculations. Notes: This table reports average hourly earnings (USD/hour) in the average small city (city employment stock < 750,000) and average big city (city employment stock \geq 750,000), as well as the city-size earnings gap (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.

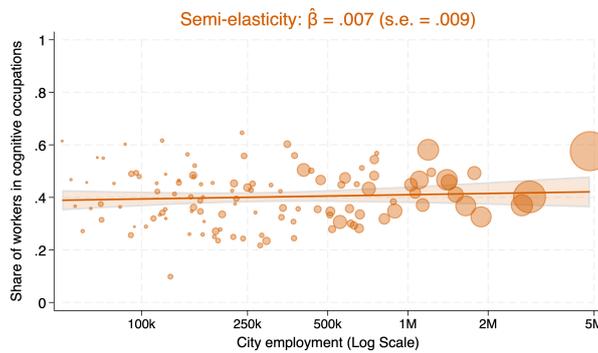
Figure 11: Fact 3 female workers



(a) US



(b) High-Income Countries



(c) Low-Income Countries

Source: ACS, World Bank Development Database, and author's calculation. 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.

C Tables

C.1 Robustness Checks Fact 1: Regressions

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

	Log Hourly Earnings				
	(1)	(2)	(3)	(4)	(5)
Panel A: Immigrants vs. Natives					
Log City Employment	0.085 (0.012)	0.085 (0.012)	0.063 (0.011)	0.068 (0.011)	0.058 (0.010)
Imm#Log City Employment	-0.098 (0.014)	-0.098 (0.014)	-0.066 (0.009)	-0.071 (0.010)	-0.065 (0.009)
Immigrants	0.979 (0.203)	0.975 (0.202)	0.635 (0.13)	0.888 (0.146)	0.841 (0.140)
Constant	1.645 (0.154)	1.645 (0.154)	1.629 (0.142)	1.324 (0.144)	1.324 (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 (0.012)	0.085 (0.012)	0.063 (0.011)	0.068 (0.011)	0.058 (0.01)
LIC#Log City Employment	-0.100 (0.013)	-0.100 (0.013)	-0.071 (0.01)	-0.076 (0.011)	-0.070 (0.01)
HIC#Log City Employment	0.020 (0.033)	0.020 (0.033)	0.013 (0.022)	0.009 (0.022)	-0.003 (0.019)
LIC	0.938 (0.181)	0.934 (0.180)	0.687 (0.140)	0.955 (0.153)	0.921 (0.152)
HIC	-0.023 (0.489)	-0.028 (0.489)	-0.170 (0.312)	-0.027 (0.315)	-0.004 (0.270)
Constant	1.645 (0.154)	1.645 (0.154)	1.629 (0.142)	1.324 (0.144)	1.324 (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					✓

Source: ACS 2010-2019, World Bank Development Database, and author's calculation. 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.

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 (0.004)	0.044 (0.004)	0.026 (0.003)	0.026 (0.003)
Imm#Log City Employment	-0.044 (0.009)	-0.044 (0.009)	-0.018 (0.004)	-0.017 (0.004)
Immigrants	0.296 (0.122)	0.294 (0.122)	0.042 (0.057)	0.102 (0.055)
Constant	0.018 (0.055)	0.018 (0.055)	0.004 (0.041)	0.000 (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 (0.004)	0.044 (0.004)	0.026 (0.003)	0.026 (0.003)
LIC#Log City Employment	-0.042 (0.008)	-0.042 (0.008)	-0.017 (0.004)	-0.017 (0.004)
HIC#Log City Employment	0.003 (0.022)	0.003 (0.022)	0.005 (0.012)	0.006 (0.011)
LIC	0.226 (0.115)	0.225 (0.115)	0.022 (0.057)	0.087 (0.057)
HIC	0.025 (0.306)	0.023 (0.306)	-0.054 (0.155)	-0.034 (0.160)
Constant	0.018 (0.055)	0.018 (0.055)	0.004 (0.041)	0.000 (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				✓

Source: ACS 2010-2019, World Bank Development Database, and author's calculation. 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.

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

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Panel A: Immigrants vs. Natives					
Log City Employment	0.087 (0.011)	0.087 (0.011)	0.071 (0.01)	0.075 (0.01)	0.069 (0.009)
Imm#Log City Employment	-0.074 (0.010)	-0.074 (0.010)	-0.056 (0.008)	-0.059 (0.008)	-0.065 (0.008)
Immigrants	0.592 (0.133)	0.586 (0.132)	0.498 (0.104)	0.666 (0.114)	0.89 (0.124)
Constant	1.397 (0.145)	1.397 (0.146)	1.299 (0.131)	1.121 (0.135)	0.939 (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 (0.011)	0.087 (0.011)	0.071 (0.010)	0.075 (0.010)	0.069 (0.009)
LIC#Log City Employment	-0.077 (0.01)	-0.076 (0.01)	-0.060 (0.008)	-0.063 (0.008)	-0.069 (0.009)
HIC#Log City Employment	0.016 (0.017)	0.017 (0.017)	0.016 (0.015)	0.014 (0.015)	0.004 (0.015)
LIC	0.585 (0.134)	0.580 (0.133)	0.539 (0.107)	0.697 (0.116)	0.941 (0.129)
HIC	-0.269 (0.253)	-0.283 (0.254)	-0.276 (0.214)	-0.130 (0.233)	-0.024 (0.222)
Constant	1.397 (0.145)	1.397 (0.146)	1.299 (0.131)	1.121 (0.135)	0.939 (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					✓

Source: ACS 2010-2019, World Bank Development Database, and author's calculation. 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.

Table 19: Regressions for fact 3: female 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	0.022 (0.002)	0.022 (0.002)	0.015 (0.002)	0.016 (0.002)
Imm#Log City Employment	0.013 (0.017)	0.013 (0.017)	0.021 (0.016)	0.021 (0.015)
Immigrants	-0.568 (0.224)	-0.567 (0.224)	-0.688 (0.199)	-0.626 (0.201)
Constant	0.552 (0.031)	0.552 (0.031)	0.513 (0.027)	0.494 (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 (0.002)	0.022 (0.002)	0.015 (0.002)	0.016 (0.002)
LIC#Log City Employment	0.018 (0.019)	0.018 (0.019)	0.025 (0.017)	0.025 (0.017)
HIC#Log City Employment	0.019 (0.016)	0.019 (0.016)	0.016 (0.012)	0.016 (0.012)
LIC	-0.677 (0.248)	-0.676 (0.249)	-0.766 (0.224)	-0.708 (0.227)
HIC	-0.365 (0.216)	-0.365 (0.216)	-0.375 (0.161)	-0.336 (0.168)
Constant	0.552 (0.031)	0.552 (0.031)	0.513 (0.027)	0.494 (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				✓

Source: ACS 2010-2019, World Bank Development Database, and author's calculation. 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.

D 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 to pay a positive rent and live in a unit rent with either two or three rooms.

D.1 Robustness Checks Fact 1: Regressions with Earnings Deflated by Living Cost

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 (0.010)	0.034 (0.010)	0.013 (0.009)	0.018 (0.008)	0.008 (0.008)
Imm#Log City Employment	-0.096 (0.011)	-0.095 (0.011)	-0.064 (0.007)	-0.069 (0.007)	-0.063 (0.007)
Immigrants	0.926 (0.158)	0.905 (0.155)	0.571 (0.092)	0.829 (0.108)	0.783 (0.110)
Constant	2.608 (0.124)	2.609 (0.126)	2.594 (0.118)	2.283 (0.102)	2.283 (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 (0.01)	0.034 (0.01)	0.013 (0.009)	0.018 (0.008)	0.008 (0.008)
LIC#Log City Employment	-0.099 (0.011)	-0.097 (0.011)	-0.069 (0.008)	-0.074 (0.009)	-0.068 (0.009)
HIC#Log City Employment	0.022 (0.029)	0.024 (0.029)	0.017 (0.017)	0.013 (0.017)	0.001 (0.016)
LIC	0.888 (0.150)	0.869 (0.147)	0.625 (0.118)	0.900 (0.130)	0.867 (0.134)
HIC	-0.088 (0.425)	-0.115 (0.425)	-0.254 (0.254)	-0.111 (0.254)	-0.088 (0.216)
Constant	2.608 (0.124)	2.609 (0.126)	2.594 (0.118)	2.283 (0.102)	2.283 (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					✓

Source: ACS 2010-2019, World Bank Development Database, and author's calculation. 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.

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

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)
Panel A: Immigrants vs. Natives					
Log City Employment	0.036 (0.006)	0.036 (0.006)	0.020 (0.006)	0.024 (0.005)	0.018 (0.005)
Imm#Log City Employment	-0.072 (0.008)	-0.07 (0.008)	-0.053 (0.006)	-0.057 (0.007)	-0.062 (0.007)
Immigrants	0.530 (0.109)	0.510 (0.106)	0.422 (0.083)	0.596 (0.09)	0.815 (0.096)
Constant	2.371 (0.079)	2.372 (0.081)	2.275 (0.073)	2.092 (0.063)	1.913 (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 (0.006)	0.036 (0.006)	0.02 (0.006)	0.024 (0.005)	0.018 (0.005)
LIC#Log City Employment	-0.074 (0.008)	-0.073 (0.008)	-0.057 (0.007)	-0.06 (0.007)	-0.066 (0.008)
HIC#Log City Employment	0.014 (0.015)	0.017 (0.015)	0.016 (0.014)	0.014 (0.014)	0.004 (0.015)
LIC	0.516 (0.112)	0.499 (0.109)	0.458 (0.088)	0.623 (0.094)	0.86 (0.105)
HIC	-0.275 (0.216)	-0.318 (0.219)	-0.312 (0.194)	-0.167 (0.207)	-0.064 (0.212)
Constant	2.371 (0.079)	2.372 (0.081)	2.275 (0.073)	2.092 (0.063)	1.913 (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					✓

Source: ACS 2010-2019, World Bank Development Database, and author's calculation. 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.

E Derivation of the Change in Hourly Earnings

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 $k \in \{\text{Native, Immigrants}\}$ is:

$$\ln(\bar{w}_j^k) = \alpha + \beta \ln(\text{Population}_j) + \nu_j \quad (34)$$

Take two cities j, j' such that

$$\text{Population}_j = \bar{q} \text{Population}_{j'} \quad (35)$$

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

$$\ln(\bar{w}_j^k) - \ln(\bar{w}_{j'}^k) = \beta \left[\ln(\bar{q} \text{Population}_{j'}) - \ln(\text{Population}_{j'}) \right] \quad (36)$$

$$\ln \left(\frac{\bar{w}_j^k}{\bar{w}_{j'}^k} \right) = \beta \left[\ln \bar{q} + \ln \left(\frac{\text{Population}_{j'}}{\text{Population}_{j'}} \right) \right] \quad (37)$$

$$= \beta \ln \bar{q} \quad (38)$$

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

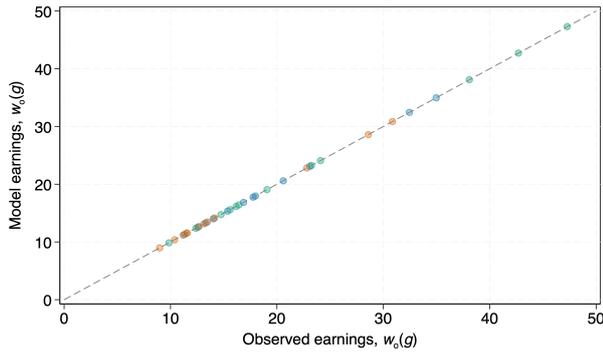
$$\frac{\bar{w}_j^k}{\bar{w}_{j'}^k} - 1 = \bar{q}^\beta - 1 \quad (39)$$

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

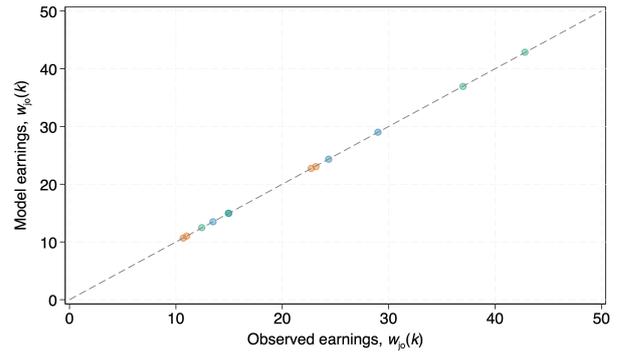
$$\Delta \bar{w} \% = (\bar{q}^\beta - 1) \times 100 \quad (40)$$

F Model fit

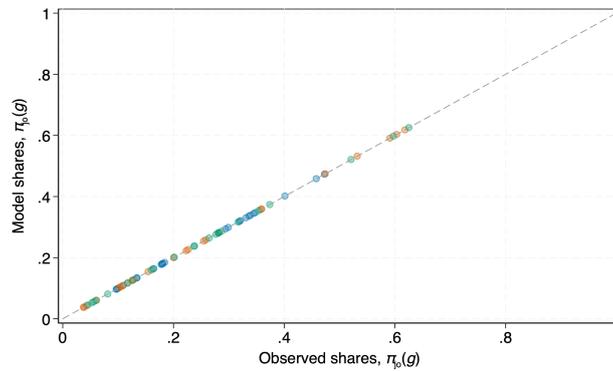
Figure 12 shows that model-generated moments closely match their empirical counterparts, lying near the 45-degree line.



(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).

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.

Table 23 shows the model fit for occupational sorting and spatial 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.