Skills, Distortions, and the Labor Market Outcomes of Immigrants across Space*

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Abstract

I study the geography of immigrants' labor market outcomes and its implications for spatial inequality. Using US micro-data, I document that, compared to natives and immigrants from high-income countries, immigrants from low-income countries i) do not earn a premium from working in big cities and ii) are more likely to work in non-cognitive occupations and live in big cities. To shed light on the mechanisms driving these facts, I build a quantitative general equilibrium spatial model where the technology of firms in cities favors cognitive skills, workers are heterogeneous in human capital and tastes for cities and occupations, and immigrants face labor market distortions. Removing all sources of heterogeneity between immigrants and natives reduces their earnings gap by 29 percent at the expense of an increase in the earnings gap between cities by 2.3 percent. An immigration policy opening borders to non-college-educated workers increases the earnings gap between immigrants and natives by 2.6 percent but reduces the earnings gap between cities by 0.3 percent.

Keywords: Immigrants, Human Capital, Inequality, Spatial Equilibrium

JEL Classification: J21, J31, J61, R13

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1 Introduction

Immigrants are vital to US productivity (Prato, 2022) but are paid, on average, 15% less than native workers (Amo-Agyei et al., 2020). Explanations for this disparity include differences in workers' human capital due to cross-country variations in schooling quality (Schoellman, 2012) and returns to experience before migration (Lagakos et al., 2018a). Second, different tasks specialization between immigrants and natives (Peri and Sparber, 2009). Furthermore, the existence of labor market barriers that prevent immigrants' from working in occupations where they would be more productive (Birinci et al., 2021). Underperforming in the labor market may bias natives' perceptions of immigration, leading to negative consequences for social cohesion and aggregate economic outcomes.

Among the studies on labor market disparities between immigrants and natives, none consider the geographical differences in labor market outcomes among these workers. However, recent evidence shows that immigrants disproportionately reside in large and expensive cities (Albert and Monras, 2022) that reward jobs with high-intensity in cognitive task (Atalay et al., 2022). For example, an immigrant aiming to live in New York may only find janitorial positions available. This job choice may result not only from the immigrant's comparative advantage or preference but also from specific distortions within the New York labor market. Thus, how critical is it for immigrants' labor market outcomes to choose the right occupation in the right location? Are there location-specific barriers that limit access to certain occupations, influencing these choices? If so, how do these barriers compare to human capital or preferences in influencing the immigrant-native earnings gap and spatial earnings inequality? Given these factors influencing immigrants' occupational choices across different locations, how does immigration policy affect both the immigrant-native earnings gap and spatial earnings inequality?

This paper studies how the labor market outcomes of workers of different origins vary across space and the implications for earnings inequality. I use data from the American Community Survey (ACS) 2009-2011 and document three stylized facts on the earnings and occupation choices of immigrants and natives across cities. First, I show that natives earn, on average, 3.6% more per hour when the city size doubles, while immigrants do not receive a similar premium.[1] Second, I show that among immigrants, the elasticity of earnings to city size increases with the GDP per capita of their country of birth. Third, I show that immigrants from low-income countries are more likely to live in big cities and work in non-cognitive occupations compared to natives and immigrants from high-income countries.

I interpret these facts through a quantitative general equilibrium spatial model with heterogeneous cities and workers. In the model, each city is characterized by a technology that combines cognitive and non-cognitive skills, and by an endogenous housing supply. To capture the varying degrees of task specialization across space, I let the technology in big cities favor cognitive occupations.[2] Within the model, workers vary by their country of origin, education and experience and

[1] A similar fact was also documented in an earlier version of Albert and Monras (2022). They used both city prices and size as gradients for the wage gap between immigrants and natives.

[2] To this end, Giannone (2017) documents that the spatial diffusion of skill-biased technology is uneven, and Eeckhout et al. (2021) shows that different levels of investments in IT technology across cities lead to differences in task

can perform any occupation. Given their origins, they choose a city-occupation pair based on their expected earnings and tastes.

I model three channels that influence a worker's occupation choice within a given location. First, I allow for origin-specific workers' human capital to perform an occupation. For example, both a worker from a poor and a rich country can choose to work in a cognitive occupation, but their productivity in this occupation might be different. This channel captures cross-country differentials in human capital accumulation and schooling quality which determine output per worker differences.[3]

Second, I model origin-specific differences in tastes for occupations and locations to capture the existence, for instance, of home bias for natives (Heise and Porzio, 2022), and ethnic networks or cultural background for immigrants. On the one hand, the existence of ethnic networks is an important factor that immigrants consider when they move to a new country (Munshi, 2003; Egger et al., 2021). On the other hand, large ethnic networks cause wage losses and reduce the quality of job matches in the long run, especially for low-skilled immigrants (Battisti et al., 2022).

Third, I incorporate local labor market distortions specific to the country of origin as sources of human capital misallocation. I model these distortions as wedges that affect earnings in the form of "taxes" (Hsieh et al., 2019). These wedges are proxies for various barriers faced by immigrants arising from undocumented immigration status, lack of job licensing, or simply from discrimination based on immigrants' country of origin.[4]

Taken together, human capital, tastes, and labor market distortions are the channels that affect a worker's occupation choices across US cities. Human capital determines a worker's comparative advantage in an occupation, while wedges on earnings lead her to choose an occupation where she does not have a comparative advantage. Similarly, tastes for locations and occupations that vary by origins are an additional force that drive differences in occupational sorting across space. By incorporating each of these factors in the model, I aim to capture the complexities of labor market dynamics for immigrant workers, highlighting the spatial mechanisms contributing to earnings disparities with native workers.

I bring the model to the data by making two key identifying assumptions. First, I assume that the taste for living in the smallest city and working in the non-cognitive occupation is the same for all workers. Therefore, the estimated taste parameters for other occupations in other locations are relative to this base group for all workers. Second, I assume that only immigrants are subject to local labor market distortions. As a result, the wedges that immigrants face in various occupations within a given location are relative to natives.

I use this framework to conduct a series of counterfactual experiments in which I let immigrants become more similar to natives and quantify how the earnings gap between these workers and

specialization.

[3] Lagakos et al. (2018b) shows substantial differences in human capital accumulation between workers in rich and poor countries. Martellini et al. (2024) estimate that college-educated workers in rich countries have significantly more human capital than college-graduate workers in poor countries.

[4] Dustmann et al. (2013) provide evidence that immigrants often downgrade upon arrival in the host country's earnings distribution even when they are better educated than natives. See Kleiner and Soltas (2023) on the role of occupational licensing in the US. Oreopoulos (2011) finds evidence of substantial discrimination across occupations towards applicants with foreign experience or those with Asian names.

across cities changes. If immigrants had the same human capital as natives but differ in tastes for cities and occupations and are subject to labor market distortions, the aggregate earnings gap with natives would reduce by 19 percent while the earnings gap between big and small cities would increase by 1.1 percent. A similar result emerges when I assign to immigrants the same tastes for cities and occupations as natives. In this case, earnings inequality among workers reduces by 6.2 percent and spatial earnings inequality increases by 3 percent. In contrast, removing local labor market distortions has a positive effect on earnings inequality, both among workers and across cities. Overall, the model uncovers a trade-off between reducing inequality among workers and increasing it across space: when there are no channels of heterogeneity between immigrants and natives left, the earnings gap between them reduces by 29 percent, but spatial earnings inequality increases by 2.3 percent.

In the next exercise, I find that U.S. GDP per worker would increase by 1.8 percent if immigrants supply the same human capital of natives with similar demographic characteristics. In contrast, there is limited role for tastes and labor market distortions on this outcome: when removed together, the U.S. GDP per worker increases by 0.9 percent. Focusing on spatial differences in housing prices, I show that when workers have the same taste for occupations and locations, the reallocation of immigrants from low-income countries to small cities and cognitive occupations generates a 2.6 percent increase in the big-to-small city hosing price ratio. In this case, local labor market distortions "protect" natives from a larger increase in housing prices in bigger cities.

Finally, I use the model to study the potential effects of changing immigration policy on the aggregate earnings gap between immigrants and natives and the earnings gap between big and small cities. I simulate two selective immigration policies based on immigrants' educational attainment allowing for for general equilibrium responses. I find that an inflow of immigrants without college education increases earnings inequality between immigrants and natives by 2.6 percent, while an inflow of college educated immigrants reduces it by 5.9 percent. Under both policies, however, the model predicts that immigration alleviates spatial earnings inequality.

Overall, this paper makes two main contributions. First, it provides robust empirical evidence on the spatial nature of the earnings gap between immigrants and natives and how it relates to their occupational choices in various locations. To the best of my knowledge, this is the first paper that documents how the occupational choices of workers from different origins vary across space. Second, it provides a theoretical foundation for factors that influence workers' occupational choices in a spatial equilibrium. The model offers a tractable framework to measure and quantify sources of earnings inequality between US immigrants and natives, such as occupation-specific human capital, city-occupation-specific preferences, and local labor market barriers. Furthermore, the counterfactual exercises conducted using this framework reveal the existence of a trade-off between reducing earnings inequality among workers while increasing earnings inequality across space.

Relation to the Literature This paper contributes to several strands of the literature. First, it relates to the literature on the relationship between immigration and inequality in the labor market. Works by Card (2009), Advani et al. (2022), Dustmann et al. (2023), Amior and Stuhler (2024), Lebow

(2024) study the relationship between immigration and inequality. I contribute to the literature by documenting a novel stylized fact concerning the spatial distribution of immigrants' occupational choices. This fact highlights the importance of looking at workers' occupational choices and their geographical nature to study earnings inequality. Moreover, I emphasize the role of the complementarity between workers' human capital and local labor market characteristics in shaping earnings disparities among workers. To this end, I exploit the unique characteristics of US immigrants, who originate from a large set of countries with different labor market institutions and occupational structures (Caunedo et al., 2021). Cross-country differences in labor market characteristics reflect the degree of complementarity between immigrants' human capital and the production structure in the US economy (Lagakos et al., 2018a).

This paper also contributes to the literature that uses structural models to study economic outcomes related to immigration. Recent papers are Llull (2018), Lessem (2018), Monras (2020), Burstein et al. (2020) Piyapromdee (2021), Albert et al. (2021), Albert and Monras (2022), and Adda et al. (2022). Consistent with this literature, I do not find large effects of immigration on natives' wages. Compared to them, I introduce three origin-specific sources of earnings disparities within a spatial equilibrium framework: occupation-specific human capital, preferences for cities and occupations, and local labor market distortions. When workers are limited to an occupation not only because of labor market barriers but also because of tastes and human capital, their labor market outcomes result from the interplay among these factors. The structural model provides a tool for measuring the quantitative importance of these channels. Moreover, the quantitative exercises carried out with the model reveal a trade-off between reducing earnings inequality between immigrants and natives and earnings inequality across space. These exercises also highlight that differences in preferences for jobs and locations are crucial in explaining spatial earnings inequality.

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). Recently, Birinci et al. (2021) quantify large output gains from eliminating labor market barriers faced by immigrants in the US labor market. My structural model extends this analysis by introducing a spatial and origin-based dimension to the labor market barriers that immigrants face. Compared to Birinci et al. (2021), my framework reveals that the output gains from removing these barriers are smaller in magnitude, as they would induce minimal, yet optimal, reallocation of workers across cities and occupations. In contrast, removing origin-specific local labor market barriers reduces earning inequality among workers without increasing it across space.

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

Here I describe the data sources used to document the three stylized facts and to estimate the structural parameters of the spatial equilibrium model. I assemble a dataset on workers and cities characteristics using the Integrated Public Use Microdata Series (IPUMS)(Ruggles et al., 2020), the World Bank Database, and the O*NET Database.

IPUMS Data. The main data source is the Integrated Public Use Microdata Series (IPUMS), a database that contains samples of the American population. I select a 3 percent pooled cross-sectional sample from the American Community Survey (ACS) (2009-2011), an annual demographic survey that gathers information about people in the US. For all individuals in the sample, the ACS provides the country of birth and citizenship status. I combine this information together and I define immigrants as foreign-born workers who are either born abroad from American parents or naturalized citizens or do not have citizen status. The ACS also contains other individuals' demographic characteristics such as age, gender, and level of education which I use to compute each worker's potential experience in the labor market and to assign them to the college/no-college category.[5] Individual reports also information on their labor market outcomes such as annual earnings, employment status, number of weeks and hours worked, and occupation.[6] I use this information to compute a worker's hourly earnings. The dataset also includes information on the Metropolitan Statistical Area where an individual lives that I use to identify US cities.[7].

World-Bank Development Database. I collect information on countries' GDP per capita from the World Bank Development Indicators. This dataset contains information at the country level for a set of indicators of economic development. I select the variable measuring GDP per capita at PPP constant 2017 international US dollars. With this information, I divide immigrant workers into those who come from low-income countries (GDP per capita $< \$30,000$) and high-income countries (GDP per capita greater or equal to $\geq \$30,000$).

O*NET Database. For the purpose of the analysis, I collect information on the task content of occupations from the O*NET database. This database contains descriptors for various requirements to perform an occupation such as knowledge, skills, abilities, work activities, work context, work styles, and work values. In O*NET each occupation is classified using the Standard Occupation Classification (SOC). I build the task intensity for each occupation following Acemoglu and Autor

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

[6]Wages are top-coded. To deal with this, I follow the procedure in Albert et al. (2021).

[7]Measuring cities through MSAs is common practice in urban economics literature (see Moretti (2013), among others), since their definition lies on the intersection among geographical boundaries, demographic information, and economic activities. More precisely, the US Office of Management and Budget (OMB) defines a Metropolitan Statistical Area as one or more one or more (contiguous) counties having one urbanized area with a population of at least 50,000 individuals.

(2011) and use this measure to assign each of them to a cognitive or non-cognitive occupation category.[8]

Analysis Sample. I build the sample for the analysis by merging the information collected from IPUMS, the World-Bank Development Database and the O*NET database. The sample consists of male workers in working age (18-64) who have between 0 and 40 years of potential experience in the labor market, are employed in the private sector, do not live in group quarters, are not enrolled in school at the time of the interview, who worked at least one week in the previous year and report positive hourly earnings that do not exceed 250 US dollars.[9] I focus on first-generation immigrants, that is foreign-born individuals who migrated to the US after 18 years old, who plausibly did not receive any education from a US institution. Since the ACS does not provide information on the location/country where individuals received their education, I follow Schoellman (2012) and use the information on year of arrival in the US, age, and years of completed schooling to exclude immigrants who are more likely to have studied in the United States. The earnings of immigrants who are left in the sample are thus netted of the benefits originating from studying at a US institution and from the acquisition of US-specific human capital. I select only immigrants from top-sending countries, i.e. immigrants from countries whose population falls above the 10th percentile of the total immigrant population.

From this sample, I drop the individuals who live in areas not identifiable as a MSA and I select the MSAs where there are at least 200 foreign-born workers for each of the two country of origin categories (low-income and high-income, defined as above). I proxy the size of US cities using the employment stock in each of them and I split them into small and big cities.

The final sample for the analysis includes workers from 69 countries of origin (the US included) and 122 MSAs. Table 20 and Table 19 in Appendix A present summary statistics for the main socio-demographic characteristics of the sampled population and cities.

2.1 Empirical Evidence

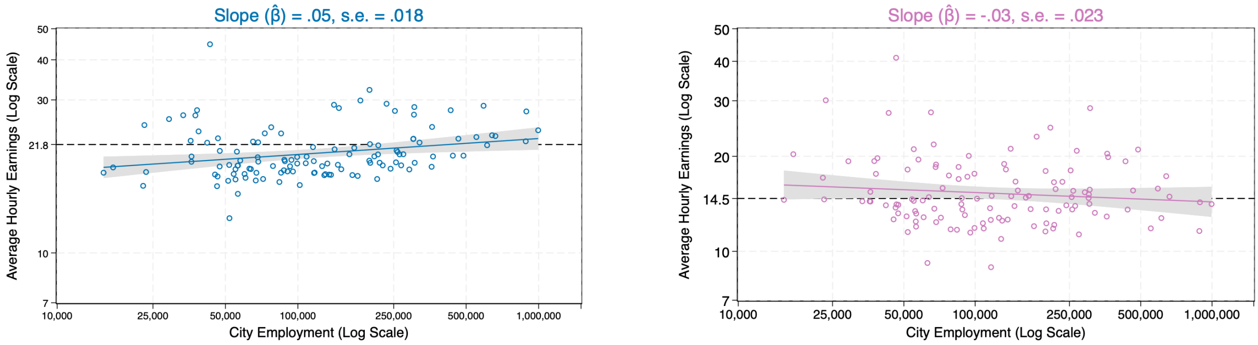
Fact 1: There is no City-Size Earnings Premium for Immigrants. Figure 1 shows how the log of average hourly earnings of US native and immigrants workers varies across US cities of different size. The average hourly earnings of US workers are about 22$ per hour (Panel 1a). By moving from small to big cities, average hourly earnings increase, especially in cities with a population greater than 500,000. The estimated slope from a linear regression of log hourly earnings on the log of city size is statistically significant. More precisely, an estimated elasticity of 0.05 tells that the average earnings of a native worker increase by about 3.5 percent by doubling the city size.[10]

[8] More details on how I build the task measures, task categories, and the criterion to assign occupation to the cognitive/non-cognitive category can be found in Appendix A.

[9] Due to changes in female workers' participation rates during the selected years, I focus only on male workers. Additional results using the sample of female workers can be found in Appendix B. Plus, following De La Roca and Puga (2017), I drop individuals working in agriculture, fishing, and mining industries since, even if they might live in urban areas, their place of work could be located in rural areas.

[10] The derivation for the change in average wages for a change in the city-size can be found in Appendix E.

Figure 1: Cities hourly earnings premia



(a) Natives (b) Immigrants

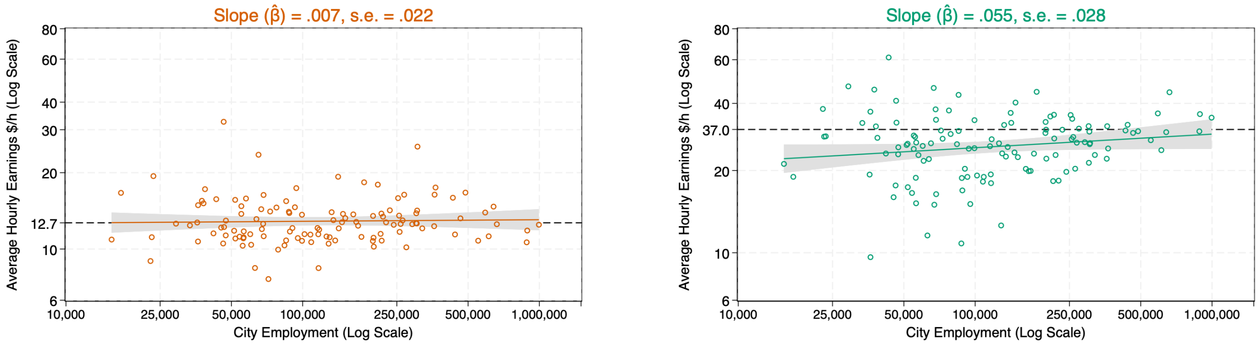
Source: ACS, World Bank Development Database, and author's calculation. Notes: This figure shows the relationship between the natural logarithm of the average hourly earnings of each metropolitan statistical area and the natural logarithm of the employment stock of each metropolitan statistical area. Each dot corresponds to the natural logarithm of the average hourly earnings in a 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 natural logarithm of the average hourly earnings on the log of the city employment stock. The grey area in each panel represents the estimated confidence intervals at the 5 percent significance level. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Panel 1b shows that the average hourly earnings for US immigrants are 14.5$ per hour, i.e. about 8$ per hour less than natives. On top of this, immigrants' hourly earnings show a larger degree of dispersion around the mean and do not increase with the size of US cities. The estimated elasticity of earnings to city size is negative and not statistically significant at a 10 percent significance level. To place these values in context, on average, the hourly earnings of an immigrant who works in Manchester NH (the smallest city in the sample) are as high as the earnings of an immigrant working in Chicago IL. On the contrary, a native who works in Chicago earns about 12.2 percent more than a native who works in Manchester NH.

Taken together, Fact 1 shows that as cities grow larger, the earnings gap between immigrant and native workers increases.

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 low-income countries and from high-income countries 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 immigrants from high-income countries are about three times as high as those of immigrants from low-income countries. In addition, the hourly earnings of immigrants from high-income are more dispersed around the mean compared to the earnings of other immigrants. The estimated elasticity of hourly earnings to city size is not significant at 10 percent for immigrants from low-income countries (Panel 2a), while it is significant at 5 percent for immigrants from high-income countries (Panel 2b). In other words, doubling the city size leads to a 3.9 percent increase in the average hourly earnings of an immigrant from a high-income country. Conversely, the average hourly earnings of an immigrant from a low-income country remain unchanged.

Figure 2: Cities hourly earnings premia



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

Source: ACS, World Bank Development Database, and author's calculation. Notes: This figure shows the relationship between the natural logarithm of the average hourly earnings of each metropolitan statistical area and the natural logarithm of the employment stock of each metropolitan statistical area for immigrants from low-income countries (GDP pc $< \$30,000$, Panel a) and immigrants high-income countries (GDP pc $< \$30,000$, Panel b). Each dot corresponds to the natural logarithm of the average hourly earnings in a Metropolitan Statistical Area. At the top of the figures, I report the estimated coefficient and the corresponding standard error robust to heteroscedasticity for the slope of this relationship obtained by regressing the natural logarithm of the average hourly earnings on the log of the city employment stock. The grey area in each panel represents the estimated confidence intervals at the 5 percent significance level. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

To gain more insight into the relationship between earnings, workers' origins, and the size of US cities, I report the average hourly earnings of natives and immigrants from low and high-income countries by splitting the sample into big and small cities. 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 US workers are 21$ per hour and increase to 23.8$ per hour in big cities, roughly by 13 percent. Interestingly, immigrants from high-income countries earn more on average than all other workers. As a result, these workers receive a city-size premium even larger than that of native workers (+6.4$ per hour vs. +2.8$ per hour). On the opposite, the earnings of immigrants from low-income countries decrease by 1.4$ per hour (roughly 10.5 percent) when moving from the small to the big city. Hence, not only do immigrants from lower-income countries earn less than all the other workers but also do not receive any city-size earnings premium for living in big cities.

Table 1: Hourly Earnings: Big vs Small Cities

	Small City (Pop. $<$ 500,000)	Big City (Pop. $\geq$ 500,000)	City-Size Gap
	(1)	(2)	(3)
Natives	21.0	23.8	+2.8
High-Income	33.2	39.6	+6.4
Low-Income	13.3	11.9	-1.4

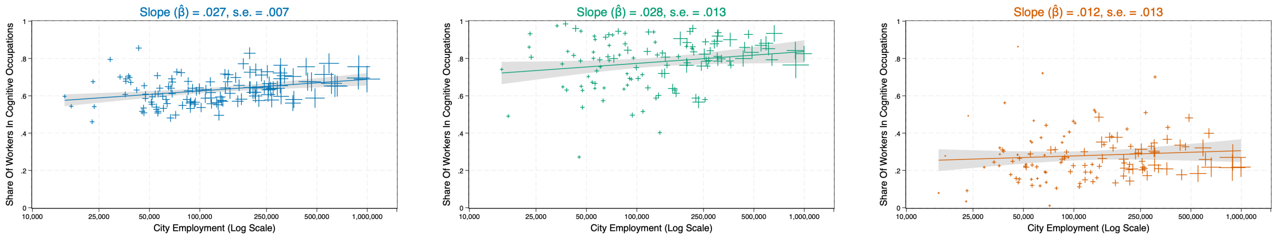
Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the average hourly earnings (US dollars/hour) in small cities and big cities and the city-size earnings gap (avg. earnings in the big city - avg. earnings in the small city) for natives, immigrants from high-income countries (GDP PC $\geq \$30,000$), and immigrants from low-income countries (GDP PC $< \$30,000$). Average earnings are calculated from a sample of male workers reporting to be employed. Individual sample weights rescaled by the annual number of hours worked and used in the 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. How do workers from different origins sort across occupations in cities? Figure 3 shows the relationship between the shares of workers in cognitive occupations and the size of cities for natives, immigrants from high-income countries, and low-income countries. Both natives and immigrants from high-income countries work more in cognitive occupations, compared to immigrants from low-income countries. Furthermore, the propensity of natives and immigrants from high-income countries to perform a cognitive occupation is larger in big cities compared to small cities (Panel 3a and Panel 3b). In contrast, panel 4c reveals that not only immigrants from low-income countries work less in cognitive occupations, but their propensity to choose these occupations does not change with city size.

To illustrate these patterns more precisely, I present in Table 2 the share of workers in cognitive occupations in both big and small cities for the three groups. Immigrants from high-income countries have the highest share of workers in cognitive occupations both in small and big cities, followed by US workers. Moving from small to big cities, the share of immigrants from high-income countries working in cognitive occupations increases by about 9 percentage points.

Figure 3: Sorting into Cognitive Occupations across Cities



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

Source: ACS, World Bank Development Database, and author's calculation. Notes: This figure shows the relationship between the share of 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 $< \$30,000$, Panel a) and immigrants from high-income countries (GDP pc $< \$30,000$, 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 employment stock. The grey area in each panel represents the estimated confidence intervals at the 5 percent significance level. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Similarly, the share of US workers in cognitive occupations is larger by 4.9 percentage points in big cities. In addition, natives and immigrants from high-income countries show also a similar spatial distribution. As they move from small cities to large cities, their shares increase by 64.4 and 61.3 percentage points, respectively.

Conversely, the share of immigrants from low-income countries who work in cognitive occupations drops by 2.8 percentage points when moving from small to large cities. However, in comparison to all other workers, immigrants from low-income countries are more likely to work in big cities (89.3% vs 82.3% for natives and 80.7% for immigrants from high-income countries). Overall, the evidence in Figure 3 and Table 2 suggest that the sorting of workers into occupations varies across cities for workers of different origins.

Summary. In this section I documented three stylized facts about workers' earnings and sorting across cities and occupations. Compared to small cities, in big cities: 1. Natives earn more, while immigrants do not. 2. Among immigrant workers, immigrants from high-income countries earn as much as natives. 3. Natives and immigrants from high-income countries work more in cognitive occupations, while immigrants from low-income countries do not. 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 spatial equilibrium model that accounts for workers' heterogeneity in human capital and tastes to understand the determinants of these patterns in the data.

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

		Small City (Pop. $<$ 500,000)	Big City (Pop. $\geq$ 500,000)	Δ
		(1)	(2)	(3)
Natives	% Cognitive	63.9	68.8	4.9
	% Total	17.7	82.3	64.6
High-Income	% Cognitive	71.6	80.4	8.9
	% Total	19.3	80.7	61.3
Low-Income	% Cognitive	27.5	24.7	-2.8
	% Total	10.7	89.3	78.7

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 small and big cities expressed in percentage terms for natives, immigrants from high-income countries (GDP PC $\geq \$30,000$), and immigrants from low-income countries (GDP PC $< \$30,000$). For each outcome, Column (3) reports the difference in the shares between 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 rescaled by the annual number of hours worked and used in the calculations.

3 A Quantitative General Equilibrium Spatial Model

The data shows diverging patterns in earnings across US cities for workers of different origins and workers' allocation in occupations and US cities. Here I build a spatial equilibrium model with heterogeneous cities and workers that replicates the patterns observed in the data and guides the quantitative analysis.

3.1 Model Setup

Consider a static economy with $j \in \{1, ..., J\}$ cities and a continuum of workers i, where $i \in [0, 1]$. In each city, a representative firm produces a homogeneous and tradable consumption good combining labor (in efficiency units) in cognitive occupations D and non-cognitive occupations M. Workers are indexed by group g. Each worker i belongs to group $g = (k, e, x)$ that consists of individuals from the same country of origin $k \in \mathcal{K}$ with education $e \in \mathcal{E}$ and potential experience $x \in \mathcal{X}$. Each group g has a measure ϕ_g, such that $\sum_g \phi_g = 1$. Each worker i from group g is endowed with a vector of human capital $\boldsymbol{s} = (s_{Mg}, s_{Dg})$ in efficiency units to perform the two occupations and draw tastes $(\varepsilon_{jM}, ..., \varepsilon_{j'D})$ for each city-occupation pair. The tastes for city-occupation pairs follow a Gumbel distribution and are i.i.d across all workers.[11] Workers from all groups are mobile across locations, decide where to live and which occupation to perform and earn wages. A competitive housing market characterizes each city: absentee landlords own land T that can be used both for production and housing.

Production Technology. A firm in city j uses a CES technology that combines units of human capital in cognitive and non-cognitive occupations to produce a final good Y. The firm demands skills and pays wages according to workers' marginal product of labor in each occupation. [12] Each firm is characterized by a labor productivity bias θ_j in cognitive occupations. The bias reflects how the demand for labor is biased towards workers with higher levels of human capital and ensures differences in productivity across cities. Thus, the production function in each city is:

$$Y_j = f(D_j, M_j) = \left[M_j^{\frac{\sigma-1}{\sigma}} + (\theta_j D_j)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

I assume that the elasticity of substitution σ between the cognitive and non-cognitive occupation is the same across cities.

Workers Preferences. The utility function of a worker i from group g who chooses a city j and an occupation o is Cobb-Douglas over a consumption good and a housing good:

$$U_{jog} = c^{(1-\alpha)} h^{\alpha} \tilde{z}_{jog} \tag{2}$$

where c is the consumption good, h is the housing good, $\tilde{z}_{jog}$ is the value of amenities of a location-occupation pair of workers from group g, and α represents the expenditure share on the housing good.[13] Amenities are defined as:

$$\tilde{z}_{jog} = z_{jog} \exp\{\varepsilon_{jo}\} \tag{3}$$

where z_{jog} is the average value of amenities for the location-occupation pair jo for a worker from group g, ε_{jo} is the idiosyncratic taste draw for the city-occupation pair jo.

A worker i from group g has a budget constraint:

$$c + p_j h \leq w_{jog} \tag{4}$$

where the price for the consumption good is the numeraire, p_j is the price for the city-specific housing good, and w_{jog} are earnings.

The expression for the indirect utility of a worker i from group g living in a city j and working

[11] I assume that the location parameter for the Gumbel distribution is 0 and that the scale parameter is equal to 1, $G(0, 1)$.

[12] I assume perfect substitutability in the human capital of workers from all countries within an occupation.

[13] Workers consume the housing good in the same place as the workplace.

in occupation o is:

$$V_{jog} = v\left(w_{jog}, p_j\right) z_{jog} \exp\{\varepsilon_{jo}\} \tag{5}$$

where $v\left(w_{jog}, p_j\right)$ is the portion of the indirect utility that depends on earnings and housing prices which I define in the next subsection. Eq.(5) shows that a worker's choice to live in a city j and work in an occupation o depends on three factors. First, the worker considers earnings w_{jog} when they choose where to live and work. The second factor that influences the choice of where to live and work is the price of the housing good p_j. The last component of a worker's indirect utility is the value of amenities z_{jog} that a worker from group g assigns to a specific location-occupation pair.

Workers Earnings And Labor Market Distortions. Conditional on the chosen city and occupation, a workers i from group g supply inelastically their occupation-specific human capital in exchange for wages per efficiency units of human capital r_{jo}. All workers in group g are subject to a wedge on earnings τ_{jog} that is specific to a city-occupation pair. Aligned to Hsieh et al. (2019), I model the labor market distortions as compensation wedges between earnings and the marginal product of labor specific to a city-occupation pair. Thus, the earnings of a worker i from group g in a city j and an occupation o is the product of wages, the occupation-specific human capital supplied, and the wedges that the workers are subject to:

$$w_{jog} = r_{jo} s_{og} \tau_{jog} \tag{6}$$

Therefore, a wedge affects earnings either in the form of a subsidy (if it is larger than 1) or taxes (if it is less than 1) that are specific to cities and occupations.

Housing Technology. In each city, a group of absentee landlords own land T_j and combine it with the final good Y_j to produce the housing good using Cobb-Douglass technology. The production function for housing is:

$$H_j = f\left(Y_j, T_j\right) = \omega Y_j^{\iota_j} T_j^{\left(1-\iota_j\right)} \tag{7}$$

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

3.2 Model Solution and Spatial Equilibrium

The Problem of the Firm and Labor Demand in a City. Consider the representative firm in the city j. Given the technology in production, the firm solves the following problem:

$$\max_{D_j, M_j} \quad \left[M_j^{\frac{\sigma-1}{\sigma}} + \left(\theta_j D_j\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - r_{jD} D_j - r_{jM} M_j \tag{8}$$

A necessary condition for an interior solution to the problem of the firm reads as follows:

$$r_{jM} = \left(\frac{Y_j}{M_j}\right)^{\frac{1}{\sigma}} \tag{9}$$

$$r_{jD} = \left(\frac{Y_j}{D_j}\right)^{\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{10}$$

By taking the ratio of Eq. (10) and Eq. (9), I derive an expression for the skills price ratio of cognitive skills and non-cognitive human capital:

$$\frac{r_{jD}}{r_{jM}} = \left(\frac{D_j}{M_j}\right)^{-\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{11}$$

Eq. (11) shows that the relative price in efficiency units of cognitive skills in a city j is regulated by two components. The first component is the ratio of labor in efficiency units of human capital used in cognitive and non-cognitive occupations. When the skills ratio increases, the relative price of cognitive skills decreases proportionately according to the degree of concavity of the technology and the productivity bias. The second component of the skills price ratio is the productivity bias k_j: if $\sigma > 1$, whenever there is an efficiency improvement in using cognitive skills, the relative price of cognitive skills increases. If inputs are substitutes, advances in technology used in cognitive occupations shift the demand for those skills, and the premium for cognitive skills grows. When inputs in production are complements, i.e. $\sigma < 1$, the relative price of cognitive skills decreases. Intuitively, when the cognitive and non-cognitive skills are complements in production, an increase in the efficiency of technology in cognitive task-intensive occupations makes workers in those occupations more productive and increases the demand for workers in non-cognitive occupations.

The Problem of the Worker. Given her city-occupation choice, a worker i from group g maximizes utility by choosing an optimal bundle of consumption and housing goods subject to her budget constraint. The utility maximization problem is:

$$\begin{aligned} \max_{c_{jog}, h_{jog}} \quad & U_{jog} = c_{jog}^{(1-\alpha)} h_{jog}^{\alpha} z_{jog} \exp\{\varepsilon_{jo}\} \\ \text{s.t.} \quad & c_{jog} + p_j h_{jog} \leq w_{jog} \end{aligned} \tag{12}$$

The worker's optimal demands for the consumption and housing goods are:

$$c_{jog} = (1-\alpha)\, w_{jog} \quad , \quad h_{jog} = \alpha \frac{w_{jog}}{p_j} \tag{13}$$

By plugging the demand functions into the utility function, I obtain an expression for the indirect utility of a worker i from group g who chooses a city-occupation pair jo:

$$V_{jog} = \gamma p_j^{-\alpha} w_{jog} z_{jog} \exp\{\varepsilon_{jo}\} \tag{14}$$
$$= \gamma p_j^{-\alpha} r_{jo} s_{og} \tau_{jog} z_{jog} \exp\{\varepsilon_{jo}\} \tag{15}$$

where where $\gamma = (1-\alpha)^{(1-\alpha)}\alpha^{\alpha}$ is a constant term. Taking the log of Eq.(14), I obtain:

$$\ln V_{jog} = \ln \gamma - \alpha \ln p_j + \ln r_{jo} + \ln s_{og} + \ln \tau_{jog} + \ln z_{jog} + \varepsilon_{jo} \tag{16}$$

Given the realization of the taste shock, a worker chooses a city-occupation pair that provides her with the highest indirect utility. The distributional assumption on ε_{jo} leads this setup to have the form of a multinomial logit choice model. In this framework, the share of workers from group g living in a city j and working in an occupation o can be approximated by the probability that workers from group g pick a city-occupation pair jo. The expression for the share of workers from group g living in a city j and working in an occupation o is:

$$\pi_{jog} = \frac{V_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} V_{j'o'g}} \tag{17}$$
$$\text{where} \quad V_{jog} = \gamma p_j^{-\alpha} r_{jo} s_{og} \tau_{jog} z_{jog}$$

This formulation for the share of workers from group g in a city j and occupation o represents the idea that cross-city differences in workers' allocations measure the average utility that these workers derive from each city-occupation pair. Differences in the spatial distribution of workers across cities and occupations will depend on differences in human capital s_{og}, the value of amenities z_{jog}, and the values of labor market distortions τ_{jog}.

The Problem of the Absentee Landlords and Housing Supply in Cities. In each city, the absentee landlords solve:

$$\max_{Y_j} \quad p_j \left(\omega_j Y_j^{\iota_j} T_j^{1-\iota_j} \right) - Y_j \tag{18}$$

Solving the first-order condition and rearranging the terms yields:

$$Y_j = \left(p_j \omega_j \iota_j \right)^{\frac{1}{1-\iota_j}} T_j \tag{19}$$

By substituting Eq.(19) into Eq.(7) and rearranging the terms, I obtain the following expression for the housing supply:

$$p_j = \left(\frac{H_j}{T_j} \right)^{\frac{1}{\zeta_j}} \tag{20}$$

where ζ_j is the elasticity of the housing supply in city j. In equilibrium, the workers' demand for housing is equal to the amount of housing supplied, and the city-specific housing demand is:

$$H_j = \alpha \frac{\bar{w}_j}{p_j} \tag{21}$$

where $\bar{w}_j$ is the average earnings in city j. As a result, the housing supply in equilibrium is:

$$p_j = \left(\frac{\alpha \bar{w}_j}{T_j} \right)^{\frac{1}{\zeta_j - 1}} \tag{22}$$

Labor Supply in a Local Labor Market. The labor supply in city j for an occupation o is given by the share of workers i in the whole economy times their probability of choosing a city-occupation pair times their level of human capital, summed across all workers. More precisely, the labor supply in the non-cognitive occupation in city j is:

$$M_j = \sum_g \pi_{jMg} s_{Mg} \phi_g \tag{23}$$

Similarly, the labor supply in the cognitive occupation in city j is:

$$D_j = \sum_g \pi_{jDg} s_{Dg} \phi_g \tag{24}$$

Spatial Equilibrium. A spatial equilibrium for this economy is defined as a sequence of skills prices $\{r^\star_{jo}\}_{j \in \mathcal{J}, o \in \mathcal{O}}$, housing prices $\{p^\star_j\}_{j \in \mathcal{J}}$, distribution of workers across locations and occupations $\{\pi^\star_{jog}\}_{j \in \mathcal{J}, o \in \mathcal{O}}$ for all g, such that:

1. The share of workers from group g in a city-occupation pair jo is:

$$\pi^\star_{jog} = \frac{V^\star_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} V^\star_{j'o'g}} \tag{25}$$

$$\text{where} \quad V^\star_{jog} = \gamma p_j^{\star - \alpha} r^\star_{jo} s_{og} \tau_{jog} z_{jog} \tag{26}$$

2. Labor supply satisfies:

$$M^\star_j = \sum_g \pi^\star_{jMg} s_{Mg} \phi_g \tag{27}$$

$$D^\star_j = \sum_g \pi^\star_{jDg} s_{Dg} \phi_g \tag{28}$$

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

$$r^{\star}_{jM} = \frac{\left[M^{\star\frac{\sigma-1}{\sigma}}_{j} + (\theta_j D^{\star}_{j})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}}{M^{\star\frac{1}{\sigma}}_{j}} \tag{29}$$

$$r^{\star}_{jD} = \frac{\left[M^{\star\frac{\sigma-1}{\sigma}}_{j} + (\theta_j D^{\star}_{j})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}}{D^{\star\frac{1}{\sigma}}_{j}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{30}$$

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

$$p^{\star}_{j} = \left[\frac{\alpha}{T_j}\bar{w}^{\star}_{j}\right]^{\frac{1}{\zeta-1}} \tag{31}$$

$$\text{where} \quad \bar{w}^{\star}_{j} = \sum_{o}\sum_{g} \pi^{\star}_{jog}\phi_g r^{\star}_{jo} s_{og} \tau_{jog} \tag{32}$$

4 Bringing The Model To The Data

In this section, I discuss the identifying assumptions, describe the externally calibrated parameters, discuss the identification and estimates of the internally calibrated parameters, and show the model fit with the data.

Dimensionality Reduction and Identifying Assumptions. The model describes the US economy as populated by workers from different origins who can 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 where workers can perform either a cognitive occupation or a non-cognitive occupation. Workers differ in human capital from each other because of their country of origin, education, and potential experience in the labor market. Workers could be from one of three different countries of origin: the US, low-income countries, and high-income countries. These workers could have either received or not received a college education. Finally, each worker belongs to one of three groups of potential experience in the labor market. In other words, In calibrate the model on: $j \in \{\text{Small City}, \text{Big City}\}$, $o \in \{M, D\}$, $k \in \{\text{US}, \text{Low-Income}, \text{High-Income}\}$, $e \in \text{Non-College}, \text{College}\}$, $x \in \{0-14, 15-29, 30+\}$.

Under these assumptions, 18 groups of workers choose where to live and which occupation to perform across 4 alternatives: small city and non-cognitive occupation, small city and cognitive occupation, big city and non-cognitive occupation, big city and cognitive occupation. I normalize the amenities in the small city and in non-cognitive occupations to one, $z_{SM} = 1$. Thus, the estimated amenities for other city-occupation pairs are relative to this category.

I assume that the wedge on earnings varies across cities and occupations only conditional on the country of origin (i.e., $\tau_{jog} = \tau_{jok}$). When $\tau_{2jok} > 1$ a worker receives a "reward" on their earnings, while when $\tau_{jok} < 1$ a worker receives a "penalty" on their earnings. I also assume that native workers are not subject to wedges on their earnings (i.e., $\tau_{joUS} = 1 \quad \forall j \in \mathcal{J}, o \in \mathcal{O}$).

Overall, the model features a vector of 106 structural parameters that can be split into two groups. One group consists of 6 parameters for macroeconomic aspects of the US economy that I calibrate directly from the literature, or using data from the ACS 2010. The other group consists of the parameters that govern the earnings and the allocation of workers across cities and occupations and that I estimate internally to the model using the simulated method of moments.

Externally Calibrated Parameters. Table 3 describes the set of parameters that I calibrate following the literature or that I compute from the data. I rely on existing values estimated by the literature the elasticity of substitution between input in technology, the housing elasticity, and the share of expenditure in housing. I set the elasticity of substitution between cognitive and non-cognitive human capital as in Hsieh et al. (2019). For the elasticity of the housing supply, I use the value estimated by Saiz (2010). I take the value for the share of expenditure in housing from Albouy (2008). I compute the proportion of workers in each human capital cell (k, e, x) using the ACS 2010 and obtain the exogenous distribution of workers in the economy. Finally, I assume that the small and the big city have the same amount of land for the production of housing.[14]

Table 3: External Parameters

Description	Symbol (1)	Value (2)	Source (3)
Elasticity of substitution	σ	3	Hsieh et al. (2019)
Housing supply elasticity	ζ	1.54	Saiz (2010)
Share of expenditure in housing	α	0.32	Albouy (2008)
Share of group g in the economy	ϕ		ACS 2010
Small And Big City Land	T	1	Assumed

Internally Estimated Parameters. I now turn to discuss the identification and present the estimated values of the remaining parameters. Other than the 6 parameters described in the previous paragraph, the structural model includes a vector of 100 structural parameters that govern the allocation of workers across cities and occupations. The vector of parameters can be divided into five sub-categories, each one measuring some specific feature of the model. These are the city-specific productivity bias in cognitive occupations, worker's level of human capital specific to an occupation, city-occupation-specific wedges on earnings, and city-occupation amenities by workers' origins. I estimate these parameters by using the simulated method of moments (SMM).[15]

Identification And Estimates Of The City-Productivity Bias I target the city-specific average earnings of native workers who work in cognitive occupations as moments to estimate the city pro-

[14] I carried out the model estimation with alternative values for the externally calibrated parameters such as the elasticity of substitution between cognitive and non-cognitive skills σ, the elasticity of housing supply ζ, and different values for the available land T. The estimation results are qualitatively the same.

[15] See McFadden (1989).

ductivity bias. Table 4 compares the estimated values for the productivity bias in the cognitive occupation in the small and big city.

Table 4: Estimated productivity bias in cognitive occupations

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

Notes: The table reports point estimates for the parameter θ measuring the productivity bias in cognitive occupations in the big city and the small city obtained using the simulated method of moments.

Both cities feature a productivity bias toward the cognitive occupation. Column (2) shows that the bias in the big city is greater than in the small city. By moving from small to big cities the bias in cognitive occupations increases by about 15%, changing from 1.3 to 1.5. This result is consistent with Eeckhout et al. (2021) who highlights how an uneven diffusion of technology across space drives labor market polarization and wage inequality.

Identification and Estimates of Workers' Human Capital The structural model also includes a set of 36 parameters that measure the worker's level of human capital specific to an occupation conditional to the worker's characteristics. I estimate the human capital parameters by targeting the worker's occupation-specific earnings conditional on her origins, education group, and experience class that I observe in the data. Table 5 presents summary statistics for the estimates of workers' human capital.

Table 5: Estimated human capital

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

Notes: The table reports the average values for the estimates of human capital in cognitive and non-cognitive occupations of natives, immigrants from low-income countries, and immigrants from high-income countries. Standard deviations in parenthesis. Workers' probability distribution weights (ϕ_g) are used in the calculations.

The estimates highlight differences in the stock of human capital supplied by workers of different origins. Column (1) shows that in the non-cognitive occupation natives and immigrants from high-income countries supply more human capital compared to immigrants from low-income countries. For the cognitive occupation immigrants from high-income countries supply 22.5 units of human capital, the highest value among all workers (Column (2)). Even in this case, workers from poorer countries supply the least human capital. An interpretation of this result comes from a comparison between the occupational structures (task intensity required to perform an occupation) of countries. Similar estimates of human capital between natives and immigrants from rich countries may reflect greater similarity in the occupational structures between the US and richer countries.[16] The similarity between levels of the human capital of US natives and workers from other countries, however, fades for workers from lower GDP per capita countries. As a result of larger differences in the occupational structure between low and high-GDP per capita countries, immigrants from low-income countries supply fewer units of human capital compared to all other workers.

Identification And Estimates Of The Wedges On Earnings Through the lens of the model, earnings are determined not only by the skills prices and the units of human capital supplied by workers but also by wedges specific to local labor markets. I assume that native workers are not subject to any wedge in earnings and identify the wedges on immigrants' earnings from the gap in earnings between immigrants and natives with the I estimate the 8 parameters that measure these wedges

[16] Caunedo et al. (2021) show a positive relationship between the intensity in non-routine cognitive, non-routine interpersonal, and computer use tasks and countries GDP per capita. They also find no relationship between routine cognitive tasks and countries' GDP per capita, while a negative relationship between intensity in routine manual and non-routine manual tasks and countries' GDP per capita.

by targeting the average earnings of immigrants from country k who live in a city j and work an occupation o. I present the estimated wedges for immigrants from low and high-income countries in Table 6.

Table 6: Estimated wedges on earnings

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

Notes: The table reports the estimated wedges on earnings τ_{jok} for immigrants from low-income and high-income countries. Native workers are the base group and $\tau_{joUS} = 1, \forall j, o$.

In both cities, the estimated wedges on earnings of immigrants from high-income countries are larger in magnitude than the estimated wedges on earnings of immigrants from low-income countries. A comparison *between* Column (1) and Column (3) shows that immigrants from all countries receive positive compensation by working in non-cognitive occupations. In the small city, wedges on earnings is 10 percentage points larger for immigrants from high-income countries as opposed to immigrants from low-income countries. The difference in wedges between immigrant groups increases in the big city: wedges are 20 percentage points higher for immigrants from high-income countries. By moving from the small to the big city the magnitude of the wedges reduces for both groups of immigrant workers (high-income countries -10 percentage points, low-income countries -20 percentage points). Column (2) and Column (4) show substantial differences in the estimated wedges in cognitive occupations among immigrants and between cities. Both in the small and in the big city the estimated compensations are below 1 for immigrants from low-income countries: wedges are a tax on their wages and reduce their earnings. On the opposite, the estimated wedges for workers from rich countries do not vary across cities and act as subsidies to their earnings. Similar to the estimates of wedges for the non-cognitive occupation, the wedges on earnings for the cognitive occupation are larger in both cities for immigrants from high-income countries than for immigrants from low-income countries (+20 percentage points in the small city and +40 percentage points in the big city). Interestingly, and differently from the case of the non-cognitive occupation, wedges on the earnings of immigrants from high-income countries do not vary between cities, while by moving from the small to the big city they decrease by 20 percentage points for immigrants from low-income countries.

Identification and Estimates of the City-Occupation Amenities The last set of parameters measures the city-occupation-specific amenities for each group of workers. I normalize the value of amenities in the small city and non-cognitive occupations to 1. I identify the remaining 54 parameters for amenities from the share of workers in each country, education, and experience group in each city-occupation pair. I report in Table 7 the average value of the estimated parameters in all cities and occupations for workers from all countries.

Table 7: Estimated amenities and wedges on labor supply

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

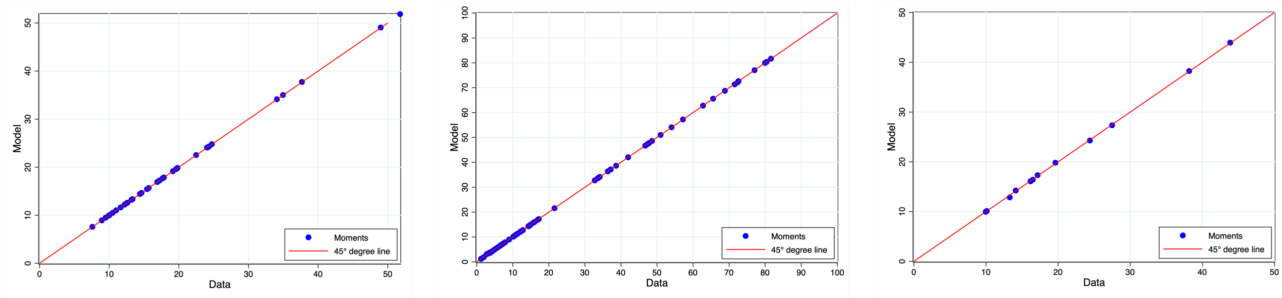
Notes: The table reports the mean estimated amenities of each location-occupation pair for native, immigrant low-income, and immigrant high-income workers. The value of amenities in small cities and in the non-cognitive occupation is normalized to 1 for all groups of workers, i.e. $z_{SMg} = 1, \forall g$.

According to Table 7, there are no substantial differences in how workers from different groups value working in the cognitive occupation in small cities. In the big city, natives and immigrants from high-income countries value, on average, three to four times more working in the non-cognitive occupation and six to seven times more working in the cognitive occupation.

In contrast, immigrants from low-income countries value, on average, more than 9 times working in the non-cognitive occupation, and about 5 times more working in the cognitive occupation. Overall, Table 7 suggests a greater similarity between the estimated values for natives and immigrants from high-income countries and natives as opposed to immigrants from low-income countries.

Model Fit. I use 100 moments computed from the data to identify the 100 structural parameters that measure the city-specific productivity bias in the cognitive occupation, workers' human capital, city-occupation amenities, and wedges on earnings. Figure 4 shows the fit between the empirical and model-generated moments. The model does quite well at fitting the data since in all panels empirical and model-based moments lie upon the 45 degrees line.

Figure 4: Model Fit



(a) Earnings w_{og} (b) Shares π_{jog} (c) Earnings w_{jok}

1

Notes: The figure reports model-based statistics against data.

Table 8 compares the values from the data and the model for the earnings of natives and immigrant workers from high and low-income countries. Overall, the model-generated earnings match quite well the data counterparts for all origin groups in both cities. The model-based earnings of natives in the small city are slightly below the value in the data counterpart (-40 cents), while the model-based earnings of immigrants from high and low-income countries are slightly above their data counterparts (+10 cents and +40 cents, respectively). For the big city, the model-based earnings of immigrants from high-income countries are 20 cents higher than the earnings computed from the data, and for natives and immigrants from low-income countries, the model-based earnings are 20 cents higher than the data counterparts, respectively. The model-based city-size gap is slightly greater than the data counterparts for natives and immigrants from high-income countries (+20 cents and +30 cents, respectively) and slightly lower for immigrants from high-income countries (-20 cents).

The model-generated moments match well also the differences in sorting across cities and occupations. Table 9 shows the model fit for the shares of workers from the three countries of origin in cognitive occupations within each city and the shares of workers from the three countries of origin across cities. Overall, model-generated moments match quite well the shares of workers who live in big cities for all groups. Data indicates that 17.7% of native workers live in the small city, and among them, 63.9% choose the cognitive occupation. The model does well at matching these values. In the case of workers from high-income countries, there are small differences between the spatial distribution of these workers between the model and the data, but the model reproduces quite effectively the occupational allocation of these workers. The model matches quite well also the shares of immigrants from low-income countries in cities and occupations: the largest data-model difference being 2.1 percentage points in the percentage of low-income immigrants working in the cognitive occupation in the small city.

Table 8: Model fit for fact 2

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

Notes: The table reports the fit between empirical moments for the earnings of workers in small and big cities for the three origins groups and the model counterparts. Earnings are measured in US dollars per hour ($/hour).

Table 9: Model fit for fact 3

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

Notes: The table reports the fit between empirical moments for the share of workers in cognitive occupations and in all cities for the three origin groups and the model counterparts. The shares are expressed in percentages, and the differences in the shares are in percentage points.

Recap on the model identification and alternative calibration. I base the identification of the model's parameters on a set of identifying assumptions. First, I normalize to 1 the amenities from working in the non-cognitive occupation in the smallest city for all groups of workers. This normalization is needed as I can only identify the amenities for occupations and locations relative to a base group. Second, I assume that $\tau_{joNex} = 1$, i.e. natives are not subject to local labor market distortions. This is an identifying assumption and, as a result, the estimates of the local labor market distortions that affect immigrants' occupational choices are relative to natives with a similar set of labor market characteristics.

Table 10: Normalization and identifying assumption

Description	Parameter	Determination	Value
Amenities in non-cognitive occupation and small city (all groups)	z_{SMg}	Normalization	1
Wedge on natives earnings	τ_{joNex}	Assumption	1

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 is related to spatial earnings inequality. I also study the role of heterogeneity in human capital, amenities, and labor market distortions for housing prices and US aggregate real output per capita. To this end, I change the value of the parameters of interest, simulate counterfactual economies, and compare them to the baseline economy. I then compare the statistics of interest to the one in the baseline economy. Apart from the parameters of interest, I leave all the other parameters constant in each scenario.

I first study the role of differences in human capital between immigrants and natives. I do so by assigning to all immigrants the same units of occupation-specific human capital as estimated for comparable natives, solve the model, and compare the outcomes of interest to the baseline economy.

In the second counterfactual, I remove the differences in how immigrants and natives value amenities. In other words, I solve the model for an economy where immigrants value working in a city and occupation as much as natives with the same observable characteristics (education and experience).

In the third counterfactual, I remove the labor market distortions faced by immigrants. By doing so, I quantify the role of labor market distortions in explaining inequality among workers and between cities.

The fourth counterfactual scenario, instead, simulates an economy where immigrants face no wedges on earnings and value amenities for cities and occupations as much as natives. In this case, immigrants and natives only differ in terms of productivity and observed distributions among education and experience groups.

In the last counterfactual, I combine all the previous scenarios. In other words, I assign immigrants the same units of human capital as natives with similar education and experience, remove wedges on immigrants' earnings, let them value amenities as much as natives, and solve the model. Note that in this scenario the only differences that remain among workers are due to the observed distribution among education and experience groups.

The Earnings Gap between Natives and Immigrants vs between Cities. How does earnings inequality between natives and immigrants change under the five counterfactuals? How does earnings inequality between big and small cities change? Is there a trade-off between reducing earnings inequality among workers and increasing earnings inequality across cities? Table 11 answers these questions.

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

$$\overline{w}_{\text{Workers}}^{\text{Gap}} = \frac{\overline{w}_{\text{US}}}{\overline{w}_{\text{Imm}}} = \frac{\sum_j \sum_o \sum_e \sum_x \pi_{joUSex} \phi_{USex} w_{joUSex}}{\sum_j \sum_o \sum_{k \neq \text{US}} \sum_e \sum_x \pi_{jokex} \phi_{kex} w_{jokex}} \tag{33}$$

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

$$\overline{w}_{\text{Cities}}^{\text{Gap}} = \frac{\overline{w}_{\text{Big}}}{\overline{w}_{\text{Small}}} = \frac{\sum_o \sum_k \sum_e \sum_x \pi_{\text{Big}okex} \phi_{kex} w_{\text{Big}okex}}{\sum_o \sum_k \sum_e \sum_x \pi_{\text{Small}okex} \phi_{kex} w_{\text{Small}okex}} \tag{34}$$

Column 1 of Table 11 shows that, compared to the baseline economy, when there is no heterogeneity in human capital between immigrants and natives with the same education and experience, earnings inequality between natives and immigrants shrinks by 19.9 percent. In contrast, earnings inequality between the big and small cities increases by 1.1 percent.

When immigrants value amenities from cities and occupations as much as natives with the same observable characteristics, the earnings gap between them reduces by 6.2 percent. The reduction in earnings inequality between workers is not substantial since immigrants are still subject to labor market distortions and differ in human capital endowments from natives. In this scenario, spatial earnings inequality increases by 3 percent.

Table 11: Changes in earnings inequality between workers and between cities

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

Notes: The table reports the percentage change in natives vs. immigrants earnings ratio and big vs. small city real output per capita ratio under the five counterfactual scenarios (Columns 1 to 5) relative to the baseline economy. The baseline values are normalized to 1.

In contrast, when immigrants are not subject to labor market distortions but differ in human capital endowments and amenities from natives, earnings inequality with natives reduces by 9.3 percent. At the same time, earnings inequality between the big and small city shrinks by 0.1 percent.

Interestingly, column (3) reveals that removing wedges on immigrants' earnings and eliminating differences in how they value city-occupation amenities relative to natives reduces the earnings gap by 19.7 percent, a similar magnitude to the case where immigrants and natives have the same human capital. However, spatial earnings inequality increases more than twice as much in this case.

Finally, when immigrants are identical in all aspects to natives (i.e., same human capital endowments, how they value city-occupation amenities, and no labor market distortions) except for their initial education and experience, the earnings gap falls by 29 percent, but cross-city inequality in production increases by 2.3 percent.

The City-Size Earnings Premium for Immigrants. How does the big-city premium of immigrants from low- and high-income countries relative to native workers change under each counterfactual economy? Figure 5 answers this question. For each country of origin k, I compute the earnings differences between the big and the small cities as:

$$\overline{w}_k^{\text{Premium}} = \overline{w}_k^{\text{Big}} - \overline{w}_k^{\text{Small}} \tag{35}$$

$$= \sum_o \sum_e \sum_x \pi_{\text{Big}okex} w_{\text{Big}okex} \phi_{kex} - \sum_o \sum_e \sum_x \pi_{\text{Small}okex} w_{\text{Small}okex} \phi_{kex} \tag{36}$$

and then define the gap in big-city premium between immigrants from country k and natives as:

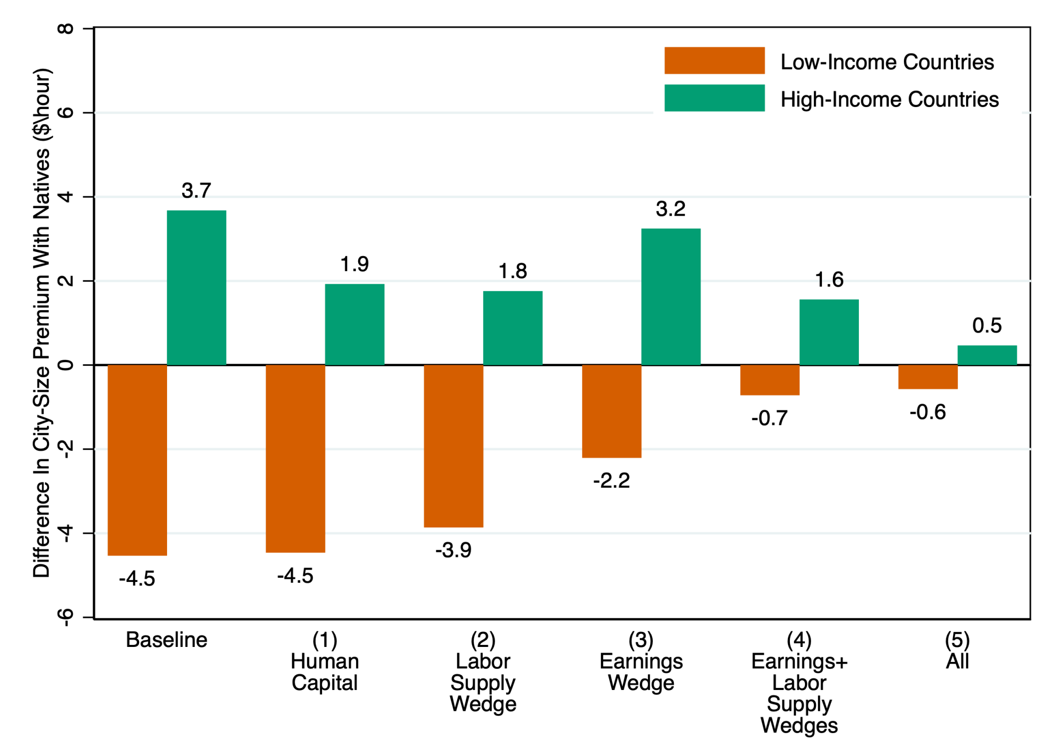
$$\overline{w}_k^{\Delta\text{Premium}} = \overline{w}_k^{\text{Premium}} - \overline{w}_{US}^{\text{Premium}} \tag{37}$$

Column (1) in Figure 5 shows that, in the baseline economy, the gap with natives is positive (+3.7$ per hour) for immigrants from high-income countries and negative (-4.5$ per hour) for immigrants from low-income countries. In this case, the differences in city-size earnings premia between immigrants and natives are influenced not only by heterogeneity in the endowment of occupation-specific human capital but also by the presence of different values of city-occupation amenities and labor market distortions.

In the first counterfactual, where the endowments of occupation-specific human capital supplied by immigrants and comparable natives are the same but the other parameters are untouched, the gap in city-size earnings premia with natives reduces, primarily for immigrants from high-income countries (Column 1 in Figure 5). In contrast, the gap in city-size earnings premia with natives only closes by approximately 2.2 percent for immigrants from low-income countries.

Column (2) of Figure 5 reveals that removing differences in how immigrants value city-occupation amenities with respect to natives leads to a substantial reduction in the difference in city-size earnings premia between immigrants and natives. The difference in big-city premium with natives closes by 48.6 percent for immigrants from high-income countries. Similarly, the difference in big-city premium with natives shrinks by 13.3 percent for immigrants from low-income countries. Although this reduction is more notable than in the previous case, disparities in city-size earnings premia with natives remain due to the presence of wedges on earnings and differences in endowments of human capital among workers.

Figure 5: Counterfactuals on earnings gap



Notes: The figure shows the difference in the city-size earnings premia between immigrants from low-income countries (orange) and natives and high-income countries and natives (green) under all the counterfactuals (Columns 1 to 5). City-size earnings premia are expressed in US dollars per hour ($/hour).

To what extent does removing wedges on earnings, by keeping all the other parameters fixed, reduce differences in city-size earnings premia with natives? Column (3) in Figure 5 shows that under this hypothesis, the differences in city-size earnings premia with natives reduces for workers from all countries. The gap in city-size earnings premia with natives almost halves immigrants from low-income countries, declining from -4.5$ per hour to -2.2$ per hour. Immigrants from high-income countries, in contrast, experience a 10 percent reduction in their spatial earnings gap with natives. This suggests that removing labor market distortions helps to reduce earnings differences with natives for immigrants from low-income countries, and also contributes to diminishing the earnings advantage of immigrants from high-income countries compared to natives.

In the fourth counterfactual, there are no sources of immigrants' spatial and occupational misallocation relative to natives. The impact of this scenario on spatial earnings inequality is remarkable, as shown in Column (4) of Figure 5. For immigrants from low-income countries, the difference in city-size earnings premia with natives reduces substantially by 84.4 percent. Likewise, for immigrants from high-income countries, the gap with natives experiences a substantial decrease of 56.7 percent. The significant reductions in the gap in city-size premia indicate that heterogeneity in values for city-occupation amenities and city-occupation-specific wedges are the main sources of labor market inequality among workers from different countries.

In the fifth counterfactual scenario, represented in Column (5) of Figure 5, I explore the impact of eliminating all differences in the determinants influencing location and occupation choices between immigrants and natives. The results indicate a substantial reduction in the gap in city-size earnings premia between all groups of immigrants and natives. Specifically, the earnings gap between immigrants from high-income countries and natives decreases significantly from 3.7$ per hour to 0.5$ per hour, while the gap between immigrants from low-income countries and natives declines from -4.5$ per hour to -0.6$ per hour. These residual gaps in earnings reflect the remaining differences in the measures ϕ_g across various groups of workers, highlighting a small role of the distribution of individual characteristics in explaining spatial earnings disparities.

Changes in Housing Prices and Real Output per Capita. How do housing prices and aggregate real output per capita change relative to the baseline economy under the five counterfactual economies? Table 12 provides insights into the changes in US real output per capita and prices relative to the baseline economy under the five counterfactual economies.

When immigrants supply the same units of human capital as comparable natives, housing prices in large cities increase by more than in small cities. This is reflected in a 1 percent increase in the big-small city ratio of housing prices compared to the baseline economy. In this case, aggregate real output per capita also increases by 1.8 percent.

Table 12: Changes in housing prices and aggregate real output per capita

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

Notes: The table reports the percentage change in real output per capita and housing prices under the five counterfactual scenarios (Columns 1 to 5) relative to the baseline economy. The baseline values are normalized to 1. Nominal output is deflated using the price for the consumption good (that does not include housing prices) in the spirit of the CPI.

Column 2, instead, shows that in an economy where immigrants value cities and occupations as much as natives, the big-small city ratio in housing prices increases by 2.6 percent and aggregate real output per capita would increase by 0.7 percent.

Interestingly, removing wedges on immigrants' earnings has a moderate impact on housing prices and real output per capita. To this end, Column 3 indicates that, compared to the baseline economy, the big-small city housing prices ratio increases by 0.8 percent, while aggregate real output per capita increases by 0.2 percent. To put this result in perspective, these output gains are smaller in magnitude than those found by Birinci et al. (2021), who did not consider heterogeneity in production across locations and workers' preferences for locations.

Removing all the sources of heterogeneity to immigrants' allocation across cities and occupations relative to natives leads to an increase in real output per capita (+0.9 percent), but also a substantial increase in cross-city disparities in housing prices (+3.4 percent), as shown in Column 4.

Finally, Column 5 presents the changes in housing prices and aggregate real output per capita when all immigrants are endowed with the same units of human capital as comparable natives, value city-occupation amenities as much as natives and are not subject to any wedge on earnings. Under this scenario, housing prices rise three more times in the big city relative to the small city. At the same time, aggregate production increases in real output per capita by 2.3 percent.

The Role of Heterogeneity in Human capital, Amenities, and Labor Market Distortions in Relocating Workers across Cities and Occupations. The main mechanism behind the changes in the earnings gaps, housing prices, and aggregate output under the five counterfactual scenarios is the workers' reallocation across cities and occupations.

Table **??** indicates that workers move from the big city to the small city in all scenarios except for the case of no wedges on immigrants' earnings. When human capital disparities among similar workers are absent but immigrants value city-occupation amenities differently than natives and are still subject to wedges, immigrants from high-income countries and natives reallocate more.

Similarly, the reallocation of workers towards small cities happens even when immigrants value city-occupation amenities as much as natives but differ from them in human capital endowments and are subject to local labor market distortions (column 2). All groups move to the small city, especially immigrants from low-income countries: their share in the big city decreases by 12.3 percentage points.

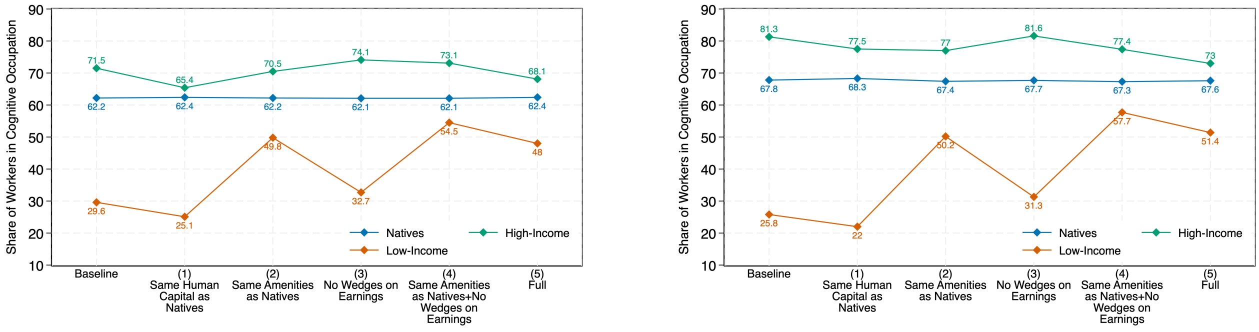
In contrast, when immigrants from all countries are not subject to wedges on earnings, only natives move to the small city, while immigrants move to the big city. Among immigrants, those from low-income countries relocate to the big city more than twice as much as those from high-income countries (+1.2pp vs. +0.5pp).

Column 4 shows the combined effect of immigrants having the same preferences for city-occupation amenities as natives and not being subject to wedges on earnings. The effect on workers' reallocation between cities of changing preferences dominates the effect of removing labor market distortions: some workers from all groups move from the big city to the small city.

In each counterfactual scenario, not only do workers move across cities, but they also relocate across occupations within each city. Figure 6 indicates that, in each city, the reallocation between occupations happens mostly for immigrants from low-income countries. Panel a indicates that in both cities, when immigrants supply as much human capital as comparable natives (in observable characteristics) but value city-occupation amenities and are subject to wedges on earnings, they all move from the cognitive to the non-cognitive occupation in both cities. On the opposite, native workers move to the cognitive occupation, particularly in the big city.

Without differences in the value attached to city-occupation amenities, instead, only the share of immigrants from low-income countries in the cognitive occupation increases significantly in both cities. Conversely, the share of immigrants from high-income countries in cognitive occupations decreases in both cities, but more in the big city (-4.3 percentage points). Only in the big city, a small share of natives move out from the cognitive occupation (-0.4 percentage points).

Figure 6: Changes in the share of workers in cognitive occupations



(a) Small City

(b) Big City

Notes: The figure shows the changes in the share of workers (natives, immigrants from high-income countries, immigrants from low-income countries) in the cognitive occupation for the small (Panel a) and big (Panel b) cities under the 5 counterfactual scenarios. The shares of workers are expressed in percentages.

Removing labor market barriers to immigrants' earnings leads to more immigrants moving into cognitive occupations in both cities, especially for immigrants from low-income countries. However, this reallocation is significantly smaller than when immigrants and natives value city-occupation amenities equally. In this case, the share of natives in the cognitive occupation drops by 0.1 percentage points in both cities.

Keeping differences in human capital endowments and the initial allocations into experience education groups but removing heterogeneity in amenities value with natives and labor market distortions induce a large reallocation of immigrants from low-income countries to the cognitive occupation in both cities. In the small city, immigrants from high-income countries move to the cognitive occupation, while in the big city they move to the non-cognitive occupation. In contrast, the share of natives in the cognitive occupation reduces in both cities.

Finally, when the only differences left between immigrants and natives are the initial allocations into education and experience groups, the share of immigrants from all countries in cognitive occupations becomes very close to that of natives. This suggests that removing differences with natives pushes immigrants from low-income countries to work in cognitive occupations, while immigrants from high-income countries partially move to non-cognitive occupations. In this scenario, the reallocation of immigrants does not significantly affect natives.

The Effect of Workers' Reallocation on Skills Prices and Average Productivity. The reallocation of workers across cities and occupations under each counterfactual affects each city's equilibrium skills prices (competition effect) and the average productivity (skills effect) in the non-cognitive and cognitive occupations. Which of the competition effect and skills effect dominates the other determines whether the earnings gap is reduced among workers, across cities, or both.

Table 13 shows the competition and skills effects in each city and occupation for each counterfactual scenario. In the small city, when immigrants are endowed with the same level of human capital as comparable natives (column 1), the skills effect compensates for the competition effect in the non-cognitive occupation. In contrast, the competition effect counterbalances the reduction in productivity in the cognitive occupation. In the big city, the magnitudes of the effects are larger, but the compensation mechanisms between the two effects are similar to those in the small city for both occupations.

Column 2 shows that the reallocation of workers between occupations induced by the change in how immigrants value amenities burdens the cognitive occupation in both cities. In the small city, competition in the non-cognitive occupation decreases due to a large reallocation of immigrants from low-income countries to the cognitive occupation. As a result, the skills price per unit of human capital increases in the non-cognitive occupation, but average productivity decreases. This suggests that the workers who replace immigrants from low-income countries in the non-cognitive occupation are less productive. The competition effect partially compensates for the loss of productivity. In contrast, the competition and skills effects do not compensate for each other in the cognitive occupation. Due to the inflow of new workers, competition increases, pushing the skills price down. The new workers are also less productive, so average productivity drops.

In the big city, the reallocation of workers to the cognitive occupation increases competition and skills, resulting in fewer but more productive workers in that occupation. However, the skills price per unit of human capital in the cognitive occupation decreases due to the increase in competition. Additionally, the new workers are on average less productive, which also reduces average productivity in the cognitive occupation.

Column 3 shows that removing wedges on immigrants' earnings has a small impact on competition and skills in the cognitive occupation. In both cities, immigrants from all countries move to cognitive occupations, which increases average productivity in non-cognitive occupations and raises the skills price due to reduced competition. In contrast, the new inflow of workers generates an increase in competition that reduces the skills price in the cognitive occupation in both cities. The new workers in this occupation are, on average, less productive than the workers already working there, and the skills effect is negative. Overall, removing labor market distortions reduces competition and improves productivity in the non-cognitive occupation, while increasing competition and reducing productivity in the cognitive occupation, albeit to a small extent.

In the scenario where immigrants are not subject to labor market distortions and value city-occupation amenities as much as natives, the effects on skills prices and average productivity are a combination of the results in columns 2 and 3. The reallocation induced by immigrants' change in tastes for cities and occupations outweighs the reallocation of eliminating labor market distortions. As a result, the competition and the skills' effects are negative in cognitive occupations in both cities.

Finally, column 5 shows that in a world where immigrants and natives are identical except for their initial allocations into education and experience groups, the skills and competition effects offset each other in small cities but align in the same direction in big cities.

Table 13: Competition vs. skills effects

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

Notes: The table reports the change in the shares of native workers, workers from low-income countries, and workers from high-income countries who reside in the big city under the five counterfactual scenarios (Columns 1 to 5). Shares are expressed as percentages, and changes in the shares are expressed in percentage points.

6 Policy experiment

I use the model to simulate two changes in immigration policies and study the new allocations of workers across cities and occupations and how they affect the earnings gap between natives and immigrants and between cities. As a result of the inflow of new immigrants, US employment increases by 1 percentage point under each policy. The first policy (Policy 1) consists of opening the US border to immigrants without a college education. In contrast, with the second policy (Policy 2), the US government opens borders only to immigrants with a college education. Once the new immigrants arrive in the US, they choose a city where to live and an occupation to perform and contribute to the local economy.

I assume that the new immigrants supply the same amount of human capital, have the same preferences for city-occupation amenities, and face the same labor market barriers as immigrants with comparable observable characteristics who are already settled in the US. To give context to this assumption, Table 14 reports the average human capital supplied by immigrants with and without college education in cognitive and non-cognitive occupations. Overall, immigrants without a college education supply twice as much human capital for the cognitive occupation than for the non-cognitive occupation. At the same time, immigrants with a college education supply more than three times human capital for the cognitive occupation than for the non-cognitive occupation. Comparing column 1 to column 2, it is possible to conclude that these patterns are independent of the immigrants' country of origin. Based only on the comparative advantage originating from human capital, Table 14 suggests that immigrants without a college education are more likely to choose to perform the non-cognitive occupation, while more educated immigrants are more likely to choose to perform the cognitive occupation.

Table 14: Immigrants human capital

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

Notes: The table reports the average value of the human capital of immigrants without college and with college education in the cognitive and non-cognitive occupations. Standard deviation in parenthesis. Workers' probability distribution weights are used in the calculations.

Changes in the spatial distribution of workers. The first block of Table 15 reports the distribution of employment between the small and the big city in the baseline economy and after the implementation of the two policies. Under both policies, the employment share in the big city increases. These changes are due the inflow of new workers and their allocation across cities. In general, new immigrants allocate in both cities, but disproportionately more in the big city compared to the small city due to the high values of amenities and distortions, as highlighted in columns (3) and (4) of Table 16. The inflow of new workers in each city generates an increase in competition in each local labor market. As a result, some workers relocate from the small to the big city. All in all, cross-city differences in employment levels become larger under the first policy.

The second block of Table 15 reports the baseline values for the shares of immigrants in the cognitive occupation and the corresponding changes after the inflows of new immigrants. Both policies imply an increase in the number of immigrants in the cognitive occupation in both cities. Column (3), however, shows that the increase in differences between cities in the share of immigrants in the cognitive occupation is larger under the second policy. While in the baseline the difference between cities is 1.6 percentage percentage points, under the second policy it increases to 1.9 percentage points.

Table 15: Changes in spatial distributions and average earnings across cities

	Small City	Big City	Big-Small City Difference
	(1)	(2)	(3)
		Employment	
Baseline	17.2%	82.8%	+65.7
Policy 1	17.0%	83.0%	+65.9
Policy 2	17.1%	82.9%	+65.8
		Immigrants In Cognitive Occupation	
Baseline	3.8%	5.4%	+1.6
Policy 1	4.0%	5.7%	+1.7
Policy 2	4.6%	6.5%	+1.9

Notes: Columns (1) and (2) reports for small and big cities the share of workers and the share of immigrants in the cognitive occupation (expressed in percentage terms) in the baseline and after the changes in immigration policy. I divide the employment shares in both cities by the new value of the population (1.01). Column (3) reports the big-small difference in employment shares and values are expressed as percentage points.

Differences in workers' allocations after changes in immigration policies can be explained by the following factors. First, although all workers, regardless of their educational attainment, can perform the cognitive occupation, a college education provides workers with more of the human capital required to perform such an occupation (see, Hanushek (2012) for example). Thus, immigrants with a college education have a comparative advantage in performing the cognitive occupation relative to immigrants without a college degree. Second, immigrants with a college education have a large taste for working in the big city, as shown in the second row of Table 16. Consequently, the share of immigrants in the cognitive occupation increases more in the big city after an inflow of immigrants with a college education.

Table 16: Immigrants amenities

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

Notes: The table reports the average value of amenities z_{jok} for each city and occupation of immigrants without college and with college education. Standard deviation in parenthesis. Workers' probability distribution weights are used in the calculations.

Changes in Earnings Gaps among Workers and across Cities. How do earnings inequality among workers and across cities change under the two new immigration policies? Table 17 answers this question. Column (1) shows that an inflow of immigrants without college degrees increases the earnings gap between immigrants and natives but reduces the earnings gap between big and small cities.

Table 17: Changes in earnings inequality among workers and across cities

	Baseline	Policies	
		Inflow No College	Inflow College
		(1)	(2)
Natives-Immigrants Earnings Gap	1	1.026	0.941
Big-Small City Earnings Gap	1	0.997	0.999

Notes: The table reports the percentage change in natives vs. immigrants earnings ratio and big vs. small city real output per capita ratio under the two simulated policy scenarios relative to the baseline economy. The baseline values are normalized to 1.

As discussed in the previous paragraph, these immigrants have a comparative advantage in choosing the non-cognitive occupation over the cognitive occupation. The increase in competition in both cities in the non-cognitive occupation has a negative impact on the wage per unit of human capital and also the average productivity in each occupation reduces, as shown in Column (1) of Table 18. At the same time, the average productivity in cognitive occupations decreases in both cities. The changes in competition and average productivity lead to an increase in the earnings gap between natives and immigrants. However, since these changes are stronger for the non-cognitive occupation in the big city with respect to all the occupations in all cities, the big-small city earnings gap reduces.

In contrast, column 2 of table 17 indicates that an inflow of immigrants with a college education induces a reduction in the earnings gaps between natives and immigrants and between the big and small cities. The new immigrants supply more human capital, have a comparative advantage in working in the cognitive occupation, and are more likely to live in the big city. As a result, in both cities, the competition effect in cognitive occupations is negative but is compensated by an increase in average productivity. The increase in average productivity induces a reduction in the earnings gap between natives and immigrants. However, the existence of labor market distortions for immigrants in the big cities reduces the positive impact of the inflow of new workers and average earnings increase more in the small city.

Table 18: Immigration policies: competition and skills effects

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

Notes: The table reports the percentage change in the competition and skills effect for the big and small cities. The competition effect measures the change in skills prices per unit of human capital and the skills effect measures the change in average workers' productivity. The baseline values are normalized to 1.

7 Conclusion

In this paper, I studied the geographical distribution of labor market outcomes for US immigrants and its implications for spatial inequality. Using US micro-data from the American Community Survey 2009-2011, I documented that, relative to natives and immigrants from high-income countries, immigrants from low-income countries do not earn a premium for working in large cities, are more likely to work in non-cognitive occupations and to live in large cities.

To understand the driving forces behind these facts, I built and structurally estimated a general equilibrium spatial model where firms in larger cities favor cognitive skills and workers are heterogeneous in human capital and tastes for cities and occupations. Conditional on their country of origin, location, and occupation choice, immigrants are subject to wedges on earnings that can either penalize or reward them.

Taken together counterfactual exercises revealed a trade-off between reducing the earnings gap between immigrants and natives and increasing the earnings gap between big and small cities. Removing all sources of heterogeneity between immigrants and natives reduces earnings inequality between them by 29 percent, but increases the earnings gap between cities by 2.3 percent. This trade-off is mainly driven by the reallocation of immigrants from low-income countries to small cities and cognitive occupations.

Finally, I used the model to quantify how opening borders to new immigrants affects earnings inequality between workers and cities. I simulated two policies: one opens the US border to immigrants without a college education and another to immigrants with a college education. The results revealed that while the earnings gap across cities decreased in both cases, only in the case of an inflow of immigrants with a college education the earnings gap between immigrants and natives decreased.

The structure of the model shows that sources of heterogeneity among workers and labor market distortions contribute to earnings inequality among them and across locations. However, the model could be expanded with scenarios of local oligopsony power, where multiple firms in each location compete among each other. Within this framework, the occupational specialization of immigrant workers with a wide set of reservation wages and different preferences for locations could be an additional factor motivating firms to set wages below the marginal product across different regions. This extension remains a topic for future research.

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Appendices

A Data Appendix

Immigrants. I define immigrants as foreign-born workers who are either naturalized citizens or do not have a citizen status or are born abroad from American parents.

Low-Income And High-Income Countries. I define as low-income those countries whose GDP per capita is less than $\$30,000$ and as high-income those countries whose GDP per capita is greater than or equal to $\$30,000$.

Years of Schooling, College, And No College. In the ACS individuals are asked to report their educational attainment. I use the detailed version for the variable "EDUC" to impute years of schooling as follows: 4 "No schooling completed" to "Grade 4", 7 "Grade 5, 6, 7, or 8", 9 "Grade 9", 10 "Grade 10", 11 "Grade 11", 12 "Grade 12" to "Some college, but less than 1 year", 13 "1 or more years of college credit, no degree", 14 "Associate's degree, type not specified", 16 "Bachelor's degree", 18 "Master's degree" or "Professional degree beyond a bachelor's degree", 21 "Doctoral degree". Based on the years of schooling, I create a dummy variable to distinguish workers without a college education (i.e., years of schooling ≤ 12) from workers with a college education (i.e., years of schooling > 12).

Potential Experience. I compute potential experience in the labor market as a worker's age-years of schooling-6. I divide workers into three categories according to their potential experience in the labor market: 0-14, 15-29, and 30+.

Hourly Earnings. I construct hourly earnings using the information in the variables "INCWAGE", "WKSWORK2", and "UHRSWORK". The first variable contains information about an individual's pre-tax wage and salary income from the previous year, the second variable provides the number of weeks that an individual worked in the previous year, and the last variable is the usual hours worked by an individual in a week. Since the weeks worked are provided in intervals, I follow Albert et al. (2021) and I impute weeks worked for the available intervals as: 7.4, 21.3, 33.1, 42.4, 48.2, and 51.9. To account for inflation, I convert hourly earnings to constant 1999 dollars using the CPI-U multiplier index available in IPUMS.

Task Intensity. I collect data from O*NET on work activities and work context importance scales. I follow Acemoglu and Autor (2011) and define the five macro-categories of occupation tasks with all their descriptors of tasks required by each occupation[17]:

- Non-routine cognitive analytical:
    - Analyzing data/information

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

- 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 mean zero and 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. Once I obtain the two vectors of exposure to cognitive and non-cognitive tasks, I standardize them to have mean zero and standard deviation one and I then normalize them to lie in the $[0,1]$ interval. To merge the task exposure measure with the ACS data, I compute the employment shares in each occupation in 2010 and I collapse them at the 3-digit SOC 2010 level. There are initially 396 occupations using the codes assigned in the "OCC1990" variable from IPUMS that I aggregate to 84 occupations defined at 3-digit SOC codes.

Finally, I divide these occupations into cognitive and non-cognitive occupations as follows. For each of the 84 occupations, I measure the exposure to cognitive and non-cognitive tasks: if the exposure to the cognitive occupation is larger than exposure to the non-cognitive tasks, then the occupation is classified as "cognitive", otherwise, it is classified as a "non-cognitive" occupation.

Small And Big Cities. I divide cities into small and big based on their employment stock. Small cities are cities with an employment stock that is less than 500,000 workers, and big cities are cities with an employment stock greater/equal than/to 500,000 workers.

Table 19: 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
Chicago-Gary-Lake IL	1	66.5	10.2	24.7
New York-Northeastern NJ	2	66.1	24.4	25.3
Los Angeles-Long Beach, CA	3	59.3	25.4	20.5
Houston-Brazoria, TX	4	61.8	17.4	24.0
Philadelphia, PA/NJ	5	65.6	4.2	24.3
Atlanta, GA	6	66.4	8.0	22.4
Washington, DC/MD/VA	7	74.6	12.7	28.9
Dallas-Fort Worth, TX	8	67.1	13.7	23.1
Detroit, MI	9	59.4	4.3	21.0
Minneapolis-St. Paul, MN	10	66.0	2.9	23.2

Notes: The table reports the share (expressed in percentages) of workers in cognitive occupations and immigrants, and the average hourly earnings for the 10 biggest cities in the sample ranked by employment stocks. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 20: Descriptive statistics

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
Natives	21.8	14.0	20.2	.	562,577
	(19.9)	(2.4)	(11.1)	(.)	
Immigrants	14.5	11.0	24.9	12.0	56,999
	(15.7)	(4.0)	(8.4)	(7.7)	
Low-Income	12.7	10.6	25.0	12.1	51,470
	(12.1)	(3.9)	(8.4)	(7.7)	
High-Income	37.0	15.2	24.7	10.2	5,529
	(30.8)	(3.2)	(8.4)	(7.8)	

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. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 21: Descriptive statistics for low-income countries

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
Mexico	10.2	8.9	23.9	12.6	20,529
	(8.6)	(2.9)	(8.3)	(7.7)	
India	25.1	15.6	23.1	9.2	2,919
	(20.3)	(3.0)	(9.0)	(7.2)	
China	15.7	13.2	26.7	11.5	2,897
	(15.6)	(4.6)	(8.0)	(7.3)	
El Salvador	10.3	8.5	24.8	13.0	2,849
	(6.4)	(3.0)	(8.4)	(8.0)	
Philippines	15.1	14.3	28.5	12.5	2,599
	(11.4)	(2.3)	(7.8)	(8.1)	
Guatemala	9.1	8.0	22.3	10.2	2,145
	(6.2)	(3.1)	(8.6)	(7.5)	
Vietnam	12.3	10.7	29.6	15.1	1,923
	(9.9)	(3.4)	(7.3)	(8.4)	
Dominican Republic	11.3	10.9	26.7	12.9	1,244
	(8.8)	(3.0)	(8.2)	(8.1)	
Honduras	9.4	8.3	22.3	9.8	1,183
	(7.7)	(2.9)	(8.3)	(6.6)	
Colombia	14.5	12.9	27.2	12.4	993
	(12.7)	(3.0)	(7.5)	(7.3)	
Ecuador	11.5	9.9	24.4	11.7	966
	(9.5)	(3.3)	(8.5)	(7.1)	
Jamaica	14.9	12.3	27.5	13.3	823
	(10.7)	(2.2)	(7.9)	(8.3)	
Haiti	11.7	12.0	28.0	14.1	819
	(8.5)	(2.3)	(8.0)	(8.4)	
Peru	13.4	13.2	27.3	12.0	797
	(12.7)	(2.6)	(7.5)	(7.2)	
Poland	17.8	13.2	30.0	15.4	755
	(11.7)	(2.6)	(7.5)	(7.5)	
Brazil	17.9	12.5	23.3	9.3	638
	(21.1)	(3.4)	(7.9)	(6.0)	

Table 21 – Continued

Country of Origin	Avg. Hourly Earnings (1)	Avg. Years of Schooling (2)	Avg. Experience (3)	Avg. Years in the US (4)	Obs. (5)
Pakistan	15.5	13.9	28.2	12.9	551
	(16.0)	(3.6)	(7.9)	(7.5)	
Russian Federation	23.1	15.8	28.0	12.9	518
	(17.2)	(3.3)	(7.4)	(6.0)	
Nicaragua	11.1	10.8	27.9	14.5	414
	(7.5)	(3.3)	(8.7)	(8.4)	
Bangladesh	12.1	14.0	26.1	11.4	404
	(12.0)	(3.2)	(8.0)	(7.2)	
Nigeria	18.0	15.1	25.1	10.1	371
	(17.8)	(2.7)	(7.8)	(6.8)	
Ethiopia	12.0	13.2	23.4	9.1	351
	(8.4)	(2.6)	(8.1)	(7.0)	
Romania	20.7	14.5	27.1	12.9	339
	(15.6)	(2.8)	(7.9)	(7.5)	
Argentina	19.4	13.2	24.5	10.7	325
	(20.0)	(3.4)	(7.8)	(6.4)	
Ghana	14.0	13.3	26.3	10.6	325
	(9.3)	(2.7)	(7.5)	(6.2)	
Trinidad and Tobago	15.2	12.6	28.1	13.8	309
	(13.3)	(2.3)	(7.2)	(6.9)	
Egypt, Arab Rep.	18.8	14.6	26.1	10.6	287
	(21.5)	(2.8)	(8.1)	(7.3)	
Iraq	17.1	12.2	23.5	8.3	252
	(19.1)	(3.5)	(7.4)	(6.9)	
Myanmar	11.2	10.5	23.1	6.9	227
	(8.6)	(4.6)	(8.9)	(6.7)	
Albania	14.1	13.1	28.5	10.1	192
	(8.1)	(2.5)	(7.0)	(4.8)	
South Africa	38.7	15.5	25.1	10.8	171
	(30.6)	(2.6)	(7.2)	(7.2)	
Morocco	13.3	12.7	22.3	9.2	164
	(9.5)	(3.0)	(7.2)	(6.0)	
Bulgaria	17.1	14.6	25.1	9.5	142
	(15.2)	(3.1)	(7.2)	(4.9)	

Table 21 – Continued

Country of Origin	Avg. Hourly Earnings (1)	Avg. Years of Schooling (2)	Avg. Experience (3)	Avg. Years in the US (4)	Obs. (5)
Bolivia	15.1	12.7	27.6	12.0	141
	(13.4)	(3.1)	(8.5)	(8.1)	
Lebanon	21.5	13.4	28.5	14.4	140
	(21.3)	(3.3)	(7.6)	(7.7)	
Costa Rica	13.4	11.1	24.8	11.0	136
	(13.4)	(3.2)	(9.0)	(7.1)	
Chile	20.4	13.9	27.1	12.8	130
	(21.5)	(3.0)	(7.6)	(7.8)	
Thailand	12.4	12.1	26.2	11.6	128
	(7.5)	(4.1)	(9.5)	(8.9)	
Nepal	11.7	14.2	20.7	6.5	123
	(9.4)	(3.1)	(8.2)	(5.2)	
Kenya	18.5	14.3	25.4	10.0	119
	(13.9)	(2.4)	(6.5)	(6.2)	
Sri Lanka	19.0	14.1	27.2	11.7	107
	(17.3)	(3.0)	(8.2)	(6.8)	
Uruguay	14.0	12.3	27.1	10.4	105
	(13.9)	(2.8)	(7.8)	(6.0)	
Fiji	16.0	14.2	25.3	12.3	102
	(11.4)	(3.1)	(7.3)	(7.0)	
Indonesia	15.2	12.4	28.8	13.4	102
	(8.5)	(2.3)	(7.6)	(7.5)	
Malaysia	22.7	13.2	25.9	13.3	95
	(25.2)	(4.3)	(8.2)	(7.4)	
Liberia	11.3	13.6	26.1	10.4	95
	(6.6)	(2.3)	(7.0)	(5.9)	
Panama	15.0	12.9	27.8	13.4	75
	(10.1)	(3.0)	(8.4)	(7.8)	
Afghanistan	12.9	12.6	29.0	15.0	74
	(8.9)	(3.7)	(7.5)	(8.8)	
Hungary	24.2	15.7	26.4	14.5	69
	(17.5)	(3.5)	(8.4)	(8.9)	
Jordan	12.8	12.9	24.6	11.8	66
	(10.7)	(3.0)	(8.1)	(8.0)	

Table 21 – Continued

Country of Origin	Avg. Hourly Earnings (1)	Avg. Years of Schooling (2)	Avg. Experience (3)	Avg. Years in the US (4)	Obs. (5)
Sierra Leone	14.8	13.8	28.0	14.2	65
	(8.6)	(2.5)	(8.2)	(7.9)	
Barbados	20.8	12.7	29.8	16.2	63
	(25.4)	(2.0)	(6.9)	(8.0)	
Sudan	12.3	13.3	24.4	10.1	62
	(8.6)	(3.1)	(6.7)	(5.5)	
Senegal	11.8	12.7	25.5	11.7	52
	(7.9)	(3.6)	(7.5)	(5.3)	

Notes: The table reports the sample of countries classified as low-income countries (GDP per capita $<$ $30,000$ 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. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 22: Descriptive statistics for high-income countries (GDP pc $\geq 30,000$)

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Avg. Years in the US	Obs.
	(1)	(2)	(3)	(4)	(5)
United Kingdom	42.5	15.4	25.5	10.7	1,411
	(34.1)	(2.8)	(7.9)	(7.4)	
Canada	38.3	15.2	25.8	10.9	1,045
	(29.9)	(2.8)	(7.7)	(6.8)	
Japan	37.1	16.0	22.1	6.2	666
	(31.0)	(2.6)	(8.1)	(7.0)	
Germany	38.4	16.3	22.7	8.9	568
	(31.0)	(3.3)	(7.8)	(6.9)	
Italy	29.4	14.4	24.6	11.5	261
	(27.5)	(3.2)	(8.6)	(8.4)	
Israel	26.8	14.1	24.0	12.6	239
	(23.9)	(3.3)	(9.7)	(9.3)	
France	39.9	16.0	22.7	8.6	232
	(33.1)	(3.2)	(8.5)	(7.2)	
Hong Kong SAR	22.5	13.5	31.1	15.7	220
	(21.6)	(3.0)	(6.5)	(7.5)	
Portugal	21.4	9.9	30.1	16.5	200
	(14.6)	(3.6)	(7.7)	(8.6)	
Ireland	33.8	14.1	24.8	12.7	186
	(28.4)	(3.0)	(8.0)	(7.8)	
Australia	36.2	15.3	23.1	7.3	174
	(26.0)	(2.9)	(8.8)	(7.1)	
Netherlands	48.0	16.8	23.1	8.9	126
	(34.7)	(2.7)	(7.4)	(7.5)	
Spain	36.0	15.4	22.0	8.9	112
	(33.7)	(3.7)	(9.6)	(8.5)	
Sweden	43.0	16.5	23.2	8.1	89
	(24.1)	(2.9)	(9.1)	(6.6)	

Notes: The table reports the sample of countries classified as low-income countries (GDP per capita $\geq 30,000$ 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. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 23: List of cognitive occupations

Occupation (SOC 3-dig)	Share Of Immigrant Workers (%)	Avg. Hourly Earnings
Advertising, Marketing, Promotions, Public Relations, and Sales Managers	0.5	54.8
Air Transportation Workers	6.3	43.1
Architects, Surveyors, and Cartographers	1.5	42.4
Art and Design Workers	3.5	39.4
Baggage Porters, Bellhops, and Concierges	4.7	35.3
Business Operations Specialists	3.8	35.0
Computer Occupations	2.4	33.4
Counselors, Social Workers, and Other Community and Social Service Specialists	13.3	32.4
Drafters, Engineering Technicians, and Mapping Technicians	2.7	32.2
Engineers	5.2	31.6
Entertainers and Performers, Sports and Related Workers	5.8	30.6
Financial Clerks	3.8	30.5
Financial Specialists	19.5	29.3
Health Diagnosing and Treating Practitioners	6.6	27.9
Health Technologists and Technicians	3.6	27.1
Information and Record Clerks	8.2	26.8
Lawyers, Judges, and Related Workers	3.5	24.7
Legal Support Workers	3.3	24.5
Librarians, Curators, and Archivists	5.6	23.1
Life Scientists	2.6	23.1
Life, Physical, and Social Science Technicians	3.7	22.5
Mathematical Science Occupations	3.5	22.0
Media and Communication Equipment Workers	4.8	21.9
Media and Communication Workers	4.6	21.5
Nursing, Psychiatric, and Home Health Aides	10.5	21.4
Operations Specialties Managers	8.2	21.2
Other Healthcare Support Occupations	4.7	20.3
Other Management Occupations	7.5	20.2
Other Office and Administrative Support Workers	7.0	20.1
Other Personal Care and Service Workers	4.8	20.0
Other Protective Service Workers	5.6	19.6
Other Sales and Related Workers	2.1	18.8
Other Teachers and Instructors	3.0	18.7
Physical Scientists	2.6	18.4
Postsecondary Teachers	4.3	18.2
Preschool, Primary, Secondary, and Special Education School Teachers	7.6	18.1
Religious Workers	1.8	18.0
Retail Sales Workers	4.5	16.7
Sales Representatives, Services	6.4	16.1
Secretaries and Administrative Assistants	5.5	15.9
Social Scientists and Related Workers	4.8	15.6
Supervisors of Building and Grounds Cleaning and Maintenance Workers	3.8	15.4
Supervisors of Construction and Extraction Workers	4.2	15.1
Supervisors of Installation, Maintenance, and Repair Workers	9.5	14.7
Supervisors of Office and Administrative Support Workers	6.5	14.2
Supervisors of Personal Care and Service Workers	16.1	14.2
Supervisors of Production Workers	6.9	12.4
Supervisors of Protective Service Workers	10.5	12.0
Supervisors of Sales Workers	17.2	11.6
Supervisors of Transportation and Material Moving Workers	3.9	11.6
Top Executives	11.2	11.2

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 rescaled by the annual number of hours worked and used in the calculations.

Table 24: List of non-cognitive occupations

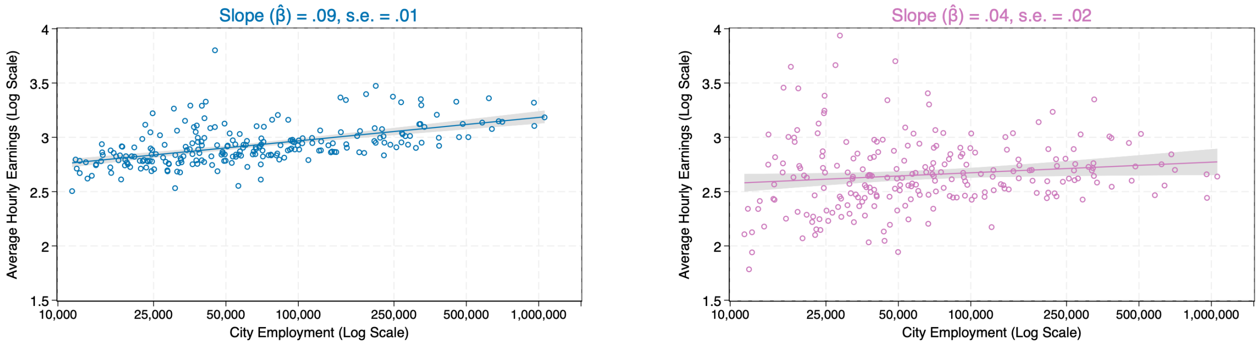
Occupation (SOC 3-dig)	Share Of Immigrant Workers (%)	Avg. Hourly Earnings
Assemblers and Fabricators	4.4	21.4
Building Cleaning and Pest Control Workers	1.0	19.3
Communications Equipment Operators	3.2	18.6
Construction Trades Workers	4.6	18.0
Cooks and Food Preparation Workers	5.6	14.9
Electrical and Electronic Equipment Mechanics, Installers, and Repairers	14.1	14.8
Entertainment Attendants and Related Workers	10.5	14.7
Extraction Workers	9.1	14.6
Food Processing Workers	29.3	14.4
Food and Beverage Serving Workers	15.9	14.1
Helpers, Construction Trades	11.5	13.8
Material Moving Workers	17.5	13.3
Material Recording, Scheduling, Dispatching, and Distributing Workers	8.9	13.0
Metal Workers and Plastic Workers	9.3	12.6
Motor Vehicle Operators	23.2	12.5
Other Construction and Related Workers	7.0	12.1
Other Installation, Maintenance, and Repair Occupations	21.6	12.0
Other Production Occupations	12.6	11.9
Other Transportation Workers	25.4	11.5
Personal Appearance Workers	40.5	11.5
Plant and System Operators	26.9	11.2
Printing Workers	26.7	10.3
Rail Transportation Workers	29.2	10.2
Supervisors of Food Preparation and Serving Workers	47.0	9.9
Textile, Apparel, and Furnishings Workers	18.3	9.5
Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	21.2	9.2
Water Transportation Workers	33.1	9.1
Woodworkers	41.8	7.2

Notes: The table reports the list of occupations categorised as "non-cognitive" and the share (expressed in percentages) of immigrant workers in these occupations. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

B Figures

B.1 Robustness Checks Fact 1: Unconditional Mean

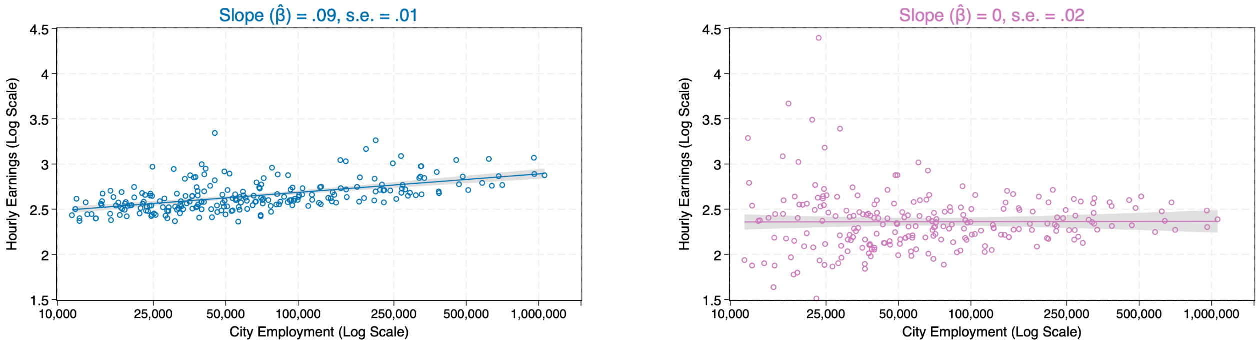
Figure 7: Raw data: male workers



(a) Natives (b) Immigrants

Notes: Each dot corresponds to the log of average hourly earnings in a Metropolitan Statistical Area. Individual sample weights are rescaled by the annual number of hours worked and used in the calculations.

Figure 8: Raw data: female workers

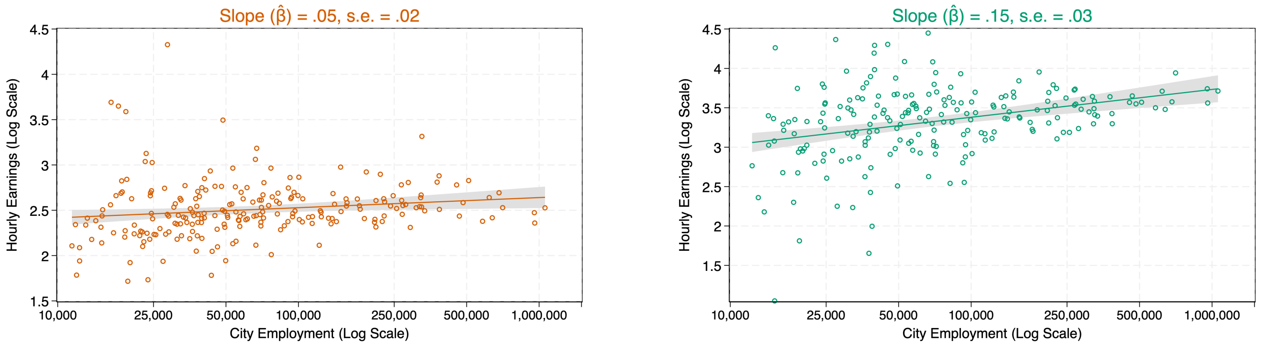


(a) Natives (b) Immigrants

Notes: Each dot corresponds to the log of average hourly earnings in a Metropolitan Statistical Area. Individual sample weights are rescaled by the annual number of hours worked and used in the calculations.

B.2 Robustness Checks Fact 2: Unconditional Means

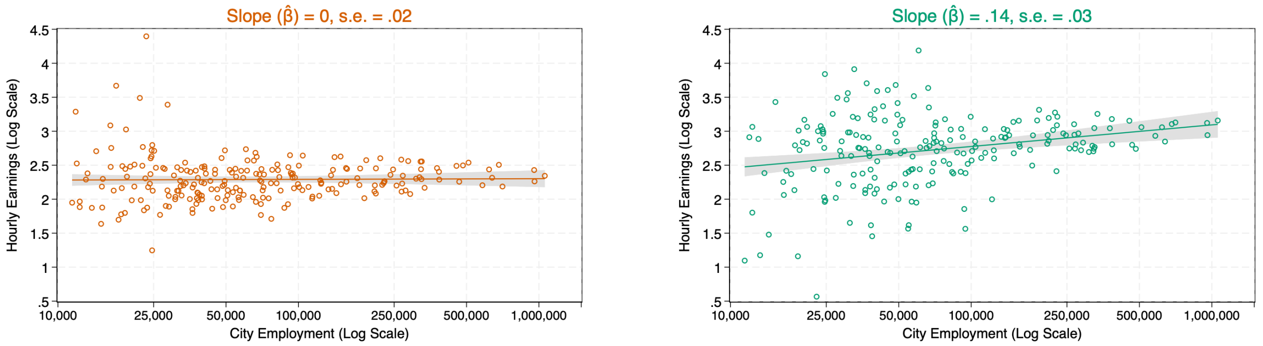
Figure 9: Raw data: male workers



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

Notes: Each dot corresponds to the log of average hourly earnings in a Metropolitan Statistical Area. Individual sample weights are rescaled by the annual number of hours worked and used in the calculations.

Figure 10: Raw data: female workers



(a) Natives (b) Immigrants

Notes: Each dot corresponds to the log of average hourly earnings in a Metropolitan Statistical Area. Individual sample weights are rescaled by the annual number of hours worked and used in the calculations.

C Tables

C.1 Robustness Checks Fact 1: Regressions

Table 25: Regressions for Fact 1: Males

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), and a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), years of schooling, years of potential experience and occupation fixed effects (column 5), and years of schooling, years of potential experience, occupation, and country of origin fixed effects (column 6). The model is estimated separately for workers who are US-born and foreign-born. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 26: Conditional regressions for Fact 1: Males

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Immigrants		
Log City Employment	−0.026	−0.030	−0.015	−0.031	−0.026
	(0.014)	(0.024)	(0.013)	(0.015)	(0.016)
Constant	2.302	3.333	2.151	2.567	2.612
	(0.176)	(0.310)	(0.168)	(0.189)	(0.195)
N. Obs	38,747	18,252	6,181	30,139	20,679
Adj.R2	0.03	0.01	0.36	0.23	0.12
			Natives		
Log City Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.010)
Constant	1.777	1.840	1.500	1.852	1.950
	(0.090)	(0.170)	(0.143)	(0.144)	(0.124)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.13	0.08	0.17	0.16	0.12
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born and foreign-born. Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 27: Regressions for Fact 1: Females

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), and a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), years of schooling, years of potential experience and occupation fixed effects (column 5), and years of schooling, years of potential experience, occupation, and country of origin fixed effects (column 6). The model is estimated separately for workers who are US-born and foreign-born. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 28: Conditional regressions for Fact 1: Females

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Immigrants		
Log City Employment	−0.020	0.025	0.003	0.003	−0.016
	(0.017)	(0.018)	(0.018)	(0.017)	(0.016)
Constant	2.109	2.285	1.819	1.939	2.261
	(0.202)	(0.252)	(0.229)	(0.203)	(0.201)
N. Obs	26,646	14,148	2,835	20,619	17,340
Adj.R2	0.01	0.00	0.24	0.17	0.13
			Natives		
Log City Employment	0.040	0.074	0.059	0.067	0.060
	(0.010)	(0.020)	(0.016)	(0.016)	(0.015)
Constant	01.533	01.675	01.296	01.508	01.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.08	0.04	0.17	0.14	0.11
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born and foreign-born. Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

C.2 Robustness Checks Fact 2: Regressions

Table 29: Regressions for Fact 2: Males

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), and years of schooling, years of potential experience and occupation fixed effects (column 5). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc < 30,000 US \$), and born in a high-income country (GDP pc $\geq$ 30,000 US \$). Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 30: Conditional regressions for Fact 2: Males

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Low-Income		
Log City Employment	−0.023	−0.035	−0.025	−0.030	−0.019
	(0.014)	(0.025)	(0.013)	(0.016)	(0.014)
Constant	02.251	03.283	02.277	02.544	02.499
	(0.170)	(0.317)	(0.173)	(0.198)	(0.173)
N. Obs	37,308	14,162	5,568	27,059	18,843
Adj.R2	0.03	0.01	0.3	0.17	0.08
			High-Income		
Log City Employment	0.030	0.081	0.082	0.054	0.087
	(0.026)	(0.032)	(0.046)	(0.025)	(0.037)
Constant	2.274	2.237	1.625	2.111	1.724
	(0.353)	(0.406)	(0.597)	(0.327)	(0.459)
N. Obs	1,439	4,090	613	3,080	1,836
Adj.R2	0.00	0.03	0.10	0.17	0.17
			Natives		
Log City Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.01)
Constant	1.777	1.840	1.500	1.852	1.950
	(0.090)	(0.170)	(0.143)	(0.144)	(0.124)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.13	0.08	0.17	0.16	0.12
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc < 30,000 US $), and born in a high-income country (GDP pc $\geq$ 30,000 US $). Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 31: Regressions for Fact 2: Females

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), and years of schooling, years of potential experience and occupation fixed effects (column 5). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc $<$ 30,000 US \$), and born in a high-income country (GDP pc $\geq$ 30,000 US \$). Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 32: Conditional regressions for Fact 2: Females

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Low-Income		
Log City Employment	−0.016	0.031	0.001	0.004	−0.009
	(0.016)	(0.018)	(0.020)	(0.016)	(0.016)
Constant	2.048	2.12	1.826	1.917	2.160
	(0.201)	(0.247)	(0.252)	(0.194)	(0.199)
N. Obs	25,450	12,081	2,520	18,995	16,016
Adj.R2	0.01	00	0.2	0.15	0.12
			High-Income		
Log City Employment	0.019	0.057	0.000	0.107	−0.023
	(0.030)	(0.045)	(0.055)	(0.04)	(0.042)
Constant	2.076	2.213	2.318	1.072	2.634
	(0.406)	(0.572)	(0.719)	(0.502)	(0.536)
N. Obs	1,196	2,067	315	1,624	1,324
Adj.R2	0.00	0.01	0.13	0.13	0.13
			Natives		
Log City Employment	0.040	0.074	0.059	0.067	0.060
	(0.010)	(0.020)	(0.016)	(0.016)	(0.015)
Constant	1.533	1.675	1.296	1.508	1.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.08	0.04	0.17	0.14	0.11
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc < 30,000 US $), and born in a high-income country (GDP pc ≥ 30,000 US $). Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and 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 33: Regressions for Fact 1 using avg. city prices as deflator: Males

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

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings deflated by the average gross monthly rental cost of the housing unit on the natural logarithm of cities' employment (column 1) controlling for years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), and a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), years of schooling, years of potential experience and occupation fixed effects (column 5), and years of schooling, years of potential experience, occupation, and country of origin fixed effects (column 6). The model is estimated separately for workers who are US-born and foreign-born. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 34: Conditional regressions for Fact 1 using avg. city prices as deflator: Males

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Immigrants		
Log City Employment	−0.137	−0.116	−0.133	−0.135	−0.124
	(0.049)	(0.059)	(0.05)	(0.051)	(0.052)
Constant	−2.911	−2.219	−2.966	−2.732	−2.802
	(0.593)	(0.726)	(0.609)	(0.621)	(0.633)
N. Obs	38,747	18,252	6,181	30,139	20,679
Adj.R2	0.06	0.03	0.34	0.23	0.12
			Natives		
Log City Employment	−0.087	−0.047	−0.073	−0.056	−0.055
	(0.026)	(0.024)	(0.026)	(0.024)	(0.025)
Constant	−3.246	−3.204	−3.414	−3.199	−3.112
	(0.313)	(0.285)	(0.307)	(0.281)	(0.291)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.14	0.09	0.15	0.14	0.10
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings deflated by the average gross monthly rental cost of the housing unit on the natural logarithm of cities' employment controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born and foreign-born. Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 35: Regressions for Fact 1 using avg. city prices as deflator: Females

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), and a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), years of schooling, years of potential experience and occupation fixed effects (column 5), and years of schooling, years of potential experience, occupation, and country of origin fixed effects (column 6). The model is estimated separately for workers who are US-born and foreign-born. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 36: Conditional regressions for Fact 1 using avg. city prices as deflator: Females

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Immigrants		
Log City Employment	-0.131	-0.070	-0.119	-0.103	-0.119
	(0.044)	(0.049)	(0.057)	(0.044)	(0.045)
Constant	-3.145	-3.191	-3.297	-3.386	-3.134
	(0.533)	(0.575)	(0.705)	(0.532)	(0.547)
N. Obs	26,646	14,148	2,835	20,619	17,340
Adj.R2	0.04	0.01	0.23	0.17	0.14
			Natives		
Log City Employment	-0.08	-0.053	-0.076	-0.052	-0.058
	(0.027)	(0.024)	(0.028)	(0.023)	(0.023)
Constant	-3.488	-3.294	-3.538	-3.511	-3.357
	(0.319)	(0.286)	(0.339)	(0.271)	(0.279)
N. Obs	161,996	317,101	162,052	179,563	137,482
Adj.R2	0.09	0.04	0.14	0.12	0.09
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc < 30,000 US $), and born in a high-income country (GDP pc $\geq$ 30,000 US $). Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

D.2 Robustness Checks Fact 2: Regressions with Earnings Deflated by Living Cost

Table 37: Regressions for Fact 2 using avg. city prices as deflator: Males

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), and years of schooling, years of potential experience and occupation fixed effects (column 5). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc $<$ 30,000 US \$), and born in a high-income country (GDP pc $\geq$ 30,000 US \$). Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 38: Conditional regressions for Fact 2 using avg. city prices as deflator: Males

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
			Low-Income		
Log City Employment	−0.133	−0.117	−0.141	−0.135	−0.117
	(0.050)	(0.065)	(0.056)	(0.054)	(0.051)
Constant	−2.967	−2.288	−2.870	−2.744	−2.921
	(0.603)	(0.771)	(0.683)	(0.652)	(0.621)
N. Obs	37,308	14,162	5,568	27,059	18,843
Adj.R2	0.06	0.03	0.30	0.17	0.09
			High-Income		
Log City Employment	−0.106	−0.009	−0.058	−0.043	−0.009
	(0.068)	(0.041)	(0.043)	(0.046)	(0.057)
Constant	−2.643	−3.321	−3.254	−3.313	−3.739
	(0.849)	(0.514)	(0.557)	(0.529)	(0.685)
N. Obs	1,439	4,090	613	3,080	1,836
Adj.R2	0.02	0.03	0.08	0.17	0.18
			Natives		
Log City Employment	−0.087	−0.047	−0.073	−0.056	−0.055
	(0.026)	(0.024)	(0.026)	(0.024)	(0.025)
Constant	−3.246	−3.204	−3.414	−3.199	0 − 3.112
	(0.313)	(0.285)	(0.307)	(0.281)	(0.291)
N. Obs	210,105	352,472	183,107	221,225	158,245
Adj.R2	0.14	0.09	0.15	0.14	0.1
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc < 30,000 US $), and born in a high-income country (GDP pc $\geq$ 30,000 US $). Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 39: Regressions for Fact 2 using avg. city prices as deflator: Females

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

Source: ACS, 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 years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), and years of schooling, years of potential experience and occupation fixed effects (column 5). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc $<$ 30,000 US \$), and born in a high-income country (GDP pc $\geq$ 30,000 US \$). Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 40: Conditional regressions for Fact 2 using avg. city prices as deflator: Females

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

Source: ACS, 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 controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is estimated separately for workers who are US-born, born in a low-income country (GDP pc < 30,000 US \$), and born in a high-income country (GDP pc $\geq$ 30,000 US \$). Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and 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 $k \in \{\text{Native}, \text{Immigrants}\}$ is:

$$\ln(\bar{w}_j^k) = \alpha + \beta \ln(\text{Population}_j) + \nu_j \tag{38}$$

Take two cities j, j' such that

$$\text{Population}_j = \bar{q}\text{Population}_{j'} \tag{39}$$

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

$$\ln(\bar{w}_j^k) - \ln(\bar{w}_{j'}^k) = \beta \left[\ln(\bar{q}\text{Population}_{j'}) - \ln(\text{Population}_{j'})\right] \tag{40}$$

$$\ln\left(\frac{\bar{w}_j^k}{\bar{w}_{j'}^k}\right) = \beta \left[\ln \bar{q} + \ln\left(\frac{\text{Population}_{j'}}{\text{Population}_{j'}}\right)\right] \tag{41}$$

$$= \beta \ln \bar{q} \tag{42}$$

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

$$\frac{\bar{w}_j^k}{\bar{w}_{j'}^k} - 1 = \bar{q}^{\beta} - 1 \tag{43}$$

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

$$\Delta\bar{w}\% = (\bar{q}^{\beta} - 1) \times 100 \tag{44}$$