Skills, Distortions, And The Labor Market Outcomes Of Immigrants Across Space*

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- PRELIMINARY AND INCOMPLETE -

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Abstract

What is the geography of the labor market outcomes of immigrant workers? How do the earnings and jobs of immigrants differ across space? What are the implications for spatial earnings inequality? I answer these questions using US micro-data and document that US native workers earn a premium for working in big cities, while immigrant workers do not. A positive relationship between earnings and city size is associated with the GDP per capita of the immigrants' country of origin. Immigrants from developing countries are more likely to live in big cities and work more in non-cognitive occupations compared to natives and immigrants from rich countries. To interpret these facts, I build a spatial equilibrium model with heterogeneous workers and cities. Workers trade off higher earnings with higher utility from living and working in a specific location and are subject to distortions that affect their earnings, occupation and location choices. Estimated to match the observed earnings and employment shares across cities, the model provides a laboratory to study spatial inequality among workers and across cities. By removing sources of immigrants' spatial misallocation, earnings inequality between workers from low-income countries and natives would reduce by 85%. Were all the sources of spatial earnings inequality between immigrants and natives removed, the US real output would be higher by 2.5%. A comparison between immigration policies that increase the share of immigrants by 1 percentage point shows that real output gains and increases in housing prices are larger when immigrants are college graduates compared to non-college graduates.

Keywords: City-Size Earnings Premium, Immigrants, Human Capital, Cognitive And Non-Cognitive Occupations, Inequality, Housing, Spatial Equilibrium

JEL Classification: J21, J31, J61, R13

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1 Introduction

Every year large flows of people migrate from one country to another. Many destination countries rely on foreign-born individuals to complement their labor force and sustain high levels of productivity. Among all, high-income countries are the main destination of many immigrants, even though, in these countries, they are paid about 13% less than natives.[1] Recent work by Albert and Monras (2022) shows that once arrived in the host country, immigrants are more likely than natives to live in large and expensive cities. Workers in big cities receive a premium on their earnings (De La Roca and Puga, 2017) that is partially explained by the production structure and the degree of tasks specialization of big cities (Atalay et al., 2022). In the US, for example, nominal earnings in big cities are 33% higher than in non-urban areas (Glaeser and Mare (2001)). How do immigrants' labor market outcomes vary across space? How do they compare to those of native workers? Are there implications for spatial inequalities? Understanding how differences in human capital and spatial allocation among workers generate spatial differences in labor market outcomes is crucial to design effective policies that aim to reduce inequalities among workers of different origins and across cities.

In this paper, I study the geography of labor market outcomes of immigrant workers and its implications on spatial inequalities. I use microdata from the American Community Survey (ACS) and document three novel stylized facts on immigrants' labor market outcomes and occupational distribution across cities relative to native workers. In the first fact, I show that while native workers earn a premium (on nominal earnings) of about 3$ per hour by working in big cities, US immigrants do not. As a result, the earnings gap between immigrants and natives increases with the size of US cities. In the second fact, I show that among immigrants higher earnings in big cities are associated with the GDP per capita in the immigrant's country of origin. As a result, not only there exists earnings inequality between immigrants and natives, but also among immigrants from different origins. With the third fact, I provide evidence about the spatial distribution of workers across cities and occupations. I document that while natives and immigrants from high-income countries work more in occupations intensive in cognitive tasks, especially in big cities, immigrants from low-income countries work more in occupations intensive in non-cognitive tasks. However, immigrants from low-income countries are more likely to live in big cities relative to natives and immigrants from high-income countries.

I interpret these facts through the lens of a spatial equilibrium model with heterogeneous workers and cities. In the model, the US economy is represented by a set of cities, each characterized by a productivity bias in occupations intensive in cognitive tasks and an endogenous housing supply. In each city, a representative firm produces a homogeneous consumption good combining human capital (in efficiency units) in occupations intensive in cognitive and non-cognitive tasks. Workers from different origins who differ from each other in their human capital populate the economy. Workers choose where to live and work by trading off higher

[1] "The migrant pay gap: Understanding wage differences between migrants and nationals", ILOSTAT.

earnings with higher utility from living and working in a specific city. Foreign-born workers are subject to city-occupation-specific wedges on earnings and their labor supply. Human capital and wedges affect a worker's earnings both exogenously, by determining how much each worker earns, and endogenously, by influencing her allocation in cities and occupations.

Wedges are the forces that generate the misallocation of immigrant workers across cities and occupations. In the spirit of Hsieh et al. (2019), I model wedges on earnings as a "tax" that proxies for labor market discrimination due to, for example, immigrants' undocumented status and lack of economic assimilation. A large body of literature shows that immigrants downgrade along the distribution of earnings once they arrive in the host country (Dustmann et al., 2013) and go through a process of economic assimilation (Albert et al., 2021). Wedges on immigrants' labor supply, instead, distort the sorting of immigrants across locations and occupations relative to native workers. These distortions capture the utility that immigrants receive from choosing a specific city and working in a particular occupation due to the existence of ethnic networks. The existence of ethnic networks is an important factor that immigrants consider when they move to a new country (Borjas, 1998), but 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).

I estimate the structural parameter that determines workers' allocations and earnings through the simulated method of moments (McFadden, 1989) using individual-level data from the 2010 American Community Survey (ACS). The model generates the allocations of workers in cities and occupations and the pattern in earnings observed in the data. The estimated productivity bias in cognitive occupations increases by 9.5% moving from small to big cities. In line with Lagakos et al. (2018), the estimated stock of human capital varies between cognitive and non-cognitive occupations for workers from different origins. More in detail, all workers are endowed with large amounts of human capital to perform cognitive occupations. Among immigrants, those from low-income countries are relatively more abundant in human capital specific to non-cognitive occupations, while immigrants from high-income countries are more abundant in human capital specific to cognitive occupations. The estimated wedges on the labor supply of immigrants from developing countries indicate that the propensity of these workers to live in big cities and work in non-cognitive occupations is about three times higher than that of natives and other immigrants.

I use the model to study how immigrants' human capital and wedges determine differences in city-size earnings premia between immigrant and native workers. I show that had it been no wedges on earnings, the difference in city-size earnings premia between immigrants from low-income countries and natives would be halved. Also, had all wedges been removed, differences in city-size earnings premia with native workers would decrease by 85% for immigrants from low-income countries and by 60% for immigrants from high-income countries. Overall, these results indicate that, despite the role of human capital to determine earnings, immigrants' misallocation across cities and occupations generated by distortions to their labor supply and wedges on earnings is the main source of spatial earnings inequality between foreign-born workers and natives.

I then use the model to evaluate how the real output per capita and prices would change by reducing spatial earnings inequality between immigrants and natives. I find that when immigrant workers are endowed with the same human capital as comparable native workers, US real output per capita increases by about 1.5%. The increase in real output per capita is 0.2 percentage points higher when all the distortions that determine immigrants' spatial misallocation relative to native workers are removed. Had all the determinants of spatial earnings inequality between immigrants and native workers been removed, the real output per capita would increase by 2.5%. Wedges on earnings and labor supply explain about 70% of these changes. Under this scenario, there would be an increase by 23% in inequality in production across cities (big cities would gain more than small cities from the reallocation of workers across space), but the big-small cities ratio in housing prices would decrease by 0.8%.

Finally, I simulate a change in immigration policy to study how an inflow of foreign-born workers would impact the US real output per capita and housing prices. The new immigration policy aims to open the US borders to immigrants such that the overall population increases by one percentage point. I compare the case in which new immigrants are all without a college degree with the opposite case in which immigrants are all college graduates. The result indicates that the increase in the US real output per capita would be larger in the case of an inflow of immigrants with a college degree compared to an inflow of immigrants without a college degree (+2.3% vs +1.5%, respectively). These greater output gains result from an increase in the average productivity of workers in the economy since immigrants with college education supply more human capital in cognitive occupations than immigrants without a college education. However, in the case of an inflow of more skilled immigrants, the increase in housing prices would also be higher by 0.3 percentage points compared to the case of an inflow of immigrants without a college degree. Keeping the available land area for housing fixed, the increase in workers' average productivity would generate an increase in average earnings that would provoke an increase in the demand for housing.

2 Relation to the Literature

This paper contributes to several strands of the literature. First, I contribute to the literature on city-size earnings premia. The seminal works by Glaeser and Mare (2001) and, more recently, De La Roca and Puga (2017) focus on understanding why wages are higher in big cities compared to small cities or rural areas. The three novel stylized facts that I document complement this literature by highlighting that another important source of the premium that large cities pay to their workers is a worker's country of origin. US immigrants arrive from many countries and their comparative advantage to perform specific occupations depends on the institutional framework and occupational structure specific to their country of origin (see, for example, Lagakos et al. (2018), Caunedo et al. (2021)).

This paper also contributes to the emerging literature that uses spatial equilibrium models to study economic outcomes related to immigration. Recent papers using spatial equilibrium models to study immigration-related issues are Albert and Monras (2022), Burstein et al. (2020), Piyapromdee (2021). In this dimension, I introduce a granular heterogeneity in workers' human capital and tastes in a spatial equilibrium framework. In my model, workers' spatial distribution depends on the trade-off between earning more and receiving higher utility from living and working in a specific city. Through the estimates of human capital and wedges on the labor supply, I demonstrate the importance of considering these two channels when modeling the labor supply decisions of workers from various origins.

Finally, this paper contributes to the literature on human capital misallocation. The seminal work by Hsieh et al. (2019) highlights the importance of removing labor market barriers to underrepresented workers to obtain substantial output gains. More recently, Birinci et al. (2021) quantify the output gains from removing wedges to immigrants in the US. To this extent, I estimate that the labor market distortions not only vary among immigrants but are also more severe in specific cities and occupations.

The rest of the paper is organized as follows. In section 3 I describe the sources of data and present the stylized facts about immigrants' labor market outcomes across space. In section 4 I introduce the spatial equilibrium model. In section 5 I describe the estimation procedure. In section 6 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 7 I show and discuss the results of the policy exercise. In section 8 I summarise the findings and discuss ideas for future research.

3 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.

3.1 IPUMS Data

I collect information workers and cities from a 3% pooled sample from the American Community Survey (ACS) (2009-2011)[2]. I construct hourly earnings as total pre-tax wage and salary income divided by hours worked. In line with the literature, I identify top-coded wages and multiply them by 1.5. I focus on male workers aged 18-64 who have been in the labor market for at most 40 years, are employed in the private sector, do not live in group quarters and are not enrolled in school at the time of the interview.[3] Among these workers, I select those who

[2]I will use the term ACS 2010 and pooled ACS 2009-2011 interchangeably throughout the paper.

[3]Due to changes in female workers' participation rates during the selected years, I focus only on male workers.

worked at least one week in the previous year and report positive hourly earnings that do not exceed 250 US dollars.[4] I define first-generation immigrants as foreign-born individuals who migrated to the US after 18 years old.[5]

I use years of schooling to identify college graduates, that is, workers with at least 16 years of education. The census does not provide information on the location/country where individuals received their education. I focus on the sample of immigrants who did not received education from a US institution. To this purpose, I follow Schoellman (2012) and use 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 so from the acquisition of US-specific human capital.

I use Metropolitan Statistical Areas to identify US cities.[6]. The MSAs definitions available on IPUMS, however, are not constant through time. As explained more in detail in the appendix, I use the 1999 MSAs geographical delineations available from the US Census Bureau website and I build a geographical crosswalk of time consistent MSAs boundaries. I end up with 220 time consistent MSAs observed from 1980 to 2010 plus one additional category containing individuals living in places classified as "Not Identifiable in a MSA". I do not include individuals who live in areas not identifiable as an MSA and restrict the sample to those MSAs populated by at least 300 foreign born workers. Table 1 (put in Appendix) presents summary statistics for the main socio-demographic characteristics of the sampled population. I use the log of the employment stock in each city as a proxy for the size of US cities.

The final sample for the analysis includes workers from 69 countries of origin (US included) and 111 MSAs.

3.2 World-Bank Development Database

I collect information on countries GDP per capita from the World Bank Development Indicators. This dataset contains information at 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.

[4] 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.

[5] I exclude from the sample immigrants from countries whose population falls below the 10th percentile of the total immigrant population. This sample selection relies on the idea that an uneven spatial distribution of underrepresented workers may be a source of bias when measuring the human capital level of these workers.

[6] 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) define a Metropolitan Statistical Area as one or more one or more (contiguous) counties having one urbanized area with population of at least 50,000 individuals. More precisely, I use the variable PWMETRO.

3.3 O*NET Database

Task intensity data are built following Acemoglu and Autor (2011). The main source of data for task measures is O*NET. I first create five categories to classify tasks as follows: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual. In turn, each of these definitions is composed of a number of subcategories which are descriptors of tasks required by each occupation. For example, the category non-routine cognitive analytical is a combination of tasks such as: analyzing data and information, thinking creatively, and interpreting information for others.[7]

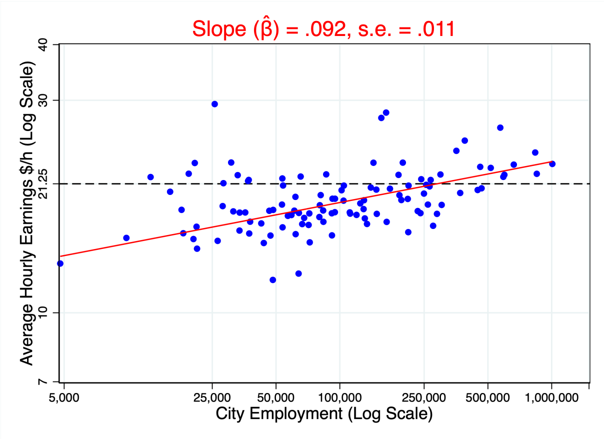
3.4 Empirical Evidence

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 19.5$ 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 0.092 tells that the earnings of a native worker increase by about 9% percent by doubling the city size.

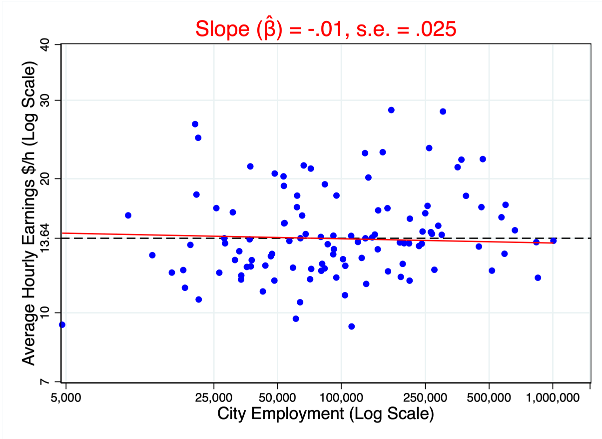
On the opposite, Panel 1b shows that the average hourly earnings for US immigrants are 13.7$ per hour, i.e. about 8$ per hour less than natives. On top of this, immigrants' hourly earnings show a larger degree of dispersion around the mean and do not increase with the size of US cities. The estimated elasticity of earnings to city size is negative and not statistically significant at a 10% significance level. To place these values in context, the average hourly earnings of immigrants in Chicago IL are as high as the earnings of immigrants living in Ann Arbor MI. On the contrary, a native who lives in Chicago earns more relatively than a native who chooses to live in Ann Arbor MI. These two panels suggest the existence of spatial disparities in earnings between immigrant and native workers.

[7] More details about each task category composition can be found in the Appendix.

Figure 1: Cities hourly earnings premia



(a) Natives

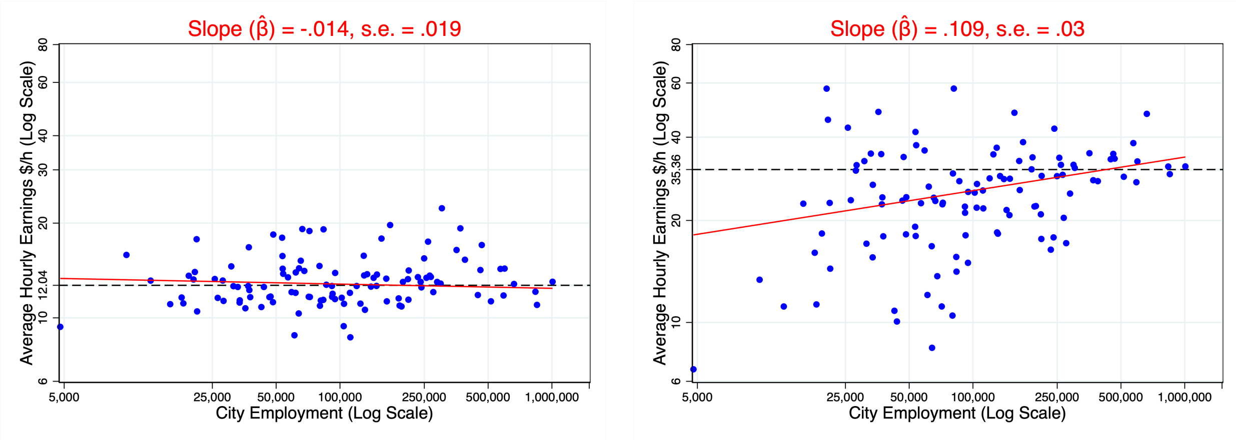


(b) Immigrants

Notes: Notes: Each dot corresponds to the log of average hourly earnings in a Metropolitan Statistical Area. Individual sample weights are rescaled by the usual number of hours worked per week and used in the calculations. At the top of the figures, I report in red the estimated slope of the regression of the log of average hourly earnings on the log of the city employment stock and the corresponding standard error. Regressions are weighted by the share of immigrants from specific origins in each city and standard errors are robust to heteroscedasticity.

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. Figure 2 shows the relationship between the average hourly earnings with respect to the size of US cities for these groups. Overall, there are substantial differences in hourly earnings among immigrants. The average hourly earnings of immigrants from high-income countries are more than twice 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 a 10% significance level for immigrants from low-income countries (Panel 2a), while it is significant at a 5% significance level for immigrants from high-income countries (Panel 2b).

Figure 2: Cities hourly earnings premia



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

Notes: Each dot corresponds to the log of average hourly earnings in a Metropolitan Statistical Area. I defined low-income countries as those countries with a GDP per capita lower than 30,000 US dollars. Individual sample weights are rescaled by the usual number of hours worked per week and used in the calculations. At the top of the figures, I report in red the estimated slope of the regression of the log of average hourly earnings on the log of the city employment stock and the corresponding standard error. Regressions are weighted by the share of immigrants from specific origins in each city and standard errors are robust to heteroscedasticity.

To gain more insight into the relationship between earnings, workers' origins, and the size of US cities, I report the same facts for big and small cities. , and for each group of workers (US natives, immigrants from low and high-income countries) I compute average hourly earnings in each city category.

Table 1: Hourly Earnings: Big vs Small Cities

	Small Cities (Pop. $<$ 500,000)	Big Cities (Pop. $\geq$ 500,000)	City-Size Gap
Natives	20.1	23.2	3.1
Low-Income	12.6	11.7	-.908
High-Income	30.6	37.4	6.76

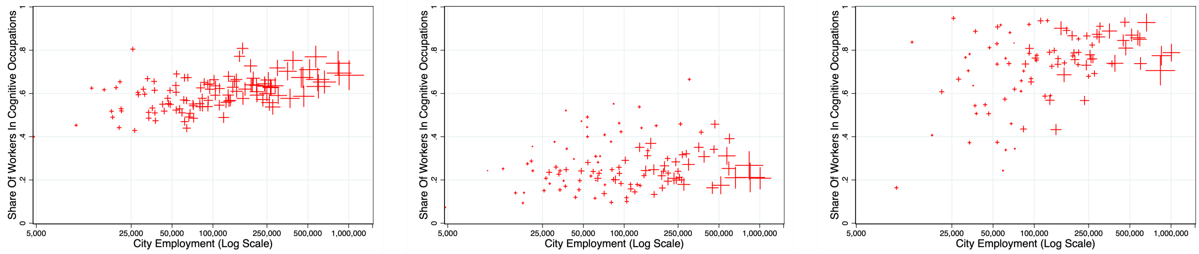
* Earnings are calculated in US dollars and deflated by the CPI99 index. The earnings gap is computed as the difference in earnings between small cities and big cities. Individual sample weights are rescaled by the usual number of hours worked per week and used in the calculations.

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 20$ per hour and increase to 23$ per hour in big cities, roughly by 16%. Immigrants from high-income countries earn more on average than all other workers, and the city-size gap is even larger than that of natives (+6.7$ per hour vs +3.1$ per hour). At the opposite, the earnings of immigrants from low-income countries decrease of roughly 1$ per hour when moving from small to big cities (by about 7.2%). 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.

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. Here, I document sorting patterns of workers into cities and occupations. To do so, I compare employment shares of US native workers and immigrants from low and high gdp per capita countries.

Figure 3: Sorting Into Cities And Cognitive Occupations



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

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Notes: Each marker corresponds to a Metropolitan Statistical Area and measures the share of workers in cognitive occupations in that unit of observation. The size of the marker corresponds to the share of workers who live in each Metropolitan Statistical Area. Individual sample weights are rescaled by the usual number of hours worked per week and used in the calculations.

Figure 3 shows the spatial distribution for the shares in cognitive occupations of native and immigrant workers from low-income and high-income countries. Overall, US natives and immigrants from rich countries are more likely to work in cognitive occupations. There are more workers of these groups who work in cognitive occupations in big cities compared to small cities (Panel 3a and Panel 4c). Panel 3b reveals a different sorting of immigrant workers from low-income countries into occupations. They are less likely to work in cognitive occupations, even though they are more likely to live in big cities. [8]

Next, I compute the percentages of workers in cognitive occupations in big and small cities.

[8]The sorting of immigrants in big and expensive cities is documented and analysed in Albert and Monras (2022).

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

		Small Cities (Pop. $<$ 500,000)	Big Cities (Pop. $\geq$ 500,000)	Δ
Natives	% Cognitive	61.5	68.1	6.63
	% Total	16.2	83.8	67.7
Low-Income	% Cognitive	25.8	23.7	-2.15
	% Total	8.99	91	82
High-Income	% Cognitive	65.6	76.2	10.7
	% Total	18.1	81.9	63.9

* The shares are expressed in percentage terms. Individual sample weights are rescaled by the usual number of hours worked per week and used in the calculations.

For each origins group, Table 2 shows the share of workers in cognitive occupations in small and big cities and the big-small cities change. 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 rich countries working in cognitive occupations increases by about 10 points. Similarly, US workers are more likely to choose cognitive occupations if they live in big cities (+ 6.7 percentage points). On the other hand, there is not a spatial increase in sorting into cognitive occupations for immigrants from low-income countries. In big cities, the share of these workers performing cognitive occupations decreases by 2.15 percentage points. Immigrants from low-income countries, though, are those with the highest share in big cities among all workers (91.2% vs 84% for natives and 82.5% for immigrants from high-income countries). Overall, the evidence in Figure 3 and Table 2 suggest that workers' sorting into occupations varies by origin and across cities.

4 A Spatial Equilibrium Model With Heterogeneous Human Capital

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 simple spatial equilibrium model with heterogeneous locations and workers that replicates the patterns observed in the data and guides the quantitative analysis.

4.1 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 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 is endowed with a vector of human capital $\boldsymbol{s} = (s_M, s_D)$ in efficiency units to perform the two occupations and draw tastes $\big(\varepsilon_{jM}(i), ..., \varepsilon_{j'D}(i)\big)$ for each city-occupation pair. The tastes for city-occupation pairs follow a Gumbel distribution and are i.i.d across all workers.[9] 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 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 the marginal product of labor in each occupation. [10] 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 And Labor Supply Distortions. The utility function of a worker i from group g who lives in a city j and works in an occupation o is Cobb-Douglass over a consumption good and a housing good:

$$U(i) = c^{(1-\alpha)} h^{\alpha} z_{jog} \exp\{\varepsilon_{jo}(i)\} \tag{2}$$

where c is the consumption good, h is the housing good, z_{jog} is a distortion to the city-occupation choices of all workers in the group g, ε_{jo} is the idiosyncratic taste draw for the city-occupation pair jo, and α represents the expenditure share on the housing good.[11] A

[9] I assume that the location parameter of the Gumbel distribution is zero, while I do not impose any restriction on the scale parameter.

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

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

worker's budget constraint is:

$$c + p_j h \leq w_{jog} \tag{3}$$

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 and working in occupation o is:

$$V_{jog}(i) = v\left(w_{jog}, p_j\right) z_{jog} exp\{\varepsilon_{jo}(i)\} \tag{4}$$

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.(4) shows that a worker's choice to live in a city j and work in an occupation o depends on three factors. The first factor is earnings w_{jog}. The second factor is the price of the housing good p_j. The third component is the labor supply distortion z_{jog} that captures the non-monetary value that workers associate with a city-occupation pair.

Workers Earnings And Labor Market Distortions. Conditional on the chosen city and occupation, all workers 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 also subject to labor market distortions τ_{jog} 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. I interpret compensation wedges as measures of distortions specific to local labor markets, such as labor market discrimination, lack of assimilation to the US economy, or information frictions.[12]. Thus, the earnings of a worker i 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:

$$w_{jog} = r_{jo} s_{og} \tau_{jog} \tag{5}$$

Wedges can influence earnings in the form of subsidies or taxes that vary across cities and occupations. When they take a value larger than 1, the

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

$$H_j = f\left(Y_j, T_j\right) = \omega Y_j^{\iota} T_j^{(1-\iota)} \tag{6}$$

where H_j is the housing supply, $1 - \iota$ is the weight of land in the production of housing supply,

[12]Information friction could decrease a worker's earnings by reducing the probability of a "good" match between a worker's human capital and occupation.

and $\omega = \iota^{-\iota}$ is a constant.

4.2 Model Solution and Spatial Equilibrium

The Problem Of The Firms And Labor Demand In Cities. Consider the representative firm in the city j. Given the technology in production, the firm solves the following problem:

$$\max_{D_j, M_j} \quad \left[M_j^{\frac{\sigma-1}{\sigma}} + (\theta_j D_j)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} - r_{jD} D_j - r_j M_j \tag{7}$$

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

$$r_{jM} = \left(\frac{Y_j}{M_j} \right)^{\frac{1}{\sigma}} \tag{8}$$

$$r_{jD} = \left(\frac{Y_j}{D_j} \right)^{\frac{1}{\sigma}} \theta_j^{\left(1 - \frac{1}{\sigma}\right)} \tag{9}$$

By taking the ratio of Eq. (9) and Eq. (8), I derive an expression for the skills price ratio of cognitive skills and non-cognitive human capital:

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

Eq. (10) tells 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 two factors: 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, advance in technology used in cognitive occupations shifts 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 production function is Leontief, 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. A worker i in city j employed in an occupation o maximizes utility by choosing an optimal bundle of consumption and housing goods subject to her budget constraint. She observes her human capital and has rational expectations about potential earnings in each city-occupation pair. The utility maximization problem is:

$$\max_{c,h} \quad U(i) = c^{(1-\alpha)} h^{\alpha} z_{jog} \exp\{\varepsilon_{jo}(i)\} \tag{11}$$
$$\text{s.t.} \quad c + p_j h \leq w_{jog}$$

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

$$c_{jog} = (1-\alpha)\, w_{jog} \quad , \quad h_{jog} = \alpha \frac{w_{jog}}{p_j} \tag{12}$$

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

$$V_{jog}(i) = \gamma p_j^{-\alpha} w_{jog} z_{jog} \exp\{\varepsilon_{jo}(i))\} \tag{13}$$

Taking the log of Eq.(13), I obtain:

$$\ln V_{jo}(i) = \ln \gamma - \alpha \ln p_j + \ln w_{jog} + \ln z_{jog} + \varepsilon_{jo}(i) \tag{14}$$

where $\gamma = (1-\alpha)^{(1-\alpha)} \alpha^{\alpha}$ is a constant term. Given the realization of the taste shock, a worker chooses a city-occupation pair that provides her with the highest indirect utility. Given the distributional assumption on ε_{jo}, this setup leads to 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 a workers from group g living in a city j and working in an occupation o is:

$$\begin{aligned} \pi_{jog} &= \frac{V_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} V_{j'o'g}} \\ &= \frac{\gamma p_j^{-\alpha} w_{jog} z_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} \gamma p_{j'}^{-\alpha} z_{j'o'g} w_{j'o'g}} \end{aligned} \tag{15}$$

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.

The Problem Of The Absentee Landlords And Housing Supply In Cities. In each city, the absentee landlords solve:

$$\max_{H_j} \quad p_j \left(\omega Y_j^{\iota} T_j^{1-\iota} \right) - Y_j \tag{16}$$

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

$$Y_j = \left(p_j \omega \iota\right)^{\frac{1}{1-\iota}} T_j \tag{17}$$

By substituting Eq.(17) into Eq.(6) and rearranging the terms, I obtain the following expression for the housing supply:

$$p_j = \left(\frac{H_j}{T_j}\right)^{\frac{1}{\zeta}} \tag{18}$$

where ζ is the elasticity of the housing supply and H_j is the aggregate demand for housing in city j.

Labor Supply In Each 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:

$$M_j = \sum_g \pi_{jMg} s_{Mg} \phi_g \tag{19}$$

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

$$D_j = \sum_g \pi_{jDg} s_{Dg} \phi_g \tag{20}$$

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: $\pi^{\star}_{jog} = \frac{V^{\star}_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} V^{\star}_{jog}}$

2. Labor supply satisfies Eq.(19) and Eq.(20)

3. Labor markets clear for each city-occupation pair, that is: $r^{\star}_{jM} = \left[\frac{Y_j}{M^{\star}_j}\right]^{\frac{1}{\sigma}}, \quad r^{\star}_{jD} = \left[\frac{Y_j}{D^{\star}_j}\right]^{\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)}, \quad \forall j \in \mathcal{J}$

4. Housing market clears

5 Bringing The Model To The Data

In this section, I describe the model calibration, show the model fit with the data, comment on the internally estimated parameters, and quantify the determinants of spatial earnings inequality.

The model describes the US economy as populated by workers from 3 countries of origin (US, low-income,high-income) who can choose to live either in a small or a big city and whether to work in a cognitive or non-cognitive occupation. Workers differ in their human capital according to whether they are college graduates or not, and for the potential experience in the labor market (0-14, 15-29, 30+). I calibrate the model to replicate the stylized facts presented in Table 1 and Table 2 in Section 3. In the model, there are 18 groups of workers that decide where to live and which occupation to perform across 4 alternatives. I assume that the compensation wedge varies across cities and occupations only conditional on the country of origin (i.e., $\tau_{jog} = \tau_{jok}$) and that native workers are not subject to them (i.e., $\tau_{joUS} = 1 \quad \forall j \in \mathcal{J}, o \in \mathcal{O}$). When $\tau_{jok} > 1$ a worker receives a subsidy, while $\tau_{jok} < 1$ a worker's earnings are taxed. I normalize the labor supply distortion in the small city and in non-cognitive occupations for all workers to 1, $z_{SMg} = 1, \forall g$. Thus, the estimated labor supply distortions for other city-occupation pairs are relative to this category.

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.

Table 3: External Parameters

(1) **Description**	(2) **Symbol**	(3) **Value**	(4) **Source**
Elasticity of substitution	σ	3	Hsieh et al. (2019)
Housing supply elasticity	ζ	1.54	Saiz (2010)
Share of expenditure in housing	α	0.32	Albouy (2008)
Share of group g in the economy	ϕ		ACS 2010
Small City Land	T	5,000km2	Assumed
Big City Land	T	15,000km2	Assumed

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). On the other hand, 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. I assume the value of the available land in big and small cities.

Internally Estimated Parameters. I now turn to present the estimation strategy and 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.[13] The vector of parameters can be divided into four sub-categories, each one measuring some specific feature of the model. These are productivity bias in cognitive occupations specific to each city, worker's level of human capital specific to an occupation, distortions to the labor supply, and wedges that immigrants face in local labor markets. I estimate these parameters by using the simulated method of moments (SMM).[14].

I target the city-specific average earnings of native workers who work in cognitive occupations as moments to estimate the city productivity 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	1.45	1.64

Both cities feature a productivity bias toward 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 9.5%, changing from 1.47 to 1.62.[15] This result is consistent with Atalay et al. (2022), who document that part of the city-size earnings premia results from the higher intensity in computer software technology required by jobs.

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 contains summary statistics for the estimates of workers' human capital.

[13] The prices of human capital and housing are endogenous equilibrium outcomes from the model.

[14] See McFadden (1989))

[15] The relatively higher importance of cognitive occupation for production in big cities is likely to reflect a greater adoption of new technology in these cities (Eeckhout et al. (2021)).

Table 5: Estimated human capital

Workers Origins	Non-Cognitive (1)	Cognitive (2)	Overall (3)
Natives	6.7	13	9.6
	(1.3)	(4.6)	(4.5)
Low-Income	4.4	11	7.6
	(0.6)	(3.7)	(4.1)
High-Income	5.9	16	11
	(0.7)	(4.9)	(6.3)

* Standard deviations in parenthesis. Worker's probability distribution weights ($\phi\left(k, e, x\right)$) are used in the calculations .

The estimates in Table 5 highlight differences in the stock of human capital supplied by workers of different origins. Column (1) shows that in non-cognitive occupations natives and immigrants from high-income countries supply more human capital compared to immigrants from low-income countries. In cognitive occupations, immigrants from high-income countries supply 18.2 units of human capital, the highest value among all workers (Column (2)). Even in this case, workers from poorer countries supply the least amount of human capital. An interpretation of this result comes from a comparison between the occupational structures (task intensity required to perform an occupation) of countries.[16] Overall, 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. 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. The fact that the estimates of human capital are more similar between natives and immigrants from high-income countries than for immigrants from low-income countries suggests, thus, that the level of human capital is related to countries' development (measured through GDP per capita).

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 estimate the 8 parameters that measure compensation wedges by targeting the average earnings of immigrants from country k who lives in a city j and works an occupation o. I present the estimated wedges for immigrants of low and high-income countries in Table

[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.

6.

Table 6: Estimated wedges

	Small City		Big City	
Workers Origins	Non-Cognitive	Cognitive	Non-Cognitive	Cognitive
	(1)	(2)	(3)	(4)
Natives	1	1	1	1
Low Income	1.15	.777	1.04	.632
High Income	1.29	1.31	1.21	1.29

A comparison *between* Column (1) and Column (3) shows that immigrants from all countries receive positive compensation by working in non-cognitive occupations. By moving from small to big cities the magnitude of the compensation reduces for both immigrant workers (low-income countries -11 percentage points, high-income countries -7 percentage points). A comparison of the estimated wedges for the non-cognitive occupation *within* each city, however, suggests immigrants from high-income receive higher compensations than immigrants from low-income countries (+5 percentage points in small cities and +9 percentage points more in big cities).

Column (2) and Column (4) show substantial differences among immigrants and across cities in the estimated wedges in cognitive occupations. In every city, estimated compensations are below 1 for immigrants from low-income countries: wedges are a tax on wages and reduce their earnings. On the opposite, the estimated wedges for workers from rich countries enter as subsidies to their earnings. For cognitive occupations, the *within*-city difference in the estimated wedges between immigrants from high and low-income countries is +18 percentage points in small cities and +70 percentage points in big cities.

The last set of parameters measures distortions to labor supply specific to each group of workers. In total, I estimate 54 parameters and 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 labor supply distortions

	Small City		Big City	
Workers Origins	Non-Cognitive	Cognitive	Non-Cognitive	Cognitive
	(1)	(2)	(3)	(4)
Natives	1	1.37	4.53	8.4
		(.785)	(.243)	(5.34)
Low-Income	1	.281	13.2	3.6
		(.302)	(2.11)	(3.45)
High-Income	1	1.31	3.68	9.02
		(.661)	(1.19)	(6.18)

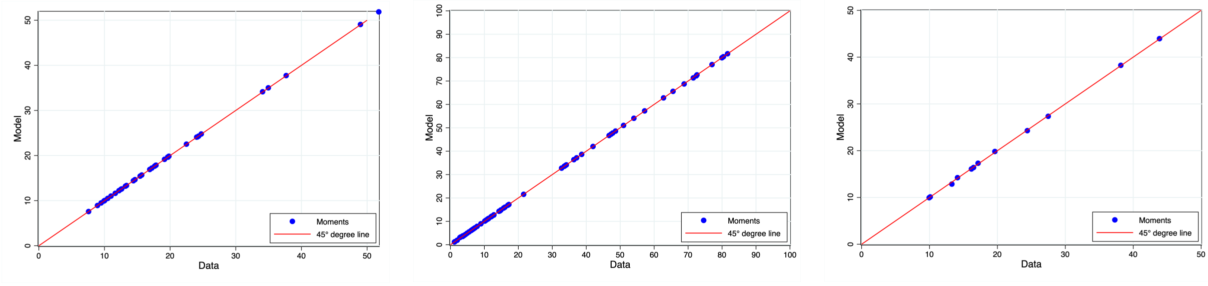
[*] I assume that labor supply distortions in small cities and in the non-cognitive occupation are equal to 1 for all groups of workers, i.e. $z_{SMg} = 1 \quad \forall g$. The values in columns (2), (3), and (4) correspond to the average labor supply distortions for native, low-income, and high-income immigrant workers. Standard deviations in parenthesis. Worker's probability distribution weights ($\phi\,(k, e, x)$) are used in the calculations .

A comparison of all columns indicates that distortions towards the big city are high for all workers. The estimated distortions for native workers and immigrants from high-income countries are almost identical across all cities and occupations. All these workers have higher distortions towards working in the cognitive occupation in both cities. However, the distortions of immigrants from low-income countries follow an opposite pattern from all other workers. For these workers, the estimated distortion towards performing the non-cognitive occupation in the big city is about three times larger than for all other workers. On the opposite, the distortions towards working in the cognitive occupation are about four times lower than for all other workers both in the big and small city. Overall, the estimates in Table 7 indicate substantial heterogeneity in the distortions to the labor supply across cities and occupations between workers from rich and poor countries (natives and immigrants from high-income countries vs immigrants from low-income countries).

5.1 Model Fit

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

Figure 4: Model Fit



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

1

Table 8 compares the values from the data and the model for the earnings of natives and immigrant workers from low and high-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 (-30 cents), while the model-based earnings of immigrants from low and high-income countries are slightly above their data counterparts (+20 cents and +30 cents, respectively). For the big city, the model-based earnings of immigrants from low-income countries perfectly fit the data, while for natives and immigrants from high-income countries, the model-based earnings are 20 cents and 10 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 low-income countries (+13 cents and +11 cents, respectively) and slightly lower for immigrants from high-income countries (-13 cents).

Table 8: Model Fit For Fact 2

	Small City (Pop. $<$ 500,000)		Big City (Pop. $\geq$ 500,000)		City-Size Gap	
	Data	Model	Data	Model	Data	Model
Natives	20.1	19.8	23.2	23	3.1	3.23
Low-Income	12.6	12.8	11.7	11.7	-.908	-1.02
High-Income	30.6	30.9	37.4	37.5	6.76	6.63

* 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.

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. Data indicates 16.2% of native workers live in the small city, and among them, 61.5% choose the cognitive occupation. The sorting pattern across cities and occupation of immigrants from high-income countries is similar to that of natives. On the opposite, about 9% of workers from low-income countries decide to live in small cities and only 25.8% of them choose the cognitive occupation. The model matches these moments quite well, with the largest data-model difference being 1.6 percentage points in the percentage of low-income immigrants working in the cognitive occupation.

Table 9: Model Fit For Fact 3

		Small City (Pop. $<$ 500,000)		Big City (Pop. $\geq$ 500,000)		Δ	
		Data	Model	Data	Model	Data	Model
Natives	% Cognitive	61.5	60	68.1	67	6.63	6.99
	% Total	16.2	16.4	83.8	83.6	67.7	67.2
Low-Income	% Cognitive	25.8	27.4	23.7	24.4	-2.15	-2.97
	% Total	8.99	8.38	91	91.6	82	83.2
High-Income	% Cognitive	65.6	66.8	76.2	76.7	10.7	9.88
	% Total	18.1	16.1	81.9	83.9	63.9	67.7

* 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. Workers' shares are expressed in percentages.

The model-generated moments match quite well the shares of workers who live in big cities for all groups, apart from immigrants from high-income countries. For these workers, in fact, there is a difference of 2 percentage points between the percentages generated by the model and the data. The model-generated percentage of workers in the cognitive occupation in big cities is also matched quite well. The share of native workers in the cognitive occupation generated by the model has the highest distance to its data counterpart (1.1 percentage points).

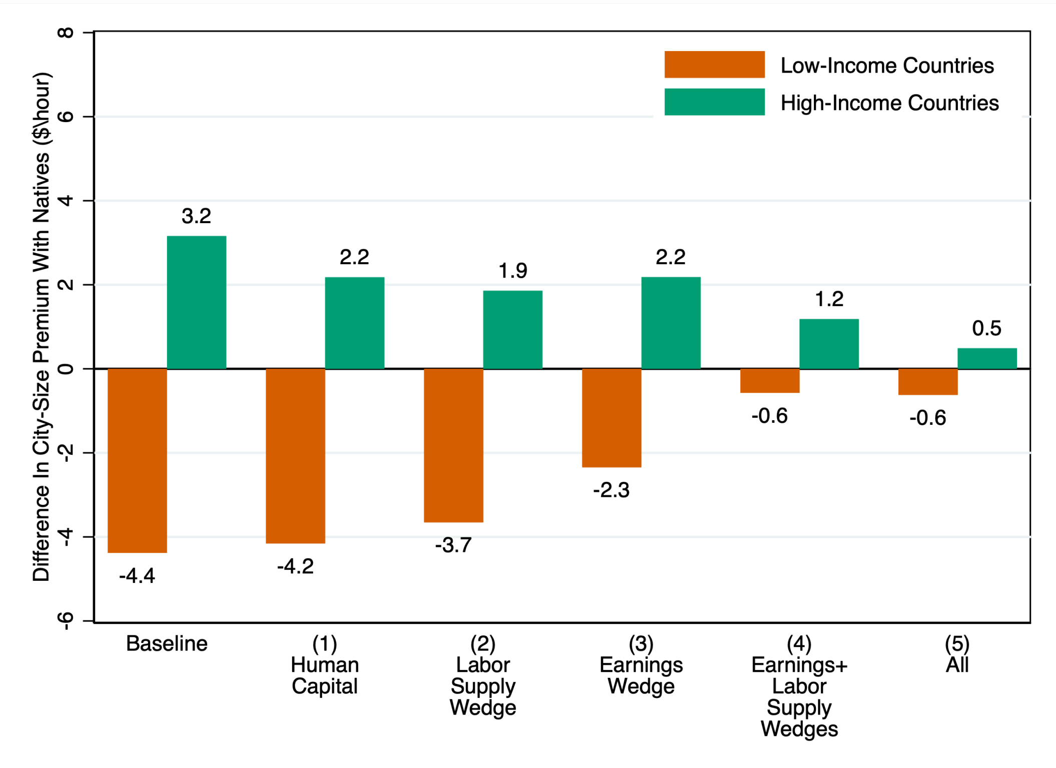
6 Counterfactual Analysis

In this section, I interpret the facts documented in Section 3 using the spatial equilibrium model. I evaluate to what extent channels that determine the allocation of workers across cities and occupations can explain spatial inequalities. I construct five counterfactual economies that I compare with the baseline economy. In the first counterfactual, I assign the same units of the occupation-specific human capital of comparable US natives to workers from all countries, keeping fixed all the other parameters. In the second, third, and fourth counterfactuals, I remove the sources of spatial misallocation of immigrant workers relative to natives, that is wedges on the earnings and the labor supply of immigrant workers, keeping all the other parameters fixed. In the last counterfactual, I remove all the channels that determine spatial inequality in earnings between immigrants and natives, that is I assign to immigrants the same values of human capital of comparable natives and I remove the sources of spatial misallocation.

I first show how earnings inequality among workers and US real output per capita change and then illustrate the changes in the allocations of workers across cities and occupations that generate the results. In Figures **??** and 6, and Tables 10 and 11- columns (1)-(5) present the results of the counterfactuals in the order described above.

The Gap In The City-Size Earnings Premium. How do differences in city-size earnings premia between immigrants and native workers change under the five counterfactuals? To answer this question, I compute the differences in city-size earnings premia between natives and immigrants from all origin groups in each counterfactual economy. Figure 5 shows the results from this exercise. In the baseline economy, immigrant workers differ from natives not only because they supply different levels of their occupation-specific human capital, but also because they are subject to wedges on earnings and on their labor supply. Column (1) in Figure 5 shows the immigrants' city-size earnings premia relative to native workers in the baseline economy: the gap with natives is positive (+3.2$ per hour) for immigrants from high-income countries and negative (-4.4$ per hour) for immigrants from low-income countries.

Figure 5: Counterfactuals on earnings gap



Notes:

Keeping all the other parameters fixed, when there are no differences in the units of occupation-specific human capital supplied by immigrants and natives, the difference in city-size earnings premia with natives reduces of mostly for immigrants from high income countries (Column 1 in Figure 5)). Relative to native workers, in the baseline economy immigrants from high-income countries do not face substantial distortions to their supply of labor and, on average, supply 0.9 units of human capital specific to the non-cognitive occupation and 1.3 units of human capital specific to the cognitive occupation (as shown in Table 5). In this exercise the levels of human capital of these workers are reduced and, as a result, the big-city premium on earnings relative to native workers reduces. In the baseline economy, immigrants from low-income countries supply fewer units of human capital than native workers in both occupations. Even though they are now endowed with higher levels of human capital to perform both occupations, wedges on labor supply stop them to move towards the cognitive occupation, and wedges on earnings reduce their higher earnings in both cities. As a result, the gap in city-size earnings premium with natives is closed only by about 4.5%.

When I remove wedges on the labor supply of immigrant workers, the difference in city-size earnings premia between immigrants and natives shrinks, as shown by Column (2) in Figure 5. The gap between immigrants from high-income countries and natives is closed by 40%, while the gap between immigrants from low-income countries and natives is reduced by 16%. Even though the gap has reduced, there are still differences in city-size earnings premia with natives for both groups of immigrants since they are still subject to wedges on earnings and their supply of human capital is different from that of natives.

To what extent does removing wedges on earnings, keeping all the other parameters fixed, reduce differences in city-size earnings premia? Column (3) in Figure 5 shows that without wedges on earnings, inequality among workers reduces. The difference in the city-size earnings premia of immigrants from high-income countries relative to natives drops from 3.2$ to 2.2$ per hour, a reduction of 31%. Also, the gap between immigrants from low-income countries and natives almost halves, from -4.4$ per hour to -2.3$ per hour.

In the fourth counterfactual, I remove all the sources of immigrants' spatial misallocation relative to native workers. As a result, the differences in city-size earnings premia with natives reduce significantly for all immigrants (Column (4) in Figure 5). More in detail, the gap with natives reduces by about 86% for immigrants from low-income countries and 62.5% for immigrants from high-income countries.

Finally, column (5) in Figure 5 shows that when there are no differences in the determinants between immigrants' and natives' location and occupation choices, the gap in city-size earnings premium between foreign-born workers and natives is almost closed. The gap between immigrants from high-income countries and natives reduces from 3.2$ per hour to 0.5$ per hour, while the gap between immigrants from low-income countries and natives reduces from -4.4$ per hour to -0.6$ per hour. These residual gaps reflect differences in the measures ϕ_g across groups of workers.

Changes In US Real Output Per Capita And Housing Prices. How do the US real output per capita and prices change relative to the baseline economy under the five counterfactual economies? Table 10 answers this question. When the human capital endowment of immigrants is the same as US workers with the same level of education and labor market experience

(Column 1), the US real output per capita increases by 1.5%. Higher levels of human capital benefit more the big city: real output per capita increases in the big city, while it slightly reduces in the small city. Workers are all more productive and earn more, so their demand for consumption and housing goods increases (prices go up).

Table 10: Percent change in real output and city prices

Parameters	Baseline	Counterfactuals				
		Human Capital	Wedge On Labor Supply	Wedge On Earnings	Wedges On Earnings & Labor Supply	Full
		(1)	(2)	(3)	(4)	(5)
$s_o(\cdot)$	-	x	-	-	-	x
$z_{jo}(\cdot)$	-	-	x	-	x	x
τ_{jok}	-	-	-	x	x	x
			Real Output Per Capita			
US	1	1.015	1.012	1.005	1.017	1.025
Big City	1	1.018	1.055	1.000	1.050	1.058
Small City	1	0.998	0.809	1.037	0.854	0.857
Big-Small City Ratio	1	1.020	1.305	0.965	1.229	1.236
			Housing Prices			
Big City	1	1.004	1.001	1.001	1.002	1.004
Small City	1	1.002	1.011	0.999	1.009	1.012
Big-Small City Ratio	1	1.000	0.990	1.002	0.993	0.992

The US real output per capita also increases when I remove wedges on immigrants' labor supply (Column (2) 10). In this case, immigrants from all countries and natives value amenities in cities and occupations the same. In the big city, the real output increases by 5.5%, while it decreases by 20% in the small city. Inequality in output per capita across cities increases by 30%, and housing prices rise more in the small city than in the big city.

Column 3 in Table 10 indicates that when there are no wedges on earnings in all cities and occupations, real output per capita increases by 0.5%. The change in output per capita is larger in small cities, and inequality across cities reduces.

When I removed all the sources of immigrants' spatial misallocation relative to natives (Column 4), the real output per capita increases by 1.7%. However, also inequality in real output per capita across cities increases by 23%. The big-small city ratio in housing prices, on the other hand, reduces by 0.7%.

Finally, under the hypothesis that there are no differences between immigrants and natives in human capital and immigrants are not subject to any wedge, the real output per capita increases by 2.5%, inequality in real output per capita increases by 23.5% and cross-city differences in housing prices reduce.

The allocation of workers across cities and occupations. Table 11 shows how the share of workers in the big city changes relative to the baseline economy under the five counterfactual scenarios for workers from the three origin groups. Column (1) indicates that when there are no differences in human capital between immigrants and natives some workers from all groups relocate from the big to the small city. In the new scenario immigrants' earnings in the non-cognitive occupation increase in both cities, as in the baseline economy the largest differences in human capital between immigrants and natives are relative to the human capital used in the non-cognitive occupation. All else equal, in both cities, some immigrants from low and high-income countries move from the cognitive to the non-cognitive occupation, while the shares of natives in cognitive occupations increase, as shown in Panel (a) of Figure 6.

Table 11: Change in the share of workers in big cities (pp)

	Baseline	**Counterfactuals**				
Parameters		Human Capital	Wedge On Labor Supply	Wedge On Earnings	Wedges On Earnings & Labor Supply	Full
		(1)	(2)	(3)	(4)	(5)
$s_o(\cdot)$	-	x	-	-	-	x
$z_{jog}(\cdot)$	-	-	x	-	x	x
τ_{jok}	-	-	-	x	x	x
		Share Of Workers In Big Cities				
Natives	83.6	-0.1	0.2	-0.0	0.1	0.2
Low-Income	91.7	-0.1	-11.8	1.1	-9.2	-9.4
High-Income	84.0	-0.4	-0.6	0.5	-0.2	-0.3

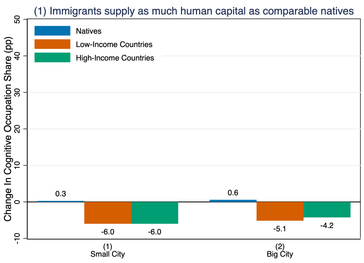
As a second experiment, I solve the model after removing the wedges on the labor supply of immigrants and I compare the results to the baseline economy. In this counterfactual economy, foreign-born workers value amenities of city-occupation pairs the same as native workers since they are not subject to wedges to their labor supply. In the big city, the share of immigrants from low and high-income countries decreases, while the share of native workers increases. The outflow of workers is particularly significant for immigrants from low-income countries (-11.8pp in their share in the big city). The outflow from the big city of foreign-born workers generates a relocation of native workers from the small to the big city.

Workers also reallocate between the two occupations in each city. Panel (b) in Figure 6 indicates that the share of native workers in the cognitive occupation decreases in both cities since, without wedges on the labor supply, there is an increase in competition due to more immigrants from low-income (in both cities) and high-income (in the small city) who choose to work in the cognitive occupation. In the big city, the massive increase in the share of immigrants from low-income countries in the cognitive occupation generates an increase in competition that results in a drop in the share of immigrants from high-income countries in the same occupation.

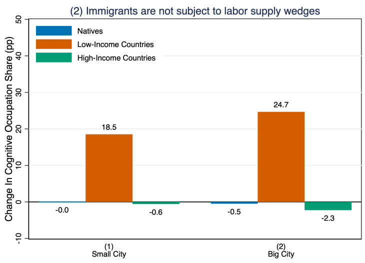
How does the allocation of workers into cities and occupation change after removing wedges on earnings? Column (3) in Table 11 and Panel (c) in Figure 6 answer this question. Overall, removing wedges on earnings generates an inflow of immigrants from all countries to the big city. A small number of native workers move from the big to the small city. Since workers from low-income countries do not receive discounts on earnings from working in the cognitive occupation, more of them choose to work in this occupation in both cities. As a result, some native workers and immigrants from high-income countries reallocate to the non-cognitive occupation in both cities.

In Column (4) I remove all sources of immigrants' spatial misallocation relative to native workers. The results from this counterfactual are a combination of the results presented in Columns (2) and (3). The share of immigrants from all countries decreases in the big city and the decrease is especially severe for immigrants from low-income countries (-9.2 pp). On the opposite, the share of native workers in the big city increases by 0.1 percentage points. The share of native workers in this occupation decreases in the small city since there are more immigrants who choose to work in the cognitive occupation, (Panel (d) in Figure 6). In the big city, as a result of the increase in the share of immigrants from low-income countries in the cognitive occupation, the shares of natives and immigrants from high-income countries in the same occupation decrease by 0.6 and 1.8 percentage points, respectively.

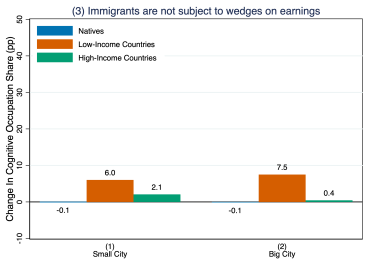
Figure 6: Change in the share of workers in the cognitive occupation: small and big city



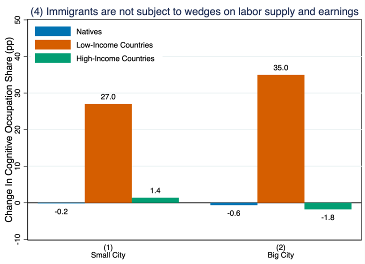
(a)



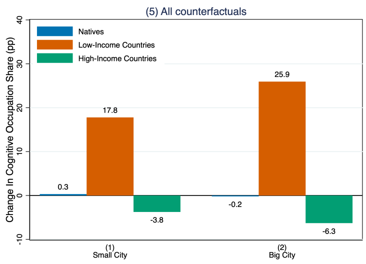
(b)



(c)



(d)



(e)

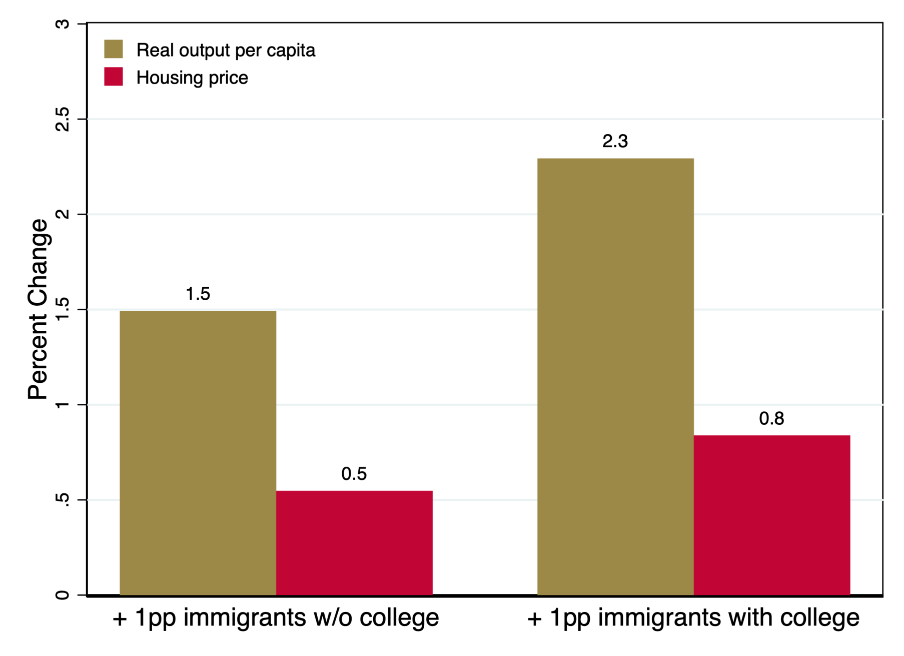
Finally, the last counterfactual shows how immigrants and natives reallocate across cities in an economy where immigrants are not subject to any wedge and are endowed with the same units of human capital as comparable natives. In other words, immigrants from low-income countries supply more human capital in both occupations, are not subject to wedges in the cognitive occupation, and do not face any wedge to their labor supply. Similarly, immigrants from high-income countries are not subject to any wedge (both in terms of earnings and labor supply) and are more abundant in human capital specific to the non-cognitive occupation, but less abundant in human capital in the cognitive occupation. Column (5) in Table 11 immigrants from all origins move out from the big city: the share of immigrants from low-income countries reduces by 9.3 percentage points and the share of immigrants from high-income countries reduces by 0.3 percentage points. The share of native workers in the big city, as a result, increases by 0.2 percentage points. Panel (e) in Figure 6 indicates that in the small city, the share of natives and immigrants from low-income countries in the cognitive occupation increases. As a response to this, the share of immigrants from high-income countries in the cognitive occupation decreases by about 3.8 percentage points. In the big city, more immigrants from low-income countries choose to work in the cognitive occupation and the higher level of competition leads to a reallocation of some natives and immigrants from high-income countries to the non-cognitive occupation (-0.2 percentage points and -6.3 percentage points, respectively).

7 Policy experiment

I simulate two policies under which the overall US population increases by 1 percentage point. Under the first policy, the increase in the overall population results from an inflow of immigrants without a college degree. Under the second scenario, the US government opens borders to foreign-born workers with college degrees. I simulate the policies and study how the real output per capita and housing prices compare to the baseline economy.

Real Output Per Capita and Prices. Figure 7 presents the percentage change in real output per capita and housing prices after the changes in immigration policies.

Figure 7: A new inflow of immigrants



Notes:

Under both policies, the real output and housing prices increase. The real output is 0.8 percentage points higher when the new immigrants have a college degree. Both policies generate an increase in the total number of workers with and without college education but do not affect immigrants' average human capital, the distortions to their labor supply, and wedges on earnings. Human capital in cognitive occupation is complementary to the production structure in each city. The model estimates indicate that immigrants with college education supply more intensive human capital in cognitive occupations than immigrants without college, as shown in Table 12. Therefore, the increase in real output per capita results from an increase in the average productivity of the workers in the economy. Higher levels of productivity generate also a positive change in housing prices. For a given value of available land, more workers demand housing under both policies. However, an inflow of college graduates in the economy generates an increase in the average earnings in non-cognitive and cognitive occupations (last row of Table 12) that leads to an increase in housing prices larger than when the new immigrants are workers without a college degree.

Table 12: Immigrants human capital and change in earnings

		Non-cognitive Occupation	Cognitive Occupation
		(1)	(2)
		Avg. Human Capital	
W/o college		4.2	9.2
		(0.4)	(0.8)
College		5.4	17.8
		(0.5)	(2.0)
		% Change In Avg. Earnings	
+1pp immigrants w/o college	1	1.0	1.0
+1pp immigrants with college	1	1.3	1.2

Notes:

8 Conclusion

What are the labor market outcomes of immigrants across space? How do they differ from that of native workers? What are the implications for spatial inequalities? In this paper, I document that the nominal earnings of natives workers are higher in big cities, while there are no significant differences in nominal earnings of immigrants between small and big cities. I then document that the lack of city-size premium results from the composition of the immigrant sample: immigrants from high-income countries do earn a premium for working in big cities, while the average earnings of immigrants from low-income countries do not change across cities. As a third fact, there a that the spatial distribution immigrants from high-income countries across locations and occupations is similar to that of native workers. On the opposite, immigrants from low-income countries work more in non-cognitive occupations and are more likely than natives and immigrants from high-ncome countries to live in big cities.

To interpret these facts, I build a spatial equilibrium model with heterogeneous cities and workers. I model differences in cities in production and occupational structure and the determinants of workers' allocation across cities and occupations. Workers are endowed with different levels of human capital and immigrant workers are subject to wedges on earnings and their labor supply that distort their allocation across cities relative to native workers. In their city-occupation choice, workers trade off higher earnings with higher level of utility from living in a specific city. I estimate the structural parameters of the model using data from the ACS 2010 and study the determinants of the gap in earnings premia. Spatial earnings inequality between immigrants and natives reduces by 80% once wedges on immigrants' earnings and labor supply generate are removed. The US real output per capita would increase by 2.5% by removing sources of immigrants misallocation relative to native workers and differences in human capital among workers, even though also inequality in real output per capita would increase between big and small cities.

A new inflow of immigrants with a college degree generates a larger increase in output per capita than in the case that the new immigrants are workers with no college education. However, when immigrants are college graduates also the housing price increases significantly more.

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Appendices

A Data Appendix

Table 13: Descriptive statistics

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Observations
	(1)	(2)	(3)	(4)
Natives	21.3	13.9	21.1	463,915
	(21.1)	(2.4)	(11.9)	
Immigrants	13.6	10.5	27.2	50,595
	(15.0)	(4.0)	(10.3)	
Selected Countries				
Canada	39.0	15.1	26.6	794
	(34.9)	(2.9)	(8.3)	
United Kingdom	41.1	15.1	26.4	1,097
	(37.3)	(2.9)	(8.8)	
China	14.0	12.3	29.9	2,651
	(13.9)	(4.7)	(10.0)	
India	23.0	15.2	24.4	2,242
	(20.0)	(3.3)	(10.3)	
Philippines	14.5	14.0	30.6	2,314
	(10.7)	(2.5)	(8.8)	
Vietnam	11.8	10.2	33.0	1,876
	(8.5)	(3.6)	(9.2)	
Mexico	10.0	8.6	26.6	19,498
	(8.1)	(3.0)	(10.6)	
El Salvador	10.1	8.2	27.4	2,779
	(6.2)	(3.0)	(10.5)	
Guatemala	9.2	7.9	23.8	1,929
	(6.4)	(3.2)	(10.0)	

Table 14: Descriptive statistics

Metropolitan Statistical Area	Rank By Employment	Workers In Cognitive Occupations (%)	Immigrants (%)	Avg. Hourly Wage
Chicago-Gary-Lake IL	1	65.1	11.5	23.9
Los Angeles-Long Beach, CA	2	57.1	29.5	20.0
New York-Northeastern NJ	3	63.8	26.4	22.7
Houston-Brazoria, TX	4	60.9	18.7	23.9
Philadelphia, PA/NJ	5	63.6	4.3	23.2
Atlanta, GA	6	66.1	7.9	22.7
Washington, DC/MD/VA	7	73.9	13.0	28.4
Dallas-Fort Worth, TX	8	65.9	14.7	22.9
Detroit, MI	9	59.1	4.6	21.7
Minneapolis-St. Paul, MN	10	65.9	3.0	23.7

Table 15: Descriptive statistics

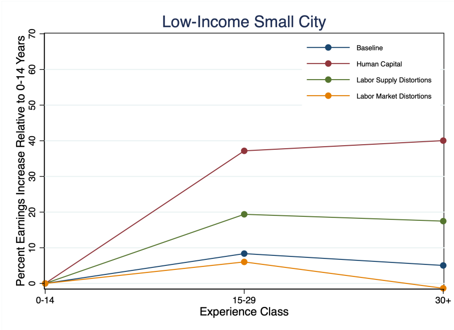
Occupation (SOC 3-dig)	Share Of Immigrant Workers (%)	Avg. Hourly Earnings
Advertising, Marketing, Promotions, Public Relations, and Sales Managers	0.4	58.98
Air Transportation Workers	6.0	46.26
Architects, Surveyors, and Cartographers	1.3	42.98
Art and Design Workers	4.9	40.29
Assemblers and Fabricators	4.3	36.90
Baggage Porters, Bellhops, and Concierges	3.6	36.56
Building Cleaning and Pest Control Workers	12.4	33.77
Business Operations Specialists	2.2	33.30
Communications Equipment Operators	2.4	32.77
Computer Occupations	4.6	32.75
Construction Trades Workers	5.2	31.20
Cooks and Food Preparation Workers	3.6	31.03
Counselors, Social Workers, and Other Community and Social Service Specialists	20.2	29.50
Drafters, Engineering Technicians, and Mapping Technicians	5.5	28.36
Electrical and Electronic Equipment Mechanics, Installers, and Repairers	3.1	27.96
Engineers	7.7	27.76
Entertainers and Performers, Sports and Related Workers	3.1	25.74
Entertainment Attendants and Related Workers	3.2	24.79
Extraction Workers	5.3	24.44
Financial Clerks	3.3	22.93
Financial Specialists	2.0	22.25
Food Processing Workers	3.5	22.15
Food and Beverage Serving Workers	4.2	22.00
Health Diagnosing and Treating Practitioners	8.8	21.91
Health Technologists and Technicians	4.9	21.79
Helpers, Construction Trades	7.4	21.71
Information and Record Clerks	4.8	20.55
Lawyers, Judges, and Related Workers	7.5	20.47
Legal Support Workers	4.7	20.23
Librarians, Curators, and Archivists	7.6	20.10
Life Scientists	5.3	19.77
Life, Physical, and Social Science Technicians	2.4	19.07
Material Moving Workers	2.0	18.95
Material Recording, Scheduling, Dispatching, and Distributing Workers	2.0	18.55
Mathematical Science Occupations	8.1	18.23
Media and Communication Equipment Workers	4.0	18.17
Media and Communication Workers	3.5	18.07
Metal Workers and Plastic Workers	6.1	16.87
Motor Vehicle Operators	4.7	16.73
Nursing, Psychiatric, and Home Health Aides	4.8	15.95
Operations Specialties Managers	6.0	15.87
Other Construction and Related Workers	3.8	15.81
Other Healthcare Support Occupations	4.5	15.23
Other Installation, Maintenance, and Repair Occupations	14.1	15.21
Other Management Occupations	11.2	14.60
Other Office and Administrative Support Workers	6.6	14.38
Other Personal Care and Service Workers	10.6	12.23
Other Production Occupations	7.0	12.16
Other Protective Service Workers	19.3	12.02
Other Sales and Related Workers	3.9	11.70
Other Teachers and Instructors	10.9	11.19

Table 16: List of non-cognitive occupations

Occupation (SOC 3-dig)	Share Of Immigrant Workers (%)	Avg. Hourly Earnings
Assemblers and Fabricators	4.6	21.31
Building Cleaning and Pest Control Workers	0.3	18.84
Communications Equipment Operators	1.9	18.80
Construction Trades Workers	4.7	18.05
Cooks and Food Preparation Workers	2.6	15.00
Electrical and Electronic Equipment Mechanics, Installers, and Repairers	14.8	14.50
Entertainment Attendants and Related Workers	11.7	14.47
Extraction Workers	8.9	14.47
Food Processing Workers	29.7	14.43
Food and Beverage Serving Workers	16.8	14.23
Helpers, Construction Trades	11.9	13.71
Material Moving Workers	18.5	13.11
Material Recording, Scheduling, Dispatching, and Distributing Workers	9.3	12.85
Metal Workers and Plastic Workers	24.8	12.37
Motor Vehicle Operators	8.2	12.21
Other Construction and Related Workers	7.9	12.14
Other Installation, Maintenance, and Repair Occupations	22.7	11.90
Other Production Occupations	13.4	11.73
Other Transportation Workers	24.3	11.48
Personal Appearance Workers	38.0	11.27
Plant and System Operators	28.4	11.02
Printing Workers	28.0	10.28
Rail Transportation Workers	28.6	10.00
Supervisors of Food Preparation and Serving Workers	51.1	9.69
Textile, Apparel, and Furnishings Workers	19.4	9.53
Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	21.7	9.32
Water Transportation Workers	34.4	8.97
Woodworkers	44.0	7.34

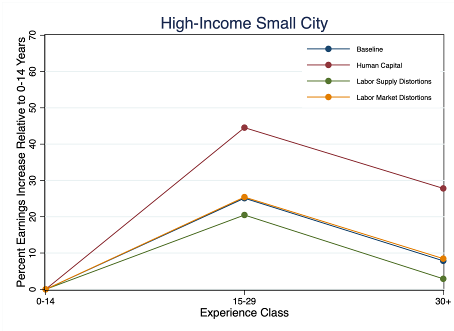
Earnings Profiles

Figure 8: Earnings profiles by country of origin and cities



(a)

(b)



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