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

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Abstract

This paper studies the geography of the labor market outcomes of immigrant workers in the US, and its implications for spatial inequality. Using US micro-data, I document that immigrants do not earn a premium from working in big cities, relative to natives. Among immigrants, those from high-income countries are the only ones who receive a city-size earnings premium. Natives and immigrants from high-income countries work more in cognitive occupations, especially in big cities. To rationalize this evidence I build a spatial equilibrium model where cities' technology is biased toward cognitive occupations, workers are heterogeneous in human capital, and wedges on earnings and labor supply distort immigrants' allocation across cities and occupations relative to natives. Counterfactual results indicate that removing wedges reduces spatial earnings inequality among workers, but increases disparities in production across cities. An immigration policy that opens borders to college-educated immigrants would also boost real output per capita, but increase housing prices unevenly across cities.

Keywords: Immigrants, Human Capital, Inequality, Spatial Equilibrium

JEL Classification: J21, J31, J61, R13

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1 Introduction

Every year, millions of people move from one country to another. A recent report by the International Labour Organization (ILOSTAT) found that immigrants in high-income countries are paid about 13% less than native workers. These earnings disparities arise for various reasons. First, immigrants may earn less than natives because they lack skills specific to the host country and need to undergo a process of economic assimilation (see, Albert et al. (2021)). Second, immigrants' lower earnings could arise from cross-country differences in education quality and years of schooling (see, Schoellman (2012)). Third, immigrants and natives tend to specialize in different occupations (see, Peri and Sparber (2009)), with immigrants being more likely to work in low-wage occupations. Finally, since immigrants and natives allocate differently across space (see, Albert and Monras (2022)), they could be exposed to different labor market opportunities.

The intertwined relationship between immigrants' allocation across space and occupations, their labor market outcomes, and spatial inequality is an understudied area of research. The empirical evidence for many high-income countries suggests that immigrant workers are fundamental to maintaining high levels of economic growth (see, Portes and Forte (2017) and Prato (2022)). Even though the role of immigrants is pivotal in modern economies, these workers are subject to substantial labor market barriers that distort their allocation into occupations (see, Birinci et al. (2021)). Thus, a question that follows is whether the geography of immigrants' labor market outcomes is the same as that of natives. If not, what are the implications for spatial inequalities?

This paper precisely studies the geography of labor market outcomes of immigrant workers and how they contribute to spatial inequalities. Once in the host country, immigrants choose where to live and which job to perform and these choices could be distorted by barriers in the labor market and their own preferences. To examine this perspective, I use data from the American Community Survey (ACS) to provide evidence about how earnings and occupational choices vary with the size of US cities for workers of various origins. I first show that while native workers earn a premium in nominal earnings of about 3$ per hour by working in big cities, this premium is not observed for US immigrants. Consequently, the earnings gap between immigrants and natives widens as cities' size increases. In the second fact, I show that the relationship between earnings and city size is positive and statistically significant for immigrants from high-income countries, while there is no increase in earnings as the city size grows for immigrants from low-income countries. As a third fact, I document that, especially in larger cities, both natives and immigrants from high-income countries work more in occupations intensive in cognitive tasks than immigrants from low-income countries. However, immigrants from low-income countries are more likely to reside in big cities compared to both natives and immigrants from high-income countries. To the best of my knowledge, this paper is the first to document spatial patterns in occupational choices that vary with workers' origins.

I interpret these facts through the lens of a spatial equilibrium model with heterogeneous workers and cities. In the model, each city is characterized by a productivity bias in occupations that are intensive in cognitive tasks and by an endogenous housing supply. I allow for differences in production technology among cities to capture the varying degrees of task specialization across cities.[1] In each city, a representative firm produces a homogeneous consumption good combining human capital, measured in efficiency units, in occupations intensive in cognitive and non-cognitive tasks. The population of the economy consists of workers from different origins, each possessing unique levels of human capital. Foreign-born workers are subject to city-occupation-specific wedges on earnings and their labor supply that contribute to generating disparities in earnings and spatial allocation relative to native workers. All workers make choices regarding their location of residence and employment based on a trade-off between higher earnings and higher utility derived from living and working in a particular city. Human capital and wedges influence workers' earnings both exogenously, by determining how much workers earn, and endogenously, by influencing their allocation in cities and occupations.

Wedges are the forces of immigrants' misallocation across cities and occupations. I model wedges on earnings as "taxes" that serve as proxies for various sources of labor market discrimination faced by immigrants, in the spirit of Hsieh et al. (2019). Discrimination may arise from issues such as undocumented immigration status, lack of job licensing, or be based simply on the country of origin of immigrants. [2]. 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 (see, Borjas (1998)). However, large ethnic networks cause wage losses and reduce the quality of job matches in the long run, especially for low-skilled immigrants (see, Battisti et al. (2022)). By incorporating these wedges and their associated factors into the model, I aim to capture the complexities of labor market dynamics for immigrant workers, shedding light on the mechanisms that contribute to the spatial disparities and location-occupational choices observed in the US economy.

I estimate the structural parameters that govern workers' allocations across cities and occupations through the simulated method of moments using individual-level data from the 2009-2011 ACS. The model generates the allocations of workers in cities and occupations and the pattern in earnings observed in the data. I find that the estimated productivity bias in cognitive occupations increases by 15% moving from small to big cities. The estimated stocks of human capital indicate that all workers are endowed with large amounts of human capital

[1] To this end, (Giannone, 2017) documents that the spatial diffusion of skill-biased technology is uneven, and (Eeckhout et al., 2021) shows that the degree of task specialization also varies across cities.

[2] Dustmann et al. (2013) provide evidence that immigrants often experience a downgrading upon arrival in the earnings distribution in the host country even though they are better educated than natives. Oreopoulos (2011) finds evidence of substantial discrimination across occupations towards applicants with foreign experience or those with Asian names compared with English names.

suitable for cognitive occupations. However, immigrants from low-income countries exhibit a lower abundance of human capital specific to cognitive occupations than all other workers. For all immigrants, the estimated wedges on earnings are larger in small cities relative to big cities. However, only immigrants from low-income countries who choose cognitive occupations are subject to wedges on earnings that negatively affect their earnings. The estimated wedges on the labor supply of immigrants from low-income countries reveal that these workers have a propensity to live in big cities and work in non-cognitive occupations three times higher than that of natives and other immigrants.

I first use the model as a laboratory to study how immigrants' human capital and wedges contribute to differences in city-size earnings premia between immigrant and native workers. Results from counterfactual exercises reveal that wedges on earnings drive the disparities in city-size earnings premia among workers. Specifically, in the absence of wedges on earnings, the difference in city-size earnings premia between immigrants from low-income countries and natives reduces by 50%. Additional results indicate that eliminating both the wedges on earnings and on the labor supply would lead to a considerable reduction in differences in city-size earnings premia with native workers. Specifically, the difference in city-size earnings premia relative to natives would reduce by 85% for immigrants from low-income countries, while the decrease would be around 60% for immigrants from high-income countries.

I then use the model to assess the implications of reducing spatial earnings inequality between immigrants and native workers on real output per capita and prices in the US economy. 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 1.8%. Next, I examine the effects of removing all sources of immigrants' spatial misallocation relative to native workers. In this case, real output per capita increases by 0.9%. Finally, had all the determinants of spatial earnings inequality between immigrants and native workers been removed, real output per capita would increase by 2.3%. Wedges on earnings and labor supply explain about 40% of these changes. Taken together, these results suggest a trade-off between equity (less spatial inequality among workers) and efficiency (more productivity across location). Specifically, I show that under the extreme scenario of lack of inequality among workers across space, there would be an increase of 2.3% in inequality in production across cities, with big cities gaining more than small cities from the reallocation of workers across locations and occupations. Cross-city differences in housing prices would also increase by 3.1%.

Finally, I investigate the implications of foreign-born worker inflows with different characteristics on both US real output per capita and housing prices. I conduct simulations of two immigration policies aimed at opening the US borders to immigrants, resulting in an overall population increase of one percentage point. I compare two scenarios: one in which new immigrants lack a college degree and another in which all immigrants are college graduates. The findings reveal that cross-city differences in employment shares are more pronounced for an inflow of immigrants without college education compared to an inflow of immigrants with college degrees. In both cities, real output per capita declines when the new immigrants lack a college education. This phenomenon is primarily attributed to the average productivity change resulting from the allocation of new workers and the reallocation of existing workers across cities and occupations. Specifically, an inflow of immigrants without a college education decrease the average productivity in both small and large cities. These workers have a higher propensity to live in big cities but are more likely to work in non-cognitive occupations. As a result, they will earn less and demand less housing in both cities. Conversely, when the new immigrants are all college-educated, the real output per capita would increase in all cities. Since college-educated immigrants supply more human capital specific to cognitive occupations than to non-cognitive occupations, the share of immigrants in cognitive occupations would grow in all cities. However, the change in these employment shares would be relatively small, as wedges on earnings and labor supply still distort the allocation of immigrants across cities and occupations. Moreover, under this policy change, housing prices would increase three times more in small cities than in big cities.

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) show that workers' human capital is crucial to explaining earnings inequality across cities. I extend this literature by highlighting that heterogeneity in the human capital of workers from various origins plays a crucial role in shaping spatial earnings inequality. The study addresses the unique characteristics of US immigrants, who come from diverse countries with different labor market institutions and occupational structures (Caunedo et al., 2021). These cross-country differences in labor market characteristics are reflected in the degree of complementarity between immigrants' human capital and the production structure in the US economy (Lagakos et al., 2018).

This paper also contributes to the emerging literature that uses spatial equilibrium models to study economic outcomes related to immigration. Recent papers are Burstein et al. (2020) and Piyapromdee (2021). In this dimension, I add to the literature by explicitly modeling granular heterogeneity in workers' human capital and tastes in a spatial equilibrium framework. The model considers human capital to be country and occupation-specific, recognizing the diverse skills and abilities that workers from different origins possess. The trade-off between earnings and utility derived from living in a specific city serves as a crucial determinant of workers' allocation across cities and occupations. In line with Albert and Monras (2022), this paper emphasizes the importance of accounting for heterogeneity in location preferences when modeling labor supply decisions of workers from various origins. By explicitly modeling the distortions on the immigrants' labor supply, I highlight the importance of considering individual preferences and location-specific factors in understanding how workers make decisions about where to live and which job to perform.

Finally, this paper contributes to the literature on human capital misallocation. Recent work by Hsieh et al. (2019) highlights the substantial gains that can be achieved by removing labor market barriers that impede the allocation of underrepresented workers to specific occupations. More recently, Birinci et al. (2021) quantify the output gains from eliminating distortions specifically related to immigrants in the US labor market. My model goes further and introduces the geographical dimension of wedges on immigrants' earnings and labor supply. The spatial framework provides a deeper understanding of the sources of human capital misallocation. The estimated values of wedges on earnings and labor supply shed light on how these distortions influence immigrants' labor market outcomes across different locations and occupations. By exploring the spatial differences in sources of human capital misallocation, this paper unveils the intricate interplay between heterogeneous workers' characteristics, location preferences, and labor market dynamics.

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.

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% 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.[3] Individual reports also information on their labor market outcomes such as annual earnings, employment status, number of weeks

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

and hours worked, and occupation.[4] 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.[5].

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 (2011) and use this measure to assign each of them to a cognitive or non-cognitive occupation category.[6]

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.[7] 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

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

[5]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.

[6]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.

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

population.

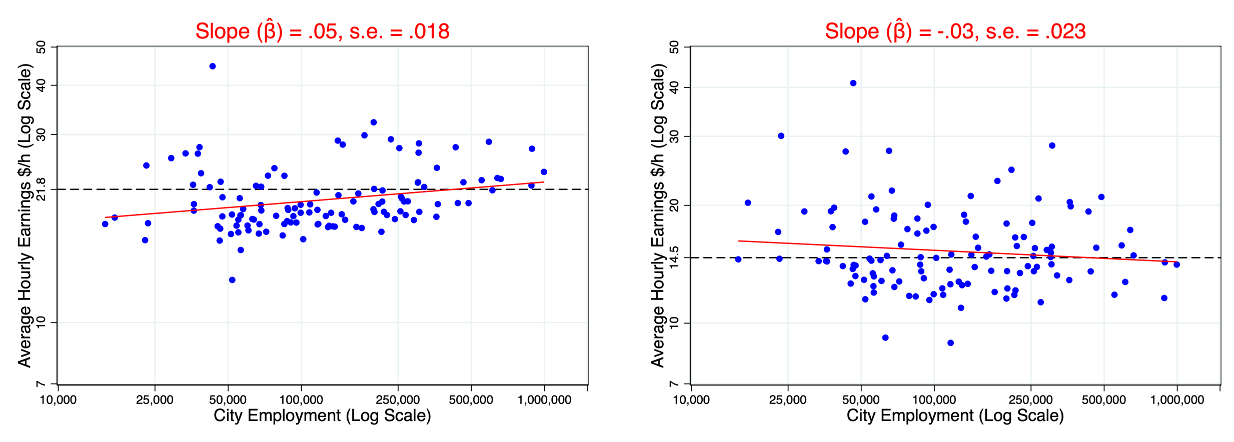
From this sample, I drop the individuals who live in areas not identifiable as a MSA and I select the MSAs where there are at least 200 foreign-born workers for each of the two country of origin categories (low-income and high-income, defined as above). I proxy the size of US cities using the employment 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 15 and Table 16 in Appendix A present summary statistics for the main socio-demographic characteristics of the sampled population and cities.

3.1 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 earnings of a native worker increase by about 5% percent by doubling the city size.

Figure 1: Cities hourly earnings premia



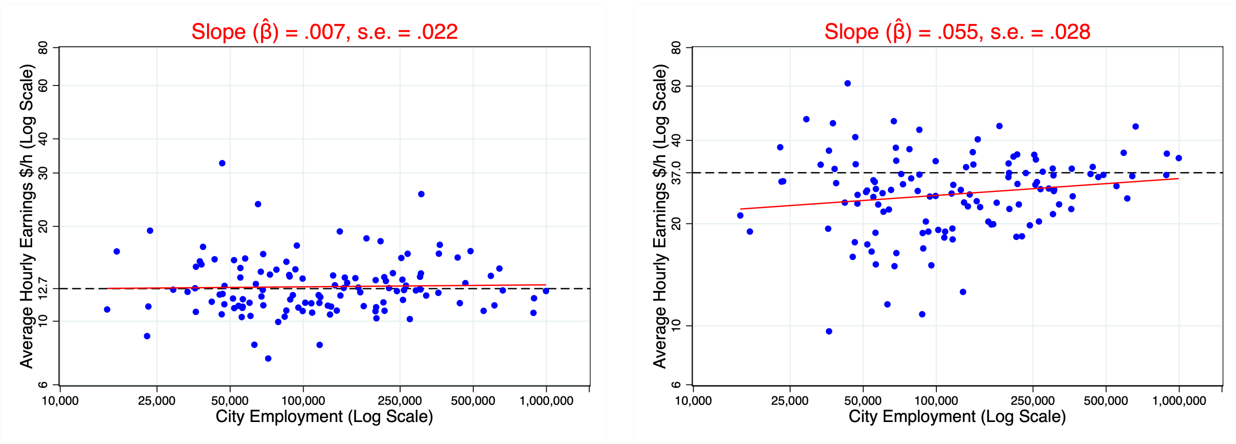
(a) Natives (b) Immigrants

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 robust to heteroscedasticity.

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% 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 50% more than a native who works in Manchester NH. These two panels suggest the existence of spatial disparities in earnings between immigrant and native workers.

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 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. 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 robust to heteroscedasticity.

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: Hourly Earnings: Big vs Small Cities

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

[*] Notes: For all groups, average earnings in the small and big city is computed as the average of the earnings of each MSA that fall in the small/big city category. The earnings gap is computed as the difference in the average earnings in the big and the small cities. Individual sample weights are rescaled by the usual number of hours worked per week and used in the calculations.

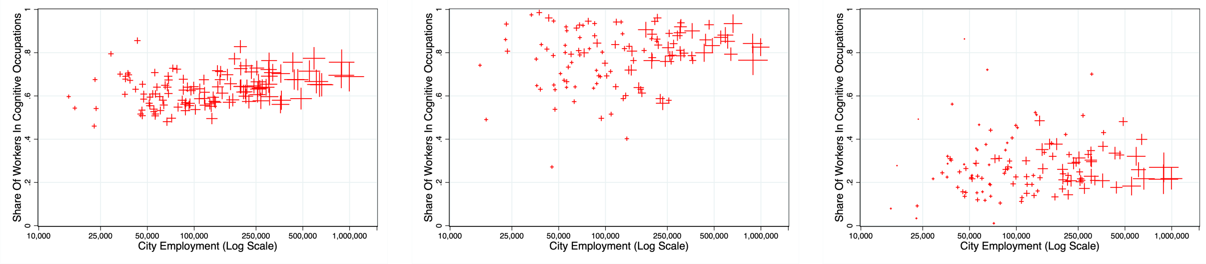
Table 1 shows the average earnings in small and big cities and the city-size gap for all groups of workers. In small cities, the hourly earnings of US workers are 21$ per hour and increase to 23.8$ per hour in big cities, roughly by 13%. Interestingly, immigrants from high-income countries earn more 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%) 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.

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 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 work more in cognitive occupations. The propensity of these workers to perform a cognitive occupation is larger in big cities compared to small cities (Panel 3a and Panel 3b). Panel 4c reveals a different spatial sorting for immigrant workers from low-income countries: they work less in cognitive occupations, their propensity to choose these occupations does not change with the city size but are more likely to live in big cities compared to natives and immigrants from high-income countries.

Figure 3: Sorting Into Cities And Cognitive Occupations



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

To show these patterns more precisely, I present in Table 2 the share of workers in cognitive occupations and the share of workers in the big and small cities categories.

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

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

* 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.

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. Similarly, the share of US workers in cognitive occupations is larger by 4.9 percentage points in big cities. Both natives and immigrants from high-income countries show also a similar spatial distribution. On the other hand, there is not an increase in the share of immigrants from low-income countries who work in cognitive occupations. The share of these workers in cognitive occupations decreases by 2.8 percentage points moving from the small to the big city. Compared to all other groups of workers, though, immigrants from low-income countries choose more frequently to locate in big citie (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. Moving from small to big cities: 1. Natives' earnings increase, while immigrants' earnings do not. 2. Among immigrant workers, earnings increase only if they come from high-income countries. 3. Natives and immigrants from high-income countries work more in cognitive occupations, while immigrants from low-income countries do not. 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.

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 spatial equilibrium model with heterogeneous cities 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 distributed on 1 unit of land T 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 $\left(\varepsilon_{jM}(i), ..., \varepsilon_{j'D}(i)\right)$ for each city-occupation pair. The tastes for city-occupation pairs follow a Gumbel distribution and are i.i.d across all workers.[8] 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

[8] For this distribution, I assume that the shape parameter is zero and that the location and scale parameters are equal to one.

demands skills and pays wages according to workers' marginal product of labor in each occupation. [9] 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 in group g who chooses a city j and an occupation o is Cobb-Douglass over a consumption good and a housing good:

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

where c is the consumption good, h is the housing good, z_{jo} is the value of amenities of a location-occupation pair, τ_{1jog} is a wedge that distorts the allocation of workers from group g across cities and occupations, ε_{jo} is the idiosyncratic taste draw for the city-occupation pair jo, and α represents the expenditure share on the housing good.[10] A 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:

$$V_{jog}(i) = v\left(w_{jog}, p_j\right) z_{jo} \tau_{1jog} exp\{\varepsilon_{jo}(i)\} \tag{4}$$

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 four 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 location-occupation choice also depends on the value of amenities z_{jo} that a worker, independently from their group g, assigns to a specific location-occupation pair. The last component of a worker's indirect utility is a wedge τ_{1jog} common to all workers from a group g that distorts their labor supply in a

[9] I assume perfect substitutability in the human capital of workers from all countries within an occupation.
[10] Workers consume the housing good in the same place as the workplace.

location-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 subject to a wedge on earnings τ_{2jog} 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. 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.[11]. 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:

$$w_{jog} = r_{jo} s_{og} \tau_{2jog} \tag{5}$$

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 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, 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:

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

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

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

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

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

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

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

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 fromgroup g who chooses a city-occupation pair jo:

$$V_{jog}(i) = \gamma p_j^{-\alpha} w_{jog} z_{jo} \tau_{1jog} \exp\{\varepsilon_{jo}(i)\} \tag{13}$$

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

$$\ln V_{jog}(i) = \ln \gamma - \alpha \ln p_j + \ln w_{jog} + \ln z_{jo} + \ln \tau_{1jog} + \varepsilon_{jo}(i) \tag{14}$$

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. The distributional assumption on ε_{jo} leads this setup 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 workers from group g living in a city j and working in an occupation o is:

$$\pi_{jog} = \frac{V_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} V_{j'o'g}} \quad (15)$$
$$\text{where} \quad V_{jog} = \gamma p_j^{-\alpha} r_{jo} s_{og} \tau_{2jog} z_{jo} \tau_{1jog}$$

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. Cities and occupations that offer high wages per efficiency unit and high amenities attract workers from any group g. Differences in the spatial distribution of workers across cities and occupations will depend on differences in human capital s_{og}, the value of wedges on earnings τ_{2jog}, and the values of distortions to their labor supply τ_{1jog}.

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

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

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

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

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

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

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

$$H_j = \alpha \frac{\bar{w}_j}{p_j} \quad (19)$$

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

$$p_j = \left(\frac{\alpha \bar{w}_j}{T_j}\right)^{\frac{1}{\zeta}} \tag{20}$$

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:

$$M_j = \sum_g \pi_{jMg} s_{Mg} \phi_g \tag{21}$$

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

$$D_j = \sum_g \pi_{jDg} s_{Dg} \phi_g \tag{22}$$

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:

$$\pi^\star_{jog} = \frac{V^\star_{jog}}{\sum_{j'\in\mathcal{J}}\sum_{o'\in\mathcal{O}} V^\star_{jog}} \tag{23}$$

2. Labor supply satisfies:

$$M^\star_j = \sum_g \pi^\star_{jMg} s_{Mg} \phi_g \tag{24}$$

$$D^\star_j = \sum_g \pi^\star_{jDg} s_{Dg} \phi_g \tag{25}$$

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

$$r^\star_{jM} = \left[\frac{Y_j}{M^\star_j}\right]^{\frac{1}{\sigma}} \tag{26}$$

$$r^\star_{jD} = \left[\frac{Y_j}{D^\star_j}\right]^{\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{27}$$

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

$$p_j^\star = \left[\frac{\alpha}{T_j}\bar{w}_j^\star\right]^{\frac{1}{\zeta-1}} \tag{28}$$

$$\text{where} \quad \bar{w}_j^\star = \sum_o \sum_g \pi_{jog}^\star w_{jog}^\star \tag{29}$$

5 Bringing The Model To The Data

In this section I describe the model calibration, show the model fit with the data, and discuss the internally estimated parameters.

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 3. Therefore, 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. I reduce the dimensionality of the model by assuming that workers could be from one of three different countries of origin: the US, low-income countries, and high-income countries. These workers could have received either non-college education or college education. Finally, each worker can belong to one of three potential experience groups: 0-14, 15-29, and more than 30.

Under these assumptions, there are 18 groups of workers that 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., $\tau_{1jog} = \tau_{1jok}$) and that native workers are not subject to them (i.e., $\tau_{1joUS} = 1 \quad \forall j \in \mathcal{J}, o \in \mathcal{O}$). When $\tau_{jok} > 1$ a worker receives a subsidy, while $\tau_{jok} < 1$ a worker's earnings are taxed.

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. I assume that the small and the big city have the same amount of land for the production of housing.

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 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.[12] 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 amenities, city-occupation distortions to workers' labor supply, and city-occupation-specific wedges on earnings. I estimate these parameters by using the simulated method of moments (SMM).[13].

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.

[12]The housing prices and wages for efficiency units are endogenous equilibrium outcomes from the model.
[13]See McFadden (1989))

Table 4: Estimated productivity bias in cognitive occupations

	Small City	Big City
	(1)	(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.

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.

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 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.[14] 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.

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 these wedges 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_{1jok} for immigrants from low-income and high-income countries. Native workers are the base group and $\tau_{1joUS} = 1, \quad \forall j, o$.

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

[14] 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.

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.

The last set of parameters measures the city-occupation-specific amenities and the distortions to the labor supply of each group of immigrant workers. Since natives are not subject to distortions to their labor supply, I estimate the 18 parameters for the amenities by targeting the share of native workers of each education and experience pair in each city-occupation pair. To obtain the 36 parameters for the distortions to the labor supply, instead, I target the share of immigrant workers from each origin group of each education and experience pair 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: Non-Cognitive Occupation (1)	Small City: Cognitive Occupation (2)	Big City: Non-Cognitive Occupation (3)	Big City: Cognitive Occupation (4)
	Amenities			
All countries	1.0	1.5	3.9	7.4
	(0.0)	(0.8)	(0.2)	(4.5)
	Wedge On Labor Supply			
High-Income	1.0	1.2	0.9	1.4
	(0.0)	(0.5)	(0.2)	(0.7)
Low-Income	1.0	0.3	2.7	0.7
	(0.0)	(0.1)	(0.4)	(0.2)

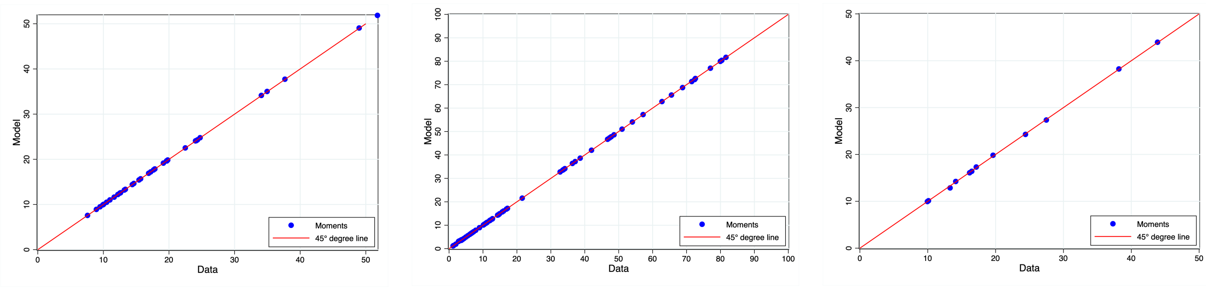
* Notes: The table reports estimated values for amenities and wedges on the labor supply of immigrant workers. I assume that natives and immigrants have the same value for amenities for each city-occupation pair. I normalize the amenities in small cities and in the non-cognitive occupation to 1 for all groups of workers, i.e. $z_{SMg} = 1 \quad \forall g$. I assume that natives are not subject to distortions to their labor supply and normalize immigrants' wedges to the labor supply in small cities and non-cognitive occupations to 1.

The first row of Table 7 shows that the estimated values for the amenities are more than three times larger in the big city than in the small city. These estimates also show that the non-cognitive occupation in the big city has the largest value of amenities. However, 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. Immigrants from high-income countries have high distortions to work in the cognitive occupation, particularly in the big city. On the opposite, immigrants from low-income countries have high distortions to work in the non-cognitive occupation in the big city. For this group of workers, the estimated value for the distortions relative to the cognitive occupation is quite small in magnitude in both cities. The estimated distortions to the labor supply of immigrants suggest a greater similarity in the labor supply decisions of immigrants from high-income countries and natives as opposed to immigrants from low-income countries and natives.

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

* 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.

Table 9: Model Fit For Fact 3

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

* 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.

6 Counterfactual Analysis

In this section, I interpret the facts documented in Section 3 using the spatial equilibrium model aiming to understand the drivers of spatial inequalities among workers and across cities. More in detail, I explore how the allocation of workers across cities and occupations affects these disparities. To this end, I construct five counterfactual economies each designed to compare against the baseline economy.

In the first counterfactual, I assign the same units of the occupation-specific human capital as estimated for comparable US natives, to all workers from different countries. All the other parameters remain constant in this scenario. With this analysis, I aim to measure the impact of differences in human capital on spatial inequalities.

Moving forward, in the second, third, and fourth counterfactuals, I delve into the role of wedges (on earnings and on labor supply) faced by immigrant workers. By removing them, I aim to quantify their role in differences in labor market outcomes and spatial inequalities among workers.

As a last exercise, I combine all the counterfactuals together. In other words, immigrants and natives do not differ in their human capital and immigrants do not face any wedge. As a result, the only differences that remain among workers are due to the initial observed distribution among education and experience groups.

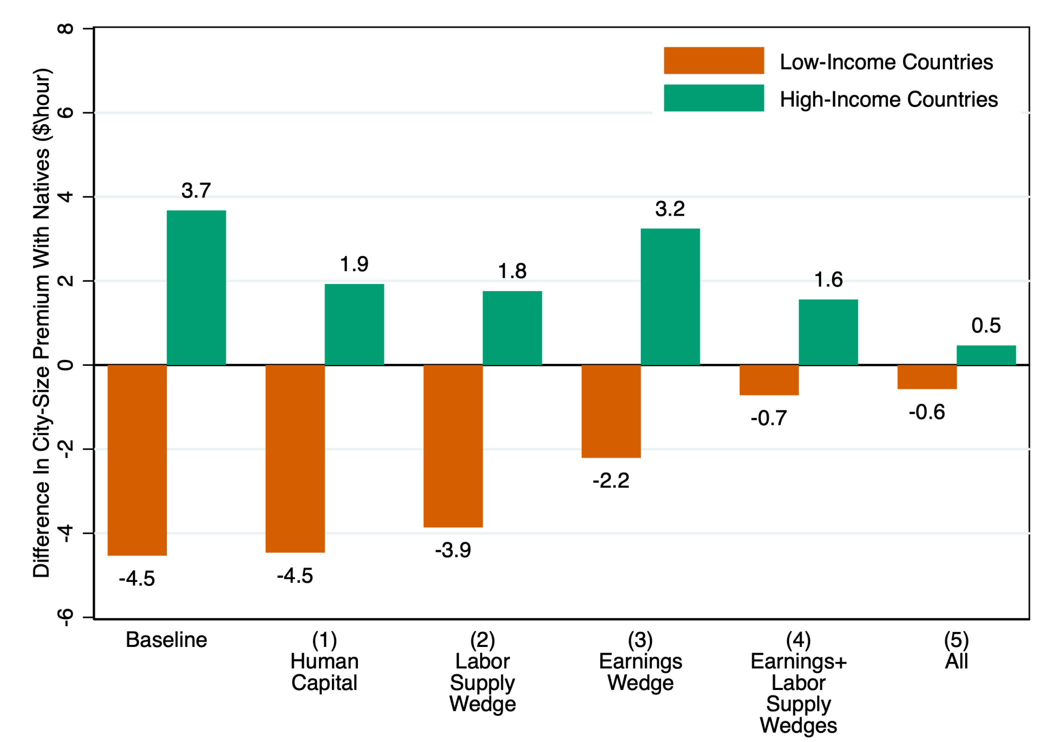
I first show how earnings inequality among workers, US real output per capita and housing prices change under each counterfactual. I then illustrate how the changes in the allocations of workers across cities and occupations generate the results. In Figures 5 and 6, and Tables 10 and 11- columns (1)-(5) 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 with natives in these premia for all origin groups in each counterfactual scenario and compare them with the value of the premia in the baseline economy. Figure 5 shows the results from these exercises. 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 immigrant and native workers are influenced not only by variations in the supply of occupation-specific human capital but also by the presence of earnings and labor supply wedges faced by immigrant workers.

In the first counterfactual, where the units of occupation-specific human capital supplied by immigrants and natives are the same, the gap in city-size earnings premia with natives reduces, primarily for immigrants from high-income countries (Column 1 in Figure 5). Immigrants from high-income countries in the baseline economy face minimal distortions in their labor supply and have an average endowment of 7.1 units of human capital specific to the non-cognitive occupation and 22.5 units specific to the cognitive occupation (as shown in Table 5). By reducing their human capital levels, the big-city premium on earnings relative to native workers also diminishes.

In contrast, immigrants from low-income countries in the baseline economy supply fewer units of human capital than native workers in both occupations. In a counterfactual economy where their human capital levels are increased for both occupations, the wedges on labor supply hinder their movement towards the cognitive occupation, and wedges on earnings reduce their earnings in both cities. As a result, the gap in city-size earnings premia with natives only closes by approximately 2.2%.

Figure 5: Counterfactuals on earnings gap



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

Column (2) of Figure 5 reveals that removing wedges on the labor supply of immigrant workers leads to a reduction in the difference in city-size earnings premia between immigrants and natives. For immigrants from high-income countries, the gap with natives closes by approximately 50%, indicating a significant decrease in the premium they receive in big cities compared to native workers. For immigrants from low-income countries, the gap with natives is reduced by about 13% after removing the wedges on labor supply. Although this reduction is more notable than in the previous case, disparities in city-size earnings premia with native workers remain due to the presence of wedges on earnings and significant dissimilarities in human capital supply.

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, spatial earnings inequality between foreign-born workers and natives reduces. For immigrants from low-income countries, the removal of earnings wedges leads to the removal of the disadvantages experienced by those who work in the cognitive occupation in both cities compared to native workers. As a result, the gap in city-size earnings premia with natives almost halves, declining from -4.5$ per hour to -2.2$ per hour. Similarly, for immigrants from high-income countries, the difference in city-size earnings premia relative to natives decreases from 3.7$ to 3.3$ per hour, resulting in a 10% reduction. This suggests that removing wedges on earnings also contributes to diminishing the earnings advantage of immigrants from high-income countries compared to native workers.

In the fourth counterfactual, I remove all sources of immigrants' spatial and occupational misallocation relative to native workers. 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 approximately 86%. Likewise, for immigrants from high-income countries, the gap with natives experiences a substantial decrease of about 57%. These significant reductions in the gap in city-size premia indicate that 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 differences in the determinants influencing location and occupation choices between immigrants and native workers. The results demonstrate a remarkable reduction in the gap in city-size earnings premia between foreign-born workers 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 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 provides insights into the changes in US real output per capita and prices relative to the baseline economy under the five counterfactual economies.

In the first counterfactual (Column 1 of Table 10), where the human capital endowment of immigrants matches that of US workers with the same education and labor market experience, the US real output per capita experiences an increase of 1.8%. The big city benefits more from higher levels of human capital, as its real output per capita rises by 1.9%, while the increase is 0.8% in the small city. As a result, inequality between the big and the small city increases by 1.1%. The productivity gains result in increased earnings for workers, leading to higher demand for consumption and housing goods. Consequently, housing prices rise in both cities.

Column (2) of Table 10 indicates that the removal of wedges on immigrants' labor supply also results in an increase in US real output per capita of 0.7%. In this scenario, immigrants from all countries and natives place the same value on cities and occupations. As a consequence, the real output in the big city experiences an increase of 1.3%, while it declines by

1.6% in the small city. However, the removal of labor supply wedges leads to an increase in inequality in output per capita between the two cities, with a rise of 3%. Additionally, housing prices respond to changes in demand, resulting in an increase in the big city and a reduction in the small city.

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	1.018	1.007	1.002	1.009	1.023
Big City	1	1.019	1.013	1.002	1.015	1.028
Small City	1	1.008	0.984	1.003	0.990	1.005
Big-Small City Ratio	1	1.011	1.030	0.999	1.025	1.023
			Housing Prices			
Big City	1	1.020	1.009	1.008	1.020	1.034
Small City	1	1.010	0.983	1.000	0.987	1.002
Big-Small City Ratio	1	1.010	1.026	1.008	1.034	1.031

* 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 3 in Table 10 indicates that the removal of wedges on earnings in all cities and occupations leads to a modest increase in US real output per capita by 0.2%. The change in real output per capita is slightly more pronounced in small cities compared to big cities. This indicates that the elimination of earnings wedges has a relatively greater impact on enhancing productivity and economic performance in smaller urban centers. Moreover, the reduction in wedges on earnings contributes to a (small) decrease in inequality across cities.

In Column 4 of Table 10, the removal of all sources of immigrants' spatial and occupational misallocation relative to natives results in a 0.9% increase in US real output per capita. Eliminating the sources of misallocation positively impacts overall economic performance, contributing to a slight improvement in productivity and economic output per person. However, it is noteworthy that the removal of spatial misallocation also leads to an increase in inequality in real output per capita across cities, with a rise of 2.5%. This suggests that while the aggregate real output per capita improves, there is a concentration of the gains in certain cities, potentially exacerbating spatial disparities in economic performance. Additionally, the big-small city ratio in housing prices increases by 3.4%. Thus, removing sources of spatial and occupational misallocation has differential effects on housing markets, resulting in relatively larger price increases in big cities compared to small cities.

Under the assumption that there are no differences between immigrants and natives in human capital, and immigrants are not subject to any wedges, the real output per capita experiences a significant increase of 2.3%. Thus, equalizing human capital and removing all wedges for immigrants has a substantial positive impact on overall economic performance, resulting in higher productivity and economic output per person. This result is mostly driven by the big city. However, the counterfactual analysis also indicates that cross-city differences in housing prices grow. This suggests that while the increase in real output per capita is beneficial for economic growth, it may also have implications for housing markets, potentially leading to greater divergence in housing prices between cities.

The allocation of workers across cities and occupations. Table 11 presents the changes in the share of workers from the three origin groups in the big city under the five counterfactual scenarios relative to the baseline economy. Column (1) indicates that when disparities in human capital between immigrant and native populations are absent, some workers from all groups relocate from the big to the small city. Since 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, immigrants' earnings in the non-cognitive occupation increase in both cities more than the earnings in the cognitive occupation. All else equal, in both cities, immigrants originating from both low and high-income nations display a propensity to transition from cognitive to non-cognitive occupations, 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)

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	-	x	-	-	-	x
z_{jog}	-	-	x	-	x	x
τ_{jok}	-	-	-	x	x	x
			Share Of Workers In Big Cities			
Natives	82.0	-0.2	-0.4	-0.1	-0.5	-0.4
High-Income	82.8	-0.6	-1.5	0.5	-1.0	-1.1
Low-Income	90.0	-0.1	-12.3	1.2	-9.5	-9.6

* 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). Changes are expressed in percentage points.

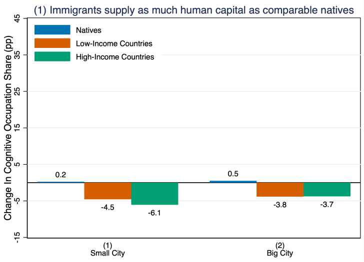
As a second experiment, I remove the wedges on the labor supply of immigrants so that these workers value amenities of city-occupation pairs the same as native workers. I then solve the model and compare the results to the baseline economy. Workers from all countries leave the big city. The emigration trend is particularly pronounced among immigrants from low-income countries resulting in a substantial decline of 12.3 percentage points in their representation in the big city. There is also a reallocation of workers between the two occupations within each city. Panel (b) in Figure 6 indicates that there are fewer natives and immigrants from high-income countries in the cognitive occupation in both cities. Without wedges on the labor supply, in fact, immigrants from low-income countries are more inclined to work in the cognitive occupation in both cities. As a result, the competition in the labor market for the cognitive occupation increases and some natives and immigrants from high-income countries move from the cognitive to the non-cognitive occupation.

How does the allocation of workers into cities and occupation change after wedges on earnings are removed? Column (3) in Table 11 and Panel (c) in Figure 6 answer this question. Overall, removing wedges on earnings leads to an inflow of immigrants from all countries to the big city. On the opposite, a small number of native workers relocate from the big to the small city. Within each city, more workers from low-income countries choose the cognitive occupation, since they do not receive any more discount on earnings from working in this occupation. Similarly, also the share of immigrants from high-income countries who work in the cognitive occupation increases in both cities. Interestingly, the change in occupational choices is more pronounced in the big city among immigrants from low-income countries, while it is more pronounced in the small city for immigrants from high-income countries. Since the competition in the cognitive occupation has increased in each city, a small fraction of native workers move from the cognitive to the non-cognitive occupation in both cities.

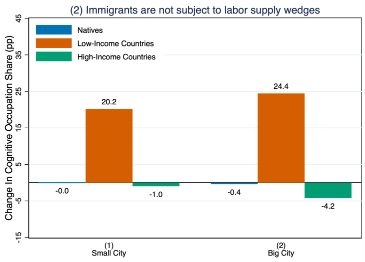
In Column (4) I remove all sources of immigrants' spatial and occupational misallocation relative to native workers. The results from this counterfactual are a combination of the results presented in Columns (2) and (3). Overall, some workers from all countries of origin relocate from the big to the small city. The outflow of workers from the big city is particularly severe for immigrants from low-income countries (-9.5 pp). The reallocation between occupations in each city follows different dynamics for all workers. In the small city, the share of native workers in the cognitive occupation decreases since there are more immigrants from all countries who choose to work in this occupation, (Panel (d) in Figure 6). In the big city, the effect of removing distortions on the reallocation of workers between the two occupations is larger. There are more immigrants from low-income countries that choose the cognitive occupation (+31.9 percentage points). As a result, not only some native workers move to the non-cognitive occupation, but also some immigrants from high-income countries (there is a decrease in their shares in the cognitive occupation of 0.5 and 3.9 percentage points, respectively).

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. Column (5) in Table 11 shows that workers from all origins move out from the big city: the share of natives reduces f 0.4 percentage points, the share of immigrants from high-income countries reduces by 1.1 percentage points and the share of immigrants from low-income countries reduces by 9.6 percentage points. Panel (e) in Figure 6 indicates that in the small city, there are more natives and immigrants from low-income countries in the cognitive occupation. As a response to this, the share of immigrants from high-income countries in the cognitive occupation decreases by about 3.4 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 -8.3 percentage points, respectively).

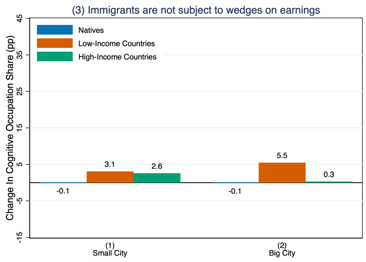
Figure 6: Change in the share of workers in the cognitive occupation: small and big city



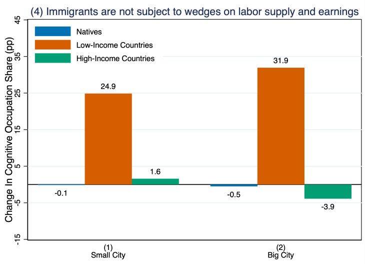
(a)



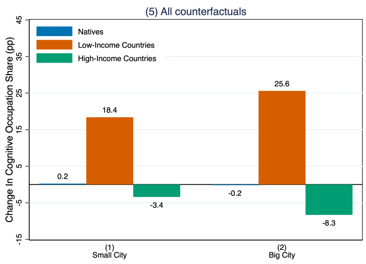
(b)



(c)



(d)



(e)

Notes: Each panel in the figure shows the change in the shares of native workers (blue), immigrant workers from low-income countries (orange), and immigrant workers from high-income countries (green) who choose the cognitive occupation in the big city and the small city under the five counterfactual scenarios. Changes are expressed in percentage points.

7 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 real output per capita and housing prices. The first policy (Policy 1) consists of opening the US border to immigrants without a college degree. With the second policy (Policy 2), the US government opens borders only to foreign-born workers with college education. Under both policies, the inflow of new immigrants generates an increase in US employment of 1 percentage point. New immigrants are endowed with the same human capital and are subject to the same wedges on earnings and labor supply as other immigrants with comparable observable characteristics who are already settled in the US. Table 12 reports the average human capital supplied by immigrants with and without college education. Overall, immigrants without college education supply twice as much human capital for the cognitive occupation, and immigrants with college education supply about three times more human capital for the cognitive occupation. This suggests that, only based on human capital, immigrants without college are more likely to choose to work in the non-cognitive occupation, while more educated immigrants work in the cognitive occupation.

Table 12: Immigrants human capital

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

* 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 13 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 14. The inflow of new workers in each city generates an increase in competition in each local labor market. As a result of the higher competition, some workers relocate from the small to the big city and from the small to the big city. All in all, cross-city differences in employment levels become larger under the first policy.

Table 13: 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

* 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.

In the second block of Table 13 I report the baseline values for the shares of immigrant workers in the cognitive occupation and how they change with the inflows of new immigrants. Both policies imply an increase in the number of immigrants in the cognitive occupation in both cities. More competition in both cities leads some native workers to change their jobs, moving from the cognitive to the non-cognitive occupation. Cross-city differences in the proportion of immigrants in the cognitive occupation increase under both policies, as highlighted in column (3).

When the new immigrants are college educated, there are more immigrants who work in the cognitive occupation in both cities compared to the first policy scenario. Under this policy, the big-small city difference in the share of immigrants in cognitive occupations changes from +1.6 percentage points in the baseline to +1.9 percentage points. As a result, differences in the spatial distribution of immigrants in the cognitive occupation increase.

Table 14: Immigrants amenities and distortions

Education	Small City		Big City	
	Non-Cognitive Occupation	Cognitive Occupation	Non-Cognitive Occupation	Cognitive Occupation
	(1)	(2)	(3)	(4)
No College	1.0	0.2	11.2	1.7
	(0.0)	(0.3)	(1.1)	(0.6)
College	1.0	1.3	8.3	10.1
	(0.0)	(1.0)	(1.7)	(5.9)

* The table reports the average value of amenities and distortions on the labor supply $z_{jo}\tau_{2jok}$ for each city and occupations of immigrants without college and with college education. Standard deviation in parenthesis. Workers' probability distribution weights are used in the calculations.

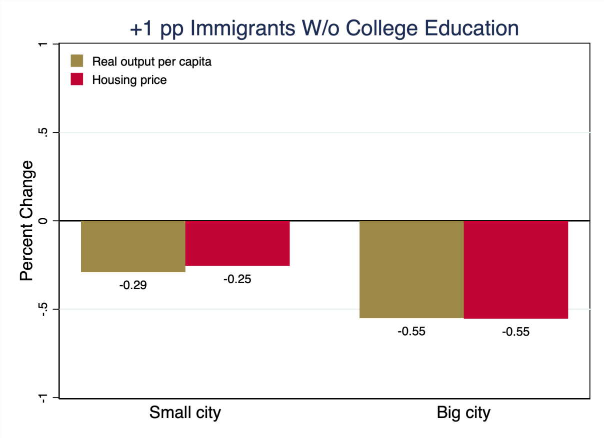
The different magnitudes of the changes in the employment shares in the cognitive occupation generated by the new immigration policies can be rationalized as follows. Even though all workers -with or without college education- can perform a cognitive occupation, a college degree provides workers with more human capital required to perform a cognitive occupation. Moreover, amenities and distortions to the labor supply of immigrants with a college degree are larger in the big city (second row of Table 14). Thus, the change in the share of immigrants in the cognitive occupation is larger in magnitude under the second policy.

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.

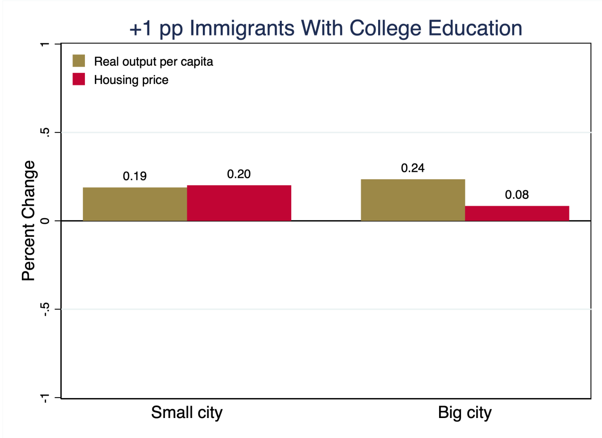
Under the first policy (Panel 7a), the real output per capita reduces in both cities. Most of the new immigrants choose to live in the big city compared to the small city, even though their productivity is lower and they are subject to larger wedges on earnings. As a result, the decrease in real output is about twice as larger in the big city. Interestingly, the increase in the overall population does not generate an increase in housing prices and the reduction in housing prices is proportional to the reduction in real output per capita.

On the other hand, when the immigration policy only allows for an inflow of college-educated immigrant workers, workers supply larger levels of human capital in both occupations. As a result of the new spatial allocations, there is a similar change in the real output per capita of both cities (Panel 7b). The new immigrants are endowed with larger levels of human capital that enhance the average productivity of each city. Since these workers are more productive, their earnings and housing consumption are also higher. As a result, housing prices increase in both cities. Compared to the result of the first policy, the changes in housing prices follow the opposite direction when the new immigrants are without college education.

Figure 7: Change in real output per capita and housing prices by city



(a) Policy 1



(b) Policy 2

Notes: The figure shows the percent change in real output per capita and housing prices for an increase of 1 percentage point in the share of immigrants without and with a college degree.

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 native 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 immigrants from low-income countries do not. As a third fact, I document that the spatial distribution immigrants from high-income countries across locations and occupations is similar to that of native workers. Conversely, immigrants from low-income countries work more in non-cognitive occupations and are more likely than natives and immigrants from high-income 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 immigrants are subject to wedges on earnings and on their labor supply. Earnings, wedges, and housing prices determine the allocation of workers across cities and occupations.

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 are removed. By removing sources of immigrants misallocation relative to native workers and differences in human capital among workers the US real output per capita would increase by 2.5%, but cross-city inequality in production would increase.

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 Variables definition and task intensity measure

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[15]:

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

[15] 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 15: Descriptive statistics

Country of Origin	Avg. Hourly Earnings	Avg. Years of Schooling	Avg. Experience	Observations
	(1)	(2)	(3)	(4)
Natives	21.8	14.0	20.2	562,680
	(19.9)	(2.4)	(11.1)	
Immigrants	14.5	11.0	24.9	57,004
	(15.7)	(4.0)	(8.4)	
<u>Selected Countries</u>				
Canada	38.3	15.2	25.8	1,045
	(29.9)	(2.8)	(7.7)	
United Kingdom	42.5	15.4	25.5	1,411
	(34.1)	(2.8)	(7.9)	
China	15.7	13.2	26.7	2,897
	(15.6)	(4.6)	(8.0)	
India	25.1	15.6	23.1	2,919
	(20.3)	(3.0)	(9.0)	
Philippines	15.1	14.3	28.5	2,600
	(11.4)	(2.3)	(7.8)	
Vietnam	12.3	10.7	29.6	1,923
	(9.9)	(3.4)	(7.3)	
Mexico	10.2	8.9	23.9	20,531
	(8.6)	(2.9)	(8.3)	
El Salvador	10.3	8.5	24.8	2,849
	(6.4)	(3.0)	(8.4)	
Guatemala	9.1	8.0	22.3	2,145
	(6.2)	(3.1)	(8.6)	

Table 16: Descriptive statistics

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

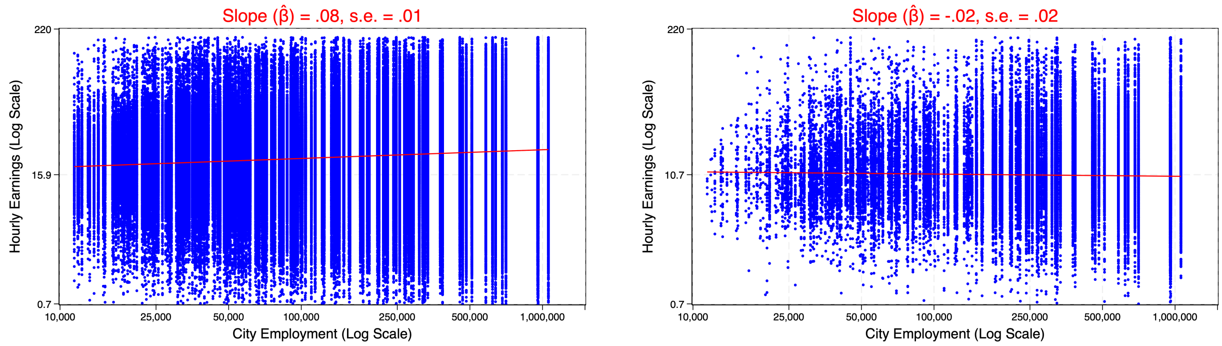
Table 17: Descriptive statistics

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 18: 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

Figure 8: Hourly earnings and city size: raw data male workers

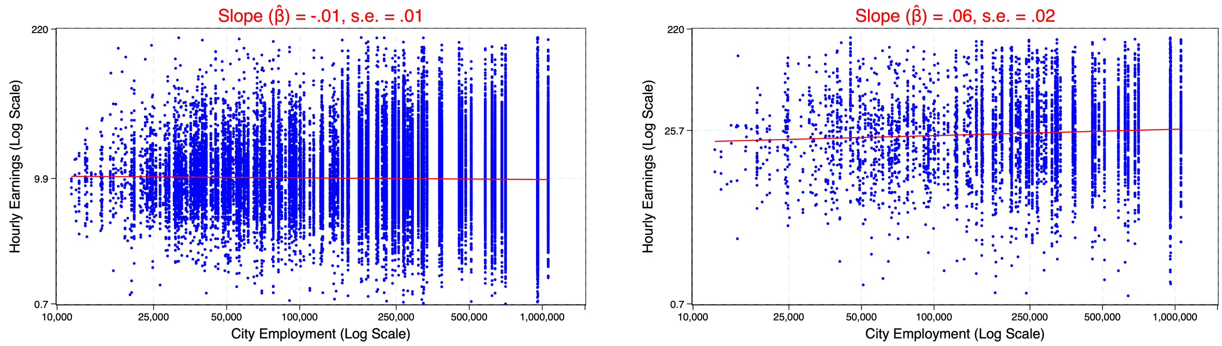


(a) Natives

(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 usual number of hours worked per week and used in the calculations.

Figure 9: Hourly earnings and city size by immigrants' country of origin: raw data male workers

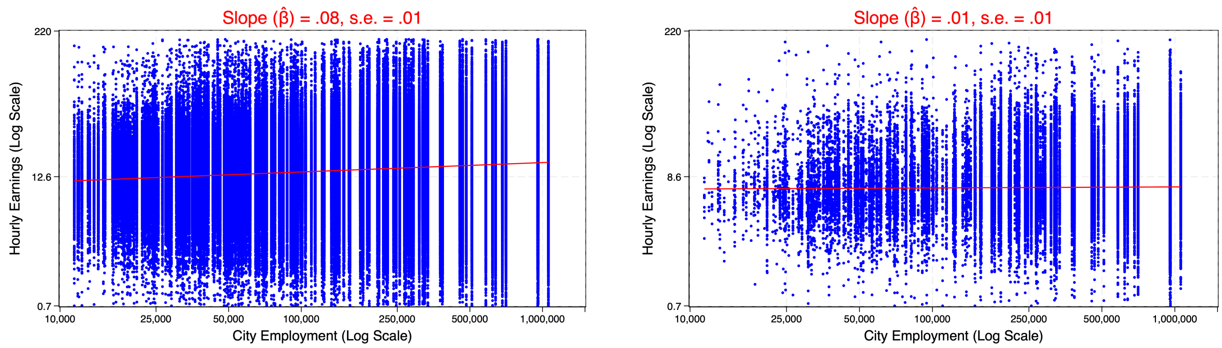


(a) Low-Income

(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 usual number of hours worked per week and used in the calculations.

Figure 10: Hourly earnings and city size for female workers: raw data female workers

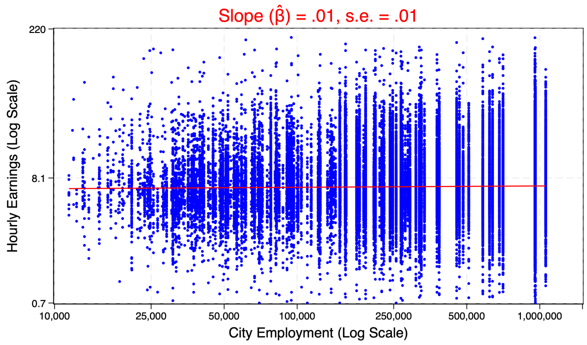


(a) Natives

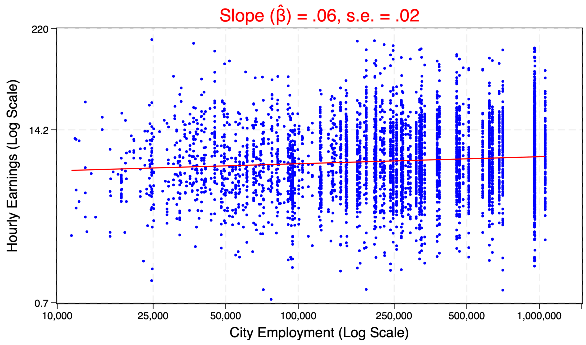
(b) Immigrants

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

Figure 11: Hourly earnings and city size by immigrants' country of origin: 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 usual number of hours worked per week and used in the calculations.