Essays on Immigration and Regional Economics

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Doctor of Philosophy.

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Introduction

People have always been on the move, but in recent decades, international migration has reached unprecedented levels. People from all over the world are leaving their homes in search of better lives. Some are fleeing violence or persecution, while others are seeking economic opportunity, family reunification, or simply a new adventure. Whatever their reasons, migrants play an important role in the global economy and society.

The consequences of international migration on the host economy and on migrants themselves are a complex issue and are not yet well understood. On the one hand, immigration can boost the economic growth of receiving countries by filling labor shortages and bringing new ideas and perspectives. On the other hand, immigration can increase competition in the labor market and lower wages for native-born workers. Additionally, poor economic and cultural integration of immigrants can lead to social unrest and divisions.

In this essay, I study the causes and consequences of immigrants' labor market performance in the host country at a regional and aggregate level. To this extent, I focus on understanding (i) how immigrants' spatial sorting is related to their labor market performance, and (ii) how the economic condition at arrival affects immigrants' economic assimilation.

In the first chapter of this essay, titled *"Skills, Distortions, and the Labor Market Outcomes of Immigrants across Space"*, I study how immigrants' earnings vary across different geographic areas and how this affects earnings inequality with natives and between cities. I use data from the American Community Survey and document that immigrants from low-income countries are more likely to live and work in big cities, but do not earn a premium for doing so, unlike natives and immigrants from high-income countries. To understand the mechanisms behind these facts, I build a quantitative general equilibrium spatial model that features differences in production technology across cities and heterogeneity in human capital and tastes for cities and occupations among workers. In addition, immigrants are subject to labor market distortions. I calibrate the model to match the observed earnings and shares of immigrants and native workers in two representative cities in the U.S., one big city and one small city. I find that heterogeneity in human capital is quantitatively important to explain the earnings gap between immigrants and natives. I show that removing all sources of heterogeneity between immigrants and natives reduces their earnings gap by 29 percent, at the expense of an increase in the earnings gap between cities by 2.3 percent. I also study the impact on the earnings gap between workers and cities of changes in immigration policy: opening borders to non-college-educated workers increases the earnings gap between immigrants and natives by 2.6 percent but reduces the earnings gap between cities by 0.3 percent.

In the second chapter of this essay, titled *"Unlucky Migrants: Scarring Effect of Recessions on the Assimilation of the Foreign Born"* coauthored with Alessandro Ruggieri, we study how aggregate labor market conditions affect the intra-generational assimilation of immigrants in the hosting country. Using data from the American Community Survey, we leverage variation in the national unemployment rates in the U.S. at the time of arrival of different cohorts of immigrants to identify short- and long-run effects of recessions on their careers. We document that immigrants who enter the U.S. when the labor market is slack face large and persistent earnings reductions. We find that a 1 p.p. rise in the unemployment rate at the time of migration reduces annual earnings by 4.9 percent on impact and 0.7 percent after 12 years since migration, relative to the average U.S. native. We demonstrate that changes in the employment composition across occupations with different skill contents are the key drivers. We show that were occupational attainment during periods of high unemployment unchanged for immigrants, assimilation in annual earnings would slow down on average by only 3 years, instead of 12. We also quantify the assimilation costs of entering the U.S. labor market when unemployment is high: in this scenario, immigrants lose between 1.7 and 2.4 percent of their lifetime earnings.

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Chapter 1

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

1.1 Introduction

Immigrants are vital to the US economy but are paid, on average, 15% less than native workers (Amo-Agyei et al., 2020). Explanations for this fact include differences in workers' productivity due to cross-country variations in schooling quality (Schoellman, 2012) and the pace of human capital accumulation before migration (Lagakos et al., 2018a). Furthermore, the existence of labor market distortions amplifies the challenges faced by immigrants and prevents them from working in occupations where they would be more productive (Birinci et al., 2021). Underperforming in the labor market could potentially bias natives' perception of immigration, leading to important consequences for social cohesion and aggregate outcomes.

Among the studies on labor market disparities between immigrants and natives, none consider the geographical differences in labor market outcomes among these workers. However, evidence shows that immigrants disproportionately reside in large cities (Albert and Monras, 2022) and that these cities reward jobs that require more intensity in cognitive tasks (Atalay et al., 2022). For example, an immigrant might aspire to live in New York but could only find opportunities for employment as a janitor there. This job choice could result not only from the immigrant's comparative advantage or preference but also from specific distortions within the New York labor market. How important is it for the labor market outcome of an immigrant to choose the right occupation in the right location? Are there location-specific barriers to access a particular occupation that influence this choice? If so, how important are they compared to the immigrant's human capital or preferences? What are the consequences for the immigrant's earnings gap relative to natives and spatial earnings inequality?

In this paper, I study how the labor market outcomes of workers of different origins vary across space and the consequences on earnings inequality. I use data from the American Community Survey (ACS) 2009-2011 and document three stylized facts on the earnings and occupation choices of immigrants and natives across cities. First, I show that natives earn $3 more per hour in big cities than in small cities, whereas immigrants do not receive such a premium on their earnings. Second, I show that among immigrants, the elasticity of earnings to city size increases with the GDP per capita of the country of birth. Third, I show that immigrants from low-income countries are more likely to live in big cities and work in non-cognitive occupations relative to natives and immigrants from high-income countries.

I interpret these facts through a quantitative general equilibrium spatial model with heterogeneous cities and workers. In the model, each city is characterized by a technology that combines cognitive and non-cognitive skills, and by an endogenous housing supply. To capture the varying degrees of task specialization across space, I let the technology in big cities favor cognitive occupations.[1] Within the model, workers vary

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

by their country of origin, education and experience and can perform any occupation. Given their origins, they choose a city-occupation pair based on their expected earnings and tastes.

I model three channels that influence a worker's occupation choice within a given location. First, I allow for origin-specific workers' human capital to perform an occupation. For example, both a worker from a poor and a rich country can choose to work in a cognitive occupation, but their productivity in this occupation might be different. This channel captures cross-country differentials in human capital accumulation and schooling quality which determine output per worker differences.[2]

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

Third, I incorporate local labor market distortions specific to the country of origin as sources of human capital misallocation. I model these distortions as wedges that affect earnings in the form of "taxes" (Hsieh et al., 2019). These wedges are proxies for various barriers faced by immigrants arising from undocumented immigration status, lack of job licensing, or simply from discrimination based on immigrants' country of origin.[3]

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cities lead to differences in task specialization.

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

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

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

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

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

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

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

Overall, this paper makes two main contributions. First, it provides robust empirical evidence on the spatial nature of the earnings gap between immigrants and natives and how it relates to their occupational choices in various locations. To the best of my knowledge, this is the first paper that documents this fact. Second, it provides a theoretical foundation for the determinants of workers' occupational choices in a spatial context and how they also relate to their origins. The model informs on the sources of inequality between US immigrants and natives and provides a tractable framework to measure and quantify them. Furthermore, the counterfactual exercises conducted using the spatial equilibrium framework reveal the existence of a trade-off between reducing earnings inequality among workers while increasing earnings inequality across space.

1.1.1 Relation to the Literature

This paper contributes to several strands of the literature. First, it relates to the literature on the relationship between immigration and inequality in the labor market. Works by Card (2009), Advani et al. (2022), Dustmann et al. (2023), Amior and Stuhler (2024), Lebow (2024) study the relationship between immigration and inequality. I contribute to the literature by documenting a novel stylized fact concerning the spatial distribution of immigrants' occupational choices, emphasizing the importance of workers' allocation across space to understand earnings inequality. Moreover, using a general equilibrium spatial model, I emphasize the role of the complementarity between workers' human capital and local labor market characteristics in shaping these outcomes. To this end, I exploit the unique characteristics of US immigrants, who originate from a large set of countries with different labor market institutions and occupational structures (Caunedo et al., 2021). Cross-country differences in labor market characteristics reflect the degree of complementarity between immigrants' human capital and the production structure in the US economy (Lagakos et al., 2018a).

This paper also contributes to the literature that uses structural models to study economic outcomes related to immigration. Recent papers are Llull (2018), Lessem (2018), Burstein et al. (2020) Piyapromdee (2021), Albert et al. (2021), Albert and Monras (2022), and Adda et al. (2022). Consistent with this literature, I do not find large effects of immigration on natives' wages. In this paper, instead, I quantify the sources of earnings disparities between immigrants and natives in a spatial equilibrium framework. I demonstrate that differences in human capital play the most quantitatively significant role in explaining earnings disparities among workers with different origins. Moreover, I uncover a trade-off between reducing earnings inequality between immigrants and natives and increasing earnings inequality between big and small cities. By allowing for labor market distortions and heterogeneity in tastes for cities and occupations, I show the importance of considering location-specific factors and individual preferences in determining the labor market decisions of immigrants and natives. Workers' choices influence aggregate earnings inequality among workers and across locations.

Finally, this paper contributes to the literature on the misallocation of production factors (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Gopinath et al., 2017; Hsieh et al., 2019; Bryan and Morten, 2019; Guner and Ruggieri, 2022). Recently, Birinci et al. (2021) quantify large output gains from eliminating wedges to immigrants' performance in the US labor market. My model goes further and introduces a geographical and origin dimension of wedges on immigrants' earnings. I show that, within a spatial equilibrium context, the output gains from removing labor market barriers to immigrants are small in magnitude, as they would induce minimal reallocation of workers across cities and occupations. Conversely, I show that substantial output gains can be achieved by eliminating differences in human capital between immigrants and natives. When workers are constrained to an occupation not only because of labor market distortions but also because of tastes and human capital, their labor market outcomes result from the intricate interplay between these factors.

The rest of the paper is organized as follows. In section 1.3 I describe the sources of data and present the stylized facts about immigrants' labor market outcomes across space. In section 1.4 I introduce the spatial equilibrium model. In section 1.5 I describe the estimation procedure. In section 1.6 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 1.7 I show and discuss the results of the policy exercise. In section 1.8 I summarise the findings and discuss ideas for future research.

1.2 Data and Motivating Facts

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

1.3 Data Sources

IPUMS Data. The main data source is the Integrated Public Use Microdata Series (IPUMS), a database that contains samples of the American population. I select a 3 percent pooled cross-sectional sample from the American Community Survey (ACS) (2009-2011), an annual demographic survey that gathers information about people in the US. For all individuals in the sample, the ACS provides the country of birth and citizenship status. I combine this information together and I define immigrants as foreign-born workers who are either born abroad from American parents or naturalized citizens or do not have citizen status. The ACS also contains other individuals' demographic characteristics such as age, gender, and level of education which I use to compute each worker's potential experience in the labor market and to assign them to the college/no-college category.[4] Individual reports also information on their labor market outcomes such as annual earnings, employment status, number of weeks and hours worked, and occupation.[5] 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.[6].

[4]For the definition of this variable and others see Appendix 2.9.2.

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

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

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.[7]

1.3.1 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.[8] I focus on first-generation immigrants, that is foreign-born

having one urbanized area with a population of at least 50,000 individuals.

[7] 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 2.9.2.

[8] Due to changes in female workers' participation rates during the selected years, I focus only on male workers. Additional results using the sample of female workers can be found in Appendix 1.9.2.

individuals who migrated to the US after 18 years old, who plausibly did not receive any education from a US institution. Since the ACS does not provide information on the location/country where individuals received their education, I follow Schoellman (2012) and use the information on year of arrival in the US, age, and years of completed schooling to exclude immigrants who are more likely to have studied in the United States. The earnings of immigrants who are left in the sample are thus netted of the benefits originating from studying at a US institution and from the acquisition of US-specific human capital. I select only immigrants from top-sending countries, i.e. immigrants from countries whose population falls above the 10th percentile of the total immigrant population.

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

The final sample for the analysis includes workers from 69 countries of origin (the US included) and 122 MSAs. Table 1.21 and Table 1.20 in Appendix 2.9.2 present summary statistics for the main socio-demographic characteristics of the sampled population and cities.

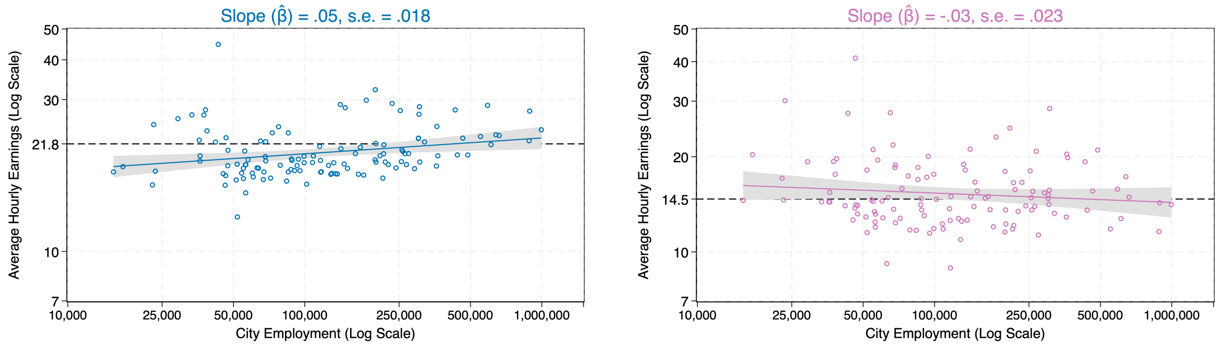
1.3.2 Empirical Evidence

Fact 1: There Is No City-Size Earnings Premium For Immigrants. Figure 1.1 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 1.1A). By moving from small to big cities, average hourly earnings

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.

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 3.6 percent by doubling the city size.

Figure 1.1: Cities hourly earnings premia



(A) Natives **(B)** Immigrants

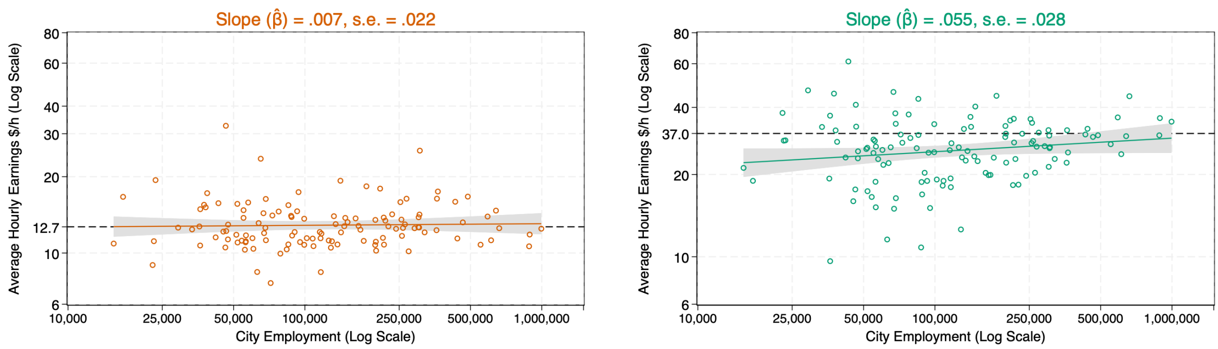
Source: ACS, World Bank Development Database, and author's calculation. Notes: This figure shows the relationship between the natural logarithm of the average hourly earnings of each metropolitan statistical area and the natural logarithm of the employment stock of each metropolitan statistical area.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

Panel 1.1B shows that the average hourly earnings for US immigrants are 14.5$ per hour, i.e. about 8$ per hour less than natives. On top of this, immigrants' hourly earnings show a larger degree of dispersion around the mean and do not increase with the size of US cities. The estimated elasticity of earnings to city size is negative and not statistically significant at a 10 percent significance level. To place these values in context, on average, the hourly earnings of an immigrant who works in Manchester NH (the smallest city in the sample) are as high as the earnings of an immigrant working in Chicago IL. On the contrary, a native who works in Chicago earns about 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 1.2. 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 1.2A), while it is significant at a 5 percent significance level for immigrants from high-income countries (Panel 1.2B). In other words, while for an immigrant from a high-income country doubling the city size results in an increase of 3.9 percent in hourly earnings, for an immigrant from a low-income country living in a small city or in a big city does not make a difference in terms of earnings.

Figure 1.2: Cities hourly earnings premia



(A) Low-Income

(B) High-Income

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

To gain more insight into the relationship between earnings, workers' origins, and the size of US cities, I report the average hourly earnings of natives and immigrants from low and high-income countries by splitting the sample into big and small cities.

Table 1.1: Hourly Earnings: Big vs Small Cities

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

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the average hourly earnings (US dollars/hour) in small cities and big cities and the city-size earnings gap (avg. earnings in the big city - avg. earnings in the small city) for natives, immigrants from high-income countries (GDP PC $\geq$ \$30,000), and immigrants from low-income countries (GDP PC $<$ \$30,000). Average earnings are calculated from a sample of male workers reporting to be employed. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

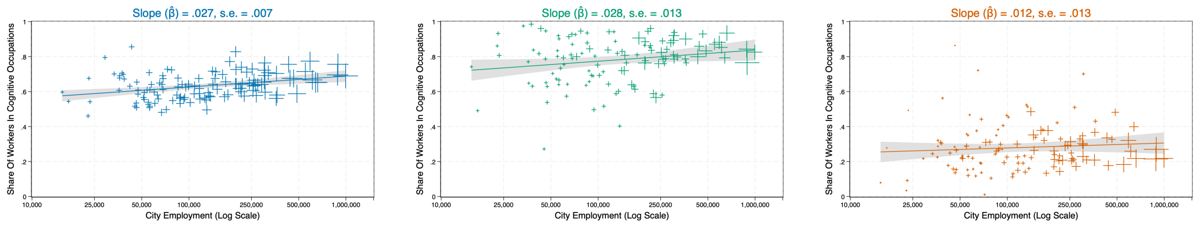
Table 1.1 shows the average earnings in small and big cities and the city-size gap for all groups of workers. In small cities, the hourly earnings of US workers are 21$ per hour and increase to 23.8$ per hour in big cities, roughly by 13 percent. Interestingly, immigrants from high-income countries earn more on average than all other workers. As a result, these workers receive a city-size premium even larger than that of native workers (+6.4$ per hour vs. +2.8$ per hour). On the opposite, the earnings of immigrants from low-income countries decrease by 1.4$ per hour (roughly 10.5 percent) when moving from the small to the big city. Hence, not only do immigrants from lower-income countries earn less than all the other workers but also do not receive any city-size earnings premium for living in big cities.

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 1.3 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 2.6A and Panel 2.6B). Panel 2.6C 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 1.3: Sorting Into Cities And Cognitive Occupations



(A) US **(B)** High-Income **(C)** Low-Income

1

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

To show these patterns more precisely, I present in Table 1.2 the share of workers in cognitive occupations and the share of workers in the big and small cities categories. 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 cities (89.3% vs 82.3% for natives and 80.7% for immigrants from high-income countries). Overall, the evidence in Figure 1.3 and Table 1.2 suggest that the sorting of workers into occupations varies across cities for workers of different origins.

Table 1.2: Shares of workers in cognitive occupations: small vs big cities

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

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the share of workers who work in a cognitive occupation (% cognitive) and the spatial distribution (% total) of workers between small and big cities expressed in percentage terms for natives, immigrants from high-income countries (GDP PC $\geq$ \$30,000), and immigrants from low-income countries (GDP PC $<$ \$30,000). For each outcome, Column (3) reports the difference in the shares between big and small cities expressed in percentage points. The shares are calculated from a sample of male workers reporting to be employed. Individual sample weights rescaled by the annual number of hours worked and used in the calculations.

Summary. In this section I documented three stylized facts about workers' earnings and sorting across cities and occupations. Compared to small cities, in big cities: 1. Natives earn more, while immigrants do not. 2. Among immigrant workers, immigrants from high-income countries earn as much as natives. 3. Natives and immigrants from high-income countries work more in cognitive occupations, while immigrants from low-income countries do not. Appendix 1.9.2 presents robustness checks for these facts. I show that the facts are consistent also for female workers and robust to the inclusion of a wide set of controls. 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.

1.4 A Quantitative General Equilibrium Spatial Model

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

1.4.1 Model Setup

Consider a static economy with $j \in \{1, ..., J\}$ cities and a continuum of workers i, where $i \in [0, 1]$. In each city, a representative firm produces a homogeneous and tradable consumption good combining labor (in efficiency units) in cognitive occupations D and non-cognitive occupations M. Workers are indexed by group g. Each worker i belongs to group $g = (k, e, x)$ that consists of individuals from the same country of origin $k \in \mathcal{K}$ with education $e \in \mathcal{E}$ and potential experience $x \in \mathcal{X}$. Each group g has a measure ϕ_g, such that $\sum_g \phi_g = 1$. Each worker i from group g is endowed with a vector of human capital $s = (s_{Mg}, s_{Dg})$ in efficiency units to perform the two occupations and draw tastes $\varepsilon_{jM}, ..., \varepsilon_{j'D})$ for each city-occupation pair. The tastes for city-occupation pairs follow a Gumbel distribution and are i.i.d across all workers.[9] Workers from all groups are mobile across locations, decide where to live and which occupation to perform and earn wages. A competitive housing market characterizes each city: absentee landlords own land T that can be used both for production and housing.

[9] I assume that the shape parameter for the Gumbel distribution is zero and that the location and scale parameters are equal to one.

1.4.1.1 Production Technology.

A firm in city j uses a CES technology that combines units of human capital in cognitive and non-cognitive occupations to produce a final good Y. The firm demands skills and pays wages according to workers' marginal product of labor in each occupation. [10] Each firm is characterized by a labor productivity bias θ_j in cognitive occupations. The bias reflects how the demand for labor is biased towards workers with higher levels of human capital and ensures differences in productivity across cities. Thus, the production function in each city is:

$$Y_j = f(D_j, M_j) = \left[M_j^{\frac{\sigma-1}{\sigma}} + (\theta_j D_j)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1.1}$$

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

1.4.1.2 Workers Preferences.

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

$$U_{jog} = c^{(1-\alpha)} h^{\alpha} \tilde{z}_{jog} \tag{1.2}$$

where c is the consumption good, h is the housing good, $\tilde{z}_{jog}$ is the value of amenities of a location-occupation pair of workers from group g, and α represents the expenditure share on the housing good.[11] Amenities are defined as:

$$\tilde{z}_{jog} = z_{jog} \exp\{\varepsilon_{jo}\} \tag{1.3}$$

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

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

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

A worker i from group g has a budget constraint:

$$c + p_j h \leq w_{jog} \tag{1.4}$$

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

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

$$V_{jog} = v\left(w_{jog}, p_j\right) z_{jog} \exp\{\varepsilon_{jo}\} \tag{1.5}$$

where $v\left(w_{jog}, p_j\right)$ is the portion of the indirect utility that depends on earnings and housing prices which I define in the next subsection. Eq.(1.5) shows that a worker's choice to live in a city j and work in an occupation o depends on three factors. First, the worker considers earnings w_{jog} when they choose where to live and work. The second factor that influences the choice of where to live and work is the price of the housing good p_j. The last component of a worker's indirect utility is the value of amenities z_{jog} that a worker from group g assigns to a specific location-occupation pair.

1.4.1.3 Workers Earnings And Labor Market Distortions.

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

$$w_{jog} = r_{jo} s_{og} \tau_{jog} \tag{1.6}$$

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

1.4.1.4 Housing Technology.

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

$$H_j = f\left(Y_j, T_j\right) = \omega_j Y_j^{\iota_j} T_j^{(1-\iota)} \tag{1.7}$$

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

1.4.2 Model Solution and Spatial Equilibrium

1.4.2.1 The Problem Of The Firm And Labor Demand In A City.

Consider the representative firm in the city j. Given the technology in production, the firm solves the following problem:

$$\max_{D_j, M_j} \quad \left[M_j^{\frac{\sigma-1}{\sigma}} + (\theta_j D_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - r_{jD}D_j - r_{jM}M_j \tag{1.8}$$

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

$$r_{jM} = \left(\frac{Y_j}{M_j}\right)^{\frac{1}{\sigma}} \tag{1.9}$$

$$r_{jD} = \left(\frac{Y_j}{D_j}\right)^{\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{1.10}$$

By taking the ratio of Eq. (1.10) and Eq. (1.9), I derive an expression for the skills price ratio of cognitive skills and non-cognitive human capital:

$$\frac{r_{jD}}{r_{jM}} = \left(\frac{D_j}{M_j}\right)^{-\frac{1}{\sigma}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{1.11}$$

Eq. (1.11) shows that the relative price in efficiency units of cognitive skills in a city j is regulated by two components. The first component is the ratio of labor in efficiency units of human capital used in cognitive and non-cognitive occupations. When the skills ratio increases, the relative price of cognitive skills decreases proportionately according to the degree of concavity of the technology and the productivity bias. The second component of the skills price ratio is the productivity bias k_j: if $\sigma > 1$, whenever there is an efficiency improvement in using cognitive skills, the relative price of cognitive skills increases. If inputs are substitutes, advances in technology used in cognitive occupations shift the demand for those skills, and the premium for cognitive skills grows. When inputs in production are complements, i.e. $\sigma < 1$, the relative price of cognitive skills decreases. Intuitively, when the cognitive and non-cognitive skills are complements in production, an increase in the efficiency of technology in cognitive task-intensive occupations makes workers in those occupations more productive and increases the demand for workers in non-cognitive occupations.

1.4.2.2 The Problem Of The Worker.

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

$$\begin{aligned} \max_{c_{jog},h_{jog}} \quad & U_{jog} = c_{jog}^{(1-\alpha)} h_{jog}^{\alpha} z_{jog} \exp\{\varepsilon_{jo}\} \\ \text{s.t.} \quad & c_{jog} + p_j h_{jog} \leq w_{jog} \end{aligned} \tag{1.12}$$

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

$$c_{jog} = (1-\alpha)\, w_{jog} \quad , \quad h_{jog} = \alpha \frac{w_{jog}}{p_j} \tag{1.13}$$

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

$$V_{jog} = \gamma p_j^{-\alpha} w_{jog} z_{jog} \exp\{\varepsilon_{jo}\} \tag{1.14}$$

$$= \gamma p_j^{-\alpha} r_{jo} s_{og} \tau_{jog} z_{jog} \exp\{\varepsilon_{jo}\} \tag{1.15}$$

where where $\gamma = (1-\alpha)^{(1-\alpha)}\alpha^{\alpha}$ is a constant term. Taking the log of Eq.(1.14), I obtain:

$$\ln V_{jog} = \ln \gamma - \alpha \ln p_j + \ln r_{jo} + \ln s_{og} + \ln \tau_{jog} + \ln z_{jog} + \varepsilon_{jo} \tag{1.16}$$

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

$$\begin{aligned} \pi_{jog} &= \frac{V_{jog}}{\sum_{j' \in \mathcal{J}} \sum_{o' \in \mathcal{O}} V_{j'o'g}} \\ \text{where} \quad V_{jog} &= \gamma p_j^{-\alpha} r_{jo} s_{og} \tau_{jog} z_{jog} \end{aligned} \tag{1.17}$$

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

1.4.2.3 The Problem Of The Absentee Landlords And Housing Supply In Cities.

In each city, the absentee landlords solve:

$$\max_{Y_j} \quad p_j \left(\omega Y_j^{\iota} T_j^{1-\iota} \right) - Y_j \tag{1.18}$$

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

$$Y_j = \left(p_j \omega \iota\right)^{\frac{1}{1-\iota}} T_j \tag{1.19}$$

By substituting Eq.(1.19) into Eq.(1.7) and rearranging the terms, I obtain the following expression for the housing supply:

$$p_j = \left(\frac{H_j}{T_j}\right)^{\frac{1}{\zeta}} \tag{1.20}$$

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:

$$H_j = \alpha \frac{\bar{w}_j}{p_j} \tag{1.21}$$

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

$$p_j = \left(\frac{\alpha \bar{w}_j}{T_j}\right)^{\frac{1}{\zeta}} \tag{1.22}$$

1.4.2.4 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:

$$M_j = \sum_g \pi_{jMg} s_{Mg} \phi_g \tag{1.23}$$

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

$$D_j = \sum_g \pi_{jDg} s_{Dg} \phi_g \tag{1.24}$$

1.4.2.5 Spatial Equilibrium.

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

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

$$\pi^\star_{jog} = \frac{V^\star_{jog}}{\sum_{j'\in\mathcal{J}}\sum_{o'\in\mathcal{O}} V^\star_{j'o'g}} \tag{1.25}$$

$$\text{where} \quad V^\star_{jog} = \gamma p_j^{\star-\alpha} r^\star_{jo} s_{og} \tau_{jog} z_{jog} \tag{1.26}$$

2. Labor supply satisfies:

$$M^\star_j = \sum_g \pi^\star_{jMg} s_{Mg} \phi_g \tag{1.27}$$

$$D^\star_j = \sum_g \pi^\star_{jDg} s_{Dg} \phi_g \tag{1.28}$$

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

$$r^\star_{jM} = \frac{\left[M_j^{\star\frac{\sigma-1}{\sigma}} + (\theta_j D^\star_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}}{M_j^{\star\frac{1}{\sigma}}} \tag{1.29}$$

$$r^\star_{jD} = \frac{\left[M_j^{\star\frac{\sigma-1}{\sigma}} + (\theta_j D^\star_j)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}}{D_j^{\star\frac{1}{\sigma}}} \theta_j^{\left(1-\frac{1}{\sigma}\right)} \tag{1.30}$$

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

$$p_j^\star = \left[\frac{\alpha}{T_j}\bar{w}_j^\star\right]^{\frac{1}{\zeta-1}} \tag{1.31}$$

$$\text{where} \quad \bar{w}_j^\star = \sum_o \sum_g \pi_{jog}^\star \phi_g r_{jo}^\star s_{og} \tau_{jog} \tag{1.32}$$

1.5 Bringing the Model to the Data

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

1.5.1 Dimensionality Reduction and Identifying Assumptions

The model describes the US economy as populated by workers from different origins who can choose where to live and which occupation to perform. I calibrate the model to replicate the stylized facts presented in Table 1.1 and Table 1.2 in Section 1.3. I represent the US economy as one small city and one big city where workers can perform either a cognitive occupation or a non-cognitive occupation. Workers differ in human capital from each other because of their country of origin, education, and potential experience in the labor market. Workers could be from one of three different countries of origin: the US, low-income countries, and high-income countries. These workers could have either received or not received a college education. Finally, each worker belongs to one of three groups of potential experience in the labor market. In other words, In calibrate the model on: $j \in \{\text{Small City}, \text{Big City}\}$, $o \in \{M, D\}$, $k \in \{\text{US}, \text{Low-Income}, \text{High-Income}\}$, $e \in$ Non-College, College$\}$, $x \in \{0-14, 15-29, 30+\}$.

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

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

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

1.5.2 Externally Calibrated Parameters.

Table 1.3 describes the set of parameters that I calibrate following the literature or that I compute from the data. I rely on existing values estimated by the literature the elasticity of substitution between input in technology, the housing elasticity, and the share of expenditure in housing. I set the elasticity of substitution between cognitive and non-cognitive human capital as in Hsieh et al. (2019). For the elasticity of the housing supply, I use the value estimated by Saiz (2010). I take the value for the share of expenditure in housing from Albouy (2008). I compute the proportion of workers in each human capital cell (k, e, x) using the ACS 2010 and obtain the exogenous distribution of workers in the economy. Finally, I assume that the small and the big city have the same amount of land for the production of housing.[12]

Table 1.3: External Parameters

Description	Symbol	Value	Source
	(1)	(2)	(3)
Elasticity of substitution	σ	3	Hsieh et al. (2019)
Housing supply elasticity	ζ	1.54	Saiz (2010)
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

Notes: The table reports the set of parameters calibrated taking values from the literature or assumed.

1.5.3 Internally Estimated Parameters.

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

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

using the simulated method of moments (SMM).[13].

1.5.3.1 Identification and Estimates of the City-Productivity Bias

I target the city-specific average earnings of native workers who work in cognitive occupations as moments to estimate the city productivity bias. Table 1.4 compares the estimated values for the productivity bias in the cognitive occupation in the small and big city.

Table 1.4: 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 obtained using the simulated method of moments.

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

1.5.3.2 Identification and Estimates of Workers' Human Capital

The structural model also includes a set of 36 parameters that measure the worker's level of human capital specific to an occupation conditional to the worker's character-

[13]See McFadden (1989)

istics. 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 1.5 presents summary statistics for the estimates of workers' human capital.

Table 1.5: Estimated human capital

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

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

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

1.5.3.3 Identification and Estimates of the Wedges on Earnings

Through the lens of the model, earnings are determined not only by the skills prices and the units of human capital supplied by workers but also by wedges specific to local labor markets. I assume that native workers are not subject to any wedge in earnings and identify the wedges on immigrants' earnings from the gap in earnings between immigrants and natives with the I estimate the 8 parameters that measure these wedges 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 1.6.

In both cities, the estimated wedges on earnings of immigrants from high-income countries are larger in magnitude than the estimated wedges on earnings of immigrants from low-income countries. A comparison *between* Column (1) and Column (3) shows that immigrants from all countries receive positive compensation by working in non-cognitive occupations. In the small city, wedges on earnings is 10 percentage points larger for immigrants from high-income countries as opposed to immigrants from low-income countries. The difference in wedges between immigrant groups increases in the big city: wedges are 20 percentage points higher for immigrants from

[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.

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.

Table 1.6: Estimated wedges on earnings

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

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

1.5.3.4 Identification and Estimates of the Tastes for Cities and Occupation

The last set of parameters measures the city-occupation-specific amenities for each group of workers. I normalize the value of amenities in the small city and non-cognitive occupations to 1. I identify the remaining 54 parameters for amenities from the share of workers in each country, education, and experience group in each city-occupation pair. I report in Table 1.7 the average value of the estimated parameters in all cities and occupations for workers from all countries.

According to Table 1.7, there are no substantial differences in how workers from different groups value working in the cognitive occupation in small cities. In the big city, natives and immigrants from high-income countries value, on average, three to four times more working in the non-cognitive occupation and six to seven times more working in the cognitive occupation.

In contrast, immigrants from low-income countries value, on average, more than 9 times working in the non-cognitive occupation, and about 5 times more working in the cognitive occupation. Overall, Table 1.7 suggests a greater similarity between the estimated values for natives and immigrants from high-income countries and natives as opposed to immigrants from low-income countries.

Table 1.7: Estimated amenities and wedges on labor supply

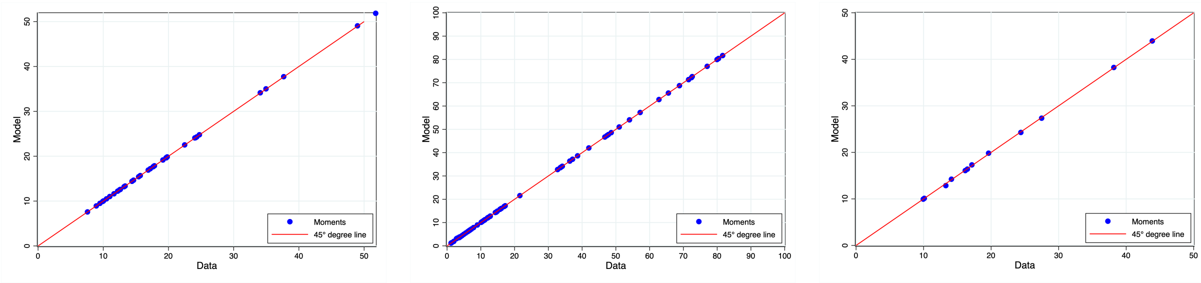
Workers Origins	Small City		Big City	
	Non-Cognitive Occupation	Cognitive Occupation	Non-Cognitive Occupation	Cognitive Occupation
	(1)	(2)	(3)	(4)
	Amenities			
Natives	1.0	1.3	3.9	6.4
	(0.0)	(0.8)	(0.2)	(4.5)
High-Income	1.0	1.3	3.2	7.1
	(0.0)	(1.1)	(1.4)	(7.7)
Low-Income	1.0	0.5	9.5	4.7
	(0.0)	(0.4)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

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

1.5.4 Model Fit

I use 100 moments computed from the data to identify the 100 structural parameters that measure the city-specific productivity bias in the cognitive occupation, workers' human capital, city-occupation amenities, and wedges on earnings. Figure 1.4 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 1.4: Model Fit



(A) Earnings w_{og} **(B)** Shares π_{jog} **(C)** Earnings w_{jok}

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

Table 1.8 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 1.9 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 1.8: Model Fit For Fact 2

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

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

Table 1.9: Model Fit For Fact 3

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

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

1.5.5 Recap on the model identification and alternative calibration

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

Table 1.10: Normalization and identifying assumption

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

1.6 Counterfactual Analysis

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

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

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

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

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

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

1.6.1 The Earnings Gap Between Natives And Immigrants vs Spatial Earnings Inequality.

How does earnings inequality between natives and immigrants change under the five counterfactuals? How does earnings inequality between big and small cities change? Is there a trade-off between reducing earnings inequality among workers and increasing earnings inequality across cities? Table 1.11 answers these questions.

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

$$\overline{w}^{\text{Gap}}_{\text{Workers}} = \frac{\overline{w}_{\text{US}}}{\overline{w}_{\text{Imm}}} = \frac{\sum_j \sum_o \sum_e \sum_x \pi_{joUSex}\phi_{USex}w_{joUSex}}{\sum_j \sum_o \sum_{k\neq \text{US}} \sum_e \sum_x \pi_{jokex}\phi_{kex}w_{jokex}} \tag{1.33}$$

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

$$\overline{w}^{\text{Gap}}_{\text{Cities}} = \frac{\overline{w}_{\text{Big}}}{\overline{w}_{\text{Small}}} = \frac{\sum_o \sum_k \sum_e \sum_x \pi_{\text{Big}okex} \phi_{kex} w_{\text{Big}okex}}{\sum_o \sum_k \sum_e \sum_x \pi_{\text{Small}okex} \phi_{kex} w_{\text{Small}okex}} \tag{1.34}$$

Column 1 of Table 1.11 shows that, compared to the baseline economy, when there is no heterogeneity in human capital between immigrants and natives with the same education and experience, earnings inequality between natives and immigrants shrinks by 19.9 percent. In contrast, earnings inequality between the big and small cities increases by 1.1 percent.

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

Table 1.11: Percent change in earnings inequality between workers and between cities

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

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

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

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

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

1.6.2 The City-Size Earnings Premium For Immigrants.

How does the big-city premium of immigrants from low- and high-income countries relative to native workers change under each counterfactual economy? Figure 1.5 answers this question. For each country of origin k, I compute the earnings differences between the big and the small cities as:

$$\overline{w}_k^{\text{Premium}} = \overline{w}_k^{\text{Big}} - \overline{w}_k^{\text{Small}} \tag{1.35}$$

$$= \sum_o \sum_e \sum_x \pi_{\text{Big}okex} w_{\text{Big}okex} \phi_{kex} - \sum_o \sum_e \sum_x \pi_{\text{Small}okex} w_{\text{Small}okex} \phi_{kex} \tag{1.36}$$

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

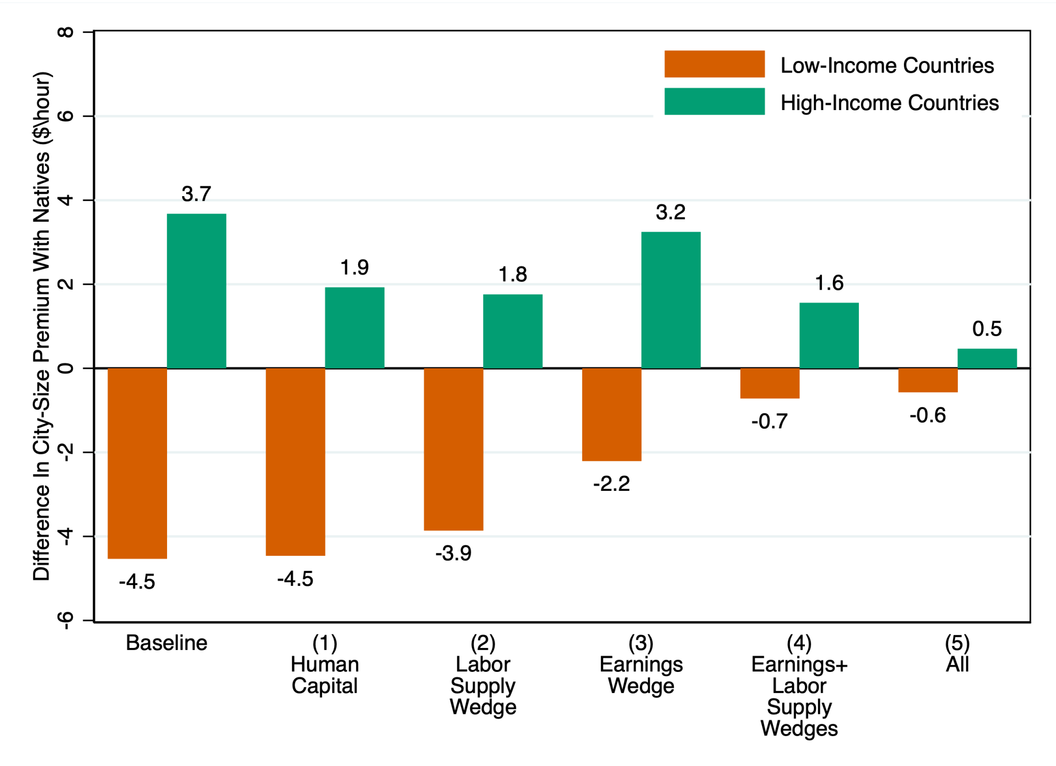
$$\overline{w}_k^{\Delta\text{Premium}} = \overline{w}_k^{\text{Premium}} - \overline{w}_{US}^{\text{Premium}} \tag{1.37}$$

Column (1) in Figure 1.5 shows that, in the baseline economy, the gap with natives is positive (+3.7$ per hour) for immigrants from high-income countries and negative (-4.5$ per hour) for immigrants from low-income countries. In this case, the differences in city-size earnings premia between immigrants and natives are influenced not only by heterogeneity in the endowment of occupation-specific human capital but also by the presence of different values of city-occupation amenities and labor market distortions.

In the first counterfactual, where the endowments of occupation-specific human capital supplied by immigrants and comparable natives are the same but the other parameters are untouched, the gap in city-size earnings premia with natives reduces, primarily for immigrants from high-income countries (Column 1 in Figure 1.5). In contrast, the gap in city-size earnings premia with natives only closes by approximately 2.2 percent for immigrants from low-income countries.

Column (2) of Figure 1.5 reveals that removing differences in how immigrants value city-occupation amenities with respect to natives leads to a substantial reduction in the difference in city-size earnings premia between immigrants and natives. The difference in big-city premium with natives closes by 48.6 percent for immigrants from high-income countries. Similarly, the difference in big-city premium with natives shrinks by 13.3 percent for immigrants from low-income countries. Although this reduction is more notable than in the previous case, disparities in city-size earnings premia with natives remain due to the presence of wedges on earnings and differences in endowments of human capital among workers.

Figure 1.5: Counterfactuals on earnings gap



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

To what extent does removing wedges on earnings, by keeping all the other parameters fixed, reduce differences in city-size earnings premia with natives? Column (3) in Figure 1.5 shows that under this hypothesis, the differences in city-size earnings premia with natives reduces for workers from all countries. The gap in city-size earnings premia with natives almost halves immigrants from low-income countries, declining from -4.5$ per hour to -2.2$ per hour. Immigrants from high-income countries, in contrast, experience a 10 percent reduction in their spatial earnings gap with natives. This suggests that removing labor market distortions helps to reduce earnings differences with natives for immigrants from low-income countries, and also contributes to diminishing the earnings advantage of immigrants from high-income countries compared to natives.

In the fourth counterfactual, there are no sources of immigrants' spatial and occupational misallocation relative to natives. The impact of this scenario on spatial earnings inequality is remarkable, as shown in Column (4) of Figure 1.5. For immigrants from low-income countries, the difference in city-size earnings premia with natives reduces substantially by 84.4 percent. Likewise, for immigrants from high-income countries, the gap with natives experiences a substantial decrease of 56.7 percent. The significant reductions in the gap in city-size premia indicate that heterogeneity in values for city-occupation amenities and city-occupation-specific wedges are the main sources of labor market inequality among workers from different countries.

In the fifth counterfactual scenario, represented in Column (5) of Figure 1.5, I explore the impact of eliminating all differences in the determinants influencing location and occupation choices between immigrants and natives. The results indicate a substantial reduction in the gap in city-size earnings premia between all groups of immigrants and natives. Specifically, the earnings gap between immigrants from high-income countries and natives decreases significantly from 3.7$ per hour to 0.5$ per hour, while the gap between immigrants from low-income countries and natives declines from -4.5$ per hour to -0.6$ per hour. These residual gaps in earnings reflect the remaining differences in the measures ϕ_g across various groups of workers, highlighting a small role of the distribution of individual characteristics in explaining spatial earnings disparities.

1.6.3 Changes In Housing Prices And Aggregate Real Output Per Capita.

How do housing prices and aggregate real output per capita change relative to the baseline economy under the five counterfactual economies? Table 1.12 provides insights into the changes in US real output per capita and prices relative to the baseline economy under the five counterfactual economies.

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

Table 1.12: Percent change in housing prices and aggregate real output per capita

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

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

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

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

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

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

1.6.4 The role of heterogeneous human capital, amenities, and labor market distortions in reallocating workers across cities and occupations.

The main mechanism behind the changes in the earnings gaps, housing prices, and aggregate output under the five counterfactual scenarios is the workers' reallocation across cities and occupations.

Table 1.13 indicates that workers move from the big city to the small city in all scenarios except for the case of no wedges on immigrants' earnings. When human capital disparities among similar workers are absent but immigrants value city-occupation amenities differently than natives and are still subject to wedges, immigrants from high-income countries and natives reallocate more.

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

their share in the big city decreases by 12.3 percentage points.

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

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

Table 1.13: Change in the share of workers in big cities (pp)

	Baseline	Counterfactuals				
		Same Human Capital As Natives	Same Amenities As Natives	No Wedges On Earnings	Same Amenities As Natives & No Wedge On Earnings	Full
		(1)	(2)	(3)	(4)	(5)
Parameters						
$s_{okex} = s_{oUSex}$	-	x	-	-	-	x
$z_{jokex} = z_{joUSex}$	-	-	x	-	x	x
$\tau_{jok} = 1$	-	-	-	x	x	x
		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

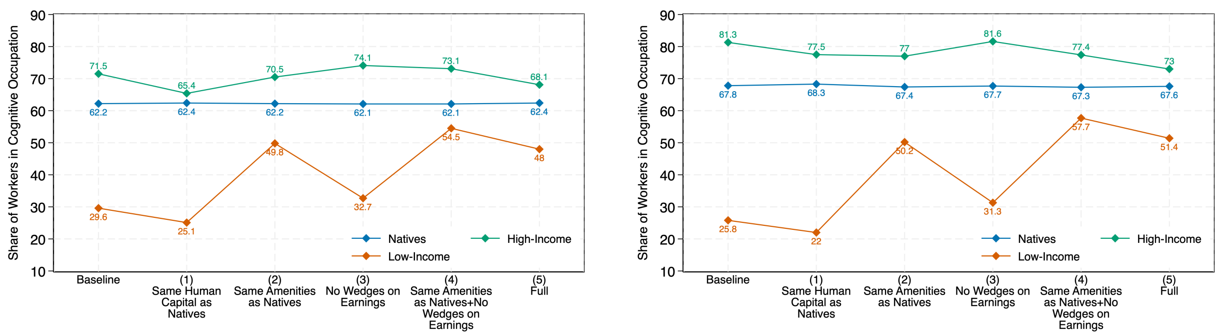
Notes: The table reports the change in the shares of native workers, workers from low-income countries, and workers from high-income countries who reside in the big city under the five counterfactual scenarios (Columns 1 to 5). Shares are expressed as percentages, and changes in the shares are expressed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

Finally, in the scenario where the only differences between immigrants and natives are their initial shares in education and experience groups, the reallocation of workers towards the small city prevails.

In each counterfactual scenario, not only do workers move across cities, but they also relocate across occupations within each city. Figure 1.6 indicates that, in each city, the reallocation between occupations happens mostly for immigrants from low-income countries. Panel a indicates that in both cities, when immigrants supply as much human capital as comparable natives (in observable characteristics) but value city-occupation amenities and are subject to wedges on earnings, they all move from the cognitive to the non-cognitive occupation in both cities. On the opposite, native workers move to the cognitive occupation, particularly in the big city.

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

Figure 1.6: Changes in the Share of Workers in Cognitive Occupations



(A) Small City

(B) Big City

Notes: The figure shows the changes in the share of workers in cognitive occupations for each country of origin in the small (panel A) and big cities (panel B) under each counterfactual.

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

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

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

1.6.5 The effect of workers' reallocation on skills prices and average productivity.

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

Table 1.14 shows the competition and skills effects in each city and occupation for each counterfactual scenario. In the small city, when immigrants are endowed with the same level of human capital as comparable natives (column 1), the skills effect compensates for the competition effect in the non-cognitive occupation. In contrast, the competition effect counterbalances the reduction in productivity in the cognitive occupation. In the big city, the magnitudes of the effects are larger, but the compensation mechanisms between the two effects are similar to those in the small city for both occupations.

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

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

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

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

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

Table 1.14: Competition vs. Skills Effects

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

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

1.7 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 the earnings gap between natives and immigrants and between cities. As a result of the inflow of new immigrants, US employment increases by 1 percentage point under each policy.

The first policy (Policy 1) consists of opening the US border to immigrants without a college education. In contrast, with the second policy (Policy 2), the US government opens borders only to immigrants with a college education. Once the new immigrants arrive in the US, they choose a city where to live and an occupation to perform and contribute to the local economy.

I assume that the new immigrants supply the same amount of human capital, have the same preferences for city-occupation amenities, and face the same labor market barriers as immigrants with comparable observable characteristics who are already settled in the US. To give context to this assumption, Table 1.15 reports the average human capital supplied by immigrants with and without college education in cognitive and non-cognitive occupations. Overall, immigrants without a college education supply twice as much human capital for the cognitive occupation than for the non-cognitive occupation. At the same time, immigrants with a college education supply more than three times human capital for the cognitive occupation than for the non-cognitive occupation. Comparing column 1 to column 2, it is possible to conclude that these patterns are independent of the immigrants' country of origin. Based only on the comparative advantage originating from human capital, Table 1.15 suggests that immigrants without a college education are more likely to choose to perform the non-cognitive occupation, while more educated immigrants are more likely to choose to perform the cognitive occupation.

Table 1.15: 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)

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

Changes in the spatial distribution of workers. The first block of Table 1.16 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 1.17. The inflow of new workers in each city generates an increase in competition in each local labor market. As a result, some workers relocate from the small to the big city. All in all, cross-city differences in employment levels become larger under the first policy.

The second block of Table 1.16 reports the baseline values for the shares of immigrants in the cognitive occupation and the corresponding changes after the inflows of new immigrants. Both policies imply an increase in the number of immigrants in the cognitive occupation in both cities. Column (3), however, shows that the increase in differences between cities in the share of immigrants in the cognitive occupation is larger under the second policy. While in the baseline the difference between cities is 1.6 percentage percentage points, under the second policy it increases to 1.9 percentage points.

Table 1.16: 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.

Differences in workers' allocations after changes in immigration policies can be explained by the following factors. First, although all workers, regardless of their educational attainment, can perform the cognitive occupation, a college education provides workers with more of the human capital required to perform such an occupation (see, Hanushek (2012) for example). Thus, immigrants with a college education have a comparative advantage in performing the cognitive occupation relative to immigrants without a college degree. Second, immigrants with a college education have a large taste for working in the big city, as shown in the second row of Table 1.17. Consequently, the share of immigrants in the cognitive occupation increases more in the big city after an inflow of immigrants with a college education.

Table 1.17: 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	0.4	7.3	2.1
	(0.0)	(0.3)	(4.4)	(0.8)
College	1.0	1.4	5.4	9.7
	(0.0)	(1.0)	(3.0)	(6.3)

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

Changes in earnings inequality among workers and across cities. How do earnings inequality among workers and across cities change under the two new immigration policies? Table 1.18 answers this question. Column (1) shows that an inflow of immigrants without college degrees increases the earnings gap between immigrants and natives but reduces the earnings gap between big and small cities. As discussed in the previous paragraph, these immigrants have a comparative advantage in choosing the non-cognitive occupation over the cognitive occupation. The increase in competition in both cities in the non-cognitive occupation has a negative impact on the wage per unit of human capital and also the average productivity in each occupation reduces, as shown in Column (1) of Table 1.19. At the same time, the average productivity in cognitive occupations decreases in both cities. The changes in competition and average productivity lead to an increase in the earnings gap between natives and immigrants. However, since these changes are stronger for the non-cognitive occupation in the big city with respect to all the occupations in all cities, the big-small city earnings gap reduces.

Table 1.18: Changes in Earnings Inequality

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

Notes: This table shows the effect of an inflow of immigrant workers on the ratio of average earnings of natives vs. average earnings of immigrants (first row) and on the ratio of average earnings in the big city vs. average earnings in the small city (second row). Column 1 shows the outcomes after an inflow of immigrants without a college education. Column 2 shows the outcomes after an inflow of immigrants with a college education.

In contrast, column 2 of table 1.18 indicates that an inflow of immigrants with a college education induces a reduction in the earnings gaps between natives and immigrants and between the big and small cities. The new immigrants supply more human capital, have a comparative advantage in working in the cognitive occupation, and are more likely to live in the big city. As a result, in both cities, the competition effect in cognitive occupations is negative but is compensated by an increase in average productivity. The increase in average productivity induces a reduction in the earnings gap between natives and immigrants. However, the existence of labor market distortions for immigrants in the big cities reduces the positive impact of the inflow of new workers and average earnings increase more in the small city.

Table 1.19: Immigration Policies: Competition and Skills Effects

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

Notes: This table shows the effect of an inflow of immigrant workers on skills prices (i.e., wage per unit of human capital) and the average productivity of workers in each city and occupation. Column 1 shows the outcomes after an inflow of immigrants without a college education. Column 2 shows the outcomes after an inflow of immigrants with a college education.

1.8 Conclusion

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

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

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

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

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

1.9 Appendix A

1.9.1 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
  - 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

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

  - 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 1.20: List of the 10 biggest MSAs for ranked by employment stock

Metropolitan Statistical Area	Rank By Employment	Workers In Cognitive Occupations (%)	Immigrants (%)	Avg. Hourly Wage
Chicago-Gary-Lake IL	1	66.5	10.2	24.7
New York-Northeastern NJ	2	66.1	24.4	25.3
Los Angeles-Long Beach, CA	3	59.3	25.4	20.5
Houston-Brazoria, TX	4	61.8	17.4	24.0
Philadelphia, PA/NJ	5	65.6	4.2	24.3
Atlanta, GA	6	66.4	8.0	22.4
Washington, DC/MD/VA	7	74.6	12.7	28.9
Dallas-Fort Worth, TX	8	67.1	13.7	23.1
Detroit, MI	9	59.4	4.3	21.0
Minneapolis-St. Paul, MN	10	66.0	2.9	23.2

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

Table 1.21: Descriptive statistics

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

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

Table 1.22: List of cognitive occupations

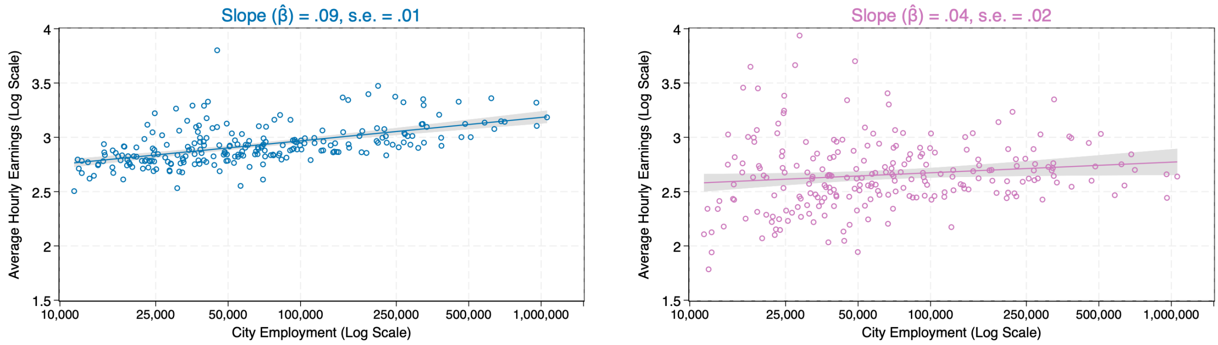
Occupation (SOC 3-dig)	Share Of Immigrant Workers (%)	Avg. Hourly Earnings
Advertising, Marketing, Promotions, Public Relations, and Sales Managers	0.4	58.98
Air Transportation Workers	6.0	46.26
Architects, Surveyors, and Cartographers	1.3	42.98
Art and Design Workers	4.9	40.29
Assemblers and Fabricators	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 1.23: 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

1.9.2 Robustness checks for stylised fact

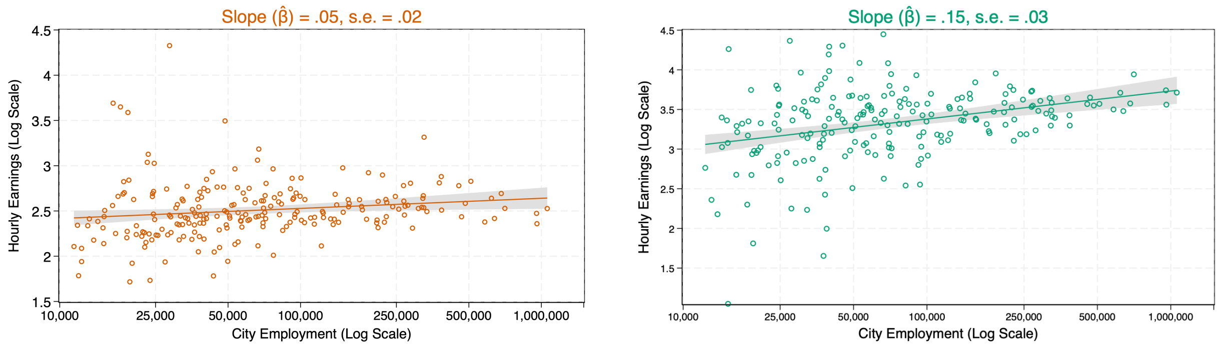
Figure 1.7: Hourly earnings and city size: raw data male workers



(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 annual number of hours worked and used in the calculations.

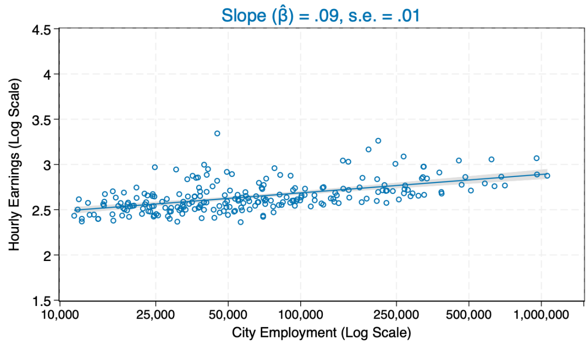
Figure 1.8: Hourly earnings and city size by immigrants' country of origin: raw data male workers



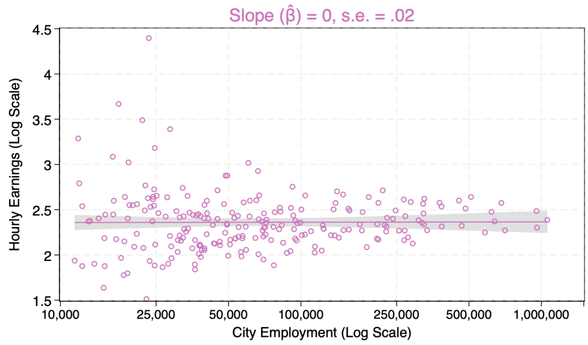
(A) Low-Income **(B)** High-Income

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

Figure 1.9: Hourly earnings and city size for female workers: raw data female workers



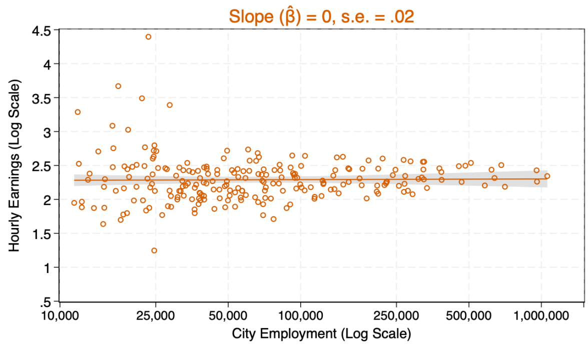
(A) Natives



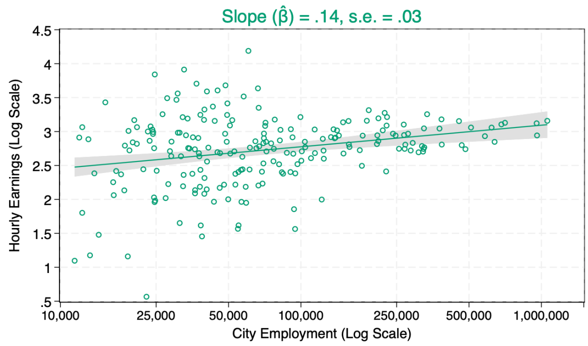
(B) Immigrants

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

Figure 1.10: 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 annual number of hours worked and used in the calculations.

Table 1.24: Regressions for Fact 1: Males

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)	Log Hourly Earnings (6)
Log City Employment	0.068	0.039	0.046	0.049	0.042	0.042
	(0.013)	(0.008)	(0.008)	(0.008)	(0.012)	(0.007)
Imm#Log City Employment	−0.049	−0.021	−0.024	−0.025	−0.014	−0.009
	(0.021)	(0.011)	(0.012)	(0.014)	(0.012)	(0.010)
Immigrants	1.050	0.655	0.785	1.633	1.076	0.709
	(0.203)	(0.119)	(0.162)	(0.216)	(0.155)	(0.142)
Constant	1.950	1.705	0.639	−0.646	1.720	1.720
	(0.155)	(0.095)	(0.102)	(0.105)	(0.096)	(0.096)
N. Obs	619,576	619,576	619,576	619,576	619,576	619,576
Adj.R2	0.04	0.26	0.36	0.35	0.47	0.47
Years of School FE	✗	✓	✓	✗	✓	✓
Linear Years of School	✗	✗	✗	✓	✗	✗
Experience FE	✗	✗	✓	✗	✓	✓
Cubic Experience	✗	✗	✗	✓	✗	✗
Occupation FE	✗	✗	✗	✗	✓	✓
Origin FE	✗	✗	✗	✗	✗	✓

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

Table 1.25: Regressions for Fact 2: Males

	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
Log Employment	0.068	0.039	0.046	0.049	0.042
	(0.013)	(0.008)	(0.008)	(0.008)	(0.007)
Low-Income#Log Employment	−0.039	−0.020	−0.024	−0.025	−0.016
	(0.018)	(0.012)	(0.012)	(0.014)	(0.011)
High-Income#Log Employment	0.059	0.052	0.063	0.067	0.048
	(0.027)	(0.020)	(0.020)	(0.022)	(0.016)
Low-Income	0.850	0.636	0.794	1.810	0.808
	(0.193)	(0.126)	(0.171)	(0.226)	(0.206)
High-Income	0.613	0.361	0.121	−0.271	0.325
	(0.310)	(0.262)	(0.266)	(0.335)	(0.229)
Constant	1.950	01.705	0.639	−0.646	1.720
	(0.155)	(0.095)	(0.102)	(0.105)	(0.096)
N. Obs	619,576	619,576	619,576	619,576	619,576
Adj.R2	0.05	0.09	0.37	0.36	0.47
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment (column 1) controlling for years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), and years of schooling, years of potential experience and occupation fixed effects (column 5). The model is fully interacted with a categorical variable that distinguishes immigrants who arrive from low-income countries v.s. immigrants who arrive from high-income countries. Results are based on a sample of male workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 1.26: Conditional regressions for Fact 1: Males

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
Log City Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.010)
Immigrants#Log City Employment	−0.026	−0.030	−0.015	−0.031	−0.026
	(0.014)	(0.024)	(0.013)	(0.015)	(0.016)
Immigrants	0.525	01.493	0.650	0.715	0.662
	(0.162)	(0.316)	(0.16)	(0.182)	(0.207)
Constant	1.777	1.840	1.500	1.852	1.950
	(0.090)	(0.17)	(0.143)	(0.144)	(0.124)
N. Obs	248,852	370,724	189,288	251,364	178,924
Adj.R2	0.14	0.08	0.19	0.23	0.17
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

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

Table 1.27: Conditional regressions for Fact 2: Males

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
Log Employment	0.031	0.073	0.054	0.058	0.058
	(0.007)	(0.014)	(0.012)	(0.012)	(0.01)
Low-Income#Log Employment	−0.023	−0.035	−0.025	−0.030	−0.019
	(0.014)	(0.025)	(0.013)	(0.016)	(0.014)
High-Income#Log Employment	0.030	0.081	0.082	0.054	0.087
	(0.026)	(0.032)	(0.045)	(0.025)	(0.037)
Low-Income	0.475	01.443	0.777	0.692	0.549
	(0.155)	(0.346)	(0.219)	(0.200)	(0.190)
High-Income	0.497	0.397	0.124	0.259	0 − .226
	(0.350)	(0.319)	(0.535)	(0.278)	(0.419)
Constant	1.777	1.840	1.500	1.852	01.95
	(0.090)	(0.170)	(0.143)	(0.144)	(0.124)
N. Obs	248,852	370,724	189,288	251,364	178,924
Adj.R2	0.14	0.09	0.19	0.24	0.18
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

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

Table 1.28: Regressions for Fact 1: Females

	Log Hourly Earnings (1)	Log Hourly Earnings (2)	Log Hourly Earnings (3)	Log Hourly Earnings (4)	Log Hourly Earnings (5)	Log Hourly Earnings (6)
Log City Employment	0.073	0.045	0.050	0.051	0.044	0.044
	(0.017)	(0.011)	(0.013)	(0.013)	(0.012)	(0.012)
Imm#Log City Employment	−0.015	−0.003	−0.004	0.000	−0.007	−0.004
	(0.018)	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
Immigrants	0.694	0.503	0.582	1.498	0.615	0.562
	(0.185)	(0.132)	(0.157)	(0.184)	(0.207)	(0.183)
Constant	1.670	1.438	0.587	−0.614	1.786	1.786
	(0.21)	(0.138)	(0.164)	(0.165)	(0.158)	(0.158)
N. Obs	519,891	519,891	519,891	519,891	519,891	519,891
Adj.R2	0.04	0.23	0.30	0.29	0.44	0.44
Years of School FE	✗	✓	✓	✗	✓	✓
Linear Years of School	✗	✗	✗	✓	✗	✗
Experience FE	✗	✗	✓	✗	✓	✓
Cubic Experience	✗	✗	✗	✓	✗	✗
Occupation FE	✗	✗	✗	✗	✓	✓
Origin FE	✗	✗	✗	✗	✗	✓

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

Table 1.29: Regressions for Fact 2: Females

	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
Log Employment	0.073	0.045	0.05	0.051	0.044
	(0.017)	(0.011)	(0.013)	(0.013)	(0.012)
Low-Income#Log Employment	−0.009	0.001	−0.001	0.003	−0.007
	(0.017)	(0.012)	(0.012)	(0.011)	(0.012)
High-Income#Log Employment	0.053	0.018	0.027	0.028	0.021
	(0.032)	(0.027)	(0.027)	(0.029)	(0.024)
Low-Income	0.584	0.452	0.543	01.468	0.337
	(0.178)	(0.13)	(0.156)	(0.182)	(0.228)
High-Income	0.371	0.487	0.344	0.534	0.476
	(0.387)	(0.321)	(0.344)	(0.503)	(0.325)
Constant	1.670	01.438	0.587	−0.614	1.786
	(0.210)	(0.138)	(0.164)	(0.165)	(0.158)
N. Obs	519,891	519,891	519,891	519,891	519,891
Adj.R2	0.04	0.14	0.30	0.30	0.44
Years of School FE	✗	✓	✓	✗	✓
Linear Years of School	✗	✗	✗	✓	✗
Experience FE	✗	✗	✓	✗	✓
Cubic Experience	✗	✗	✗	✓	✗
Occupation FE	✗	✗	✗	✗	✓

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment (column 1) controlling for years of schooling fixed effects (column 2), years of schooling fixed effects and years of potential experience fixed effects (column 3), a linear trend in years of schooling and a cubic polynomial in potential experience (column 4), and years of schooling, years of potential experience and occupation fixed effects (column 5). The model is fully interacted with a categorical variable that distinguishes immigrants who arrive from low-income countries v.s. immigrants who arrive from high-income countries. Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Table 1.30: Conditional regressions for Fact 1: Females

	No College Education	College Education	0-14 Experience	15-29 ¿ Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
Log City Employment	0.040	0.074	0.059	0.067	0.060
	(0.010)	(0.020)	(0.016)	(0.016)	(0.015)
Imm#Log City Employment	−0.020	0.025	0.003	0.003	−0.016
	(0.017)	(0.018)	(0.018)	(0.017)	(0.016)
Immigrants	0.576	0.610	0.523	0.431	0.593
	(0.217)	(0.239)	(0.283)	(0.201)	(0.210)
Constant	1.533	1.675	1.296	1.508	1.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	188,642	331,249	164,887	200,182	154,822
Adj.R2	0.10	0.04	0.17	0.19	0.16
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

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

Table 1.31: Conditional regressions for Fact 2: Females

	No College Education	College Education	0-14 Experience	15-29 Experience	30+ Experience
	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings	Log Hourly Earnings
	(1)	(2)	(3)	(4)	(5)
Log Employment	0.040	0.074	0.059	0.067	0.06
	(0.01)	(0.02)	(0.016)	(0.016)	(0.015)
Low-Income#Log Employment	−0.016	0.031	0.001	0.004	−0.009
	(0.016)	(0.018)	(0.020)	(0.016)	(0.016)
High-Income#Log Employment	0.019	0.057	0.000	0.107	−0.023
	(0.03)	(0.044)	(0.054)	(0.04)	(0.042)
Low-Income	0.515	0.445	0.53	0.409	0.491
	(0.216)	(0.235)	(0.328)	(0.199)	(0.201)
High-Income	0.542	0.537	01.022	−0.436	0.966
	(0.389)	(0.511)	(0.704)	(0.459)	(0.54)
Constant	1.533	1.675	1.296	1.508	1.668
	(0.124)	(0.239)	(0.193)	(0.202)	(0.185)
N. Obs	188,642	331,249	164,887	200,182	154,822
Adj.R2	0.10	0.04	0.18	0.19	0.16
College FE	✗	✗	✓	✓	✓
Experience FE	✓	✓	✗	✗	✗

Source: ACS, World Bank Development Database and author's calculation. Notes: This table reports the estimated coefficients from regressing the natural logarithm of hourly earnings on the natural logarithm of cities' employment controlling for a dummy for college education and three dummies for potential experience (0-14, 15-29, 30+). The model is fully interacted with a categorical variable that distinguishes immigrants who arrive from low-income countries v.s. immigrants who arrive from high-income countries. Column 1 presents the results from running this regression on the sample of workers without college education, column 2 presents the results from running this regression on the sample of workers with college education, column 3 presents the results from running this regression on the sample of workers with 0-14 years of potential experience in the labor market, column 4 presents the results from running this regression on the sample of workers with 15-29 years of potential experience in the labor market, and column 5 presents the results from running this regression on the sample of workers with at least 30 years of potential experience in the labor market. Results are based on a sample of female workers reporting to be employed. Standard errors are clustered at MSA level. Native workers are the base group. Sample weights rescaled by the annual number of hours worked and used in the calculations.

Chapter 2

Unlucky Migrants: Scarring Effect of Recessions on the Assimilation of the Foreign Born

2.1 Introduction

International migration is among the most contentious items of the political agenda everywhere. While immigrants bring values and ideas to the hosting countries, there are downsides that have contributed to a widespread anti-immigration sentiment: young migrants failing in education, adults without jobs, and the lack of assimilation into the labor market are issues that shape the natives' view of immigrants and make migration a political lightning rod (Hainmueller and Hiscox, 2010).

Understanding what determines the economic assimilation of immigrants is therefore essential for policy design. Empirical evidence suggests that the wages of immigrants approach those of natives as they accumulate more experience in the host labor market (Lubotsky, 2007), although negative labor market conditions in the host country could slow down their assimilation (Bratsberg et al., 2006; Dustmann et al., 2010). How does the business cycle affect the trajectories of immigrants' earnings? This paper answers this question by studying the short- and long-term effects of entering a host country during a recession on the career and economic assimilation of immigrant workers. Adverse initial labor market conditions have persistent effects on the earnings trajectories of college-educated workers (Kahn, 2010; Oreopoulos et al., 2012). Recession entrants have lower wages and employment than those of earlier cohorts (Rothstein, 2021), higher jobs mismatch (Liu et al., 2016), and lower probability of job promotion (Kwon and Milgrom, 2005). Do immigrants subject to adverse initial labor market conditions in the hosting country at the time of migration face worse career outcomes? If so, what causes immigrants' assimilation to slow down? And what is the overall welfare cost?

We answer these questions in the context of the U.S. labor market. The United States is home to more foreign-born residents than any other country in the world: more than 40 million people living in the U.S. were born in another country, making up almost 14 percent of the overall population (Migration Policy Institute, MPI). Moreover, the population of immigrants exposed to adverse labor market conditions is large. Over 20% of the working-age foreign population who migrated to the U.S. in the last three decades entered the labor market during a year with a recession.[1] In this paper, we leverage variation in the U.S. national unemployment rates at the time of arrival of different cohorts of foreign workers who migrated between 1990 and 2021 and use data from the American Community Survey to identify short- and long-run effects of recessions on annual earnings, hourly wages, and labor supply. Because the timing of migration could potentially be affected by aggregate economic conditions, we instrument the national unemployment rate using the deviation from its best forecast: while unexpected contemporaneous changes in the unemployment rate are unlikely to correlate with the decisions to migrate, and are uncorrelated with migrants characteristics at entry, hence with migrants' characteristics, they have a direct impact on labor market outcomes.

[1] A recession is defined following the official NBER Business Cycle Dating.

We find persistent earnings reductions from entering the labor market of a hosting country during a recession: a 1 percentage point increase in the unemployment rate reduces immigrants' annual earnings by 3.9 percent at entry and by 2.5 percent after 8 years, relative to the average native in the sample. This effect reduces to 1.4 percent after 12 years since migration and becomes statically not significant thereafter. While we find similar patterns for hourly earnings, we document no systematic response in the labor supply of immigrants, both along the extensive margin, measured by the individual probability of being unemployed, or the intensive margin, measured by the number of hours worked, conditional on being employed. These findings extend to a dynamic setting the existing cross-sectional evidence of large differences in earnings and no difference in unemployment rates between the natives and the foreign-born in the United States (Bandyopadhyay et al., 2017).

We show that slower assimilation is instead driven by changes in the occupational attainment of immigrants. We document that a 1 p.p. rise in the unemployment rate increases the likelihood of having a job in a low-skill, low-paying occupation by 2.8 percent on impact, and by 0.7 percent after 12 years since migration. Had the composition of employment across jobs not changed for cohorts of migrants entering the U.S. in periods of high unemployment, annual earnings would fall on average by less than one-fourth in the year of entry in the U.S., and the effect would be much less prolonged: assimilation in annual earnings would slow down on average by only 3 years instead of 12. These findings are in line with the evidence of occupation-specific human capital accumulations (Kambourov and Manovskii, 2009; Sullivan, 2010): if the occupation specificity of human capital were sufficiently large, workers who spent substantial time in low-skill occupations at the beginning of their careers in the hosting country could get stuck in those jobs, with low mobility thereafter (Gibbons and Waldman, 2006).

The effects we document have meaningful implications for welfare: using a back-of-the-envelope calculation, we find that unlucky migrants bear an overall cost from entering the U.S. labor market during periods of high unemployment of between 1.6 and 2.4 percent of lifetime earnings, two-thirds of which can be explained by occupational attainment tilted towards low-skill jobs.

Our paper contributes to the literature on the economic assimilation of foreign-born workers. Pioneered by Chiswick (1978), a large literature has focused on understanding whether immigrants accumulate human capital in the host country and whether their earnings converge to those of native workers (Borjas, 1984, 2000; Lee et al., 2022; Albert et al., 2021). Lubotsky (2007) documents that the immigrant-native earnings gap closes by 10–15 percent during immigrants' first 20 years in the United States. Borjas (2015) argues that the observed convergence could be largely affected by changes in the skill composition of different arrival cohorts in the U.S. and suggests a negative long-run trend in the quality of U.S. immigrants. Peri and Rutledge (2020) revisit these findings and document that, while the composition of low-skill immigrants has changed much, the initial gap and speed of convergence have not worsened with recent cohorts of arrival. We depart from the standard literature on assimilation and innovate by focusing on the effect of aggregate economic conditions at the time of migration on immigrant careers.

We are not the first to study the cyclicality of immigrants' assimilation. Åslund and Rooth (2007) use Swedish data for two selected cohorts of immigrants to analyze how local labor market conditions at entry affect their employment and earnings in the subsequent years. Azlor et al. (2020) investigates the effect of labor demand in the initial location of migration on employment prospects. Both papers achieved identification by focusing on refugees and governmental refugee settlement policies. The closest paper to ours is Barsbai et al. (2022). They document comparable effects of recession on the assimilation of family-sponsored migrants in the U.S. as we do in our analysis. However, because of their sample restriction and identification strategy, they can only focus on a limited set of countries, i.e. those for which family migration is the dominant mode of migration to the U.S., de facto excluding the majority of middle and high-income countries.

This paper innovates upon the existing literature with a twofold contribution. First, we provide a new identification strategy that exploits variation in unemployment forecast error across cohorts of migrants. This allows us to expand the sample of migrants in the analysis, and to characterize the heterogeneous effects across genders, education, and different countries of origin. Second, expanding the sample of immigrants reveals a *gender*, *skill* and *development gradient* in the scarring effect of migrating in recessions: males without a college education from low-income countries are the only ones who suffer the largest scarring effects. Relative to the average native, we document no differential scarring effect for women (regardless of their education level), college-educated males, and migrants from high-income countries. This result confirms the evidence that less advantaged groups in the labor market, such as low-educated workers or minorities, experience a much larger drop in reductions in earnings during recessions (Hoynes et al., 2012).

More generally, this paper speaks to the literature on the persistent effects of initial labor market conditions on workers' careers — see von Wachter (2020) for a detailed review. Oreopoulos et al. (2012) show that Canadian young male workers who graduated during recessions suffer a significant wage loss for the first 10 years of their careers. They find that graduates with the lowest predicted earnings based on college and major are the ones suffering the most. Schwandt and Von Wachter (2019) find similar effects on a sample of US graduates. They show that minorities, and in particular non-whites and high school dropouts, bear the largest cost. Rothstein (2021) shows that workers who graduated during the Great Recession have lower employment probabilities than earlier cohorts. Schwandt and Von Wachter (2020) document that entering the labor market in a recession has also a dynamic effect on mortality, family outcomes, and various measures of economic success throughout the life-cycle until middle age. Our study extends this literature by characterizing the trajectories of earnings, hours workers, probability of unemployment, and occupation attainment of immigrants as a function of the initial aggregate labor market conditions in the hosting country, and shows that recessions have long-lasting effects on their economic assimilation.

This paper has the following structure. In Section 2.2 we introduce our main econometric framework and discuss the threats to the identification of immigrants' returns to experience in the U.S.. We describe the data source and sample selection and test the exclusion restriction in Section 2.3. In Section 2.4 we show how large and persistent the effect of recessions at the time of migration is on immigrants' assimilation, and discuss the sensitivity of our findings to alternative assumptions, and across different sub-samples. In Section 2.5 we analyze the role of occupational attainment as a plausible mechanism behind our results and conduct several counterfactual exercises. In Section 2.7 we assess the welfare implications of our findings. We conclude in Section 2.8.

2.2 Econometric framework

We start by presenting a parsimonious econometric model suitable for studying the effect of aggregate labor market conditions on the careers of immigrants in a hosting country. Let m denote immigrants and n denote U.S. natives. Let c be an index to denote the year of entry for immigrants in the United States. Then for every cohort of entry in the U.S, c, we estimate the following regression for immigrants:

$$y_{ict}^{m} = \alpha + \sum_{x \in \mathcal{X}} \theta_{cx} D_{ict}^{x} + \gamma \text{educ}_{ict} + f(\text{exp}_{ict}) + \delta_t + \varepsilon_{ict} \tag{2.1}$$

and the following regression for natives:

$$y_{it}^{n} = \alpha + \gamma \text{educ}_{it} + f(\text{exp}_{it}) + \delta_t + v_{it} \tag{2.2}$$

where y^j_{it}, $\forall j \in \{m, n\}$, is a selected outcome for an individual i, observed at time t (and belonging to a cohort c for the case of immigrants); D_{ict} is an indicator that takes a value 1 if an immigrant i belonging to cohort c has $x \in \{0, 1, 2, 3, 4, ...\}$ years of experience in the U.S. at time t; educ_{it} and exp_{it} are workers' years of schooling and experience; δ_t is a time fixed effect, which controls for changes in aggregate economic conditions; and ε_{it} and v_{it} are uncorrelated disturbances. We estimate equations (2.1) and (2.2) separately for each arrival cohort of immigrants, using native workers as the base group. Comparing natives to migrants belonging to cohort c after x years since their arrival in the U.S., we obtain that the expected gap in outcome y is equal to

$$\mathbf{E}[y^m_{ict} - y^n_{it}|x] = \theta_{cx}, \tag{2.3}$$

which measures the "excess" value of acquiring a year of experience in the United States. As common in this literature, the identification of θ_{cx} relies on the assumption that immigrants and natives face the same time trend in their outcome y (see Borjas (2018) and Borjas (2015) among the others). To estimate equations (2.1) and (2.2), we impose i) time-trend, ii) the returns to schooling, and iii) the returns to the overall experience to be the same between immigrants and natives. While assumption i) is needed to identify the aging effect conditional on cohorts,[2] assumptions ii) and iii) allow us to obtain closed form solution for the expected gap in equation (2.3).[3] Therefore we use the OLS estimates of θ_{cx} from equation (2.1), $\hat{\theta}_{cx}$, as a dependent variable in a second specification:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \text{u}^0_c + \epsilon_{cx} \tag{2.4}$$

where μ_c are cohort of entry fixed effects, μ_x are years since migration into the U.S. fixed effects, and u^0_c is the U.S. unemployment rate in the year of the arrival of each

[2] From the identity Year = Year of Arrival + Years in the U.S. it follows that these three variables are collinear. The assumption of a common time trend breaks the collinearity. See Borjas (2015) for a discussion

[3] We relax assumptions ii) and iii) as a robustness check in section 2.4.4

cohort c. Given the included fixed effects, the coefficients ω_x capture deviations from the typical assimilation profiles related to cohort-specific variation in the unemployment rate at the time of U.S. labor market entry. If ω_x were negative, a 1 p.p. higher unemployment rate in the year of entry, u_c^0, would be associated with a $\omega_x \times 100$ % larger gap between natives and immigrants after x years since migration. Since u_c^0 only varies across cohorts, we can identify ω_x, $\forall x \in \mathcal{X}$ but one. Hence we impose $\omega_{\bar{x}} = 0$, i.e. the effect of the unemployment rate in the year of entry on the gap with natives in the outcome of interest will vanish after $\bar{x}$ years since migration.

Despite its generality, specification (2.4) does not account for cohort-specific variation driven by endogenous migration timing which might bias our estimates.

2.2.1 Threats to identification

A major threat to identification is the potential endogeneity of the time of entry in the U.S. People might postpone their decision to migrate to avoid unfavorable conditions at entry or anticipate it in order to benefit from good labor market conditions. If there were selection into timing, the bias could go either way. For example, if those with lower potential earnings were more likely to migrate to the U.S. during periods of high unemployment, then we would tend to overstate the effects of initial labor market conditions on earnings assimilation.

We address this concern using two identification strategies. As a first strategy, we replace the unemployment rate at the time of migration with its deviation from its best forecast. The rationale behind this instrument is that if migration were a forward-looking decision taken before the realization of the actual unemployment rate, it would be based on the *expected* unemployment rate. Hence it would be orthogonal to any unexpected deviation of unemployment to its best forecast.

To construct our best forecast of the aggregate unemployment rate we use a highdimensional factor model (Stock and Watson, 1998).[4] Let $\hat{u}_t$ be the forecast value of the unemployment rate at time t. Then we define $\tilde{u}_t = u_t - \hat{u}_t$ as our measure of forecast error. Based on the discussion above, this measure is likely to be uncorrelated with migration decisions. Therefore we re-estimate equation (2.4) using $\tilde{u}_t$ in the year of entry for each cohort c, $\tilde{u}_c^0$, interacted with dummies for every year since migration:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \tilde{u}_c^0 + \varepsilon_{cx} \tag{2.5}$$

and achieve identification by imposing again $\omega_{\bar{x}} = 0$.

Our second identification strategy builds upon the first and exploits variation in unemployment forecast errors across U.S. states to construct a Bartik-like instrumental variable. In this case, we construct our best forecast for the unemployment rate in each state by estimating the following regression:

$$u_{st} = \alpha + \beta \hat{u}_t + u_{st-1} + \gamma_s + v_{st}$$

where u_{st} is the unemployment rate in state $s = 1, ..., S$ at time t, $\hat{u}_t$ is the forecast of the aggregate unemployment rate obtained using the factor model, γ_s are state fixed effects, and v_{st} is a residual. Let $\hat{u}_{st}$ be the predicted unemployment. We define $\bar{u}_{st} = u_{st} - \hat{u}_{st}$ as our state-specific forecast errors and aggregate them at a national level using the share of employed immigrants observed in state s out of total employed population during 1980, π_{s1980},[5] i.e.

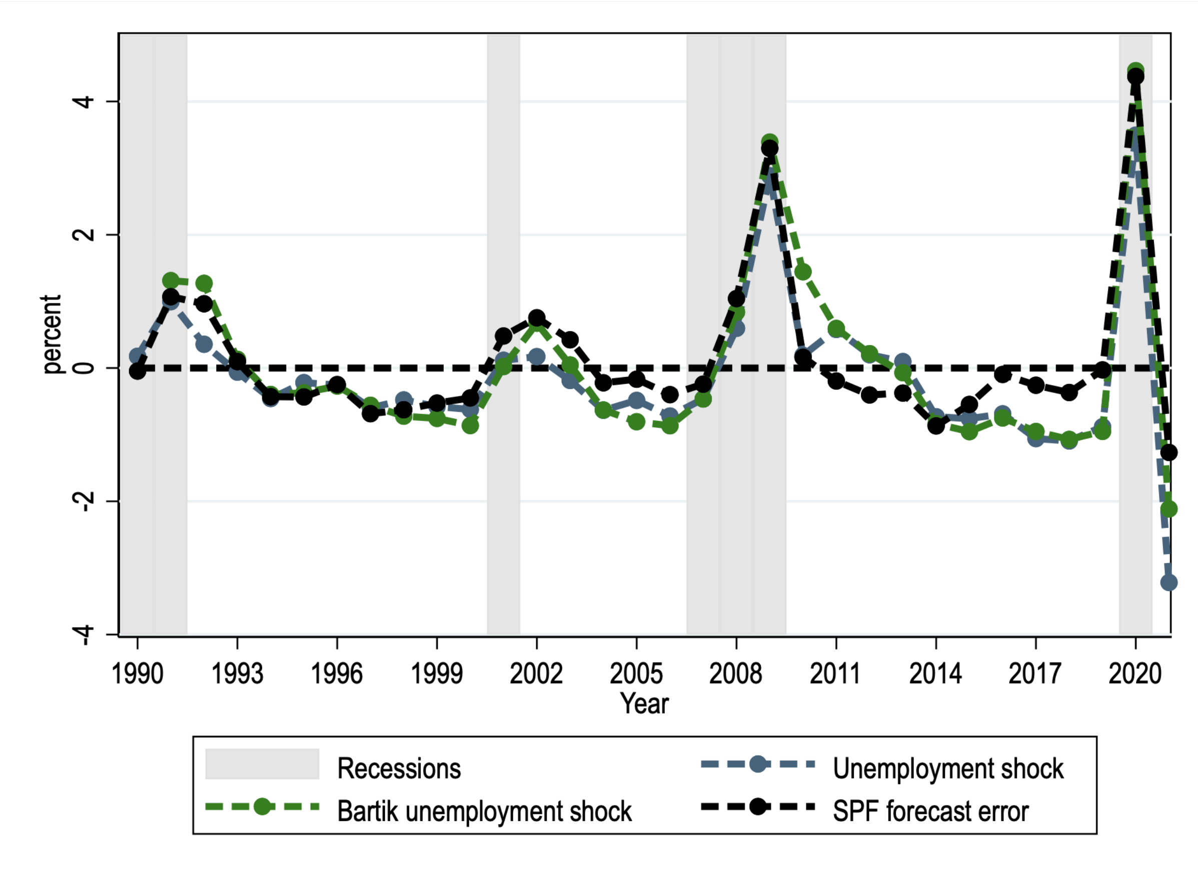
$$\bar{u}_t = \sum_{s=1}^{S} \bar{u}_{st} \pi_{s1980}$$

Finally, we re-estimate equation (2.4) using $\bar{u}_t$ in the year of entry for each cohort c, $\bar{u}_c^0$,

[4] We report details in Appendix 2.9.3.

[5] Using past employment shares of migrants, rather than the current ones, alleviates concerns related to the ability of immigrants to choose the state of arrival depending on local labor market conditions (Card, 2001).

Figure 2.1: Unemployment rate shocks



Source: FRED and the Survey of Professional Forecasters. Shaded areas refer to years of recessions according to the NBER Business Cycle Dating.

interacted with dummies for every year since migration:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \tilde{u}_c^0 + \varepsilon_{cx} \tag{2.6}$$

and achieve identification by imposing again $\omega_{\bar{x}} = 0$.

Figure 2.1 reports both types of forecast errors $\tilde{u}_c^0$ and $\bar{u}_c^0$, expressed in percentage points (blue and green line, respectively). For comparison, we report a measure of forecast errors computed using unemployment expectations from the Survey of Professional Forecasters (black line). Our forecast models generate errors that are comparable to the average of those made by professionals in the U.S.

Endogenous migration or timing in response to a recession is not contained in the unexpected shocks to the national unemployment rate since the latter is constructed as a deviation between the realized and the forecasted unemployment rate. As in Schwandt and Von Wachter (2019), our approach is to compare the results of our main specification in equation (2.4) based on the observed unemployment rate to the results from the models in equation (2.6) and (**??**) based on unemployment forecast errors. If the results were similar, this would suggest that the timing of migration might not be a problem in the sample. Differences between OLS and IV estimates would instead inform us about the nature of selection into migration.[6]

2.3 Data

The main data source for our analysis is the Integrated Public Use Microdata Series (IPUMS), a database that contains samples from surveys of the American population. From IPUMS, we select a 1% sample for every year between 2006 to 2021 from the American Community Survey (ACS). Using the ACS brings the following advantages: First, it allows us to work with a large sample of immigrant workers with a large degree of heterogeneity in observable characteristics; Second, it covers a long period, allowing us to analyze short and long-run effects of entering the labor market in years of high unemployment rates; And finally, it includes cohorts of immigrants who arrived in the U.S. at least in the last three decades, a period when the U.S .experienced four important economic recessions.

More in detail, the ACS provides all sampled individuals' country of birth and citizenship status. We use this information and define an immigrant as a foreign-born worker who is either a naturalized citizen or does not have citizen status. Foreign-born workers report the year of arrival in the U.S., which we use to compute how many years they spent in the U.S. since migration. Individuals in the ACS also report other demographic characteristics, such as their educational attainment, age, and gender.

[6] An alternative approach would be to use the unemployment forecast errors as an instrument for the actual endogenous unemployment rate a cohort faces at the year of migration in equation (2.4). Results for this strategy are similar and available upon request.

Table 2.1: Natives vs immigrants

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natives	47270.4	21.0	2208.9	13.7	19.9	-	5560376
	(62320.1)	(36.5)	(558.5)	(2.4)	(11.3)	-	-
Immigrants	42501.8	19.9	2137.3	12.8	21.0	66.5	608052
	(62358.1)	(34.8)	(520.4)	(4.1)	(9.2)	-	-

Source: ACS and authors' calculation. Notes: This table reports selected labor market outcomes for male immigrants and male natives in the sample. Average yearly earnings and average hourly earnings are measured in US dollars and deflated by the CPI99 index. Average hours worked measures the average hours worked in a year by a worker. English proficiency measures the proportion of immigrant workers that are proficient in English (i.e., they reported either speaking only English, speaking English very well, or speaking English well).

We input workers' years of schooling using the reported educational attainment and calculate their potential experience in the labor market as (age-years of schooling-6). Finally, we observe workers' employment status and their occupations and combine information on annual earnings, the number of weeks worked, and hours worked in a week to compute hourly earnings. We express both annual and hourly earnings in real terms deflated to 1999 US Dollars.

2.3.1 Sample selection

The baseline sample for our analysis consists of male workers aged 18-64 who have between 0 and 40 years of potential experience in the labor market and are employed in the private sector. We keep native workers and first-generation immigrants, i.e., immigrants who arrived in the U.S. after 18 years old. We restrict our sample to individuals in the labor force and not enrolled in school. We exclude individuals who live in group quarters, are self-employed, and work in the armed forces or military occupations. We label employed workers as those who worked at least one week in the previous year, reported positive hourly earnings, and do not report a value of usual hours worked that is top-coded. Those who do not satisfy these criteria are labeled as unemployed. Finally, we focus on the subsample of immigrants who arrived from 1990 onward, and, to balance the sample, we restrict our attention only to those with at most 16 years since their migration.

2.3.2 Descriptives

Table 2.1 reports some descriptive statistics for the population of natives and immigrants in our sample. Immigrants represent about 10% of the total workers' population. On average, they are less educated but have more years of potential experience in the labor market. Compared to natives, they earn about 5000 USD less in a year, reflecting lower hourly earnings on average (one dollar per hour less) and a lower number of hours worked (about 100 in a year). These differences hold whether we look at only females, non-college or college-educated workers, or immigrants from high or low-GDP per capita countries (see Tables 2.13 to 2.16 in Appendix 2.9.4).

2.3.3 Exclusion restriction

Our identification strategy builds on the assumption that migration decisions must not depend on aggregate labor market conditions. A violation of this assumption might imply a correlation between immigrants' characteristics and the unemployment rate observed in the U.S. at the time of migrating, leading to biased estimates. We claim that, while migrants' characteristics might be correlated to the aggregate unemployment rate, the unemployment forecast errors cannot predict the composition of migrant inflows to the U.S., hence satisfying the exclusion restrictions.

To test this claim we regress separately several migrants' characteristics observed at the time of entering the U.S. on 1) the aggregate unemployment rate, 2) the aggregate unemployment forecast error, and. Table 2.2 reports the OLS estimates.

The results confirm our claims. Immigrants who arrive during high unemployment are self-selected based on experience, years of schooling, and English proficiency: these migrants are relatively younger, better-educated (as they have more years of schooling), and have a higher level of English proficiency, compared to those who ar-

Table 2.2: Initial unemployment rate and male immigrants characteristics

	Potential Experience$_{ic0}$ (1)	Years of Scholing$_{ic0}$ (2)	English Proficiency$_{ic0}$ (3)
Unemployment rate at entry, u_c^0	-0.142***	0.066***	0.006***
	(0.035)	(0.015)	(0.002)
Aggregate unemployment forecast error at entry, $\tilde{u}_c^0$	-0.100	-0.001	0.001
	(0.054)	(0.024)	(0.003)
Bartik-like unemployment forecast error at entry, $\bar{u}_c^0$	-0.038	0.020	0.004
	(0.046)	(0.021)	(0.0025)
Number of observations	38,873	38,873	38,873

Source: ACS and authors' calculations. Notes: This table reports the OLS estimate from regressing the migrant characteristics observed at the time of migrating to the US on the unemployment rate, u_c^0, and the unemployment rate forecast errors, $\tilde{u}_c^0$ and $\bar{u}_c^0$, at the time of migrating to the US for a sample of men. The explanatory variables are years of potential experience in the labor market, years of completed schooling, and a dummy variable for English proficiency. Standard errors in parenthesis are robust. *p<0.10, **p<0.05, ***p<0.01

rive when unemployment is lower (first row of Table 2.2).[7] As a result of the observed self-selection into migration, and to the extent that better-educated immigrants can assimilate faster, we can expect the estimates of the scarring effect obtained using the aggregate unemployment rate to be downward biased.

Self-selection vanishes when we correlate immigrants' characteristics to the unemployment forecast errors (second and this rows of Table 2.2). The estimated coefficients are all small in magnitude and are not statistically significant. Both forecast errors allow us to fully randomize immigrants across observable characteristics upon their arrival in the US. The unemployment deviation from its best forecast is unpredicted by construction. By assigning immigrants to periods of expansion and contraction based on this measure, we alleviate concerns about self-selection and expect the estimates of the scarring effect to be larger in magnitude.

[7]Skill scarcity in the country of destination is a key determinant of migration decision. See, for instance, Fenoll and Kuehn (2019).

2.4 Initial Conditions and Immigrants' Assimilation

We are now ready to discuss the effect of recessions on immigrants' economic assimilation. Figure 2.2 reports the effects of the unemployment rate at entry in the U.S. on two measures of earnings, such as annual earnings (panel A) and hourly earnings (panel B). Figure 2.3 reports the effects of the unemployment rate at entry in the U.S. on two measures of labor supply, such as annual hours worked (panel A) and the probability of being unemployed (panel B). Each dot corresponds to the coefficients ω_x, i.e. the interaction of dummies for experience in the U.S. with the unemployment rate obtained from estimating either equation (2.4), or equation (2.6), or equation (**??**). The red line refers to the OLS estimates, the blue line refers to the IV estimates, and the green line refers to the Bartik-IV estimates. Tables 2.3 and 2.4 report the OLS and IV point estimates for 5 groups of experience in the U.S. (0, 1-4, 5-8, 9-12, and 13-16 years since migration), along with 90% bootstrapped confidence intervals constructed using 1000 clustered Rademacher draws.[8]

2.4.1 Annual Earnings

Immigrants' annual earnings are lower than the average U.S. native the higher the unemployment rate at the time of their entry into the U.S. The effect is large and significant: the OLS estimates from Table 2.3, column (1) imply that entering the U.S. with a 1 p.p. higher unemployment rate makes annual earnings drop by about 2.5% on impact relative to the average U.S. native. This effect is also persistent and only slowly declines with time spent in the U.S. The drop in earnings is still significantly large 8 years after entering the U.S. — it is about 1.62% for a 1 p.p. rise in the initial unemployment rate. While it vanishes to zero only after 12 years, as shown by the red line in panel A of Figure 2.4.

[8]Our inference is based on confidence intervals calculated using the wild bootstrap (1000 repetitions) procedure by Cameron et al. (2008), clustered by arrival cohort and number of years in the U.S.

Figure 2.2: Unemployment at entry and earnings assimilation of immigrants

(A) Annual earnings **(B)** Hourly earnings

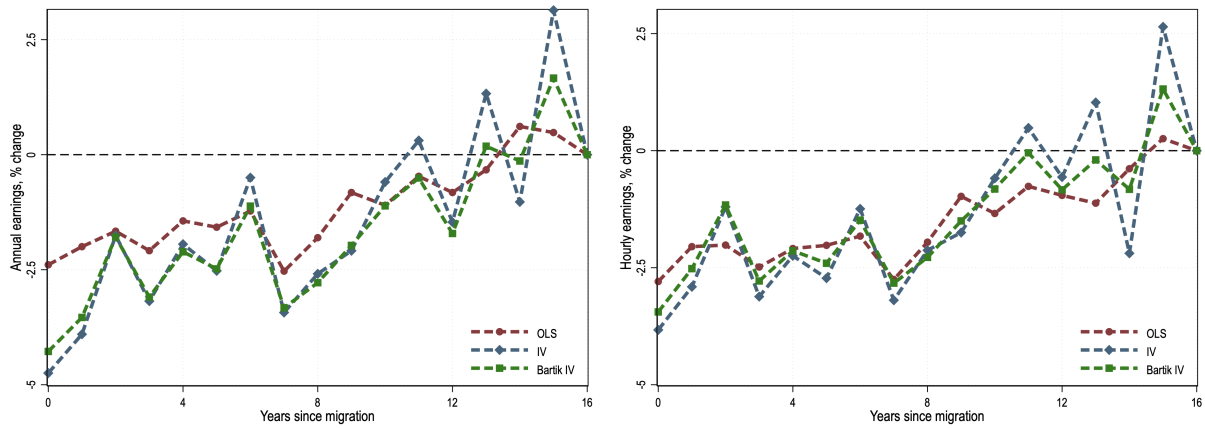
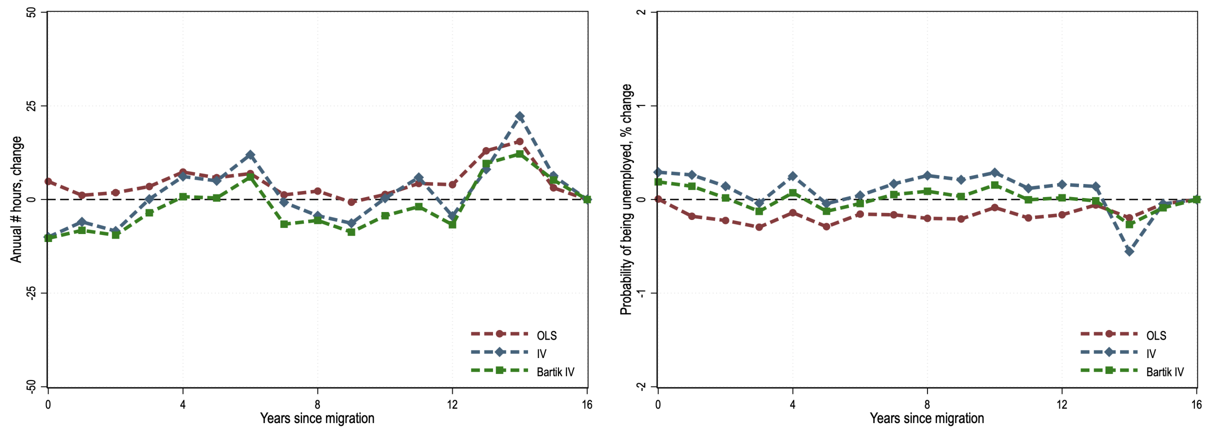


Figure 2.3: Unemployment at entry and labor supply assimilation of immigrants

(A) Annual # hours **(B)** Probability of being unemployed



Source: ACS, FRED and authors' calculation. Notes: The figures show the percent coefficients from regressing selected estimated gaps between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Panels A, B, and C are based on a sample of male workers who report to be currently employed. Panel A shows the percent change in the estimated annual earnings gap. Panel B shows the percent change in the estimated hourly earnings gap. Panel C shows the percent change in the estimated gaps in the annual number of hours worked. Panel D is based on a full sample of male workers, and it shows the percent change in the estimated gap in the probability of being unemployed. In each panel, the red lines refer to the estimates from equation (2.4). The blue lines refer to the estimates from equation (2.6). The green lines refer to the estimates from equation (**??**).

To place our results in perspective, notice that Oreopoulos et al. (2012) finds that college graduates suffer an earnings loss of approximately 1.8% on impact and of about 0.4% after 10 years for a 1 p.p. rise in the unemployment rate at the time of graduation. Alternatively, to express our results in terms of observed recessions, with an increase in the unemployment rate of 4 p.p. — roughly the same increase observed in the sample from years of economic boom to years of economic burst, annual earnings of immigrants decrease by 10% on impact and are 6.48% lower after 8 years since migration.

Both IV estimates suggest a very similar picture as the OLS estimates do. While the former appears to be a bit noisier than the latter, particularly in later years, the estimated effects are aligned across specifications. As expected, their magnitude is larger, given the nature of self-selection. Using the point estimates from columns (2) and (3) in Table 2.3, a 1 p.p. higher unemployment rate at entry implies a drop in annual earnings between 3.8% and 4.9% on impact compared to the average native worker. The magnitude is almost twice as large as that obtained using the OLS specification. The effect reduces with time spent in the US although, after 8 years since migration, a 1 p.p. higher unemployment rate is still associated with an immigrant-native gap in annual earnings of between 2.5% and 3%.

The difference between the OLS and the IV estimates confirms the existence of a positive correlation between national-level unemployment rates in the year of migration and the ability of immigrants to assimilate faster. The IV estimates are larger in magnitude, especially in the first years following entry. This confirms that immigrants with higher potential earnings might are more likely to migrate to the U.S. during periods of high unemployment. This makes the OLS estimates downward biased, and interpretable as a lower bound for the true effect.

2.4.2 Other outcomes

The ACS data allow us to decompose the effect on the assimilation in annual earnings into three margins, i.e. the effect stemming from a change in labor supply along the extensive (increase in the probability of being unemployed), the effect along the intensive margin (reduction in the number of annual hours worked), and the effect coming from a reduction in hourly wages.

Table 2.3: Effects of unemployment at entry on earnings of immigrants

	Annual Earnings			Hourly Earnings		
Years Since	OLS	IV	Bartik-IV	OLS	IV	Bartik-IV
Migration	(1)	(2)	(3)	(4)	(5)	(6)
0	-0.024	-0.049	-0.039	-0.023	-0.040	-0.031
	(-0.038,-0.010)	(-0.075,-0.021)	(-0.059,-0.018)	(-0.034,-0.011)	(-0.052,-0.018)	(-0.049,-0.016)
1-4	-0.018	-0.038	-0.030	-0.016	-0.028	-0.021
	(-0.028,-0.007)	(-0.058,-0.016)	(-0.045,-0.014)	(-0.027,-0.005)	(-0.051,-0.007)	(-0.037,-0.006)
5-8	-0.016	-0.030	-0.025	-0.015	-0.026	-0.021
	(-0.027,-0.006)	(-0.048,-0.009)	(-0.038,-0.012)	(-0.026,-0.004)	(-0.049,-0.005)	(-0.038,-0.006)
9-12	-0.007	-0.016	-0.014	-0.005	-0.009	-0.007
	(-0.017,0.002)	(-0.034,0.004)	(-0.027,-0.000)	(-0.015,0.006)	(-0.031,0.013)	(-0.022,0.008)
N.Obs.	272	271	272	272	272	271
R-sq.	0.807	0.809	0.808	0.839	0.837	0.838

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing estimated annual and hourly earnings gap between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers reporting to be employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.4: Effects of unemployment at entry on labor supply of immigrants

	Annual # Hours			Probability of Unemployment		
Years Since	OLS	IV	Bartik-IV	OLS	IV	Bartik-IV
Migration	(1)	(2)	(3)	(4)	(5)	(6)
0	-2.636	-15.21	-13.13	0.001	0.003	0.002
	(-13.07,7.553)	(-35.64,4.410)	(-27.89,2.074)	(-0.001,0.002)	(-0.000,0.006)	(-0.000,0.004)
1-4	-4.370	-13.79	-13.15	-0.001	0.002	0.001
	(-13.01,3.689)	(-30.86,2.336)	(-24.54,-1.293)	(-0.003,0.000)	(-0.001,0.005)	(-0.001,0.003)
5-8	-2.836	-6.390	-7.768	-0.001	0.002	0.001
	(-9.861,3.903)	(-21.58, 8.653)	(-18.03,2.222)	(-0.003,0.000)	(-0.001,0.004)	(-0.001,0.002)
9-12	-5.015	-10.17	-11.37	-0.001	0.002	0.001
	(-11.87,1.447)	(-25.66,4.923)	(-21.97, -1.561)	(-0.002,0.001)	(-0.000,0.005)	(-0.001,0.003)
N.Obs.	272	272	271	272	272	271
R-sq.	0.586	0.589	0.589	0.640	0.623	0.623

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in the annual number of hours worked and in the probability of being unemployed between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results in columns (1) to (3) are based on a sample of male workers reporting to be employed. Results in columns (4) and (6) are based on a full sample of male workers. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

First, unlucky cohorts of migrants experience slower assimilation in hourly earnings: on impact, the reduction in hourly earnings is large and significant, i.e. about 2.3 p.p. relative to the average U.S. native (column (4) of Table 2.3). This effect is also long-lasting: after 8 years in the U.S. labor market, the gap with the average U.S. native is still large and amounts to 1.5 p.p., and it is fully re-absorbed only by the end of the years of analysis. Notice that these estimates are based on a selected group of immigrants, i.e. those who found jobs: to the extent that these workers are positively selected — based on their education or skills — the effect we find may understate the true reduction in earnings assimilation for unlucky migrants.

On the other hand, we find no significant effect on the assimilation in labor supply of migrants: neither the probability of being unemployed nor the annual number of hours worked of immigrants respond to changes in unemployment rates at the time of entry into the U.S. labor market beyond the effect experienced by the average U.S. native, see Columns (1) and (4) of Tables 2.3. These findings are also confirmed by the IV estimates in Columns (2), (3), (5), and (6) which are negligible in magnitude and not significant at 10 percent level. These results match with those of Kahn (2010), who found a small initial effect on hours, employment, and weeks worked for male college graduates in the United States after the 1982 recession, and with those in Barsbai et al. (2022), who find very limited scarring effect of local unemployment rate on the likelihood of being employment in the future for a sample of family-sponsored migrants in the U.S.

2.4.3 State dependency: recessions vs expansions

Time variation in the national unemployment rate at the time of migration encompasses changes in unemployment rates realized during periods of economic recessions as well as economic expansions. Slower earnings assimilation for cohorts of foreign workers migrating into the U.S. when unemployment is high could be driven by either source of variations.

To disentangle these two effects we expand equation (2.4) as follows:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \mathrm{u}_c^0 + \sum_{x \in \mathcal{X}} \psi_x D^x \times \mathrm{u}_c^0 \times \iota_c^0 + \epsilon_{cx} \tag{2.7}$$

where we introduced a triple interaction between a dummy for the number of years x spent in the U.S., D^x, the unemployment rate faced by cohort c in the year of migration, u_c^0, and ι_c^0, which is an indicator function taking a value 1 if the year of entry in the U.S. was subject to a recession, 0 otherwise. We define a recession following the official NBER Business Cycle Dating. The parameter ψ_x in equation (2.7) captures state-dependency in the response of immigrant labor market outcomes to a change in the aggregate unemployment rate, and it is identified by changes in the aggregate initial unemployment rate for cohorts who experienced a recession at entry x years before they were observed.

Table 2.5 reports the OLS estimates of equation (2.7) for annual and hourly earnings. The estimates suggest a state-dependent response to aggregate unemployment shocks. Facing a recession in the year of entry into the U.S. labor market amplifies the negative effect on the earnings trajectories of immigrants. On impact, a 1 p.p. higher unemployment rate at that time of migration reduces annual earnings by 3.8% if migration happened during a year of recession (column 2) compared to a reduction of 2.2% otherwise (column 1). The same effect persists after 12 years since migration, causing a reduction in earnings of 1.4%, whereas it vanishes after 8 years for immigrants migrating in periods of expansion. The difference between responses is significant at a 5 percent significance level for every horizon up to 8 years since migration, as proved by the p-values (column 3). Finally, while the response of hourly earnings, which are reported in columns (4) and (5), mirrors the one of annual earnings, we find no state-dependent effects on the number of hours worked and the probability of being unemployed.[9]

2.4.4 Sensitivity

Our results are robust to a large array of sensitivity checks, all of which are discussed below. We present the results from all the robustness in Appendix 2.9.7.

[9]See Table 2.21 in Appendix 2.9.6.

Table 2.5: Non-linear effects of unemployment at entry on earnings of immigrants

	Annual Earnings			Hourly Earnings		
Years Since Migration	Expansion (1)	Recession (2)	p-value (3)	Expansion (4)	Recession (5)	p-value (6)
0	-0.022	-0.038	0.002	-0.023	-0.035	0.001
	(-0.033,-0.009)	(-0.051,-0.024)		(-0.034,-0.013)	(-0.045,-0.024)	
1-4	-0.019	-0.027	0.020	-0.018	-0.025	0.015
	(-0.029,-0.008)	(-0.038,-0.016)		(-0.028,-0.008)	(-0.036,-0.015)	
5-8	-0.017	-0.023	0.049	-0.017	-0.024	0.019
	(-0.027,-0.007)	(-0.033,-0.013)		(-0.027,-0.007)	(-0.034,-0.014)	
9-12	-0.009	-0.014	0.112	-0.007	-0.013	0.083
	(-0.018,0.003)	(-0.024,-0.004)		(-0.017,0.002)	(-0.022,-0.003)	
N.Obs.	272			272		
R-sq.	0.817			0.846		

Source: ACS, FRED and authors' calculation. Notes: This table reports the OLS coefficients from regressing the estimated annual and hourly earnings gap between immigrants and natives on the unemployment rate in the year of entering the U.S., interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), and with a dummy for years of recessions, controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers reporting to be employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws. The p-values refer to a F-test of equality between the estimates of expansion and recession.

2.4.4.1 Alternative model specifications

In Tables 2.22 to 2.25 we evaluate the robustness of our results to the choice of different functional forms for potential experience, years of schooling, and time trend. First, we estimate equations (2.1) and (2.2) replacing dummies for potential experience with a third-order polynomial, controlling for years of schooling and time-fixed effects. In the second alternative, we control for a cubic polynomial in potential experience and time-fixed effects, while we impose linearity in the returns to schooling. In the last alternative, we replace time dummies with a linear time trend while controlling for schooling and experience using a linear and a cubic polynomial, respectively. Our estimates are robust to each of these alternative specifications.

2.4.4.2 Heterogeneous returns to education and experience

Our baseline estimates are obtained under the assumption that the returns to education and overall labor market experience are the same between immigrants and natives. A large literature has shown that i) education quality and ii) experience profiles vary among countries (see Schoellman (2012) and Lagakos et al. (2018a), respectively). Failing to control for cross-country heterogeneity in these dimensions could bias our estimates. In Table 2.26 we relax these assumptions and allow for heterogeneous returns in schooling and labor market experience. The results of this exercise are in line with our baseline estimates.

2.4.4.3 Immigrants without US college attainment

Our dataset does not contain information that helps us to distinguish whether immigrants obtained their education in the U.S. or in another country. If a college degree from a U.S. institution allowed immigrants to assimilate faster relative to natives, and more immigrants enrolled in college during recessions, our baseline estimates could be downward biased. To deal with this issue, we re-estimate our model using only the sample of immigrants who arrived in the U.S. when they were at least 25 years old, excluding de facto those immigrants who obtained their degree in the U.S. Table 2.28 reports the results from this exercise. The estimates are not statistically different from those obtained using the full sample of immigrants. For a 1 p.p. increase in the unemployment rate at entry, the annual earnings of immigrants without a U.S. college degree decreases by 2.2% relative to the average U.S. native. This effect is also as persistent as observed using the full sample: after 8 years spent in the U.S. earnings are still 1.6% lower. Similarly to the baseline estimation, the number of hours worked and the probability of being unemployed for immigrants do not react to changes in unemployment rates at the time of their migration.

2.4.4.4 Prime age workers

Our baseline sample includes workers between 18 and 64 years old. We assess the robustness of the results to our sample selection and re-estimate the model using immigrants and native workers who are in their prime age, i.e. between 25 and 54 years old.

The results from this exercise are shown in Table 2.27. The effect of unemployment at entry on annual and hourly earnings is larger in magnitude and more persistent compared to the baseline estimate, while there is no significant change in either the probability of unemployment or the number of hours worked.

2.4.4.5 Selective outmigration

Selective outmigration of immigrants is a source of bias in the estimation of the assimilation profiles using cross-sectional data (Lubotsky, 2007; Akee and Jones, 2019). We address this concern with a two-fold strategy.

In the first approach, we follow Borjas and Bratsberg (1996) and re-weight immigrants' observations by 1 minus a measure of country-specific outmigration rates. We group immigrants into 6 categories depending on the country of origin, meaning Mexico, Other Latin America, Western Countries, Asia, and the Rest of the World. Borjas and Bratsberg (1996) provides the following country-specific outmigration rates at 10 years: 33% for Mexico, 22.7% for Other Latin America, 22.7% for Western Countries, 6.1% for Asia, and 11.5% for Rest of the World. We convert the decennial rates, r_{10} into annual ones, r_1 as $r_1 = (1 + r_{10}/100)^{1/10} - 1$ and compound them for every year since migration x, to obtain $r_x = (1 + r_1/100)^x - 1, \forall x$.

In the second approach, we re-weight immigrants' observations by 1 minus the probability that they are not in the ACS sample a year after they were initially observed, compounded for every year since migration.

To do so, we follow Rho and Sanders (2021) and use the percentage point difference between immigrants and natives in the probability of not being found in the 2010 Census, conditional on being observed in the 2000 Census, separately for three education groups (less than, exactly equal to, and more than 16 years of education) and for 10 deciles of the self-reported 1999 earnings distribution. We report these probabilities in Table 2.6. Similar to the first robustness check, we convert the decennial probabilit-

Table 2.6: Probabilies of outmigration

	Skill percentiles									
Education	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
<16 years	0	1	0	1	5	6	7	10	11	19
16 years	16	9	10	12	14	13	13	19	22	43
>16 years	18	14	15	14	12	12	15	21	23	35

Source: Rho and Sanders (2021). Notes: Each entry represents the percentage point difference between immigrants and natives in the probability of not being found in the 2010 Census, conditional on being observed in the 2000 Census, separately by education and decile of the self-reported 1999 earnings distribution

ies in annual ones and compound them for every year since migration, separately by education level and by deciles in the residual wage distribution. [10]

Tables 2.29 and 2.30 report the estimates for either robustness check, respectively. Accounting for selective out-migration does not alter the main results of the paper.

2.4.4.6 Undocumented migrants

Both the Census and the ACS systematically undercount the number of documented and undocumented immigrants (Hanson, 2006; Borjas, 2014). We correct for it following Borjas (2017). First, we identify those immigrants who are more likely to be undocumented. Specifically, we classify immigrants as "documented" if at least one of the following conditions is met: i) they were granted a "naturalized citizen" status, or ii) they receive a social security income, or iii) they are from Cuba or iv) they migrated before 1982. In both cases, we assign them to the status of "documented". Therefore, we divide the original sample weights of undocumented immigrants' by one minus a census-specific undercount rate, which is taken from Van Hook et al. (2014) and Passel and Cohn (2018). The undercount probabilities are equal to 0.22 for immigrants

[10] We retrieve residualized wages for immigrants by constructing residuals from the following regression:

$$\ln w_{it} = \alpha + \delta_{\text{educ}_{it}} + \delta_{\text{exp}_{it}} + \delta_{\text{cohort}_{it}} + \delta_t + \epsilon_{it}$$

where w_{it} denotes hourly wages of immigrant i at time t, $\delta_{\text{educ}_{it}}$ are dummies for years of education, $\delta_{\text{exp}_{it}}$ are dummies for years of overall experience, $\delta_{\text{cohort}_{it}}$ are dummies for cohort of entry in the U.S. and δ_t are time dummies.

who arrived in the U.S. before 2001, 0.11 for immigrants who arrived between 2001 and 2010, and 0.06 for immigrants who arrived in the U.S. later than 2010. Table 2.31 reports the estimates for this robustness check.

2.4.5 Re-cap.

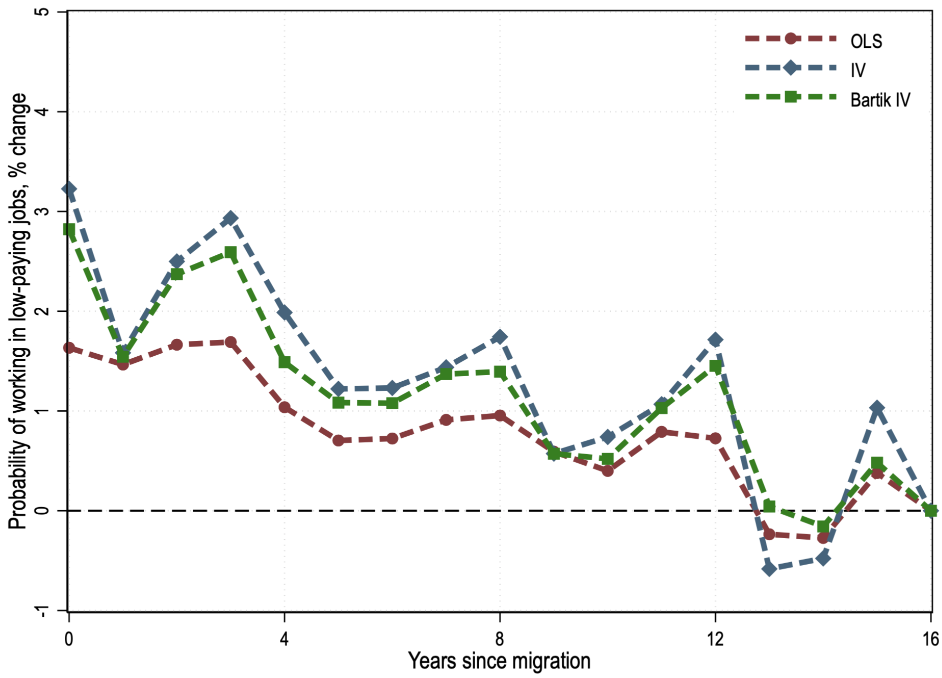
Taken together, our results suggest that, compared to those who are not, immigrants who are unlucky to enter the U.S. labor market in periods of high unemployment face a much larger discount in earnings relative to the U.S. natives. These immigrants struggle to fully assimilate and their earnings follow a lower trajectory for at least 10 years since their migration.

Slower assimilation in earnings happens to be the effect of recessions on hourly wages, while patterns of labor supply across cohorts of migrants do not respond to differences in unemployment at entry. In the next section, we explore an alternative mechanism, i.e. the role of occupation attainment and immigrants job mobility.

2.5 The Role of Occupational Attainment.

The evidence in Section 2.4 rules out reduced work time in terms of i) number of hours worked or ii) probability of being unemployed as explanations for the slower assimilation of immigrants entering the U.S. in a recession. In this section, we analyze one additional channel, the role of occupational attainment. Altonji et al. (2016) documents that much of the scarring effect of recessions for U.S. natives can be explained by initial employment in a low-paying occupation. Similarly, Huckfeldt (2022) finds that the earnings cost of job loss during recessions is concentrated among workers who find re-employment in lower-skill occupations. In what follows, we explore the hypothesis that shifts in the employment composition of immigrants from high- to low-paying occupations during recessions and a slow reallocation into high-paying jobs following recessions might explain their lack of assimilation.

Figure 2.4: Probability of working in low-paying occupations



Source: ACS, FRED and authors' calculation. Notes: The figures show the estimated coefficients (times 100) from regressing the estimated immigrant-native gap in the probability of being employed in a low-paying job on the unemployment rate in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers reporting to be currently employed. The red lines refer to the estimates from equation (2.4). The blue lines refer to the estimates from equation (2.6).

We start by classifying occupations based on their task intensity. We do so following Acemoglu and Autor (2011). We then label the occupations with the highest intensity in routine-manual tasks as low-skill occupations. This group includes occupations like Building Cleaning and Pest Control Workers, Cooks and Food Preparation Workers, Material Moving Workers, and Personal Appearance Workers. We label the remaining ones as high-skill occupations.[11] This choice is dictated by the large difference in hourly earnings between workers observed in the data (Table 2.19 in Appendix 2.9.4). On average workers employed in manual-routine occupations are paid almost 70% less than the rest. This is true for U.S. natives, whose earnings gap across occupations is on average 67%. And more so for immigrants, whose gap reaches 84%.

[11] See Appendix 2.9.2 for a detailed description of how we classify occupations.

Table 2.7: Unemployment at entry and employment in routine-manual jobs

Years Since Migration	OLS (1)	IV (2)	Bartik-IV (3)
0	0.017	0.035	0.028
	(0.009, 0.025)	(0.024,0.048)	(0.020,0.038)
1-4	0.015	0.023	0.0182
	(0.009,0.021)	(0.013,0.034)	(0.011,0.026)
5-8	0.009	0.015	0.011
	(0.003,0.015)	(0.005,0.025)	(0.004,0.018)
9-12	0.007	0.011	0.007
	(0.001,0.012)	(0.001,0.021)	(0.000,0.014)
N.Obs.	272	272	271
R-sq.	0.702	0.706	0.711

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated immigrant-native gap in the probability of being employed in a low-paying job on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers reporting to be currently employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Figure 2.4 reports the effects of the unemployment rate at entry into the U.S. on the probability of being employed in low-skill content occupations for each year since migration. We obtain each point estimate by 1) estimating equations (2.1) and (2.2) on a dummy variable taking value 1 if a worker is employed in a low-skill job, and 0 otherwise, and ii) using the estimates for the immigrant-native gaps in the probability of being employed in a low-skill job, θ_{cx}, as a dependent variable in equation (2.4). The red line refers to our OLS estimation. The blue line refers to the IV estimation. The green line refers to the Bartik-IV estimation. Table 2.7 summarises the estimated effects for 5 groups of experience in the U.S.

Relative to the average U.S. native, immigrants entering the U.S. during a recession have a higher probability of working in low-skill jobs, both on impact and in the following 12 years. The effect is large and long-lasting: a 1 p.p. rise in the unemployment rate increases the share of immigrants employed in routine-manual occupation by about 1.7% on the spot, and by about 0.66% after 12 years (Column 1, Table 2.7).

Using the IV estimates in Column (3) of Table 2.7 the effect almost doubles on impact (2.84% for a 1 p.p. increase in the unemployment rate) and it is similar after 12 years since migration (0.7% for 1 p.p. increase in the unemployment rate at entry). These effects are remarkable if compared to the mean probability of working in a routine-manual job for immigrant workers, which is approximately 25%.

Equipped with these estimates, we can predict the earnings assimilation profile under the counterfactual scenario of no changes in the probability of working in routine-manual jobs. First, for every year since migration x, we compute the wage loss faced by an average migrant because of changes in the composition of occupations as follows:

$$\text{loss}_x = \hat{\omega}_x^{\text{RM}} \Delta \log \bar{w}_x^{\text{imm}} \tag{2.8}$$

where $\{\hat{\omega}_x^{\text{RM}}\}_{x \in \mathcal{X}}$ are the coefficients reported in Figure 2.4, while $\Delta \log \bar{w}_x^{\text{imm}}$ is the difference in average annual/hourly earnings of migrants observed after x years since migration between workers employed in non-routine-manual and routine-manual jobs. Since $\hat{\omega}_x^{\text{RM}} \geq 0$ — see Figure 2.4, and because $\left(\log[\bar{w}_x^{\text{non-RM}}] \geq \log[\bar{w}_x^{\text{RM}}]\right)$ — see Table 2.19, then $\text{loss}_x \geq 0$. Therefore, we obtained counterfactual earnings losses $\hat{\omega}_x^{\text{w},C}$ as:

$$\hat{\omega}_x^{\text{w},C} = \hat{\omega}_x^{\text{w}} - \text{loss}_x \tag{2.9}$$

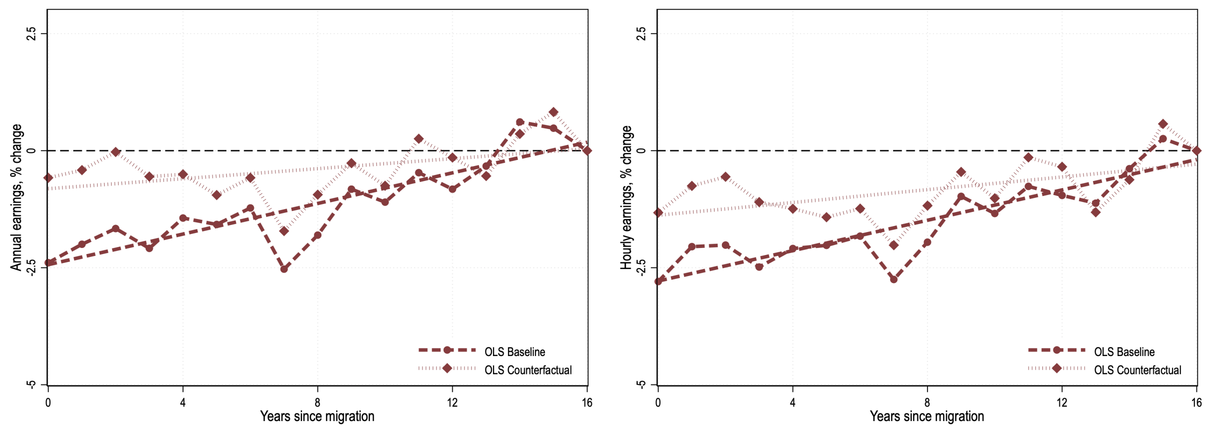
where $\hat{\omega}_x^{\text{w}}$ are the coefficients obtained from estimating equation (2.4) using annual/hourly earnings as the outcome variable. It follows $\hat{\omega}_x^{\text{w},C}$ can be interpreted as the earnings losses that would arise had the composition of employment across jobs not changed for cohorts of migrants entering the U.S. in periods of high unemployment compared to periods of low unemployment.

Figure 2.9 reports the results of this exercise and confronts actual and counterfactual annual and hourly earnings losses, using the estimates from equation (2.4).[12] Were

[12]In Appendix 2.9.8, we report the same figures using the IV estimates from equation (2.6) and the

Figure 2.5: Actual VS counterfactual earnings

(A) Annual earnings **(B)** Hourly earnings



Source: ACS, FRED and authors' calculation. Notes: The figures show the percent coefficients from regressing estimated annual and earnings gaps between immigrants and the average U.S. natives on the unemployment forecast error in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Both panels are based on a sample of male workers who report to be currently employed. Panel A shows the percent change in the estimated annual earnings gap. Panel B shows the percent change in the estimated hourly earnings gap. In each panel, the dashed lines are constructed using estimates from equation (2.4), while the shaded lines are constructed using the counterfactual estimates as in equation (2.9).

occupational attainment unchanged for immigrants, annual earnings would fall on average by less than one-fourth in the year of entry in the U.S.: the counterfactual drop will be about -0.3% — instead of -2.4%, for a 1 p.p. rise in the unemployment rate (Panel A). The effect of recessions is also much less prolonged: assimilation in annual earnings would be achieved on average by the third year since migration — instead of taking at least 12 years, as documented in Section 2.4. Counterfactual hourly earnings mirror the same pattern (Panel B): about half of the fall in earnings observed within the first 15 years since migration can be explained by the change in the probability of being employed in routine manual occupations.

Notice that our counterfactual exercise captures only a lower bound in the loss from working in manual routine occupations. Time spent in lower-paying occupations in the first few years in the U.S. might have an impact on earnings years later, holding occupation constant, since it might drive workers on different trajectories for training and skill advancement (Altonji et al., 2016).

Bartik-IV estimates from equation (**??**).

2.5.1 Discussion

Our evidence suggests that slow job mobility between low- and high-skill jobs prevents the assimilation of immigrants after an adverse initial start. This result can be interpreted through the lens of theories of job assignment, in which employers learn gradually about workers' ability and human capital is not fully portable across occupations (Gibbons and Waldman, 1999, 2006). When human capital is specific to an occupation, the state of the world in the workers' first period in the labor market influences not only current occupation assignments and wages but also, consequently, occupation assignments and wages later in these careers. Then, a worker who spends substantial time in a given occupation at the beginning of his career can get stuck in that occupation, facing low subsequent mobility, and low wage trajectory, as long as the human capital acquired in a given occupation is of limited use in the performance of other tasks. Extensive literature supports the evidence of limited portability of human capital across occupations (Kambourov and Manovskii, 2009; Sullivan, 2010; Robinson, 2018).

Moreover, faster employers' learning about college-educated workers, or workers from richer countries, could also explain the differential impacts and speeds of recovery across demographic groups (Lange, 2007).

On the other hand, while models of job search would also predict that immigrants entering the labor market in a recession might catch up through a long search process for high-paying occupations (Oreopoulos et al., 2012), the same models would be inconsistent with the evidence of no differential changes in the probability of being unemployed between natives and immigrants' entering into the U.S. in years of recessions, as documented in Section 2.4.

2.6 *Gender, Skill & Development Gradients* of Assimilation

Are the effects of adverse initial labor market conditions on immigrant assimilation heterogeneous? Our identification strategy allows us to leverage variations in the demographic characteristics of immigrants and characterize the heterogeneity in the scarring effect. In this section, we document the existence of *Gender*, a *Skill* and a *Development Gradient* in the cost of migrating during a recession: males without a college education from low-income countries are the only ones adversely affected by higher initial unemployment rates.

2.6.1 Gender

Table 2.32 in Appendix 2.9.9 reports the OLS estimates of earnings losses and the labor supply gaps for the sample of female immigrants, aged 16 to 64 y.o., over different years since migration. Figures 2.6A and 2.7A summarize this difference. The effects on earnings and hours worked of female immigrants are unambiguously close to zero: no estimate is statistically different from zero at a 10% significance level. Similarly, the occupational attainment of employed women does not react to changes in the unemployment rate at entry. The evidence points to the existence of a *gender grandient*: while women are immune, entering the U.S. during a recession primarily affects the economic assimilation of men.

2.6.2 Education

Toussaint-Comeau (2006) documents that earnings assimilation is higher for immigrants with a college education, while convergence to the U.S. natives is modest at best for those with a high-school degree or less. In Tables 2.33 and 2.34 in Appendix 2.9.9

we focus on the role of college attainment and distinguish workers with and without a college education. Figures 2.6B and 2.7B highlight the difference between college and non-college-educated workers.

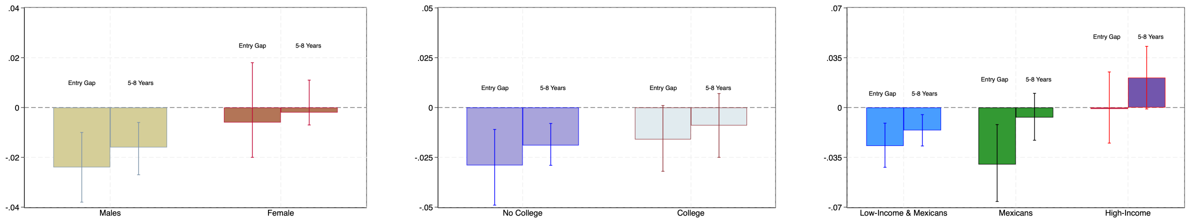
We document a *skill gradient* in the effect of the business cycle on immigrant assimilation. The effect of entering the U.S. during a recession on the wage trajectories is large and statistically significant for immigrants with no college education. Their annual earnings reduce by 2.9% for a 1 percentage point increase in the unemployment rate at entry (column 1 of Table 2.33). The effect is persistent even after 12 years in the U.S. when the coefficient reduces to 1.3%. On the other hand, recessions seem not to affect the assimilation of workers with a college education: entering the U.S. when the unemployment rate increases by 1 percentage point reduces the annual wages of immigrants with a college education by 1.6% at entry, but the effect is not statistically significant. All the other estimated coefficients on earnings lack statistical significance for this group of workers.

2.6.3 Country of origin

The returns to experience in the U.S. are heterogeneous across workers from different countries of origin and are higher for workers migrating from high-GDP per capita countries (Lagakos et al., 2018b). We explore this dimension in Tables 2.35 and 2.36 in Appendix 2.9.9 where we report OLS estimates for the sub-samples of male immigrants from high- and low-income countries. Figures 2.6C and 2.7C summarize the difference across countries of origin.

We document a *development gradient* in the scarring effect of the unemployment rate. On the one hand, the wage trajectories of immigrants from high-income countries are not affected by adverse aggregate initial conditions. On the other hand, immigrants from low-income countries face a large and persistent loss from moving into the U.S. in periods of high unemployment: the loss goes from 6% of their hourly earnings on

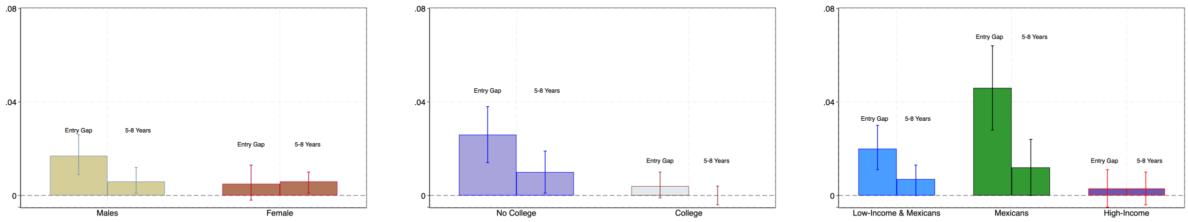
Figure 2.6: Heterogeneous effect of unemployment at entry on earnings of immigrants



(A) Gender **(B)** Education **(C)** Country of origin

Source: ACS, FRED and authors' calculation. Notes: This figure reports the OLS coefficients from regressing the estimated annual earnings gap between different groups of immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. "Entry gap" refers to the coefficient associated with 0 years since migration. "5-8 Years" refers to the coefficient associated with 5-8 years since migration. Results in 2.6A are based on samples of male and female workers. Results in 2.6B are based on samples of male workers who are either no-college or college-educated. Results in 2.6C are based on samples of male workers from low-income countries, Mexico, or high-income countries. 90% confidence intervals are bootstrapped using 1000 Clustered Rademacher draws.

Figure 2.7: Heterogeneous effect of unemployment at entry on occupational attainment



(A) Gender **(B)** Education **(C)** Country of origin

Source: ACS, FRED and authors' calculation. Notes: This figure reports the OLS coefficients obtained from regressing the estimated probability of being employed in low-skill content occupations for immigrants on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. "Entry gap" refers to the coefficient associated with 0 years since migration. "5-8 Years" refers to the coefficient associated with 5-8 years since migration. Results in 2.7A are based on samples of male and female workers. Results in 2.7B are based on samples of male workers who are either no-college or college-educated. Results in 2.7C are based on samples of male workers from low-income countries, Mexico, or high-income countries. 90% confidence intervals are bootstrapped using 1000 Clustered Rademacher draws.

impact, up to 1.8% after 12 years spent in the U.S.

Table 2.37 zooms into the pool of immigrants from low-income countries and focuses on the sample of Mexican workers, who constitute the largest group within it. Annual and hourly earnings of Mexicans migrating to the U.S. in periods of high unemployment are significantly lower than those of the average native. However, the loss arises only up to 4 years after moving to the U.S., and it is fully re-absorbed thereafter, suggesting a much faster assimilation of Mexicans than other immigrants from comparable countries.

2.7 Welfare implications

Finally, we quantify how big is the cost of recessions for immigrants. To do so, we first construct the immigrants' net present value of being employed in the host country as the discount sum of annual earnings in the first 15 years since migration, i.e.

$$\text{NPV} = \sum_{x=0}^{15} \left(\frac{1}{1+r} \right)^x \bar{w}_x^{\text{imm}} \tag{2.10}$$

where r is an average discount rate, calibrated to 5 percent annually, while $\bar{w}_x^{\text{imm}}$ is the average annual earnings of an immigrant after x years since migration.[13] Then we use the estimates of equations (2.4) and (2.6) on annual earnings, $\hat{\omega}_x^w$, to construct the net present losses from entering the U.S. with a 1 pp higher unemployment rate, i.e.

$$\text{NPL} = -\bar{w}^{\text{nat}} \sum_{x=0}^{15} \left(\frac{1}{1+r} \right)^x \hat{\omega}_x^w \tag{2.11}$$

where $\bar{w}^{\text{nat}}$ is the average annual earnings of a U.S. natives. Finally, we express the net present losses as a percent of the net present value as follows:

$$100 \times \frac{\text{NPL}}{\text{NPV}} \tag{2.12}$$

Panel A in Table 2.8 reports the estimated net present value losses for immigrants. The loss from starting to work in a recession is large and meaningful: depending on the

[13] This formula implicitly assumes that i) labor supply of immigrant entering the U.S. in recession remains unchanged relative to the average U.S. native, and ii) the difference in annual earnings between migrants and natives has decayed after 15 years since migration. Estimates in Table 2.3 suggest this is the case.

Table 2.8: Overall cost of high unemployment for immigrants

	OLS (1)	IV (2)	Bartik-IV (3)
NPV (USD)		446,083	
A.		Baseline estimates	
NPL (USD)	7,501.69	10,434.64	11,149.10
%	1.68	2.34	2.50
B.		Counterfactual estimates	
NPL (USD)	2,508.72	2,212.77	3778.00
%	0.56	0.50	0.84

Source: ACS, FRED and authors' calculation. Notes: This table reports the net present value losses (NPL) from entering the U.S. labor market in a year with 1 p.p. higher unemployment rate. NPL is reported in U.S. Dollars at the 1999 constant price level and as a percentage of immigrant net present value (NPV). Results refer to the sample of male immigrants.

specification, it varies between 7,501 and 11,149 USD, which corresponds to 1.7 and 2.5 percent of the immigrant net present value.

Panel B of Table 2.8 reports the counterfactual losses that would realized had the occupational change not changed following higher unemployment at the time of entry into the U.S. We construct it using equation (2.11) and replacing $\hat{\omega}_x^w$ with $\hat{\omega}_x^{w,C}$, as defined in equation (2.9). Depending on the specifications, the loss will amount to between 2,500 and 3,800 USD: these values correspond to 0.5 and 0.8% of their net present values and to between one-third and one-quarter of the loss computed using baseline estimates. Therefore, changes in occupational attainment can explain up to three-quarters of the overall lifetime cost of recessions faced by immigrants in the host country.

2.8 Conclusions

Adverse initial labor market conditions have short and long-run effects on the careers of workers. In this paper, we show that the recessions also deter the economic assimilation of immigrants in the U.S. Earning trajectories of immigrants who migrate in years of high unemployment rates suffer for up to 12 years since migration: 1 p.p. increase in the unemployment rate at the time of migration costs them between 1.6 and 2.5 percent of lifetime earnings. Shifts in the composition of occupations toward low-skill, low-paying jobs explain up to three-quarters of the present value losses caused by recessions.

Our results shed light on the determinants of immigrants' labor market careers in the hosting country and suggest that the welfare cost of the business cycle fluctuation is likely to be larger once the long-term effects of recessions of immigrants are taken into account. While a structural model of workers' career and migration decisions over the business cycle might shed further light on the underlying mechanisms, we leave this for future research.

2.9 Appendix A

2.9.1 Additional data sources

O*NET Database. We collect information on the task content of occupations from O*NET. Occupations in O*NET are defined by the Standard Occupation Classification (SOC). The database provides a scale of importance for a set of descriptors that determine the distinguishing characteristics of each occupation, such as knowledge, skills, abilities, work activities, work context, work styles, and work values. We employ these descriptors to build a measure of task intensity which we use to classify occupations into five task categories: non-routine cognitive, non-routine interpersonal, routine cognitive, routine manual, and non-routine manual.[14]

World-Bank Development Database. We collect information on countries' GDP per capita from the World Bank Development Indicators. This dataset contains country-level information for a set of indicators of economic development. We select GDP per capita at PPP constant 2021 international US dollars to split countries into two categories: low-income (GDP pc $<$ \$30,000) and high-income (GDP pc greater or equal than $\geq$ \$30,000).

FRED Database. We collect information on the unemployment rate from 1990 to 2021 from the FRED database.

2.9.2 Variables definition

Immigrants. We combine the information from the variables "BPLD" and "CITIZEN" to define immigrants as foreign-born workers who are either naturalized citizens or

[14] More details can be found in Appendix 2.9.2.

do not have citizen status.

Years Since Migration. We construct immigrants' years of arrival using the variable ″YRIMMIG″ and compute years since migration as the difference between the year in which we observe a foreign-born worker minus and her year of arrival in the US.

Cohort Of Arrival. Using the year of arrival in the US, we assign foreign-born workers to a cohort of arrival in the US.

Years of Schooling. In the ACS individuals are asked to report their educational attainment. We 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″.

Potential Experience. We compute potential experience in the labor market as a worker's age minus the years of schooling minus 6.

Hourly Earnings. We construct hourly earnings by combining 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. Thus, we compute hourly earnings as annual pre-tax wage and salary income divided by the number of hours worked in a year. Since the weeks worked are provided in intervals, we follow Albert et al. (2021) and 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, we convert hourly earnings to constant 1999 dollars using the CPI-U multiplier index available in IPUMS.

Low-Income And High-Income Countries. We 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.

Task Intensity Measure. We collect data from O*NET following the definitions in Acemoglu and Autor (2011). We define the five tasks macro-categories which are defined based on a set of descriptors:[15]

- Non-routine cognitive analytical:
  - Analyzing data/information
  - Thinking creatively
  - Interpreting information for others
- Non-routine cognitive interpersonal:
  - Establishing and maintaining personal relationships
  - Guiding, directing, and motivating subordinates
  - Coaching/developing others
- Routine cognitive:
  - Importance of repeating the same tasks
  - Importance of being exact or accurate
  - Structured v. Unstructured work
- Routine manual:

[15] Differently from Acemoglu and Autor (2011), we do not consider the task category "Offshorability".

- 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

O*NET provides an importance scale of each descriptor for each occupation defined using the Standard Occupation Classification (SOC) 2010 at 6 digits. We aggregate occupations at 3-digit SOC codes. and obtain 95 groups. We create a measure for each of the 5 task categories listed above by summing the values of each constituent descriptor defined at 3-digits SOC. For each category, we then standardize the measure to have a mean of zero and a standard deviation of one.

Occupation Dummies. There are $n = 1, ..., 95$ occupations in our sample and we assign each of them to one of the following task categories: non-routine cognitive analytical (NRA),non-routine cognitive interpersonal (NRI), routine cognitive (RC), routine manual (RM), non-routine manual (NRM). We do so by comparing for each occupation the intensity of each task and selecting the category with the maximum intensity. Table 2.18 reports how each occupation in our dataset is assigned to one task category.

Unemployment rate. The unemployment rate (UNRATE, source: FRED) refers to the number of unemployed as a percentage of the labor force. Labor force data are restricted to people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia, who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces.

Recession dummy. The recession dummy takes value 1 for any period identified as a recession by the NBER's Business Cycle Dating Committee, and 0 otherwise.

2.9.3 Instrumental variable

Let u_{t+1} denote the unemployment rate to be forecast, and let X_t be an N-dimensional multiple time series of predictor variables, observed for $t = 1, 2, ...T$. Following Stock and Watson (2002), we assume that (u_{t+1}, X_t) admit a dynamic factor model representation with r common dynamic factors f_t, i.e.

$$\begin{aligned} u_{t+1} &= \alpha + \beta f_t + \gamma u_t + \epsilon_{t+1}, \\ X_{it} &= \lambda_i(L) f_t + v_{it} \quad \forall i = 1, ...N \end{aligned}$$

where $v_t = (v_{1t}, v_{2t}, ..., v_{Nt})'$ is the $N \times 1$ idiosyncratic disturbance and $\lambda_i(L)$ are lag polynomials in nonnegative powers of L. It is also assumed that:

$$\mathbf{E}[\epsilon_{t+1} | f_t, u_t, X_t, f_{t-1}, u_{t-1}, X_{t-1}, ...] = 0$$

If we let $\lambda_i(L)$ to have finite orders of at most q, then we can write

$$\begin{aligned} u_{t+1} &= \alpha + \beta F_t + \gamma u_t + \epsilon_{t+1}, \\ X_t &= \Lambda F_t + v_t \end{aligned}$$

where $F_t = (f_t', f_{t-1}', ..., f_{t-q}')'$ and the i-th row of Λ is $(\lambda_{1t}, \lambda_{2t}, ...\lambda_{qt})$. Our empirical application focuses on a 1-step ahead forecast. Because α, F_t, and Γ are unknown, our forecast is constructed using a two-step procedure. First, the sample data $\{X_t\}_{t=1}^T$ are used to estimate a time series of factors (the diffusion indexes), $\{\hat{F}_t\}_{t=1}^T$. Second, the estimators $\hat{\alpha}, \hat{\beta}$ and $\hat{\gamma}$ are obtained by regressing u_{t+1} onto a constant, $\hat{F}_t$ and u_t. Stock and Watson (1998) developed theoretical results for this two-step procedure applied to the factor model. The factors are estimated by principal components because these estimators are readily calculated even for very large N and because of principal components can be generalized to handle data irregularities.

In practice, we use the $N = 5$ variables to estimate the diffusion index, meaning the first difference of log real GDP (variable GDPC1), the first difference of log real GDP per capita (variable A939RX0Q048SBEA), the first difference of the logged number of hours (variable B4701C0A222NBEA), the first difference of the logged employment rate (variable EMRATIO), and the first difference of the logged industrial production index (variable INDPRO). To train this model, we use yearly time-series data from 1970 to 2021. Table 2.9 reports the OLS estimate for the second-step regression of the unemployment rate at time $t + 1$, u_{t+1} onto a constant, the aggregate factor at time t, $\hat{F}_t$ and lagged unemployment rate u_t.

Table 2.9: Aggregate unemployment forecast model

	u_{t+1}
$\hat{F}_t$	-0.194
	(0.081)
u_t	0.615
	(0.109)
N. Obs.	51
Adj.R2	0.518

Source: ACS and authors' calculations. Notes: This table reports the OLS estimate from regressing the unemployment rate at time $t + 1$, u_{t+1} onto a constant, $\hat{F}_t$ and u_t.

Table 2.10 reports the OLS estimate for the regression of the state-level unemployment rate at time $t+1$, u_{st+1} onto a constant, the aggregate unemployment forecast, $\hat{u}_{t+1}$, the lagged state-level unemployment rate, u_{st} and a full set of state-level fixed effects.

Table 2.10: State-level unemployment forecast model

	u_{st+1}
$\hat{u}_{t+1}$	0.108
	(0.043)
u_{st}	0.624
	(0.036)
State FE	✓
N. Obs.	1581
Adj.R2	0.614

Source: ACS and authors' calculations. Notes: This table reports the OLS estimate from regressing the state-level unemployment rate at time t, u_{st} onto a constant, $\hat{t}_t$ and u_{st-1}.

2.9.4 Descriptive Statistics

Table 2.11: Descriptive statistics of immigrants by cohorts of arrival: 1990-2005

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1990	43519.3	20.0	2164.4	12.4	29.2	71.9	20873
	(61284.1)	(28.5)	(505.8)	(4.0)	(6.3)	-	-
1991	50399.9	22.9	2184.5	13.1	28.0	75.8	15434
	(70300.3)	(35.0)	(511.0)	(4.1)	(6.6)	-	-
1992	48028.0	22.3	2170.2	12.9	27.5	74.5	16926
	(66824.8)	(39.2)	(517.7)	(4.1)	(6.8)	-	-
1993	48596.6	21.8	2192.3	12.7	26.9	73.5	16391
	(70917.4)	(32.5)	(518.0)	(4.1)	(6.9)	-	-
1994	47940.4	21.7	2186.8	12.6	26.3	71.2	18371
	(70376.1)	(31.5)	(514.4)	(4.1)	(7.0)	-	-
1995	43512.0	20.0	2162.1	12.4	26.0	69.5	22987
	(63461.0)	(30.6)	(505.7)	(4.1)	(7.2)	-	-
1996	46639.1	21.8	2173.1	12.7	24.8	71.3	22741
	(66794.6)	(45.4)	(513.3)	(4.1)	(7.5)	-	-
1997	47716.3	22.4	2172.5	12.8	24.1	71.5	23644
	(65989.5)	(53.9)	(502.2)	(4.2)	(7.6)	-	-
1998	44872.6	20.7	2166.9	12.6	23.5	68.7	29739
	(63124.2)	(29.2)	(498.3)	(4.2)	(7.8)	-	-
1999	42358.8	19.6	2154.2	12.5	22.9	67.0	33389
	(60518.9)	(29.7)	(505.8)	(4.1)	(7.9)	-	-
2000	39741.8	18.6	2142.8	12.3	22.5	63.7	43218
	(57653.0)	(30.1)	(504.3)	(4.1)	(8.1)	-	-
2001	41052.7	19.1	2150.5	12.7	21.7	65.9	32630
	(59203.5)	(28.3)	(510.2)	(4.1)	(8.4)	-	-
2002	38798.9	18.2	2140.4	12.4	20.9	62.1	25134
	(59355.6)	(31.3)	(507.8)	(4.1)	(8.6)	-	-
2003	37482.5	17.9	2127.3	12.3	20.2	60.1	25234
	(58990.4)	(55.3)	(513.0)	(4.1)	(8.7)	-	-
2004	35523.4	16.8	2119.7	12.1	19.5	56.6	26970
	(55069.8)	(25.7)	(522.4)	(4.1)	(8.7)	-	-
2005	35645.1	16.7	2109.0	12.1	18.7	56.6	29530
	(54294.1)	(23.8)	(519.6)	(4.2)	(8.8)	-	-

Table 2.12: Descriptive statistics of immigrants by cohorts of arrival: 2006-2021

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2006	38769.8	18.1	2109.2	12.7	18.0	60.4	26588
	(58496.5)	(27.8)	(530.0)	(4.2)	(8.9)	-	-
2007	40827.6	19.0	2115.4	13.0	17.6	63.5	23370
	(61072.1)	(36.9)	(529.6)	(4.2)	(9.0)	-	-
2008	40775.1	19.1	2105.9	13.0	17.5	64.4	20058
	(61740.9)	(28.0)	(542.8)	(4.2)	(9.2)	-	-
2009	40220.1	19.5	2106.8	13.1	17.3	66.4	16153
	(59818.4)	(41.1)	(549.1)	(4.1)	(9.4)	-	-
2010	43037.3	20.8	2116.6	13.3	17.4	67.6	16860
	(65342.9)	(42.6)	(542.3)	(4.0)	(9.3)	-	-
2011	48590.1	23.0	2130.7	13.9	16.5	72.3	14131
	(71069.1)	(42.2)	(528.3)	(3.9)	(9.1)	-	-
2012	45949.7	21.5	2119.1	13.6	16.5	70.2	14198
	(67142.3)	(31.7)	(531.9)	(4.0)	(9.3)	-	-
2013	47188.7	22.4	2115.0	14.0	15.8	71.9	14051
	(66738.6)	(33.9)	(513.5)	(3.8)	(9.1)	-	-
2014	46290.1	21.9	2110.7	14.0	15.7	71.5	13714
	(65296.1)	(29.7)	(529.0)	(3.9)	(9.2)	-	-
2015	43956.1	20.9	2103.2	13.9	15.8	69.5	13272
	(62358.2)	(30.9)	(526.0)	(3.8)	(9.2)	-	-
2016	42671.2	20.5	2092.6	13.9	15.9	68.1	11816
	(60368.8)	(29.0)	(544.3)	(3.8)	(9.3)	-	-
2017	45424.6	21.6	2098.0	14.2	15.4	71.1	8004
	(63484.2)	(28.1)	(546.2)	(3.8)	(9.2)	-	-
2018	44878.4	22.3	2083.4	13.9	15.6	68.8	5980
	(67166.5)	(41.7)	(574.1)	(4.0)	(9.2)	-	-
2019	44750.6	22.4	2053.4	13.7	15.8	65.9	4461
	(64606.9)	(34.9)	(578.3)	(4.2)	(9.3)	-	-
2020	43699.7	22.6	2057.6	14.1	15.6	66.1	1428
	(59986.1)	(58.8)	(613.6)	(4.1)	(9.6)	-	-
2021	36550.6	18.3	2005.9	13.0	15.6	63.2	757
	(52956.8)	(24.5)	(729.8)	(4.1)	(9.3)	-	-

Source: ACS and authors' calculations. Notes: This table reports selected labor market outcomes and demographic characteristics of immigrants across different cohorts of entry in the U.S. Results are based on a sample of male workers who report being currently employed.

Table 2.13: Descriptive statistics: Females

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natives	31425.2	15.8	1958.9	13.9	19.9	-	5012367
	(37648.7)	(25.1)	(554.3)	(2.3)	(11.5)	-	-
Immigrants	29605.8	15.3	1923.9	13.3	21.9	69.6	466082
	(40247.8)	(23.1)	(563.6)	(3.7)	(9.4)	-	-

Source: ACS and authors' calculations. Notes: This table compares selected labor market outcomes and demographic characteristics of female natives against female immigrants. Results are based on a sample of workers who report being currently employed.

Table 2.14: Descriptive statistics: Non-college workers

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natives	27945.5	13.6	2046.2	12.4	20.6	-	6902560
	(26795.0)	(18.5)	(566.0)	(1.2)	(11.4)	-	-
Immigrants	21514.4	11.1	2006.1	10.6	23.4	53.5	629268
	(22992.0)	(17.4)	(547.6)	(2.8)	(8.8)	-	-

Source: ACS and authors' calculations. Notes: This table compares selected labor market outcomes and demographic characteristics of non-college-educated natives against non-college-educated immigrants. Results are based on a sample of workers who report being currently employed.

Table 2.15: Descriptive statistics: College workers

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Natives	63493.9	28.4	2183.8	16.7	18.5	-	3670183
	(77895.5)	(46.8)	(567.9)	(1.2)	(11.1)	-	-
Immigrants	64237.6	29.9	2128.1	17.2	17.9	92.5	444866
	(78120.9)	(42.5)	(541.0)	(1.5)	(9.1)	-	-

Source: ACS and authors' calculations. Notes: This table compares selected labor market outcomes and demographic characteristics of college-educated natives against college-educated immigrants. Results are based on a sample of workers who report being currently employed.

Table 2.16: Descriptive statistics: Low-Income vs Mexicans vs High-Income Immigrant workers

Origin	Avg. Yearly Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	English Proficiency	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low-Income	32844.9	16.2	2033.5	12.6	21.5	64.4	909289
	(45461.5)	(26.5)	(536.7)	(4.0)	(9.3)	-	-
Mexicans	20132.7	10.3	2022.0	10.1	22.6	41.3	244097
	(21693.2)	(16.6)	(527.0)	(3.3)	(8.6)	-	-
High-Income	67981.0	30.4	2173.1	15.6	20.5	90.9	164845
	(91952.8)	(49.2)	(608.8)	(2.9)	(9.5)	-	-

Source: ACS and authors' calculations. Notes: This table compares selected labor market outcomes and demographic characteristics of immigrants from different countries of origin. Results are based on a sample of workers who report being currently employed.

Table 2.17: Unemployment & Employment in Routine-Manual Occupations

Group	Males	Females	Non-college	College	Low-Income	Mexicans	High-Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Shares of Unemployed			
Natives	2.8	2.4	3.3	1.3	-	-	-
Immigrants	1.8	2.1	2.3	1.2	2.0	2.3	1.3
				Shares of Routine-Manual Employed			
Natives	20.1	12.9	23.5	3.4	-	-	-
Immigrants	26.7	34.3	42.8	7.4	32.6	49.1	10.3

Source: ACS and authors' calculations. Notes: This table compares the shares of unemployment and the share of employment in routine-manual jobs of natives against immigrants. Results are based on a sample of male workers.

Table 2.18: List of occupations by category and task intensity

Occupation (SOC 3-dig)	Label	Task Intensity Analytical	Task Intensity Interpersonal	Task Intensity Routine Cognitive	Task Intensity Routine Manual	Task Intensity Non-Routine Manual
Architects, Surveyors, and Cartographers	NRA	1.37	0.58	0.42	-0.44	0.18
Art and Design Workers	NRA	0.54	-0.29	-0.12	-0.34	-0.21
Business Operations Specialists	NRA	0.93	0.53	0.53	-1.07	-1.16
Computer Occupations	NRA	1.50	-0.20	0.27	-0.65	-1.00
Drafters, Engineering Technicians, and Mapping Technicians	NRA	0.38	-0.77	0.37	0.09	0.15
Engineers	NRA	1.46	0.12	-0.31	-0.92	-0.98
Life Scientists	NRA	1.94	0.56	0.29	-0.66	-0.45
Mathematical Science Occupations	NRA	2.11	-0.31	0.31	-1.40	-1.77
Media and Communication Equipment Workers	NRA	0.74	0.28	-0.04	0.30	0.24
Physical Scientists	NRA	1.97	-0.02	-0.44	-1.15	-1.01
Postsecondary Teachers	NRA	1.99	1.13	-0.26	-1.28	-1.50
Social Scientists and Related Workers	NRA	2.16	0.35	-0.43	-1.69	-1.60
Advertising, Marketing, Promotions, Public Relations, and Sales Managers	NRI	1.10	1.47	-0.41	-1.57	-1.38
Baggage Porters, Bellhops, and Concierges	NRI	-0.48	0.79	-0.78	-0.58	0.04
Counselors, Social Workers, and Other Community and Social Service Specialists	NRI	0.89	1.11	-0.61	-1.31	-1.17
Entertainers and Performers, Sports and Related Workers	NRI	0.21	0.69	-0.55	-0.50	-0.62
Occupational Therapy and Physical Therapist Assistants and Aides	NRI	0.26	0.55	-0.67	-0.18	-0.23
Operations Specialties Managers	NRI	1.01	1.71	0.83	-0.61	-0.93
Other Education, Training, and Library Occupations	NRI	1.10	1.24	-1.35	-1.46	-1.10
Other Healthcare Practitioners and Technical Occupations	NRI	0.68	0.81	0.44	-1.06	-0.66
Other Management Occupations	NRI	0.95	1.50	0.25	-0.95	-0.93
Other Personal Care and Service Workers	NRI	-0.29	0.61	-1.77	-1.07	-0.64
Other Sales and Related Workers	NRI	-0.51	-0.32	-1.44	-1.17	-0.90
Other Teachers and Instructors	NRI	0.97	1.05	-1.07	-1.61	-1.27
Preschool, Primary, Secondary, and Special Education School Teachers	NRI	0.89	1.48	-1.61	-1.20	-1.12
Religious Workers	NRI	1.04	1.79	-1.70	-1.75	-1.41
Supervisors of Building and Grounds Cleaning and Maintenance Workers	NRI	0.36	1.97	-0.23	0.66	0.74
Supervisors of Construction and Extraction Workers	NRI	0.54	0.99	0.39	0.54	0.64
Supervisors of Food Preparation and Serving Workers	NRI	0.14	1.60	0.50	1.38	0.51
Supervisors of Office and Administrative Support Workers	NRI	0.87	1.29	0.58	-0.56	-1.22
Supervisors of Personal Care and Service Workers	NRI	-0.91	1.18	0.33	-0.67	-0.83
Supervisors of Production Workers	NRI	0.42	1.52	0.58	1.35	0.41
Supervisors of Protective Service Workers	NRI	0.79	2.32	0.38	-0.41	0.86
Supervisors of Sales Workers	NRI	-0.14	1.72	0.67	-0.36	-0.64
Top Executives	NRI	1.62	2.24	0.38	-1.20	-1.42
Tour and Travel Guides	NRI	-1.12	-0.17	-1.39	-1.17	-0.36
Air Transportation Workers	RC	-0.10	-0.43	1.87	0.70	1.19
Financial Clerks	RC	-0.98	-0.86	1.91	-0.25	-1.10
Financial Specialists	RC	0.91	0.15	1.20	-1.15	-1.30
Funeral Service Workers	RC	-0.07	0.39	0.88	-0.60	0.56
Health Diagnosing and Treating Practitioners	RC	1.14	1.12	1.21	-0.53	-0.41
Health Technologists and Technicians	RC	0.11	0.18	1.25	0.50	-0.10
Information and Record Clerks	RC	-0.45	-0.28	1.60	-0.33	-1.01
Law Enforcement Workers	RC	0.67	0.46	0.87	-0.33	0.62
Lawyers, Judges, and Related Workers	RC	1.06	-1.40	1.37	-1.14	-1.58
Legal Support Workers	RC	0.21	-1.35	2.34	-0.48	-1.26
Librarians, Curators, and Archivists	RC	0.46	-0.07	0.51	-0.78	-0.55
Life, Physical, and Social Science Technicians	RC	0.49	-0.78	0.50	0.04	0.16
Material Recording, Scheduling, Dispatching, and Distributing Workers	RC	-0.91	-0.89	0.75	0.58	0.27
Media and Communication Workers	RC	0.96	-0.42	0.98	-0.59	-0.98
Nursing, Psychiatric, and Home Health Aides	RC	-0.71	-0.40	0.04	-0.09	-0.09
Other Healthcare Support Occupations	RC	-0.09	0.10	0.71	0.41	-0.00
Other Office and Administrative Support Workers	RC	-0.67	-1.11	1.40	0.24	-0.76
Other Protective Service Workers	RC	-0.26	-0.16	0.15	-0.40	0.09
Retail Sales Workers	RC	-0.87	-0.15	0.47	0.15	-0.21
Sales Representatives, Services	RC	0.22	-0.33	1.21	-1.39	-1.19
Sales Representatives, Wholesale and Manufacturing	RC	-0.68	-0.91	0.68	-1.23	-0.87
Secretaries and Administrative Assistants	RC	-0.60	-0.60	1.99	-0.66	-0.95
Supervisors of Installation, Maintenance, and Repair Workers	RC	0.77	0.61	1.97	0.20	0.97
Supervisors of Transportation and Material Moving Workers	RC	0.20	1.58	1.67	0.41	0.43
Agricultural Workers	RM	-1.60	-0.76	-1.76	0.69	0.67
Assemblers and Fabricators	RM	-1.00	-1.07	-0.41	1.12	0.77
Building Cleaning and Pest Control Workers	RM	-1.75	-1.50	-0.81	0.49	0.47
Communications Equipment Operators	RM	-0.82	-0.78	0.43	0.76	-0.74
Cooks and Food Preparation Workers	RM	-1.02	-0.91	-1.29	0.56	0.06
Entertainment Attendants and Related Workers	RM	-1.92	-1.14	-1.56	0.25	-0.26
Extraction Workers	RM	-0.89	-0.60	-0.52	2.22	1.91
Food Processing Workers	RM	-0.97	-0.92	-0.72	2.05	0.52
Food and Beverage Serving Workers	RM	-1.56	-0.08	-1.34	0.61	-0.01
Material Moving Workers	RM	-0.97	-1.00	-0.12	1.56	1.36
Metal Workers and Plastic Workers	RM	-0.84	-0.94	-0.35	2.00	1.09
Other Food Preparation and Serving Related Workers	RM	-1.79	-0.58	-1.93	0.65	0.13
Other Production Occupations	RM	-0.80	-1.08	-0.32	1.69	0.79
Personal Appearance Workers	RM	-0.78	-0.75	-0.59	0.47	0.13
Plant and System Operators	RM	0.07	-0.36	0.94	1.10	0.66
Printing Workers	RM	-0.04	-0.28	0.72	1.96	0.56
Textile, Apparel, and Furnishings Workers	RM	-1.43	-1.71	-1.15	1.63	0.45
Woodworkers	RM	-0.59	-1.71	-0.24	1.29	0.97
Animal Care and Service Workers	NRM	-0.08	-0.30	-1.22	-0.71	0.20
Construction Trades Workers	NRM	-0.78	-0.62	-0.92	1.18	1.47
Electrical and Electronic Equipment Mechanics, Installers, and Repairers	NRM	-0.03	-0.69	0.66	0.35	1.14
Fire Fighting and Prevention Workers	NRM	0.22	0.97	0.79	0.16	1.26
Fishing and Hunting Workers	NRM	-1.91	-1.83	-1.70	0.44	1.66
Forest, Conservation, and Logging Workers	NRM	-1.08	-0.73	-0.21	1.46	1.65
Grounds Maintenance Workers	NRM	-1.11	-0.74	-1.46	1.13	1.55
Helpers, Construction Trades	NRM	-0.90	-1.03	-1.93	1.06	1.44
Motor Vehicle Operators	NRM	-0.76	-1.46	-0.68	0.64	1.98
Other Construction and Related Workers	NRM	-0.30	0.04	-0.62	0.72	1.22
Other Installation, Maintenance, and Repair Occupations	NRM	-0.47	-0.70	0.07	0.86	1.38
Other Transportation Workers	NRM	-1.10	-1.17	-0.19	0.15	0.63
Rail Transportation Workers	NRM	-1.08	-0.75	-0.68	1.58	1.74
Supervisors of Farming, Fishing, and Forestry Workers	NRM	-0.64	0.15	-0.53	0.58	1.01
Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	NRM	-0.35	-0.89	-0.34	0.69	1.59
Water Transportation Workers	NRM	-0.70	-0.52	-0.06	0.98	1.96

Source: ACS and authors' calculations. Notes: This table reports task intensities for a list of 3-digit SOC occupations in the ACS dataset and their label following the classification proposed by Acemoglu and Autor (2011).

Table 2.19: Average real hourly earnings by occupation

	Low-paying jobs (Routine-Manual) (1)	High-paying jobs (Non Routine-Manual) (2)	Δ(%) (3)
Overall	11.7	23.4	-69.1
	(1,292,907)	(5,004,528)	
Natives	12.0	23.3	-66.3
	(1,111,453)	(4,448,923)	
Immigrants	10.3	23.9	-84.0
	(181,454)	(555,605)	

Source: ACS and authors' calculation. Notes: This table reports the average hourly wage for workers in low-paying and high-paying jobs. The former refers to jobs in routine-manual occupations. The latter to non-routine-manual occupations. The third column reports the percent wage differences across groups of occupations. Results are based on a sample of male workers who report to be currently employed. The number of observations for each group is reported in parentheses.

2.9.5 Exclusion restrictions

Table 2.20 reports the OLS estimates from regressing migrant characteristics observed at the time of migrating to the US, such as experience, years of schooling, and a dummy for English proficiency, on the unemployment rate, u_c^0, and the unemployment rate forecast errors, $\tilde{u}_c^0$ and $\bar{u}_c^0$, at the time of migrating to the US for both men (columns 1 to 3) and women (columns 4 to 6).

Table 2.20: Correlation between initial unemployment rate and migrant characteristics

	Men			Women		
	experience$_{ic0}$	years of scholing$_{ic0}$	english proficiency$_{ic0}$	experience$_{ic0}$	years of schooling$_{ic0}$	english proficiency$_{ic0}$
	(1)	(2)	(3)	(4)	(5)	(6)
u_c^0	-0.142***	0.066***	0.006***	-0.051	-0.038	0.002
	(0.035)	(0.015)	(0.002)	(0.061)	(0.025)	(0.003)
N. Obs.	38,873	38,873	38,873	14,649	14,649	14,649
$\tilde{u}_c^0$	-0.100	-0.001	0.001	-0.004	-0.052	0.001
	(0.054)	(0.024)	(0.003)	(0.093)	(0.035)	(0.005)
N. Obs.	38,873	38,873	38,873	14,649	14,649	14,649
$\bar{u}_c^0$	-0.038	0.020	0.004	-0.006	-0.024	0.003
	(0.046)	(0.021)	(0.0025)	(0.076)	(0.029)	(0.004)
N. Obs.	38,873	38,873	38,873	14,649	14,649	14,649

Source: ACS and authors' calculations. Notes: This table reports the OLS estimate from regressing the migrant characteristics observed at the time of migrating to the US on the unemployment rate, u_c^0, and the unemployment rate forecast errors, $\tilde{u}_c^0$ and $\bar{u}_c^0$, at the time of migrating to the US for men (columns 1 to 3) and women (columns 4 to 6). The explanatory variables are years of potential experience in the labor market, years of completed schooling, and a dummy variable for proficiency in English. Standard errors in parenthesis are robust. *p<0.10, **p<0.05, ***p<0.01

The unemployment rate correlates with the characteristics of newly arrived migrants, only in the sample of men. Therefore, we expect the OLS estimates of the scarring effect to be biased. Moreover, we expect the bias to be positive since periods of higher unemployment are associated with the migration of better-educated and more English-proficient migrants.

On the other hand, the unemployment forecast error is not correlated with the composition of migrant inflows to the U.S. All coefficients are close to zero, suggesting that migration is exogenous to unpredicted aggregate labor market conditions, hence satisfying the exclusion restrictions.

2.9.6 Non-linearity

Table 2.21: Non-linear effects of unemployment at entry on the labor supply of immigrants

	Annual # Hours			Probability of Unemployment		
Years Since Migration	Expansion (1)	Recession (2)	p-value (3)	Expansion (4)	Recession (5)	p-value (6)
0	0.300	-5.439	0.083	0.001	0.001	0.644
	(-8.680,8.818)	(-16.75,5.027)		(-0.001,0.003)	(-0.001,0.002)	
1-4	-3.485	-4.498	0.707	-0.001	-0.001	0.988
	(-11.80,4.819)	(-13.55, 4.672)		(-0.003,0.000)	(-0.002,0.000)	
5-8	-2.179	-0.912	0.497	-0.001	-0.001	0.553
	(-8.922,4.576)	(-8.282, 6.681)		(-0.003,0.000)	(-0.003,0.000)	
9-12	-5.024	-3.326	0.346	-0.001	-0.001	0.938
	(-11.64,1.658)	(-10.58,4.084)		(-0.003,0.000)	(-0.002,0.001)	
N.Obs.	272			272		
R-sq.	0.600			0.642		

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the annual number of hours worked and a dummy indicator for current unemployment on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results in columns (1) and (2) are based on a sample of male workers who report being currently employed. Results in columns (4) and (5) are based on the full sample of male workers. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

2.9.7 Robustness checks

Table 2.22: Alternative model specifications: Annual Earnings

Years Since Migration	Alternative models (1)	(2)	(3)
0	-0.024 (-0.038,-0.011)	-0.023 (-0.037,-0.010)	-0.055 (-0.073,-0.039)
1-4	-0.018 (-0.029,-0.006)	-0.016 (-0.027,-0.005)	-0.053 (-0.071,-0.036)
5-8	-0.016 (-0.026,-0.006)	-0.011 (-0.022,-0.002)	-0.034 (-0.052,-0.019)
9-12	-0.007 (-0.017,0.004)	-0.003 (-0.013,0.007)	-0.019 (-0.036,-0.004)
N. Obs	272	272	272
Adj.R2	0.77	0.71	0.57
Experience	Cubic	Cubic	Cubic
Schooling	FE	Linear	Linear
Year	FE	FE	Linear

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated annual earnings gap between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Annual earnings gaps are estimated using three alternative models: column (1) refers to a model that includes a third-order polynomial for potential experience, controlling for years of schooling fixed effects and time-fixed effects; column (2) refers to a model that controls for a cubic polynomial in potential experience and time dummies while imposing linearity in the returns from schooling; column (3) refers to a model with a linear time trend while controlling for schooling and experience using a linear and a cubic polynomial, respectively. Results are based on a sample of male workers who report being currently employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.23: Alternative model specifications: Hourly Earnings

Years Since Migration	Alternative models (1)	(2)	(3)
0	-0.023	-0.022	-0.047
	(-0.035,-0.012)	(-0.032,-0.011)	(-0.064,-0.031)
1-4	-0.016	-0.014	-0.047
	(-0.026,-0.005)	(-0.024,-0.004)	(-0.064,-0.032)
5-8	-0.015	-0.011	-0.033
	(-0.025,-0.005)	(-0.021,-0.001)	(-0.048,-0.0181)
9-12	-0.005	-0.001	-0.014
	(-0.015,0.005)	(-0.011,0.009)	(-0.030,0.000)
N. Obs	272	272	272
Adj.R2	0.81	0.72	0.53
Experience	Cubic	Cubic	Cubic
Schooling	FE	Linear	Linear
Year	FE	FE	Linear

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated hourly earnings gap between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Hourly earnings gaps are estimated using three alternative models: column (1) refers to a model that includes a third-order polynomial for potential experience, controlling for years of schooling fixed effects and time-fixed effects; column (2) refers to a model that controls for a cubic polynomial in potential experience and time dummies while imposing linearity in the returns from schooling; column (3) refers to a model with a linear time trend while controlling for schooling and experience using a linear and a cubic polynomial, respectively. Results are based on a sample of male workers who report being currently employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.24: Alternative model specifications: Annual # Hours

Years Since Migration	Alternative models (1)	(2)	(3)
0	-2.871	-3.041	-12.73
	(-13.15,6.998)	(-13.61,7.318)	(-24.95,-0.280)
1-4	-4.398	-4.251	-7.750
	(-12.12,3.607)	(-12.22,4.248)	(-18.42,3.39)
5-8	-2.770	-2.069	-1.759
	(-9.410,3.816)	(-9.235,4.406)	(-11.84,8.313)
9-12	-4.689	-4.140	-6.468
	(-11.23,1.856)	(-11.11,2.604)	(-16.23,3.717)
N. Obs	272	272	272
Adj.R2	0.50	0.51	0.38
Experience	Cubic	Cubic	Cubic
Schooling	FE	Linear	Linear
Year	FE	FE	Linear

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gap in the annual # of hours worked between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Gaps in annual # of hours worked are estimated using three alternative models: column (1) refers to a model that includes a third-order polynomial for potential experience, controlling for years of schooling fixed effects and time-fixed effects; column (2) refers to a model that controls for a cubic polynomial in potential experience and time dummies while imposing linearity in the returns from schooling; column (3) refers to a model with a linear time trend while controlling for schooling and experience using a linear and a cubic polynomial, respectively. Results are based on a sample of male workers who report being currently employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.25: Alternative model specifications: Probability of Unemployment

Years Since Migration	Alternative models (1)	(2)	(3)
0	0.001	0.001	0.003
	(-0.001,0.003)	(-0.001,0.003)	(0.000,0.006)
1-4	-0.001	-0.001	-0.002
	(-0.003,0.000)	(-0.003,0.000)	(-0.005,0.001)
5-8	-0.001	-0.001	-0.002
	(-0.003,0.000)	(-0.003,-0.000)	(-0.005,0.000)
9-12	-0.001	-0.001	-0.002
	(-0.002,0.001)	(-0.002,0.000)	(-0.004,0.001)
N. Obs	272	272	272
Adj.R2	0.58	0.61	0.30
Experience	Cubic	Cubic	Cubic
Schooling	FE	Linear	Linear
Year	FE	FE	Linear

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gap in the probability of being unemployed between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Gaps in the probability of being unemployed are estimated using three alternative models: column (1) refers to a model that includes a third-order polynomial for potential experience, controlling for years of schooling fixed effects and time-fixed effects; column (2) refers to a model that controls for a cubic polynomial in potential experience and time dummies while imposing linearity in the returns from schooling; column (3) refers to a model with a linear time trend while controlling for schooling and experience using a linear and a cubic polynomial, respectively. Results are based on the full sample of male workers. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.26: Heterogeneous Returns to Education and Experience

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.023	-0.023	-3.219	0.000	0.0167
	(-0.042,-0.006)	(-0.037,-0.009)	(-14.11,7.705)	(-0.001,0.002)	(0.009,0.0245)
1-4	-0.016	-0.014	-5.642	-0.002	0.014
	(-0.031,-0.006)	(-0.027,-0.001)	(-14.41,3.102)	(-0.003,-0.000)	(0.008,0.021)
5-8	-0.014	-0.011	-4.577	-0.001	0.007
	(-0.028,-0.006)	(-0.024,0.001)	(-11.65,2.584)	(-0.003,-0.000)	(0.001,0.014)
9-12	-0.009	-0.006	-7.519	-0.001	0.007
	(-0.023,-0.006)	(-0.019,0.007)	(-14.43,-0.566)	(-0.002,0.000)	(0.000,0.013)
N. Obs	272	272	272	272	272
Adj.R2	0.99	0.99	0.95	0.92	0.95

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Immigrant-native gaps are estimated controlling for immigrant-specific returns in years of schooling and overall experience in the labor market. Results are based on a sample of male workers. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.27: Sample of prime-age male workers (25-54 y.o.)

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.028	-0.026	-3.654	0.001	0.019
	(-0.044,-0.014)	(-0.039,-0.014)	(-13.32,6.093)	(-0.001,0.003)	(0.011,0.027)
1-4	-0.020	-0.018	-6.035	-0.001	0.016
	(-0.033,-0.014)	(-0.030,-0.007)	(-14.22,2.178)	(-0.003,0.001)	(0.010,0.022)
5-8	-0.018	-0.017	-2.975	-0.001	.010328
	(-0.030,-0.014)	(-0.028,-0.006)	(-9.941,4.088)	(-.002,.000)	(0.004,0.016)
9-12	-0.009	-0.007	-5.210	-0.001	0.008
	(-0.020,-0.014)	(-0.018,0.004)	(-12.10,1.840)	(-0.002,0.001)	(0.002,0.014)
N. Obs	272	272	272	272	272
Adj.R2	0.79	0.82	0.65	0.60	0.65

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Immigrant-native gaps are estimated using our baseline specification. Results are based on a sample of male workers in their prime working age (25-54 y.o.). 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.28: Sample of immigrants with no U.S. college

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.023	-0.022	-1.598	0.000	0.018
	(-0.037,-0.008)	(-0.033,-0.011)	(-12.07,9.075)	(-0.001,0.002)	(0.010,0.025)
1-4	-0.017	-0.015	-3.543	-0.002	0.016
	(-0.028,-0.006)	(-0.025,-0.005)	(-12.09,4.821)	(-0.003,0.000)	(0.010,0.023)
5-8	-0.016	-0.015	-2.031	-0.001	0.010
	(-0.026,-0.005)	(-0.025,-0.005)	(-9.370,5.241)	(-0.003,0.000)	(0.003,0.016)
9-12	-0.009	-0.007	-3.455	-0.001	0.007
	(-0.019,0.002)	(-0.016,0.003)	(-10.71,3.719)	(-0.003,0.001)	(0.001,0.014)
N. Obs	272	272	272	272	272
Adj.R2	0.80	0.76	0.52	0.64	0.64

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Immigrant-native gaps are estimated using our baseline specification. Results are based on a sample of male natives and immigrants who arrived in the US when they were at least 25 years old. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.29: Selective outmigration weights by country of origin

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.021	-0.020	-2.637	0.001	0.016
	(-0.035,-0.006)	(-0.032,-0.009)	(-12.94,7.647)	(-0.001,0.003)	(0.009,0.024)
1-4	-0.015	-0.013	-4.317	-0.001	0.014
	(-0.026,-.004)	(-0.024,-0.002)	(-11.99,4.182)	(-0.003,0.000)	(0.008,0.020)
5-8	-0.014	-0.013	-2.682	-0.001	0.008
	(-0.023,-0.003)	(-0.024,-0.002)	(-9.04,3.958)	(-0.002,0.000)	(0.002,0.013)
9-12	-0.005	-0.003	-4.887	-0.001	0.006
	(-0.014,0.005)	(-0.014,0.008)	(-11.41,1.796)	(-0.002,0.001)	(0.000,0.0114)
N. Obs	272	272	272	272	272
Adj.R2	0.78	0.81	0.51	0.56	0.66

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the annual number of hours worked and a dummy indicator for current unemployment on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers. Immigrants' weights are corrected to account for selective out-migration using Borjas and Bratsberg (1996) country-specific outmigration rates. 90 %confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.30: Selective outmigration weights by education and skills

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	−0.024	−0.022	−3.490	0.000	0.018
	(-0.037,-0.012)	(-.032,-0.014)	(-14.02,6.733)	(-0.001,0.002)	(0.010,0.026)
1-4	−0.017	−0.015	−5.289	−0.002	0.017
	(-0.027,-0.008)	(-0.024,-0.007)	(-13.84,2.699)	(-0.003,-0.000)	(0.010,0.023)
5-8	−0.017	−0.016	−3.653	−0.002	0.010
	(-0.026,-0.001)	(-0.024,-0.008)	(-10.90,3.483)	(-0.003,-0.000)	(0.004,0.017)
9-12	−0.010	−0.007	−5.826	−0.001	0.008
	(-0.018,-0.002)	(-0.015,0.000)	(-13.12,1.224)	(-0.003,0.000)	(0.002,0.014)
N. Obs	272	272	272	272	272
Adj.R2	0.76	0.84	0.49	0.52	0.65

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the annual number of hours worked and a dummy indicator for current unemployment on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers. Immigrants' weights are corrected to account for selective out-migration using Rho and Sanders (2021) education and skill-specific outmigration rates. 90 %confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.31: Illegal migrants weights

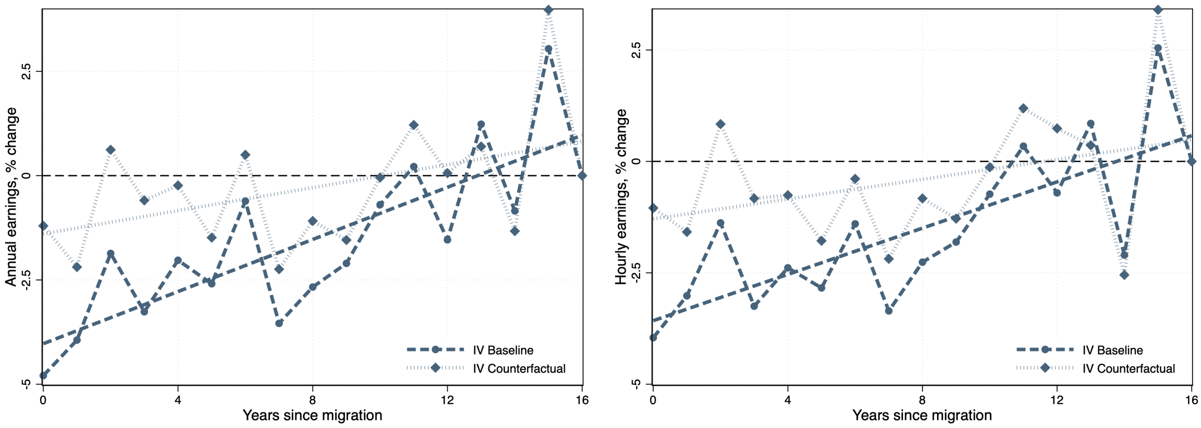
Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	−0.037	−0.037	0.956	0.001	0.025
	(-0.054,-0.020)	(-0.051,-0.023)	(-11.04,12.50)	(-0.001,0.003)	(0.018,0.033)
1-4	−0.027	−0.027	−0.201	−0.002	0.022
	(-0.041,-0.014)	(-0.041,-0.014)	(-10.24,9.211)	(-0.003,-0.000)	(0.015,0.029)
5-8	−0.023	−0.023	0.953	−0.001	0.015
	(-0.036,-0.010)	(-0.037,-0.010)	(-7.862,9.776)	(-0.003,-0.000)	(0.008,0.022)
9-12	−0.010	−0.009	−2.883	−0.001	0.011
	(-0.023,0.002)	(-0.022,0.003)	(-11.63,5.664)	(-0.003,-0.000)	(0.004,0.017)
N. Obs	272	272	272	272	272
Adj.R2	0.78	0.81	0.53	0.53	0.63

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the annual number of hours worked and a dummy indicator for current unemployment on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers. Immigrants' weights are corrected to account for the presence of undocumented workers using Van Hook et al. (2014) and Passel and Cohn (2018) undercount rates. 90 %confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

2.9.8 Counterfactuals

Figure 2.8: Actual VS counterfactual earnings - IV estimates

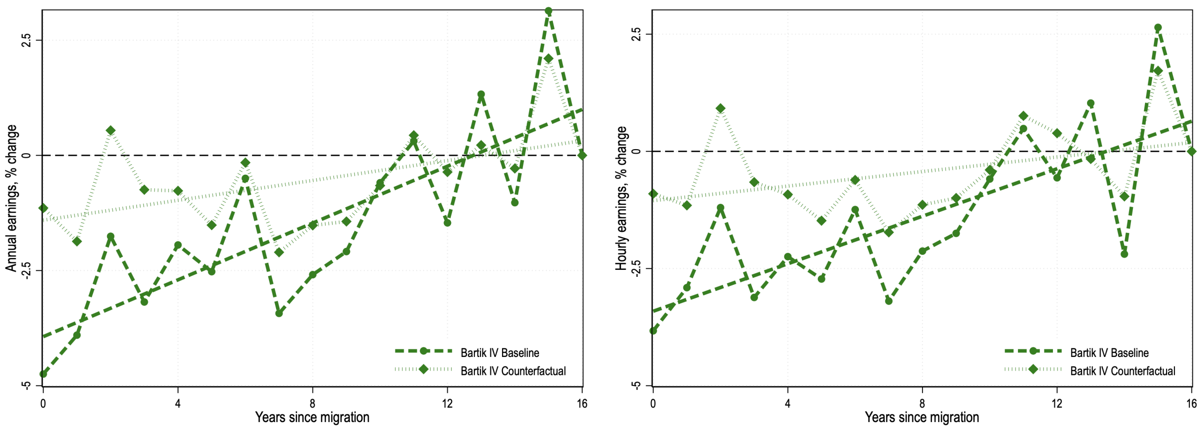
(A) Annual earnings **(B)** Hourly earnings



Source: ACS, FRED and authors' calculation. Notes: The figures show the percent coefficients from regressing estimated annual and earnings gaps between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Both panels are based on a sample of male workers who report to be currently employed. Panel A shows the percent change in the estimated annual earnings gap. Panel B shows the percent change in the estimated hourly earnings gap. In each panel, the dashed lines are constructed using estimates from equation (2.6), while the shaded lines are constructed using the counterfactual estimates as in equation (2.9).

Figure 2.9: Actual VS counterfactual earnings - Bartik-IV estimates

(A) Annual earnings **(B)** Hourly earnings



Source: ACS, FRED and authors' calculation. Notes: The figures show the percent coefficients from regressing estimated annual and earnings gaps between immigrants and the average U.S. natives on the aggregate unemployment forecast error in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Both panels are based on a sample of male workers who report to be currently employed. Panel A shows the percent change in the estimated annual earnings gap. Panel B shows the percent change in the estimated hourly earnings gap. In each panel, the dashed lines are constructed using estimates from equation (**??**), while the shaded lines are constructed using the counterfactual estimates as in equation (2.9).

2.9.9 Heterogeneity

Table 2.32: Female immigrants

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	−0.002	−0.006	5.115	0.002	0.005
	(-0.020,0.018)	(-0.017,0.005)	(-9.841,19.42)	(-0.001,0.006)	(-0.002,0.013)
1-4	−0.002	−0.005	4.130	−0.001	0.006
	(-0.013,0.010)	(-0.013,0.003)	(-4.188,12.46)	(-0.003,0.001)	(0.001,0.011)
5-8	0.002	−0.002	3.572	−0.002	0.006
	(-0.007,0.011)	(-0.009,0.006)	(-3.405,10.52)	(-0.004,-0.001)	(0.001,0.010)
9-12	0.007	0.002	6.176	−0.001	0.006
	(-0.001,0.017)	(-0.005,0.008)	(-0.697,12.82)	(-0.002,0.000)	(0.001,0.010)
N. Obs	272	272	272	272	272
Adj.R2	0.71	0.75	0.79	0.55	0.79

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. All the gaps are estimated using our baseline specification. Results are based on a sample of female workers reporting to be employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.33: Male immigrants without college degrees

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	−0.029	−0.022	−11.59	0.002	0.026
	(-0.049,-0.011)	(-0.035,-0.008)	(-25.30,1.83)	(-0.009,0.005)	(0.014,0.038)
1-4	−0.027	−0.022	−9.656	−0.002	0.027
	(-0.038,-0.015)	(-0.032,-0.010)	(-19.27,0.359)	(-0.004,0.000)	(0.017,0.036)
5-8	−0.019	−0.017	−4.790	−0.002	0.014
	(-0.029,-0.008)	(-0.027,-0.006)	(-13.65,3.561)	(-0.004,0.000)	(0.005,0.023)
9-12	−0.013	−0.010	−7.344	−0.001	0.010
	(-0.024,-0.002)	(-0.020,0.002)	(-15.51,1.081)	(-0.003,0.001)	(0.001,0.019)
N. Obs	272	272	272	272	272
Adj.R2	0.68	0.66	0.52	0.42	0.54

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. All the gaps are estimated using our baseline specification. Results are based on a sample of male immigrants without a college degree. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.34: Male immigrants with college degrees

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.016	-0.021	6.083	0.001	0.004
	(-0.032,0.001)	(-0.037,-0.004)	(-3.047,14.49)	(-0.000,0.003)	(-0.001,0.010)
1-4	-0.004	-0.005	1.490	-0.000	-0.003
	(-0.020,0.013)	(-0.020,0.012)	(-7.326,10.484)	(-0.002,0.001)	(-0.007,0.002)
5-8	-0.009	-0.009	0.695	-0.001	-0.000
	(-0.025,0.007)	(-0.025,0.006)	(-7.036,8.32)	(-0.002,0.001)	(-0.005,0.004)
9-12	0.001	0.001	1.490	-0.000	0.000
	(-0.015,0.016)	(-0.015,0.017)	(-6.119,8.909)	(-0.002,0.001)	(-0.004,0.004)
N. Obs	272	272	272	272	272
Adj.R2	0.69	0.71	0.35	0.37	0.49

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. All the gaps are estimated using our baseline specification. Results are based on a sample of male immigrants with a college degree. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws

Table 2.35: Immigrants from high-income countries

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.001	-0.013	-4.650	0.003	0.003
	(-0.025,0.025)	(-0.036,0.009)	(-22.81,13.54)	(-0.000,0.006)	(-0.005,0.011)
1-4	0.016	-0.002	2.916	0.001	0.003
	(-0.007,0.040)	(-0.024,0.019)	(-10.81,18.198)	(-0.002,0.003)	(-0.004,0.011)
5-8	0.021	0.012	-4.323	0.000	0.001
	(-0.001,0.043)	(-0.008,0.033)	(-17.34,9.685)	(-0.002,0.002)	(-0.006,0.008)
9-12	0.011	0.005	-9.063	0.000	0.003
	(-0.011,0.034)	(-0.016,0.025)	(-22.41,4.156)	(-0.002,0.002)	(-0.004,0.010)
N. Obs	272	272	272	272	272
Adj.R2	0.47	0.45	0.26	0.18	0.22

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. All the gaps are estimated using our baseline specification. Results are based on a sample of male workers. We restrict the immigrant sample to be only composed of immigrants from high-income countries. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.36: Immigrants from low-income countries

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.027	-0.025	-4.374	0.001	0.020
	(-0.042,-0.011)	(-0.037,-0.012)	(-17.43,9.430)	(-0.001,0.002)	(0.011,0.030)
1-4	-0.018	-0.016	-5.336	-0.002	0.017
	(-0.030,-0.007)	(-0.028,-0.004)	(-14.32,4.181)	(-0.003,-0.000)	(0.010,0.024)
5-8	-0.015	-0.0158	-1.596	-0.001	0.009
	(-0.027,-0.005)	(-0.027,-0.004)	(-8.879,5.860)	(-0.003,-0.000)	(0.002,0.016)
9-12	-0.005	-0.004	-3.634	-0.001	0.007
	(-0.016,0.004)	(-0.015,0.007)	(-11.02,3.957)	(-0.002,0.000)	(0.000,0.013)
N. Obs	272	272	272	272	272
Adj.R2	0.76	0.77	0.58	0.57	0.61

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. All the gaps are estimated using our baseline specification. Results are based on a sample of male workers. We restrict the immigrant sample to be only composed of immigrants from low-income countries. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 2.37: Mexicans immigrants

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.040	-0.031	-12.63	-0.001	0.046
	(-0.066,-0.012)	(-0.050,-0.012)	(-31.73,8.291)	(-0.005,0.002)	(0.028,0.064)
1-4	-0.017	-0.018	2.883	-0.005	0.030
	(-0.034,0.001)	(-0.032,-0.003)	(-10.33,16.88)	(-0.007,-0.002)	(0.017,0.044)
5-8	-0.007	-0.008	4.249	-0.005	0.014
	(-0.023,0.010)	(-0.022,0.005)	(-8.260,17.74)	(-0.008,-0.003)	(0.002,0.027)
9-12	-0.006	-0.005	0.444	-0.004	0.012
	(-0.022,0.010)	(-0.018,0.010)	(-11.45,14.03)	(-0.006,-0.002)	(0.000,0.024)
N. Obs	272	272	272	272	272
Adj.R2	0.71	0.60	0.62	0.20	0.46

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing the estimated gaps in annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) between immigrants and natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. All the gaps are estimated using our baseline specification. Results are based on a sample of male workers. We restrict the immigrant sample to be only composed of Mexican immigrants. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

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