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

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Abstract

This paper studies 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 forecast errors for national and local unemployment rates in the US 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 US when the labor market is slack face large and persistent earnings reductions: a 1 p.p. rise in the unemployment rate at the time of migration reduces annual earnings by 3.9 percent on impact and 1.4 percent after 12 years since migration, relative to the average US native. This effect is not homogeneous across migrants: males without a college education from low-income countries are the only ones who suffer a scarring effect in their assimilation path. Change in the employment composition across occupations with different skill contents is the key driver: 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. Slower assimilation costs between 1.7 and 2.5 percent of lifetime earnings to immigrants entering the US labor market when unemployment is high.

Keywords: immigration, earnings assimilation, low-skill jobs, business cycle
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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 face worse career outcomes? If so, what causes immigrants' assimilation to slow down? And what is the overall earnings cost?

We answer these questions in the context of the US 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 US were born in another country, making up almost 14 percent of the overall population (Ward and Batalova, 2023). 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 US in the last three decades entered the labor market during a year with a recession.[1] In this paper, we leverage variation in the US 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

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

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, they have a direct impact on labor market outcomes.

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 statistically 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 US in periods of high unemployment, annual earnings would fall on average by less than one-fourth in the year of entry in the US, 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 the overall costs of the business cycle: using a back-of-the-envelope calculation, we find that unlucky migrants bear an overall earnings cost from entering the US 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 US and suggests a negative long-run trend in the quality of US 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. Chiswick et al. (1997) are among the first to focus on the labor market performance of immigrants and the business cycle in the hosting country. They show that recession harms immigrants on impact but find no evidence of long-term scarring effects. Chiswick and Miller (2002) complement earlier findings and document lower earnings for those who migrate during a period of high unemployment and are fluent in English. They also highlight the importance of living in an area where the concentration of English speakers is high: immigrants who do not, have on average higher earnings losses.

More recent literature has provided a causal link between the economic conditions at entry and the economic assimilation of refugee immigrants.[2] Åslund and Rooth (2007) exploit a refugee settlement policy pursued by the Swedish government during the late 1980s and early 1990s as a source of exogenous variation in the location of migration and study the impact of initial local labor market conditions on the earn-

[2] Fasani et al. (2022) highlights the importance of distinguishing between refugees and economic migrants. They find evidence of a scarring effect of economic downturns on refugee immigrants only when compared to economic migrants.

ings of refugees. They found that entering a labor market during a recession decreases earnings for at least ten years after immigration. Similarly, Azlor et al. (2020) used Danish data to study how labor demand in the initial settlement location affects the employment prospects of refugees. They find that being assigned to a municipality with a one-percentage-point higher employment rate increases the employment probability of refugees by 0.5 percentage points two to four years after arrival in Denmark. Mask (2020) exploits the US Refugee Resettlement program as a source of exogenous variation in the time of migration. He documents that a one-percentage-point increase in the US unemployment rate at the time of entry leads to a 2% decrease in the wages of US refugees after five years. Additionally, the probability of employment declines by around 1.6% during the first five years. Aksoy et al. (2023) leverage a centralized allocation policy in Germany where refugees were exogenously assigned to live in specific counties to show that attitudes towards immigrants are as important as local unemployment rates in shaping refugees' integration outcomes.

The closest paper to ours is Barsbai et al. (2024). They document a negative effect of recessions on the assimilation of migrants in the US comparable to our findings. However, they employ a different identification strategy. They achieve identification by restricting their focus to migrants who are likely to move to the US for family reasons, i.e. family-sponsored migrants: the long and unpredictable waiting time to obtain family-sponsored visas, and the limited time window to move to the US once visas are issued, allows to decouple the migration decision from realized economic conditions at the time of immigration. On the other hand, their identification limits the analysis to a restricted set of countries, i.e. those for which family migration is the dominant mode of migration to the US, de facto excluding the majority of middle and high-income countries.

We deviate from Barsbai et al. (2024) and innovate upon the existing literature with a twofold contribution. First, we provide a new identification strategy that exploits time variation in the unemployment forecast errors at the time of entering the US. Because the forecast errors are unexpected contemporaneous changes in the unemployment rate, they are most likely orthogonal to the composition of immigrants migrating to the US. We show this is the case in the data: forecast errors are uncorrelated with migrants' characteristics at entry, including their countries of origin based on their most common types of migration. While our results are robust to restricting our sample to labor-sponsored migrants, our strategy could be valid for a larger sample of migrants and it allows us 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 we introduce our main econometric framework and discuss the threats to the identification of immigrants' returns to experience in the US. We describe the data source and sample selection and test the exclusion restriction in Section 3. In Section 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 5 we analyze the role of occupational attainment as a plausible mechanism behind our results and conduct several counterfactual exercises. In Section 7 we discuss what are the aggregate earnings costs for immigrants implied by our findings. We conclude in Section 8.

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 US 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 US, i.e. $\forall c \in \{1990, 1991, ..., 2021\}$, we estimate the following regression for immigrants,

$$y^m_{ict} = \alpha + \sum_{x \in \mathcal{X}} \theta_{cx} D^x_{ict} + \gamma \text{educ}_{ict} + f(\text{exp}_{ict}) + \delta_t + \varepsilon_{ict} \tag{1}$$

and the following regression for natives:

$$y^n_{it} = \alpha + \gamma \text{educ}_{it} + f(\text{exp}_{it}) + \delta_t + v_{it} \tag{2}$$

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 US 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 (1) and (2) jointly for each arrival cohort of immigrants, using native workers as the base group.[3] Comparing natives to migrants who belong to cohort c and are observed after x years since their arrival in the US, we obtain an expected gap in outcome y, conditional on years of education and overall experience, equal to

$$\mathbf{E}[y^m_{ict} - y^n_{it} | x] = \theta_{cx}. \tag{3}$$

[3]Specifically, we estimate 31 different models, with the estimation samples being composed of all natives plus immigrants from a given cohort $c = \{1990, ..., 2021\}$.

The parameter θ_{cx} 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 (2015) and Borjas (2018) among others). To estimate equations (1) and (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,[4] assumptions ii) and iii) allow us to obtain closed form solution for the expected gap in equation (3).[5] Therefore we use the OLS estimates of θ_{cx} from equation (1), $\hat{\theta}_{cx}$, as a dependent variable in a second specification:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \mathrm{u}_c^0 + \epsilon_{cx}. \tag{4}$$

In the last equation, μ_c are cohort-of-entry fixed effects, included to capture long-run changes in the similarity of natives and immigrants of different cohorts.[6] μ_x are years since migration fixed effects, which identify the assimilation path for the average cohort of migrants in the sample. Finally, u_c^0 is the US unemployment rate in the year of the arrival of each cohort c, which is interacted with a full set of dummy variables for $x \in \mathcal{X}$ years since migration, D^x.

Given the included fixed effects, the coefficients ω_x capture deviations from the typical assimilation profiles which are related to cohort-specific variation in the unemployment rate at the time of entry in the US labor market. 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 (4) does not account for cohort-specific varia-

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

[5]We relax assumptions ii) and iii) as a robustness check in section 4.1

[6]Albert et al. (2021) document that immigrants from earlier cohorts are on average less similar to natives upon arrival than immigrants from more recent cohorts. This is also the case in our sample — see Figure 9 in Appendix D. Controlling for cohort fixed effects allows us to account for long-run changes in immigrant quality across cohorts, and helps us isolate the cyclical component of assimilation that depends on the unemployment rate at entry.

tion driven by endogenous migration timing which might bias our estimates.

2.1 Threats to identification

Endogenous timing. A major threat to identification is the potential endogeneity of the time of entry in the US. People might postpone their decision to migrate to avoid unfavorable conditions at entry or anticipate it 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 US 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 high-dimensional factor model (Stock and Watson, 2002, 2016). 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. We label it *unemployment shock*. While immigrants could be aware of the unemployment dynamics in the US economy at the time of migration, or whether the US was in an economic recession, the unemployment shocks operate as a surprise to them and are likely to be uncorrelated with their migration decision. This is because the forecast errors capture changes in business cycle conditions above and beyond what could be predicted given past observed macroeconomic factors, including the past unemployment rate.[7] Therefore we re-estimate equation (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, D^x:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \tilde{u}_c^0 + \varepsilon_{cx} \tag{5}$$

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

[7] We report a detailed description and estimates of the factor model in Appendix C.

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

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

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}, i.e.

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

Finally, we re-estimate equation (4) using $\bar{u}_t$ in the year of entry for each cohort c, $\bar{u}_c^0$, interacted with dummies for every year since migration, D^x:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \bar{u}_c^0 + \varepsilon_{cx} \tag{6}$$

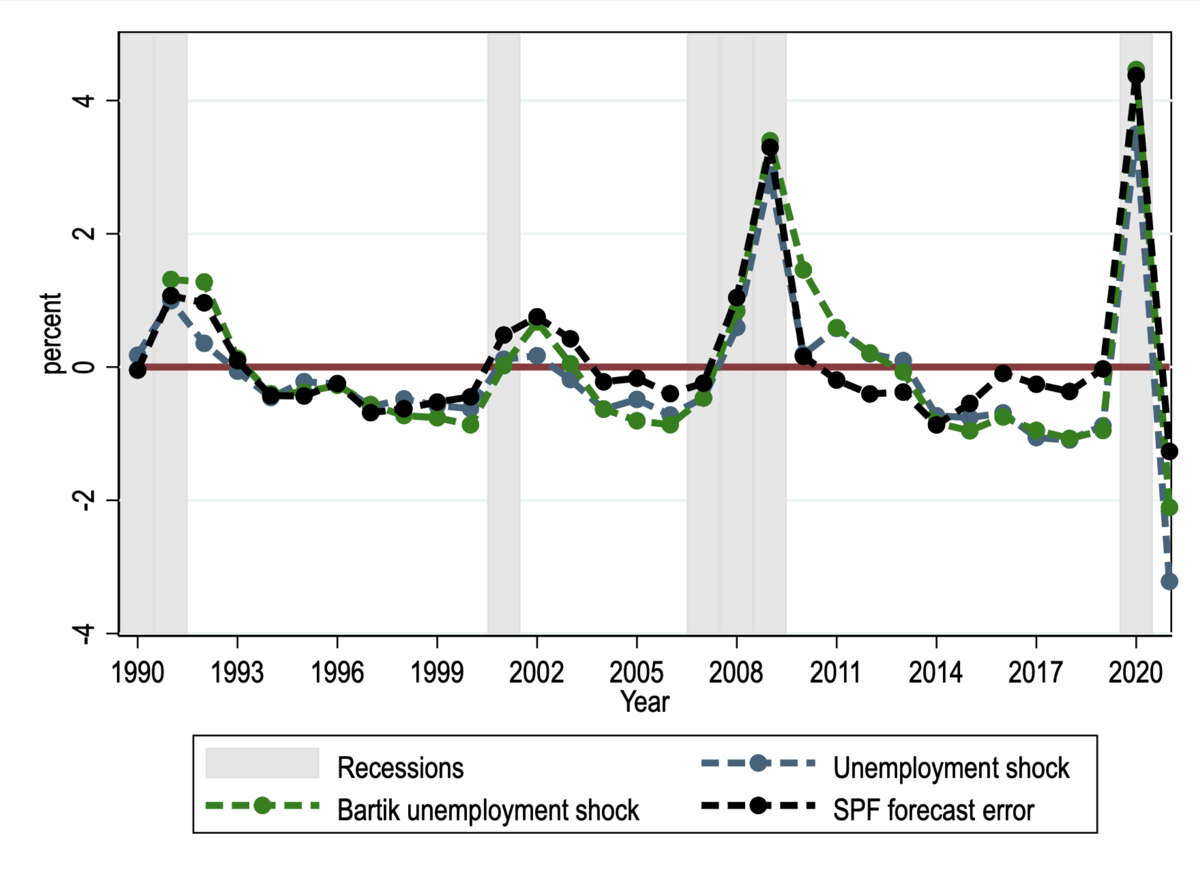
and impose again $\omega_{\bar{x}} = 0$.

Figure 1 reports both types of forecast errors (shocks), $\tilde{u}_c^0$ 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 US.

In addition, both shocks explain a large share of the variation in the realized unemployment rate. Figure 2 scatters the observed unemployment rate against both forecast errors: the R-squared of these relations ranges between 0.45 and 0.52, i.e. between 45% and 52% of the variation in the realized unemployment rate can be explained by the shocks. Such R-squared implies very large F-statistics, i.e. 40.1 and 31.1 respectively, suggesting a strong explanatory power of our instruments.

Notwithstanding their similarities, the aggregate and the Bartik-like unemployment shocks capture different sources of variation. While the former implicitly treats

Figure 1: Unemployment rate shocks

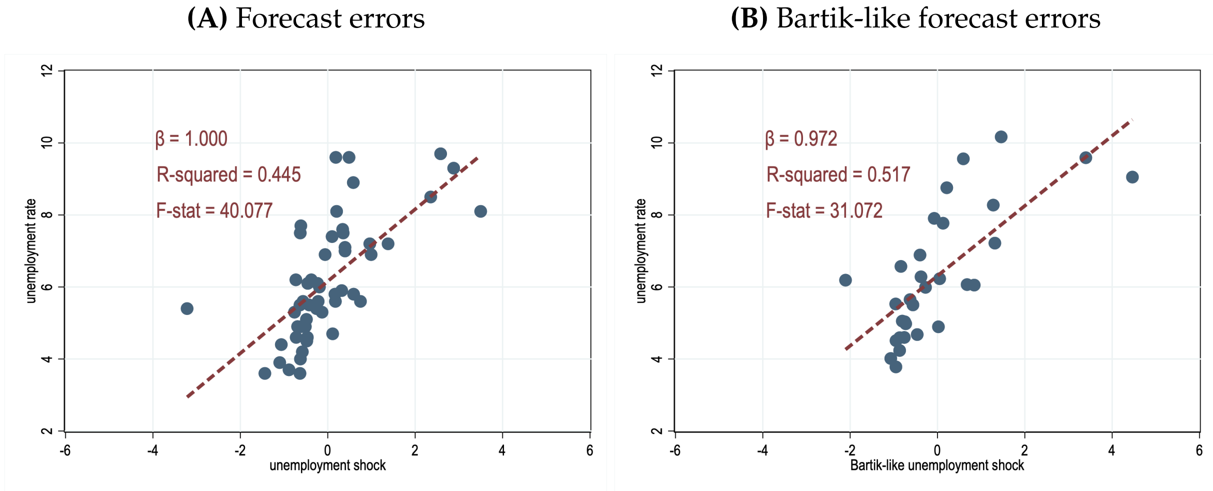


Source: FRED and the Survey of Professional Forecasters. Shaded areas refer to years of recessions according to the NBER Business Cycle Dating. The unemployment shock, $\tilde{u}_t$ is defined as the difference between the realized aggregate unemployment rate and the unemployment forecast obtained using a factor model presented in Appendix C. The Bartik unemployment shock, $\bar{u}_t$ is defined as a weighted average of the state-specific forecast errors, $\bar{u}_{st}$, where the share of employed immigrants observed in state s out of total employed population during 1980, π_{s1980} are used as weights. The SPF forecast error is defined as the difference between the realized aggregate unemployment rate and the unemployment forecast provided by the Survey of Professional Forecasters (SPF).

the entire hosting country as a unique labor market, the latter exploits granularity across states and is independent of permanent state-level characteristics and past state-specific unemployment rates, since both are used in the forecast. To the extent that international migration inflows into the US are heterogeneous across states, the Bartik-like forecast errors are more likely to satisfy the exclusion restrictions (see Table 2 in Section 3). Moreover, because we aggregate state-specific forecast errors using past employment shares of migrants, the Bartik-like unemployment shock does not reflect current changes in population shares across states, hence it is less susceptible to contemporaneous changes in the population of migrants who move across states upon arrival as a result of local labor market conditions (Card, 2001).

Endogenous migration or timing in response to a recession is not contained in the

Figure 2: Unemployment rate vs Forecast errors



Source: ACS, FRED and authors' calculation.

unexpected shocks to the aggregate 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 (4) based on the observed unemployment rate to the results from the models in equation (5) and (6) 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 the estimates would instead inform us about the nature of selection into migration.[8]

Types of migration: family- vs labor-based migrants. The US immigration system allows aliens to obtain lawful permanent residency through three major channels, i.e. i) employer sponsorship, which requires having a job offer from a US employer who acts as a *visa sponsor*, ii) family sponsorship, where a foreign citizen must be sponsored by an immediate relative who is either a US citizen or a permanent resident, or through iii) humanitarian channels, which pertains to asylees or refugees.[9]

Among a million immigrants who obtain a visa every year, family-based migrants

[8]An alternative approach would be to use the unemployment forecast errors as an instrument for the actual endogenous unemployment rate faced by a cohort at the year of migration in equation (4). We focus on reduced-form estimates because the realized unemployment rate and unemployment forecast errors are perfectly collinear, i.e. a one-percent shock in the forecast errors maps into a one-percent shock in the unemployment rate. Specifically, the first stage coefficient is by construction equal to one for the case of $\tilde{u}_c^0$ and the second-stage IV estimates are identical to the reduced form estimates. The first stage coefficient for the case of $\bar{u}_c^0$ is equal to 0.972 (the F-stat is equal to 31.07) — see Figure 2. The second-stage IV estimates are available upon request.

[9]A small portion of visas are also obtained through other channels, like for instance diversity visa lottery (Office of Immigration Statistics, 2019)

are the largest category, about two-thirds, whereas employment-based visas are 13 percent of the total, although about half of these visas are usually allocated to family members of employer-sponsored principal applicants (Gelatt, 2020).

Given the nature of the immigration system in the US, our identification strategy might not be valid for all types of immigrants, and it might work only for specific categories. In particular, while the unemployment forecast errors will be uncorrelated with the decisions of migrating for categories of immigrants with a longer planning horizon, i.e. family-sponsored migrants, this might not always be the case for migrants whose ability to move to the US is tied to the existence of a particular employment spell. Migration inflows of these workers critically depend on employers filing for their visas and on the authorities granting them. To the extent that these two decisions are not based on the expected unemployment rate, but instead, on other economic considerations, short-term fluctuations in labor demand could be captured as "forecast errors", resulting in further selection bias of our estimates.

We address this issue with a twofold strategy. First, in Section 3 we test whether the composition of immigrants at the time of entering the US is uncorrelated with the business cycle. We show that the unemployment forecast errors fully randomize across immigrants' characteristics, as well as with respect to the composition of family- and labor-based migrants. Second, in Section 4 we test our specification over a sample of *non-labor-based* migrants, i.e. we exclude migrants whose decision to migrate is tied to a labor sponsor and compare the estimates to those of the main sample.

Endogeneous selective outmigration. Finally, selective outmigration of immigrants might also be a source of bias when estimating the assimilation profiles using cross-sectional data (Lubotsky, 2007; Akee and Jones, 2019). If outmigration flows were correlated with both the pace of earnings assimilation and the changes in the unemployment rate over the business cycle, our estimates would capture some combination of scarring effects and survivor bias. To address this issue, in Section 4 we conduct a re-balancing exercise. Specifically, we adjust the population weights of immigrants in the first-stage regression using available estimates for the probability of return migration across workers and over the business cycle.

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, the American Community Survey (ACS) selects a 1% sample for every year between 2006 to 2021. 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 US at least in the last three decades, a period when the US 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 US, which we use to compute how many years they spent in the US since migration. Individuals in the ACS also report other demographic characteristics, such as their educational attainment, age, and gender. 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.

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 US 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

Table 1: Natives vs immigrants

Origin	Avg. Yearly Earnings (1)	Avg. Hourly Earnings (2)	Avg. Hours Worked (3)	Avg. Years of Schooling (4)	Avg. Potential Experience (5)	English Proficiency (6)	Observations (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).

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.

Descriptives. Table 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 12 to 15 in Appendix D).

Exclusion restriction. Our identification strategy builds on the assumption that migration patterns 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 US 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 US, hence satisfying the exclusion restrictions.

To test this claim we regress several migrants' characteristics observed at the time of entering the US separately on i) the aggregate unemployment rate, and ii) both unemployment forecast errors. Table 2 reports the OLS estimates.

The results confirm our claims. Immigrants who arrive during high unemploy-

Table 2: Initial unemployment rate and male immigrants characteristics

	Potential Experience$_{ic0}$ (1)	Years of Scholing$_{ic0}$ (2)	English Proficiency$_{ic0}$ (3)	Any child$_{ic0}$ (4)	Household Head$_{ic0}$ (5)	White$_{ic0}$ (6)	Family Migrants$_{ic0}$ (7)	Labor Migrants$_{ic0}$ (8)
u_c^0	-0.077	0.017**	0.004*	0.004*	0.007**	0.001	-0.003	0.010***
	(0.065)	(0.008)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
$\tilde{u}_c^0$	-0.050	0.022*	0.002	-0.000	0.005	0.011**	-0.006	0.008*
	(0.097)	(0.012)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
$\bar{u}_c^0$	0.011	0.017	0.002	-0.000	0.005	-0.000	-0.004	0.005
	(0.091)	(0.011)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
N. Obs.	12453	12453	12453	12453	12453	12453	12453	12453

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 separately 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, categories for years of completed schooling (less than high school, high school, some college, and college and above), a dummy variable for English proficiency, a dummy for any child below 5 years old in the household, a dummy for household heads, a dummy for white race, a dummy for being most-likely family-sponsored migrants, and a dummy for most-likely labor-sponsored migrants. Migrants are classified to be most-likely family-sponsored or most-likely labor-sponsored following Barsbai et al. (2024), Table A.2. Standard errors in parenthesis are robust. Significance level: *p<0.10, **p<0.05, ***p<0.01.

ment 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 arrive when unemployment is lower — see first row in Columns (1) to (3) of Table 2.[10] They are also more likely to be household heads and to have children in the household. 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 Bartik-like unemployment forecast errors — see the third row of Table 2. The estimated coefficients are all small in magnitude and are not statistically significant.

The last two columns of Table 2 report the OLS estimates from regressing indicators for countries of origin based on migration type, i.e. family-based migration and labor-based migration, separately on the unemployment rate and the unemployment rate forecast errors at the time of entering the US.[11] Because the two modes of migration are not exhaustive events, i.e. migrants could be assigned to none of these categories,

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

[11]Migrants are classified to be most likely family-sponsored, most likely labor-sponsored, or other, following Barsbai et al. (2024), Table A.2.

the sum of the coefficients is not equal to 0. While the composition in the population of male migrants changes over the cycle in favor of labor-sponsored immigrants — see the first of Table 2, the Bartik-like forecast errors cannot predict the mode of migrating to the US and satisfies the exclusion restriction along this dimension as well.

The Bartik-like 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.

4 Initial Conditions and Immigrants' Assimilation

We are now ready to discuss the effect of recessions on immigrants' economic assimilation. Figure 3 reports the effects of the unemployment rate at entry in the US on two measures of earnings, such as annual earnings (panel A) and hourly earnings (panel B). Figure 4 reports the effects of the unemployment rate at entry in the US 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 US with the unemployment rate obtained from estimating either equation (4), or equation (5), or equation (6). The red line refers to our baseline estimates based on the unemployment rate. The blue line to reduced-form estimates based on the unemployment shock, while the green line to reduced-form estimates based on the Bartik-like unemployment shock. Tables 3 and 4 report the point estimates for 5 groups of experience in the US (0, 1-4, 5-8, 9-12, and 13-16 years since migration), along with 90% bootstrapped confidence intervals constructed using 1000 draws, clustered by cohort of arrival and years spent in the US.[12]

Annual Earnings. Immigrants' annual earnings are lower than the average US native the higher the unemployment rate at the time of their entry into the US. The effect is large and significant: the estimates from Table 3, column (1) imply that entering the US with a 1 p.p. higher unemployment rate makes annual earnings drop by about 2.5% on impact relative to the average US native. This effect is also persistent and only

[12]Our inference is based on confidence intervals calculated using the wild bootstrap procedure by Cameron et al. (2008).

Figure 3: Unemployment at entry and earnings assimilation of immigrants

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

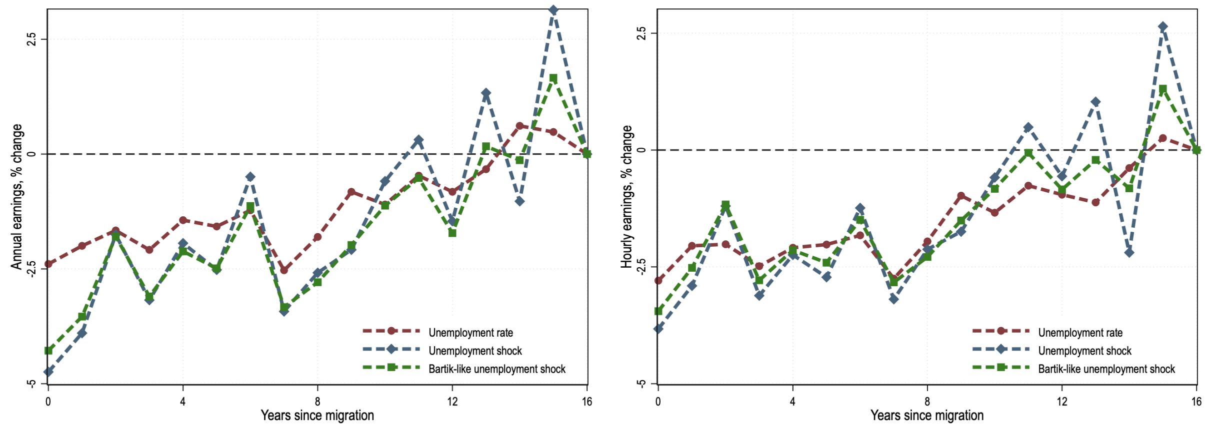
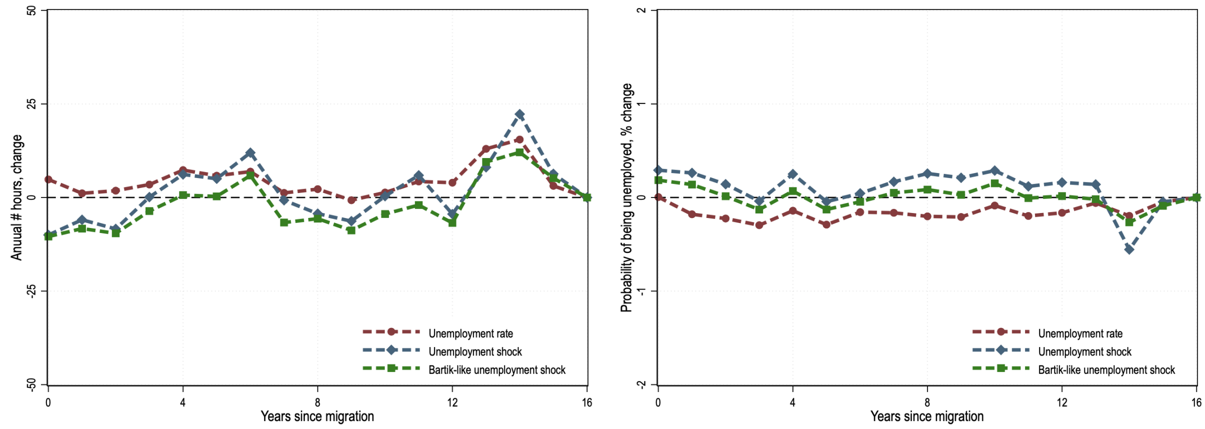


Figure 4: Unemployment at entry and labor supply assimilation of immigrants

(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 US natives on the unemployment rate in the year of entering the US 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 (4). The blue lines refer to the estimates from equation (5). The green lines refer to the estimates from equation (6). First-step regressions are population-weighted.

slowly declines with time spent in the US. The drop in earnings is still significantly large 8 years after entering the US — 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 3.

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.

Reduced-form estimates based on unemployment shocks suggest a very similar picture as our baseline 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 3, a 1 p.p. shock to 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. shock is still associated with an immigrant-native gap in annual earnings of between 2.5% and 3%.

The difference between estimates confirms the existence of a positive correlation between aggregate unemployment rates in the year of migration and the ability of immigrants to assimilate faster. The estimates based on unemployment shocks are larger in magnitude, especially in the first years following entry. This confirms that immigrants with higher potential earnings might be more likely to migrate to the US during periods of high unemployment. This makes our baseline estimates downward biased, and interpretable as a lower bound for the true effect.

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.

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 US native (column (4) of Table 3). This effect is also long-lasting: after 8 years in the US labor market, the gap with the average US native is still

Table 3: Effects of unemployment at entry on earnings of immigrants

	Annual Earnings			Hourly Earnings		
Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(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	272	271	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 US natives on the unemployment rate in the year of entering the US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 4: Effects of unemployment at entry on labor supply of immigrants

	Annual # Hours			Probability of Unemployment		
Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(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 US natives on the unemployment rate in the year of entering the US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

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 US labor market beyond the effect experienced by the average US native, see Columns (1) and (4) of Tables 4. These findings are also confirmed by the estimates based on unemployment shocks 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. (2024), who document a 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 US.

Non-labor-based migrants. We re-estimate our model excluding migrants from countries of origin with predominantly labor migration. As in Section 3, migrants are classified as labor-based following Table A.2 in Barsbai et al. (2024). In Appendix F we report the estimates for annual earnings and hourly earnings (Table 20), annual hours worked and probability of unemployment (Table 21), and probability of working in low-skill jobs (Table 22).

Non-labor-based migrants who face a 1 p.p. shock in the unemployment rate at entry experience a drop in annual earnings of about 4.2% on impact relative to the average US native — see Table 20, column (3). This effect is larger compared to what we document for the entire sample of migrants, i.e. +3.9% on impact — see Table 3, column (3), suggesting that labor migrants might be positively selected over the unemployment cycle, hence introducing a positive (although small) bias in our estimates.

The effect on annual earnings is persistent and slowly declines with time spent in the US. The drop is still significantly large 8 years after entering the US — it is about 2.3% for a 1 p.p. shock in the unemployment rate.

Unlucky cohorts of *non-labor-based migrants* also face slower assimilation in hourly earnings, which reduce on impact by about 2.7 p.p. relative to the average US native — see Table 20, column (6). This effect is also persistent: after 8 years in the US labor market, the gap with the average US native is still large and amounts to 1.6 p.p., and it is fully re-absorbed only by the end of the years of analysis.

Like in the full sample of migrants, we find almost no effect on the assimilation in the labor supply of *non-labor-based migrants*: the probability of being unemployed does not respond to changes in unemployment rates at the time of entry into the US beyond the effect experienced by the average US native, whereas the annual number of hours worked only marginally declines — see Table 21, columns (3) and (6).

Finally, *non-labor-based migrants* entering the US during a recession have a higher probability of working in low-skill jobs, relative to the average US native, both on impact and in the following 12 years. The effect is large and long-lasting: a 1 p.p. shock in the unemployment rate increases the share of immigrants employed in routine-manual occupation by about 3.6% on the spot, and by about 1.21% after 12 years — see Table 22, column (3). Overall our results are robust to the exclusion of migrants from countries of origin with predominantly labor migration from our sample.

Selective outmigration. We tackle the selection bias induced by unobserved outmigration flows by appropriately re-balancing the population weights to jointly account for heterogeneity in outmigration probabilities over the cross-section of migrants and the unemployment cycle.

First, 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 $r_x = (1 + r_1/100)^x - 1$, $\forall x$.

Second, we re-balance the population weights given the observed unemployment fluctuations. To do so, we employ the findings of Bazillier et al. (2017). They document that return migration is counter-cyclical: foreign nationals tend to leave host countries when unemployment is high while they are more likely to stay in good times (i.e. low unemployment). Specifically, they estimate that a 10% increase in the unemployment rate of the hosting country leads to a 3.47% increase in return migration (Appendix 3, Table 7, column 2)

We use their point estimate to correct the weights in the first stage regression, i.e. we multiply the weights by 1 minus $0.347 \times \log u_t$. This adjustment allows us to account for outmigration patterns that differ over the unemployment rate, u_t.

Tables 23 to 25 in Appendix G report the estimation outcomes from this exercise.[13] Controlling for outmigration patterns over the cycle does not alter any of the results, although it reduces the magnitude of the treatment effect. The effect of a 1 p.p. unemployment shock at the entry on annual earnings is -3.7% on impact, instead of -3.9%, and -1% after 12 years, instead of -1.4% — see Table 23, column (3). This suggests that migrants positively self-select themselves into out-migration, i.e. workers who would assimilate faster are more likely to return to their home countries following a recession in the US. While selective out-migration of this kind introduces an *positive survival bias* in the estimates of the scarring effect, the bias seems to be quantitatively negligible to all the outcomes of interest.

4.1 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 H.

Alternative model specifications. In Tables 30 to 33 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 (1) and (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.

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. (2018b), respectively). Failing to control for cross-

[13]In Appendix G, we report the estimation outcomes obtained using weights that account for the heterogeneity in outmigration flows across migrants with different unobserved skills, as in Rho and Sanders (2021).

country heterogeneity in these dimensions could bias our estimates. In Table 34 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.

Immigrants without US college attainment. Our dataset does not contain information that helps us to distinguish whether immigrants obtained their education in the US or another country. If a college degree from a US 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 US when they were at least 25 years old, excluding de facto those immigrants who obtained their degree in the US Table 36 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 US college degree decreases by 2.2% relative to the average US native. This effect is also as persistent as observed using the full sample: after 8 years spent in the US 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.

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 35. 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.

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 who arrived in the US before 2001, 0.11 for immigrants who arrived between 2001 and 2010, and 0.06 for immigrants who arrived in the US later than 2010. Table 37 reports the estimates for this robustness check.

Single regression model. We conduct a robustness exercise to our results by estimating a single equation. We pool natives to immigrants from all cohorts and introduce an interaction between the dummies for years since migration D_{it}^x and the unemployment rate faced in the first year in the US, u_c^0. Specifically, we estimated the following regression:

$$y_{it} = \alpha + \gamma \text{educ}_{it} + f(\text{exp}_{it}) + \delta_{c(it)} + \delta_t + \sum_{x \in \mathcal{X}} \theta_x D_{it}^x + + \sum_{x \in \mathcal{X}} \omega_x D_{it}^x u_{c(it)}^0 + \varepsilon_{ict} \tag{7}$$

where $\delta_{c(it)}$ denote cohort of entry fixed effects; μ_x denotes the gap in y_{it} between an average native and a migrant with x years of experience in the US; ω_x are the marginal effects of entering the US when the unemployment rate is 1 percentage point higher for migrants after x years of experience in the US. All the other variables are the same as in the main specification. Notice that, compared to it, we are now estimating the returns to education γ, the returns to overall experience $f(.)$, and time fixed effects, δ_t using the entire sample of migrants (and natives), instead of estimating those for each cohort of entry in the US.

Table 38 in Appendix H reports the estimation outcomes. Standard errors are robust and are clustered by cohort of arrival and years spent in the US. Despite slight differences in magnitude, the estimates are qualitatively and quantitatively similar to those obtained with a two-step estimation.

Sample restrictions. Finally, we test the robustness of our results to the exclusion of the COVID recession from the sample, and to the inclusion of people living in group quarters, self-employed, and working in the military in the sample. Tables 39 and 40 in Appendix H report the estimation outcomes for both exercises. Results for the five outcomes of interest are all robust to both sample selections.

Table 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 US, 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US. The p-values refer to a F-test of equality between the estimates of expansion and recession.

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 US when unemployment is high could be driven by either source of variations.

To disentangle these two effects we expand equation (4) as follows:

$$\widehat{\theta}_{cx} = \mu_c + \mu_x + \sum_{x \in \mathcal{X}} \omega_x D^x \times \mathrm{u}_c^0 + \sum_{x \in \mathcal{X}} \psi_x D^x \times \mathrm{u}_c^0 \times \iota_c^0 + \epsilon_{cx} \tag{8}$$

where we introduced a triple interaction between a dummy for the number of years x spent in the US, 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 US was subject to a recession, 0 otherwise. We define a recession following the official NBER Business Cycle Dating. The parameter ψ_x in equation (8) 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 5 reports the OLS estimates of equation (8) 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 US 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.[14]

4.2 Re-cap

Taken together, our results suggest that, compared to those who are not, immigrants who are unlucky to enter the US labor market in periods of high unemployment face a much larger discount in earnings relative to the US 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.

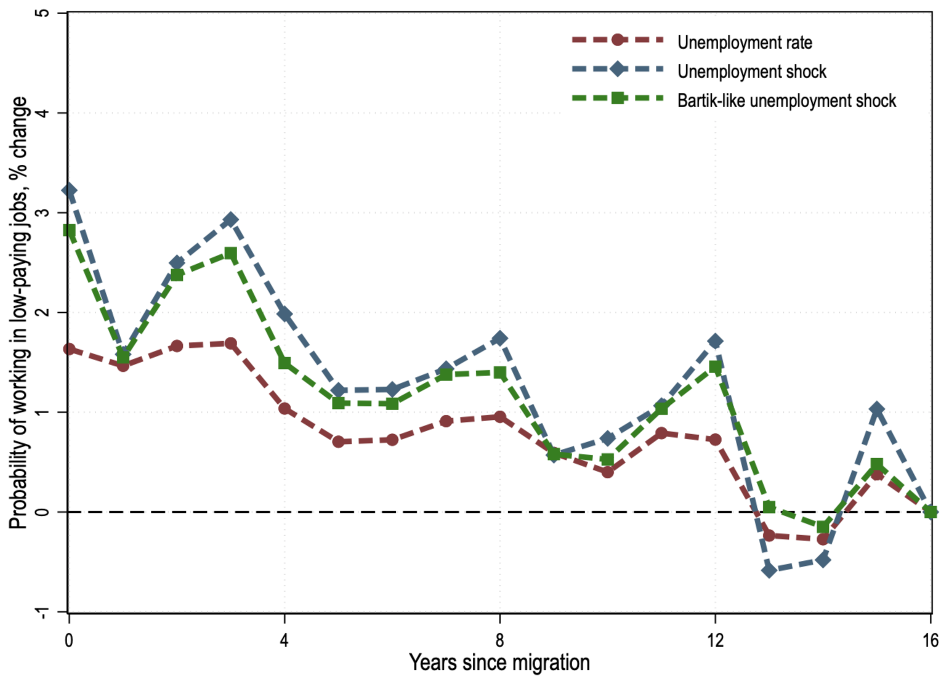
5 The Role of Occupational Attainment

The evidence in Section 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 US 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 US natives can be explained by initial

[14]See Table 41 in Appendix I.

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 5: 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 US 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 (4). The blue lines refer to the estimates from equation (5). The green lines refer to the estimates from equation (6). First-step regressions are population-weighted.

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.[15] This choice is dictated by the large difference in hourly earnings between workers observed in the data (Table 18 in Appendix D). On average workers employed in manual-routine occupations are paid almost 70%

[15]See Appendix B for a detailed description of how we classify occupations.

Table 6: Unemployment at entry and employment in routine-manual jobs

Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

less than the rest. This is true for US natives, whose earnings gap across occupations is on average 67%. And more so for immigrants, whose gap reaches 84%.

Figure 5 reports the effects of the unemployment rate at entry into the US on the probability of being employed in low-skill content occupations for each year since migration. We obtain each point estimate by, i) estimating equations (1) and (2) on a dummy variable taking value 1 if a worker is employed in a low-skill job, and 0 otherwise; 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 (4). The red line refers to our baseline estimation. The blue and green lines refer to the reduced-form estimate based on either type of unemployment shock. Table 6 summarises the estimated effects for 5 groups of experience in the US.

Relative to the average US native, immigrants entering the US 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 — see Column 1 of Table 6. Using the estimates based on the Bartik-like unemployment shock, the effect almost doubles on impact (2.84% for a 1 p.p. shock in the unemployment rate) and it is similar after 12 years since migration (0.7% for 1 p.p. shock in the unemployment rate at entry) — see Column (3) of Table 6. 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:

$$\text{loss}_x = \hat{\omega}_x^{\text{RM}} \Delta \log \bar{w}_x^{\text{imm}} \tag{9}$$

where $\{\hat{\omega}_x^{\text{RM}}\}_{x \in \mathcal{X}}$ are the coefficients reported in Figure 5, 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 5, and because $\left(\log[\bar{w}_x^{\text{non-RM}}] \geq \log[\bar{w}_x^{\text{RM}}]\right)$ — see Table 18, then $\text{loss}_x \geq 0$. Therefore, we obtained counterfactual earnings losses $\hat{\omega}_x^{\text{w},C}$ as:

$$\hat{\omega}_x^{\text{w},C} = \hat{\omega}_x^{\text{w}} - \text{loss}_x \tag{10}$$

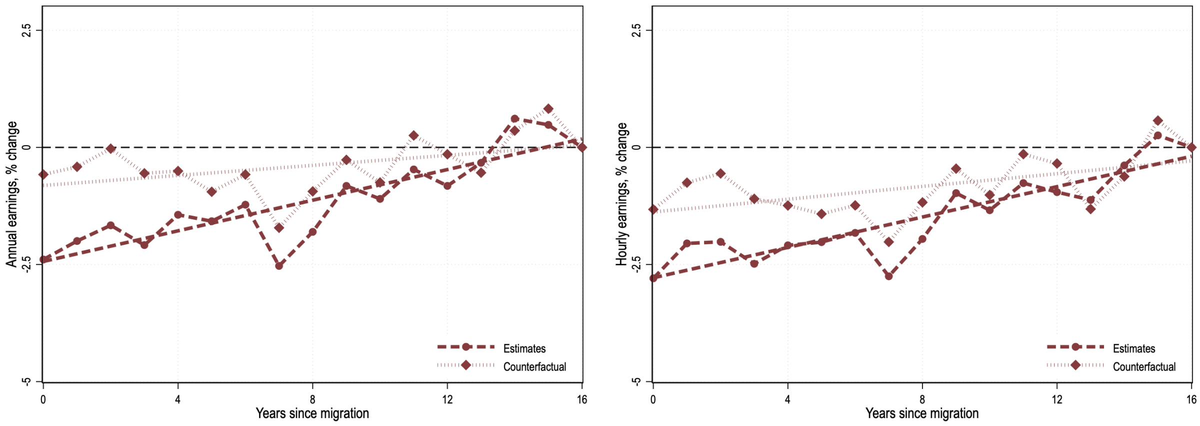
where $\hat{\omega}_x^{\text{w}}$ are the coefficients obtained from estimating equation (4) using annual/hourly earnings as the outcome variable. It follows $\hat{\omega}_x^{\text{w},C}$ can be interpreted as the earnings losses that would arise had the composition of employment across jobs not changed for cohorts of migrants entering the US in periods of high unemployment compared to periods of low unemployment.

Figure 11 reports the results of this exercise and confronts actual and counterfactual annual and hourly earnings losses, using the estimates from equation (4).[16] Were occupational attainment unchanged for immigrants, annual earnings would fall on average by less than one-fourth in the year of entry in the US: the counterfactual drop will be about -0.3% — instead of -2.4%, for a 1 p.p. shock in the unemployment rate

[16] In Appendix J, we report the same figures using the estimates from equations (5) and (6).

Figure 6: 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 US natives on the unemployment forecast error in the year of entering the US 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 (4), while the shaded lines are constructed using the counterfactual estimates as in equation (10). First-step regressions are population-weighted.

(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 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 US 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).

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 US in years of recessions, as documented in Section 4.

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.

Gender. Table 42 in Appendix K 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 7A and 8A 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 US during a recession primarily affects the economic assimilation of men.

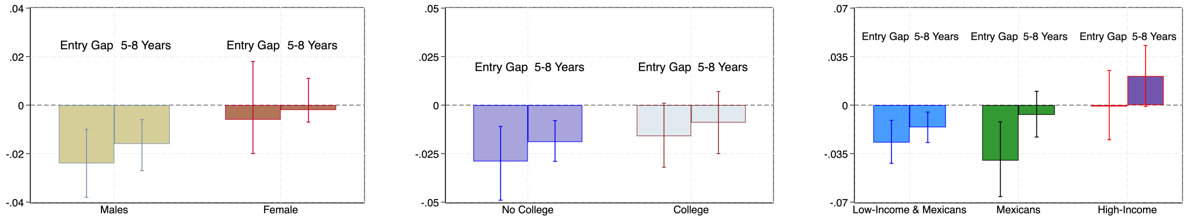
Education. Toussaint-Comeau (2006) documents that earnings assimilation is higher for immigrants with a college education, while convergence to the US natives is modest at best for those with a high-school degree or less. In Tables 43 and 44 in Appendix K we focus on the role of college attainment and distinguish workers with and without a college education. Figures 7B and 8B 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 US 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 43). The effect is persistent even after 12 years in the US 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 US 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.

Country of origin. The returns to experience in the US are heterogeneous across workers from different countries of origin and are higher for workers migrating from high-GDP per capita countries (Lagakos et al., 2018a). We explore this dimension in Tables 45 and 46 in Appendix K where we report OLS estimates for the sub-samples of male immigrants from high- and low-income countries. Figures 7C and 8C 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

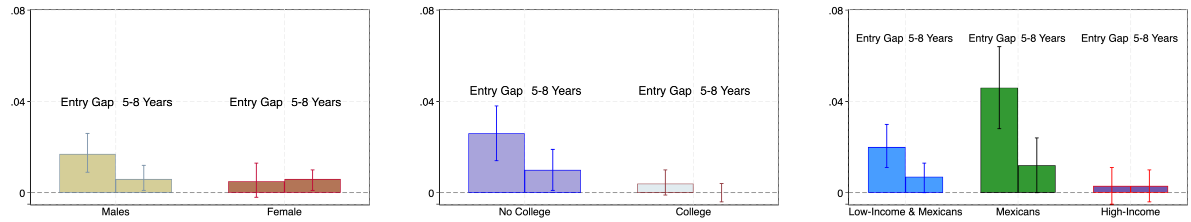
Figure 7: Heterogeneous effect of unemployment at entry on earnings of immigrants



(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 US 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 7A are based on samples of male and female workers. Results in 7B are based on samples of male workers who are either no-college or college-educated. Results in 7C are based on samples of male workers from low-income countries, Mexico, or high-income countries. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Figure 8: 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 US 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 8A are based on samples of male and female workers. Results in 8B are based on samples of male workers who are either no-college or college-educated. Results in 8C are based on samples of male workers from low-income countries, Mexico, or high-income countries. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

US in periods of high unemployment: the loss goes from 6% of their hourly earnings on impact, up to 1.8% after 12 years spent in the US.

Table 47 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 US 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 US, and it is fully re-absorbed thereafter, suggesting a much faster assimilation of Mexicans than other immigrants from comparable countries.

7 Earnings cost of business cycle.

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.

$$\text{NPV} = \sum_{x=0}^{15} \left(\frac{1}{1+r} \right)^{x} \bar{w}_{x}^{\text{imm}} \tag{11}$$

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.[17] Then we use the estimates of equations (4) and (5) on annual earnings, $\hat{\omega}_{x}^{w}$, to construct the net present losses from entering the US with a 1 p.p. shock in the unemployment rate, i.e.

$$\text{NPL} = -\bar{w}^{\text{nat}} \sum_{x=0}^{15} \left(\frac{1}{1+r} \right)^{x} \hat{\omega}_{x}^{w} \tag{12}$$

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

$$100 \times \frac{\text{NPL}}{\text{NPV}} \tag{13}$$

Panel A in Table 7 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 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 7 reports the counterfactual losses that would realized had the occupational change not changed following higher unemployment at the time of entry into the US. We construct it using equation (12) and replacing $\hat{\omega}_{x}^{w}$ with $\hat{\omega}_{x}^{w,C}$, as defined in equation (10). Depending on the specifications, the loss will amount to

[17] This formula implicitly assumes that i) labor supply of immigrant entering the US in recession remains unchanged relative to the average US native, and ii) the difference in annual earnings between migrants and natives has decayed after 15 years since migration. Estimates in Table 3 suggest this is the case.

Table 7: Overall cost of high unemployment for immigrants

NPV (USD)		446,083	
	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)
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 US labor market in a year with 1 p.p. higher unemployment rate. NPL is reported in US 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.

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.

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 US. Earning trajectories of immigrants who migrate in years of high unemployment rates suffer for up to 12 years since migration: 1 p.p. shock to 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 and suggest that the earnings cost of the business cycle fluctuation is likely to be larger once the long-term effects of recessions of immigrants are factored in. 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.

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Appendix A 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.[18]

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.

Appendix B 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 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.

[18] More details can be found in Appendix B.

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:[19]

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

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

  - Interpreting information for others

- Non-routine cognitive interpersonal:
  - Establishing and maintaining personal relationships
  - Guiding, directing, and motivating subordinates
  - Coaching/developing others

- Routine cognitive:
  - Importance of repeating the same tasks
  - Importance of being exact or accurate
  - Structured v. Unstructured work

- Routine manual:
  - Pace determined by speed of equipment
  - Controlling machines and processes
  - Spend time making repetitive motions

- Non-routine manual:
  - Operating vehicles, mechanized devices, or equipment
  - Spend time using hands to handle, control, or feel objects, tools, or controls
  - Manual dexterity
  - Spatial orientation

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 17 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.

Appendix C Unemployment Shocks

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 8 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 8: 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 9 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 9: 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}.

Appendix D Descriptive Statistics

Tables 10 and 11 report selected descriptive statistics for immigrants separately by cohort of arrival to the US.

Table 10: 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)	-	-

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 US Results are based on a sample of male workers who report being currently employed.

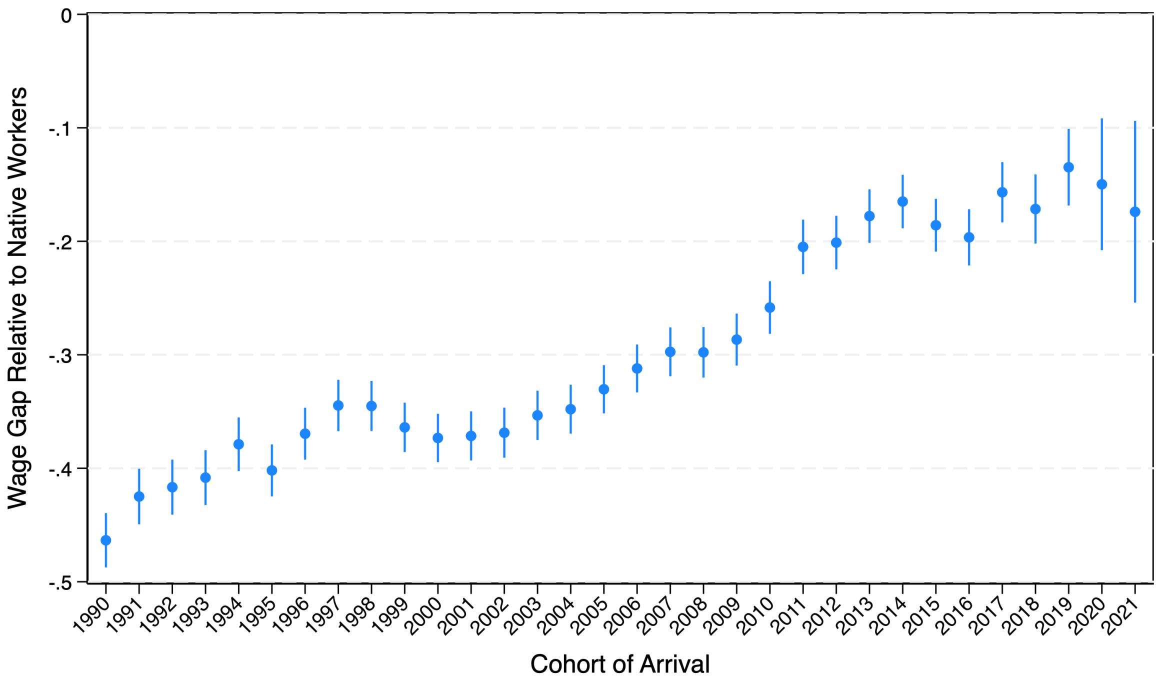
Table 11: Descriptive statistics of immigrants by cohorts of arrival: 2006-2021

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 US Results are based on a sample of male workers who report being currently employed.

Figure 9 displays the estimated cohort fixed effects from 1990 to 2021 obtained from regressing the (log) hourly wages on a set of dummies for the cohort of arrival, a set of dummies for the potential years of experience in the labor market, a set of dummies for the years since migration, a set of dummies for the years of education and a linear trend in time. Results are based on a sample of male workers reporting to be currently employed. Regressions are population-weighted.[20]

Figure 9: Cohort Effects: 1990-2021



Source: ACS and authors' calculation.

The estimated cohort fixed effects can be interpreted as the average wage gap of immigrants belonging to a specific cohort of entry in the US relative to the average native workers. Figure 9 shows that the average wage gap is lower for the more recent cohorts (about 20% for those entering in 2020, against 40% for those entering in 1990. This evidence confirms and extends the finding of Albert et al. (2021), who documents that immigrants from earlier cohorts are on average less similar to natives upon arrival than immigrants from more recent cohorts. Because our treatment varies only across cohorts, failing to control for cohort fixed effects would make the estimated treatment effects biased by its long-run trend.

[20]To break the collinearity between years since migration, cohort of arrival, and time of the observation, we follow Borjas (2015) and assume no differences in a linear time trend between immigrants and natives. In this specification, we also assume no differences in returns to experience and education between immigrants and natives.

Tables 12 to 14 compare selected descriptive statistics between natives and immigrants separately for the sample of women, non-college workers, and college workers.

Table 12: 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 13: 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 14: 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.

Tables 15 compare selected descriptive statistics between immigrants from low-income countries, Mexicans, and high-income countries. Table 16 reports the share of unemployed and the share of workers employed in routine-manual occupations, separately for natives and immigrants, and across demographics.

Table 15: 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 16: 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 17: 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 18 reports the average real hourly earnings for workers in routine-manual and non-routine-manual occupations, separately for natives and immigrants.

Table 18: Average real hourly earnings by occupation

	Low-paying jobs (Routine-Manual)	High-paying jobs (Non Routine-Manual)	Δ(%)
	(1)	(2)	(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.

Appendix E Exclusion restrictions

Table 19 reports the OLS estimates from regressing migrant characteristics observed at the time of migrating to the US, separately 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 and women.

Table 19: Initial unemployment rate and immigrants characteristics

	Potential Experience$_{ic0}$ (1)	Years of Scholing$_{ic0}$ (2)	English Proficiency$_{ic0}$ (3)	Any child$_{ic0}$ (4)	Household Head$_{ic0}$ (5)	White$_{ic0}$ (6)	Family Migrants$_{ic0}$ (7)	Labor Migrants$_{ic0}$ (8)
					Males			
u_c^0	-0.077	0.017**	0.004*	0.004*	0.007**	0.001	-0.003	0.010***
	(0.065)	(0.008)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
$\tilde{u}_c^0$	-0.050	0.022*	0.002	-0.000	0.005	0.011**	-0.006	0.008*
	(0.097)	(0.012)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
$\bar{u}_c^0$	0.011	0.017	0.002	-0.000	0.005	-0.000	-0.004	0.005
	(0.091)	(0.011)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
N. Obs.	12453	12453	12453	12453	12453	12453	12453	12453
					Females			
u_c^0	-0.164*	0.004	-0.002	0.004	0.001	-0.004	0.004	0.002
	(0.096)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
$\tilde{u}_c^0$	-0.196	0.002	-0.002	0.002	-0.007	0.002	0.007	-0.002
	(0.127)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
$\bar{u}_c^0$	-0.151	0.002	-0.002	0.003	-0.006	-0.009	0.006	-0.003
	(0.116)	(0.005)	(0.004)	(0.004)	(0.00546)	(0.006)	(0.005)	(0.006)
N. Obs.	6459	6459	6459	6459	6459	6459	6459	6459

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 separately 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, categories for years of completed schooling (less than high school, high school, some college, and college and above), a dummy variable for English proficiency, a dummy for any child below 5 years old in the household, a dummy for household heads, a dummy for white race, a dummy for being most-likely family-sponsored migrants, and a dummy for most-likely labor-sponsored migrants. Migrants are classified to be most-likely family-sponsored or most-likely labor-sponsored following Barsbai et al. (2024), Table A.2. Standard errors in parenthesis are robust. Significance level: *p<0.10, **p<0.05, ***p<0.01.

Appendix F Non-labor migrants

In Tables 20 to 22 we report the estimation outcomes excluding migrants from countries of origin with predominantly labor migration as in Barsbai et al. (2024).

Table 20: Effects of unemployment at entry on earnings of non-labor migrants

	Annual Earnings			Hourly Earnings		
Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)	(4)	(5)	(6)
0	-0.027	-0.049	-0.042	-0.020	-0.031	-0.027
	(-0.043,-0.011)	(-0.080,-0.017)	(-0.066,-0.018)	(-0.031,-0.008)	(-0.057,-0.005)	(-0.044,-0.010)
1-4	-0.022	-0.039	-0.032	-0.018	-0.023	-0.018
	(-0.034,-0.010)	(-0.063,-0.013)	(-0.049,-0.015)	(-0.029,-0.007)	(-0.049, 0.003)	(-0.035,-0.002)
5-8	-0.014	-0.025	-0.023	-0.013	-0.018	-0.016
	(-0.025,-0.003)	(-0.048,-0.002)	(-0.037,-0.008)	(-0.023,-0.002)	(-0.044,0.007)	(-0.031,-0.001)
9-12	-0.004	-0.007	-0.007	-0.001	0.002	0.002
	(-0.014,0.008)	(-0.030,0.016)	(-0.021,0.008)	(-0.011,0.009)	(-0.023,0.028)	(-0.014,0.018)
N.Obs.	272	272	271	272	272	271
R-sq.	0.77	0.77	0.77	0.77	0.77	0.77

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 US native on the unemployment rate in the year of entering the US 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. We exclude migrants from countries of origin with predominantly labor migration. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 21: Effects of unemployment at entry on labor supply of non-labor migrants

	Annual # Hours			Probability of Unemployment		
Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)	(4)	(5)	(6)
0	-10.36	-32.27	-25.51	0.002	0.003	0.002
	(-24.12,2.699)	(-56.24,-5.339)	(-45.94,-6.064)	(-0.001,0.004)	(-0.002,0.007)	(-0.001,0.005)
1-4	-7.673	-24.97	-20.87	-0.002	0.002	0.001
	(-16.81,0.834)	(-43.68,-7.244)	(-33.08,-8.647)	(-0.004,-0.000)	(-0.001,0.006)	(-0.001,0.004)
5-8	-4.029	-12.99	-11.97	-0.002	0.001	0.001
	(-11.80,3.120)	(-29.00,2.987)	(-22.26,-1.531)	(-0.004,-0.000)	(-0.003,0.005)	(-0.002,0.003)
9-12	-4.936	-15.20	-13.75	-0.001	0.003	0.001
	(-12.67,2.284)	(-30.05,0.867)	(-24.30,-3.800)	(-0.003,0.000)	(-0.001,0.006)	(-0.001,0.004)
N.Obs.	272	272	271	272	272	271
R-sq.	0.58	0.59	0.58	0.60	0.57	0.57

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 US native on the unemployment rate in the year of entering the US 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. We exclude migrants from countries of origin with predominantly labor migration. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 22: Unemployment at entry and employment in routine-manual jobs of non-labor migrants

Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)
0	0.022	0.044	0.036
	(0.012,0.032)	(0.030,0.062)	(0.025,0.047)
1-4	0.019	0.028	0.023
	(0.012,0.027)	(0.016,0.041)	(0.014,0.032)
5-8	0.010	0.017	0.012
	(0.003,0.017)	(0.005,0.030)	(0.004,0.020)
9-12	0.006	0.010	0.007
	(-0.001,0.013)	(-0.001,0.022)	(-0.001,0.015)
N.Obs.	272	272	271
R-sq.	0.63	0.62	0.63

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 US 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. We exclude migrants from countries of origin with predominantly labor migration. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Appendix G Selective out-migration

In Tables 23 to 25 we report the estimation outcomes obtained using weights in the first-stage regression that are corrected for the probability of return migration across migrants (Borjas and Bratsberg, 1996) and over the unemployment cycle (Bazillier et al., 2017).

Table 23: Effects of unemployment at entry on earnings of immigrants with re-balanced weights I

	Annual Earnings			Hourly Earnings		
Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)	(4)	(5)	(6)
0	-0.021	-0.045	-0.037	-0.019	-0.038	-0.031
	(-0.034,-0.009)	(-0.066,-0.025)	(-0.052,-0.023)	(-0.032,-0.007)	(-0.060,-0.016)	(-0.046, -0.016)
1-4	-0.016	-0.030	-0.024	-0.013	-0.025	-0.019
	(-0.028,-0.004)	(-0.051,-0.010)	(-0.039,-0.010)	(-0.026,-.002)	(-0.048,-0.004)	(-0.035,-0.004)
5-8	-0.016	-0.027	-0.024	-0.014	-0.024	-0.020
	(-0.027,-0.005)	(-0.048,-0.008)	(-0.039,-0.011)	(-0.026,-0.003)	(-0.047,-0.003)	(-0.036, -0.005)
9-12	-0.006	-0.012	-0.010	-0.003	-0.008	-0.006
	(-0.017,0.005)	(-0.032,0.008)	(-0.025,0.004)	(-0.016,0.008)	(-0.030,0.014)	(-0.022,0.009)
N.Obs.	272	272	271	272	272	271
R-sq.	0.82	0.82	0.82	0.83	0.83	0.83

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing estimated the annual and hourly earnings gap between immigrants and the average US native on the unemployment rate in the year of entering the US 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. First-step regressions are population-weighted. Immigrants' weights are corrected to account for selective out-migration using Borjas and Bratsberg (1996) country-specific outmigration rates and Bazillier et al. (2017) estimates of return migration over the business cycle. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 24: Effects of unemployment at entry on labor supply of immigrants with re-balanced weights I

	Annual # Hours			Probability of Unemployment		
Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)	(4)	(5)	(6)
0	-3.784	-15.67	-13.79	0.002	0.006	0.004
	(-12.63,3.833)	(-31.46,-0.688)	(-25.04,-3.727)	(0.001,0.004)	(0.002,0.009)	(0.002,0.007)
1-4	-4.988	-9.114	-8.877	-0.000	0.005	0.003
	(-12.36,2.335)	(-23.80,6.493)	(-18.89,1.387)	(-0.002,0.001)	(0.002,0.008)	(0.001,0.009)
5-8	-3.745	-7.742	-8.788	-0.000	0.004	0.002
	(-11.09,3.258)	(-22.49,6.456)	(-18.50,0.867)	(-0.002,0.001)	(0.001,0.007)	(0.000,0.004)
9-12	-5.085	-7.147	-9.004	0.000	0.005	0.003
	(-12.55,1.821)	(-22.12,7.244)	(-19.12,0.498)	(-0.001,0.002)	(0.001,0.008)	(0.001,0.005)
N.Obs.	272	272	271	272	272	271
R-sq.	0.27	0.28	0.28	0.57	0.54	0.55

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated from regressing the estimated gaps in the annual number of hours worked and in the probability of being unemployed between immigrants and the average US native on the unemployment rate in the year of entering the US 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. First-step regressions are population-weighted. Immigrants' weights are corrected to account for selective out-migration using Borjas and Bratsberg (1996) country-specific outmigration rates and Bazillier et al. (2017) estimates of return migration over the business cycle. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 25: Unemployment at entry and employment in routine-manual jobs with rebalanced weights I

Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)
0	0.013	0.030	0.024
	(0.010,0.021)	(0.018,0.042)	(0.016,0.033)
1-4	0.013	0.022	0.017
	(0.010,0.019)	(0.011,0.032)	(0.010,0.025)
5-8	0.007	0.013	0.010
	(0.001,0.013)	(0.002,0.023)	(0.003,0.017)
9-12	0.005	0.010	0.010
	(-0.000,0.011)	(0.000,0.020)	(0.000,0.014)
N.Obs.	272	272	271
R-sq.	0.72	0.73	0.73

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated 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 US 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. First-step regressions are population-weighted. Immigrants' weights are corrected to account for selective out-migration using Borjas and Bratsberg (1996) country-specific outmigration rates and Bazillier et al. (2017) estimates of return migration over the business cycle. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

As a complementary 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 26. Similar to the first robustness check, we convert the decennial probabilities into annual ones and compound them for every year since migration, separately by education level and by deciles in the residual wage distribution. We retrieve residualized wages for immigrants by constructing residuals from the following regression:

Table 26: 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.

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

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 US and δ_t are time dummies.

As a final step, we adjust the weights by the excess return migration rates over the business cycle and multiply them by 1 minus $0.347 \times \log u_t$. In Tables 27 to 29 we report the estimation outcomes from this exercise.

Table 27: Effects of unemployment at entry on earnings of immigrants with re-balanced weights II

Years since Migration	Annual Earnings			Hourly Earnings		
	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)	(4)	(5)	(6)
0	-0.024	-0.049	-0.040	-0.022	-0.040	-0.033
	(-0.035,-0.014)	(-0.067,-0.031)	(-0.052,-0.028)	(-0.032,-0.012)	(-0.060,-0.021)	(-0.046,-0.020)
1-4	-0.019	-0.033	-0.027	-0.016	-0.027	-0.021
	(-0.029,-0.010)	(-0.051, -0.016)	(-0.038, -0.015)	(-0.026,-0.007)	(-0.047,-0.008)	(-0.034, -0.008)
5-8	-0.019	-0.031	-0.026	-0.017	-0.027	-0.022
	(-0.028,-0.011)	(-0.048,-0.014)	(-0.037,-0.016)	(-0.027,-0.008)	(-0.046,-0.008)	(-0.034,-0.009)
9-12	-0.010	-0.017	-0.015	-0.007	-0.012	-0.010
	(-0.019,-0.002)	(-0.035,-0.000)	(-0.025,-0.004)	(-0.016,0.002)	(-0.032,0.007)	(-0.022,0.003)
N.Obs.	272	272	271	272	272	271
R-sq.	0.85	0.85	0.85	0.87	0.86	0.87

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing estimated the annual and hourly earnings gap between immigrants and the average US native on the unemployment rate in the year of entering the US 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. First-step regressions are population-weighted. Immigrants' weights are corrected to account for selective out-migration using Rho and Sanders (2021) skill-specific outmigration rates and Bazillier et al. (2017) estimates of return migration over the business cycle. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 28: Effects of unemployment at entry on labor supply of immigrants with re-balanced weights II

Years since Migration	Annual # Hours			Probability of Unemployment		
	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)	(4)	(5)	(6)
0	-5.061	-17.44	-15.16	-0.001	-0.005	-0.004
	(-13.86,2.935)	(-32.89,-2.810)	(-25.91,-4.779)	(-0.003,0.001)	(-0.007,-0.003)	(-0.006,-0.003)
1-4	-6.389	-11.08	-10.43	0.001	-0.003	-0.002
	(-14.06,1.425)	(-25.59,4.225)	(-20.55,-0.377)	(-0.001,0.002)	(-0.005,-0.000)	(-0.003,-0.000)
5-8	-5.166	-9.801	-10.49	0.001	-0.001	-0.001
	(-12.60,1.916)	(-24.21,4.238)	(-20.16, -0.881)	(0.001,0.002)	(-0.003,0.001)	(-0.002,0.001)
9-12	-6.472	-10.47	-11.54	0.001	-0.002	-0.002
	(-13.97,0.838)	(-25.44, 3.771)	(-21.91, -2.239)	(-0.001,0.002)	(-0.004,0.000)	(-0.003,-0.000)
N.Obs.	272	272	271	272	272	271
R-sq.	0.24	0.24	0.25	0.63	0.63	0.63

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated from regressing the estimated gaps in the annual number of hours worked and in the probability of being unemployed between immigrants and the average US native on the unemployment rate in the year of entering the US 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. First-step regressions are population-weighted. Immigrants' weights are corrected to account for selective out-migration using Rho and Sanders (2021) skill-specific outmigration rates and Bazillier et al. (2017) estimates of return migration over the business cycle. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 29: Unemployment at entry and employment in routine-manual jobs with re-balanced weights II

Years since Migration	Unemployment Rate	Unemployment Shock	Bartik-like Unemployment Shock
	(1)	(2)	(3)
0	0.016	0.032	0.026
	(0.008,0.024)	(0.019,0.045)	(0.017,0.035)
1-4	0.016	0.023	0.019
	(0.009,0.022)	(0.011,0.035)	(0.010,0.027)
5-8	0.010	0.014	0.011
	(0.003,0.016)	(0.003,0.026)	(0.004,0.019)
9-12	0.007	0.011	0.008
	(0.001,0.014)	(0.000,0.022)	(0.001,0.015)
N.Obs.	272	272	271
R-sq.	0.73	0.73	0.73

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated 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 US 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. First-step regressions are population-weighted. Immigrants' weights are corrected to account for selective out-migration using Rho and Sanders (2021) skill-specific outmigration rates and Bazillier et al. (2017) estimates of return migration over the business cycle. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Appendix H Robustness checks

Table 30: Alternative model specifications: Annual Earnings

Years Since Migration	Alternative models (1)	(2)	(3)
0	-0.024	-0.023	-0.055
	(-0.038,-0.011)	(-0.037,-0.010)	(-0.073,-0.039)
1-4	-0.018	-0.016	-0.053
	(-0.029,-0.006)	(-0.027,-0.005)	(-0.071,-0.036)
5-8	-0.016	-0.011	-0.034
	(-0.026,-0.006)	(-0.022,-0.002)	(-0.052,-0.019)
9-12	-0.007	-0.003	-0.019
	(-0.017,0.004)	(-0.013,0.007)	(-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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 31: Alternative model specifications: Hourly Earnings

Years Since Migration	Alternative models (1)	(2)	(3)
0	-0.023 (-0.035,-0.012)	-0.022 (-0.032,-0.011)	-0.047 (-0.064,-0.031)
1-4	-0.016 (-0.026,-0.005)	-0.014 (-0.024,-0.004)	-0.047 (-0.064,-0.032)
5-8	-0.015 (-0.025,-0.005)	-0.011 (-0.021,-0.001)	-0.033 (-0.048,-0.0181)
9-12	-0.005 (-0.015,0.005)	-0.001 (-0.011,0.009)	-0.014 (-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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 32: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 33: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 34: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 35: 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 US 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.). First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 36: Sample of immigrants with no US 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 37: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 38: One-regression model

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**	-0.023***	-2.377	0.000	0.017***
	(0.010)	(0.006)	(8.363)	(0.001)	(0.006)
1-4	-0.017**	-0.016***	-3.535	-0.002*	0.015***
	(0.006)	(0.005)	(6.080)	(0.001)	(0.004)
5-8	-0.015**	-0.014***	-2.522	-0.002*	0.009*
	(0.006)	(0.005)	(5.816)	(0.001)	(0.004)
9-12	-0.007	-0.005	-3.714	-0.001	0.005
	(0.006)	(0.005)	(5.943)	(0.001)	(0.004)
N. Obs	6,017,868	6,017,868	6,018,533	6,305,963	6,016,605
Adj.R2	0.33	0.32	0.06	0.01	0.11

Source: ACS, FRED and authors' calculation. Notes: This table reports the estimated coefficients from regressing annual wages (column 1), hourly wages (column 2), annual hours (column 3), and probability of being unemployed (column 4) 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 pooled sample of male natives and immigrants. Standard errors (in parenthesis) are clustered by cohort of arrival and years spent in the US. Significance level: *p<0.10, **p<0.05, ***p<0.01

Table 39: Sample including workers observed in years 2006-2019 (no COVID-19 years)

Years Since Migration	Annual Earnings (1)	Hourly Earnings (2)	Annual # Hours (3)	Probability of Unemployment (4)	Probability of low-paying jobs (5)
0	-0.025	-0.026	-1.144	0.001	0.017
	(-0.040,-0.010)	(-0.037,-0.015)	(-11.60,8.966)	(-0.001,0.002)	(0.010,0.025)
1-4	-0.017	-0.015	-4.121	-0.002	0.016
	(-0.029,-0.006)	(-0.025,-0.005)	(-12.51,4.621)	(-0.003,-0.001)	(0.009,0.022)
5-8	-0.016	-0.015	-2.952	-0.002	0.008
	(-0.026,-0.006)	(-0.025,-0.005)	(-9.671,4.195)	(-0.002,-0.000)	(0.002,0.015)
9-12	-0.008	-0.008	-2.515	-0.001	0.005
	(-0.018,0.002)	(-0.018,0.002)	(-9.089,4.234)	(-0.002,-0.000)	(-0.002,0.010)
N. Obs	238	238	238	238	238
Adj.R2	0.78	0.80	0.61	0.68	0.67

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 for the years 2006-2019. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Rademacher draws clustered by cohort of arrival and years spent in the US.

Table 40: Sample including workers in group quarters, self-employed, and military

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	−0.031	−2.744	0.000	0.015
	(-0.039,-0.019)	(-0.044,-0.019)	(-12.45,6.894)	(-0.002,0.002)	(0.008,0.023)
1-4	−0.020	−0.022	−5.242	−0.002	0.015
	(-0.030,-0.010)	(-0.034,-0.012)	(-12.74,2.253)	(-0.004,-0.001)	(0.009,0.021)
5-8	−0.019	−0.021	−3.856	−0.002	0.008
	(-0.029,-0.010)	(-0.031,-0.011)	(-10.55,2.564)	(-0.004,-0.001)	(0.003,0.014)
9-12	−0.011	−0.030	−4.583	−0.002	0.007
	(-0.020,-0.001)	(-0.023,-0.003)	(-11.44,1.888)	(-0.003,-0.000)	(0.002,0.012)
N. Obs	272	272	272	272	272
Adj.R2	0.81	0.79	0.54	0.57	0.68

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 including also workers in group quarters, self-employed, and military. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Rademacher draws clustered by cohort of arrival and years spent in the US.

Appendix I Non-linearity

Table 41: Non-linear effects of unemployment at entry on the labor supply of immigrants

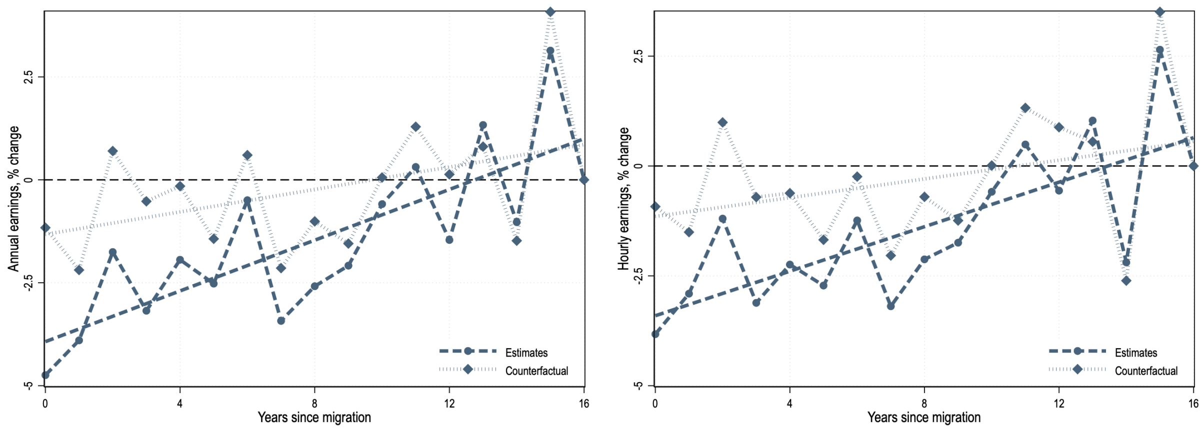
	Annual # Hours			Probability of Unemployment		
Years Since Migration	Expansion (1)	Recession (2)	p-value (3)	Expansion (4)	Recession (5)	p-value (6)
0	0.300	-5.439	0.083	0.001	0.001	0.644
	(-8.680,8.818)	(-16.75,5.027)		(-0.001,0.003)	(-0.001,0.002)	
1-4	-3.485	-4.498	0.707	-0.001	-0.001	0.988
	(-11.80,4.819)	(-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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Appendix J Counterfactuals

Figure 10: Estimated VS counterfactual earnings - Unemployment shock

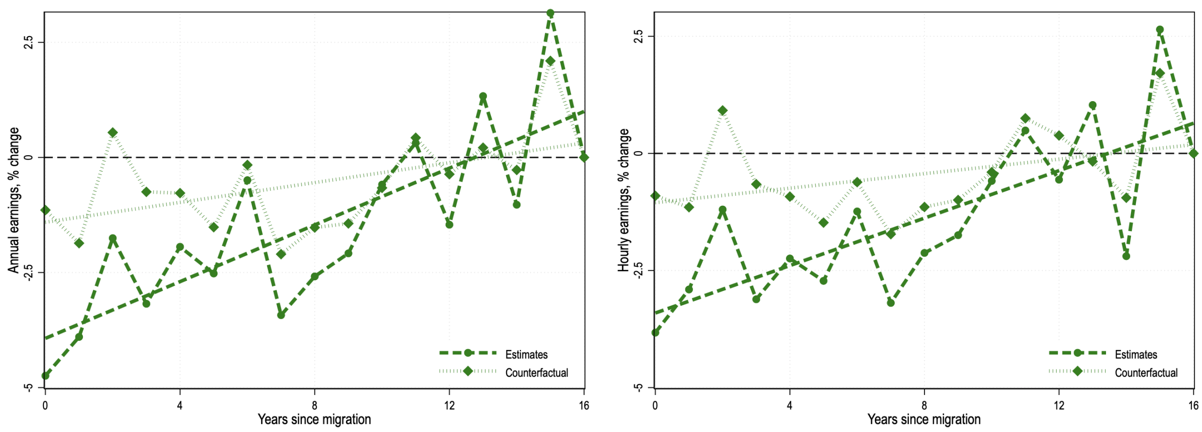
(A) Annual earnings **(B)** Hourly earnings



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 US native on the unemployment rate in the year of entering the US 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 (5), while the shaded lines are constructed using the counterfactual estimates as in equation (10).

Figure 11: Estimated VS counterfactual earnings - Bartik-like Unemployment shock

(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 US native on the aggregate unemployment forecast error in the year of entering the US 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 (6), while the shaded lines are constructed using the counterfactual estimates as in equation (10).

Appendix K Heterogeneity

Table 42: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 43: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 44: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 45: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.

Table 46: 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, by cohort of arrival and years spent in the US.

Table 47: Mexican 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 US 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. First-step regressions are population-weighted. 90% confidence intervals for the second step regression estimates (in parenthesis) are bootstrapped using 1000 Rademacher draws, clustered by cohort of arrival and years spent in the US.