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Unlucky migrants: Scarring effect of recessions on the assimilation of the foreign born

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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 national unemployment rates in the U.S. at the time of arrival of different cohorts of immigrants to identify short- and long-run effects of recessions on their careers. We document that immigrants who enter the U.S. when the labor market is slack face large and persistent earnings reductions: a 1 p.p. rise in the unemployment rate at the time of migration reduces annual earnings by 4.9 percent on impact and 0.7 percent after 12 years since migration, relative to the average U.S. native. 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 2.4 percent of lifetime earnings to immigrants entering the U.S. labor market when unemployment is high.

Keywords: immigrants, earnings assimilation, low-skill jobs, business cycle
JEL Classification: E32, J15, J31, J61

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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 (Koczan et al., 2021), 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. While empirical evidence suggests that the wages of immigrants approach those of natives as they accumulate more experience in the host labor market (Lubotsky, 2007), the literature is silent on how the business cycle affects the trajectories of immigrants' earnings. This paper fills this gap by studying the short- and long-term effects of entering a host country during a recession on the career and economic assimilation of immigrant workers. Adverse initial labor market conditions have persistent effects on the earnings trajectories of college-educated workers (Kahn, 2010; Oreopoulos et al., 2012). Recession entrants have lower wages and employment than those of earlier cohorts (Rothstein, 2021), higher jobs mismatch (Liu et al., 2016), and lower probability of job promotion (Kwon and Milgrom, 2005). Do immigrants subject to adverse initial labor market conditions in the hosting country at the time of migration face worse career outcomes? If so, what causes immigrants' assimilation to slow down? And what is the overall welfare cost?

We answer these questions in the context of the U.S. labor market. The United States is home to more foreign-born residents than any other country in the world: more than 40 million people living in the U.S. were born in another country, making up almost 14 percent of the overall population (Migration Policy Institute, MPI). Moreover, the population of immigrants exposed to adverse labor market conditions is large. Over 20% of the working-age foreign population who migrated to the U.S. in the last three decades entered the labor market during a year with a recession.[1] In this paper, we leverage variation in the U.S. national unemployment rates at the time of arrival of different cohorts of foreign workers who migrated between 1990 and 2021 and use data from the American Community Survey to identify short- and long-run effects of recessions on annual earnings, hourly wages, and labor supply. Because the timing

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

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, 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 4.9 percent at entry and by 2.9 percent after 8 years, relative to the average native in the sample. This effect reduces to 0.7 percent after 12 years since migration and becomes statically not significant thereafter. While we find similar patterns for hourly earnings, we document no systematic response in the labor supply of immigrants, both along the extensive margin, measured by the individual probability of being unemployed, or the intensive margin, measured by the number of hours worked, conditional on being employed. These findings extend to a dynamic setting the existing cross-sectional evidence of large differences in earnings and no difference in unemployment rates between the natives and the foreign-born in the United States (Bandyopadhyay et al., 2017).

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

While our findings are robust to a large array of sensitivity and robustness checks, they do not apply to all immigrants: males without a college education from low-

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

Our paper contributes to several pieces of literature. First, it 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.

Our paper also contributes to the literature on 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). Lubotsky (2007) documents that the immigrant-native earnings gap closes by 10–15 percent during immigrants' first 20 years in the United States. Borjas (2015) argues that the observed convergence could be largely affected by changes in the skill composition of different arrival cohorts in the U.S. and suggests a negative long-run

trend in the quality of U.S. immigrants. Peri and Rutledge (2020) revisit these findings and document that, while the composition of cohorts of low-skill immigrants has changed much, both the initial gap and speed of convergence have not worsened with recent cohorts of arrival. We depart from this literature and innovate by focusing on the cyclicality of immigrant assimilation. To the best of our knowledge, our paper is the first to exploit cross-cohort variation in the unemployment rate at the time of migration to characterize the wage trajectories of immigrants in their host country.

Finally, we contribute to the literature that looks at the effect of aggregate economic conditions on the labor market outcomes of immigrant workers. Bratsberg et al. (2006) study how contemporaneous labor market shocks impact the earnings of immigrants in the U.S. and find evidence of procyclical wage assimilation, suggesting that rising unemployment slows the accumulation of U.S.-specific human capital. Dustmann et al. (2010) use German and UK data to study the cyclical pattern of employment and wages of immigrants and natives. They find large unemployment responses to economic shocks for immigrants relative to natives within the same skill group and no evidence for differential wage responses. More recently, Cadena and Kovak (2016) show that Mexican immigrants are more responsive to aggregate labor market conditions as they are less likely to obtain unemployment insurance and to participate in social safety net programs. Berbée and Stuhler (2023) documents that the structural decline of immigrant-intensive industries in Germany have contributed to widening the employment gap between Turkish immigrants and native in the last 30 years, whereas changes in regional unemployment rates, conditional on sectoral employment decline, had no impact on their employment assimilation. We complement this literature by tracing the long-run effects of high unemployment rates on the earnings profiles and the occupational attainments of immigrants and show that the business cycle has persistent and long-lasting negative effects.

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 U.S.. We describe the data source and sample selection 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 con-

duct several counterfactual exercises. In Section 6 we assess the welfare implications of our findings. We conclude in Section 7.

2 Econometric framework

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

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

and the following regression for natives:

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

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

$$\mathbf{E}[y_{ict}^{m} - y_{it}^{n} | x] = \theta_{cx}, \tag{3}$$

which measures the "excess" value of acquiring a year of experience in the United States. As usual 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. 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,[2] assumptions ii) and iii) allow us to obtain closed form solution for the expected gap in equation (3).[3] Therefore we use the OLS estimates of θ_{cx} from equation (1), $\hat{\theta}_{cx}$, as a dependent variable in a second specification:

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

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

Despite its generality, specification (4) does not account for cohort-specific variation driven by endogenous migration timing which might bias our estimates.

2.1 Threats to identification

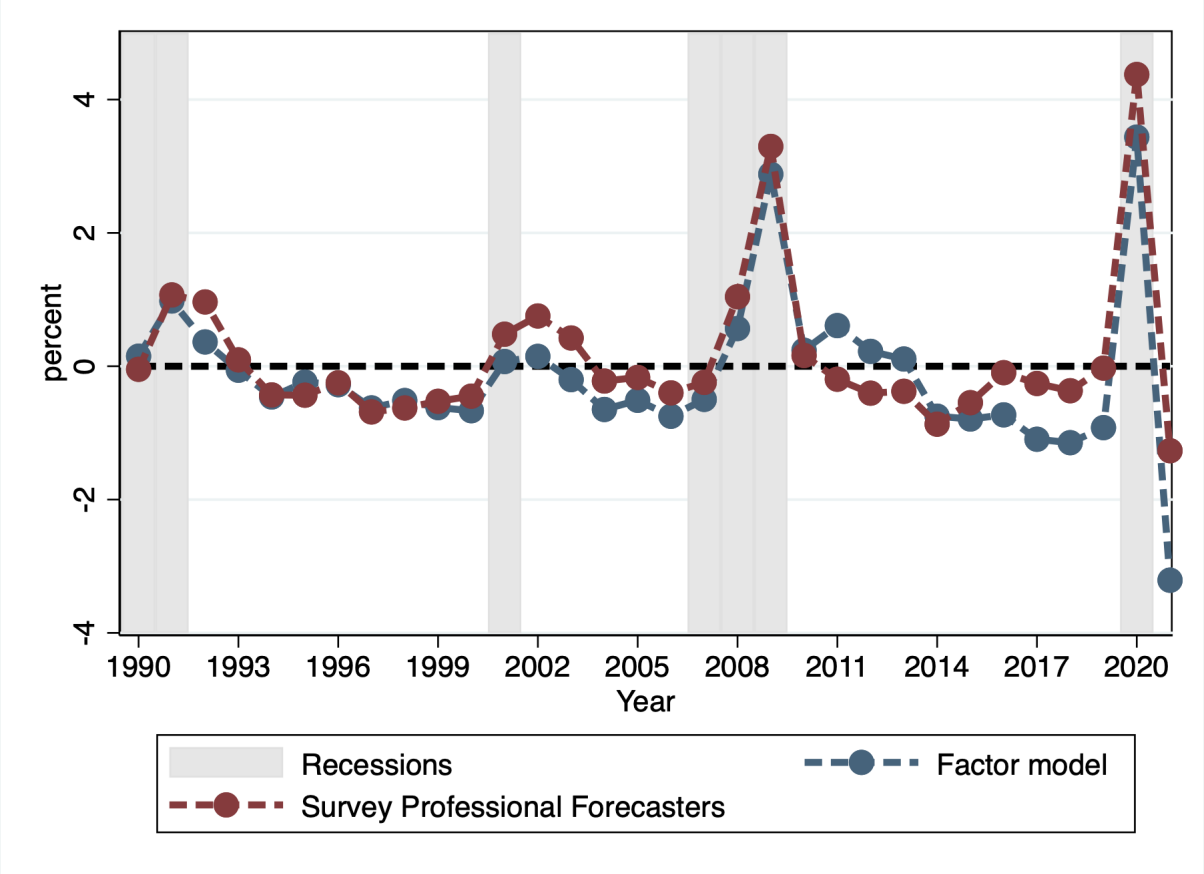
A major threat to identification is the potential endogeneity of the time of entry in the U.S. People might postpone their decision to migrate in order to avoid unfavorable conditions at entry or anticipate it in order to benefit from good labor market conditions. If there were selection into timing,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

We address this concern using the following 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

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

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

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.

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.

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

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

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

Figure 1 reports the forecast errors $\tilde{u}_c^0$, expressed in percentage points, based on our

[4] We report details in Appendix C.

measure of unemployment forecast (blue line). For comparison, we report a measure of forecast errors computed using unemployment expectations from the Survey of Professional Forecasters (red line). Our forecast model generates forecast errors that are comparable to the average of those made by professionals in the U.S. Endogenous migration or timing in response to a recession is not contained in the unexpected shocks to the national unemployment rate since it 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 model in equation (5) based on unemployment forecast errors. If the results were similar, this would suggest that the timing of migration might not be a problem in the sample. Differences between OLS and IV estimates would instead inform us about the nature of selection into migration.[5]

3 Data

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

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

[5]An alternative approach would be to use the unemployment forecast errors as an instrument for the actual endogenous unemployment rate a cohort faces at the year of migration in equation (4). Results for this strategy are available upon request.

Table 1: Natives vs immigrants

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

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 U.S. after 18 years old. We restrict our sample to individuals in the labor force and not enrolled in school. We exclude individuals who live in group quarters, are self-employed, and work in the armed forces or military occupations. We label employed workers as those who worked at least one week in the previous year, reported positive hourly earnings, and do not report a value of usual hours worked that is top-coded. Those who do not satisfy these criteria are labeled as unemployed. Finally, we focus on the subsample of immigrants who arrived from 1990 onward, and, to balance the sample, we restrict our attention only to those with at most 16 years since their migration.

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 ex-

perience 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).

4 Adverse Initial Conditions and Immigrants' Assimilation

We are now ready to discuss the effect of recessions on immigrants' economic assimilation. Figure 2 reports the effects of the unemployment rate at entry in the U.S. on two measures of earnings, such as annual earnings (panel A) and hourly earnings (panel B). Figure 3 reports the effects of the unemployment rate at entry in the U.S. on two measures of labor supply, such as annual hours worked (panel A) and the probability of being unemployed (panel B). Each dot corresponds to the coefficients ω_x, i.e. the interaction of dummies for experience in the U.S. with the unemployment rate obtained from estimating either equation (4) or equation (5). The red line refers to the OLS estimates, the blue line refers to the IV ones. Tables 2 and 3 report the OLS and IV point estimates for 5 groups of experience in the U.S. (0, 1-4, 5-8, 9-12, and 13-16 years since migration), along with 90% bootstrapped confidence intervals constructed using 1000 clustered Rademacher draws.

Annual Earnings. Immigrants' annual earnings are lower than the average U.S. native the higher the unemployment rate at the time of their entry into the U.S. The effect is large and significant: the OLS estimates from Table 2, column (1) imply that entering the U.S. with a 1 p.p. higher unemployment rate makes annual earnings drop by about 2.5% on impact relative to the average U.S. native. This effect is also persistent and only slowly declines with time spent in the U.S. The drop in earnings is still significantly large 8 years after entering the U.S. — it is about 1.62% for a 1 p.p. rise in the initial unemployment rate. While it vanishes to zero only after 12 years, as shown by the red line in panel A of Figure 4.

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

Figure 2: Unemployment at entry and earnings assimilation of immigrants

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

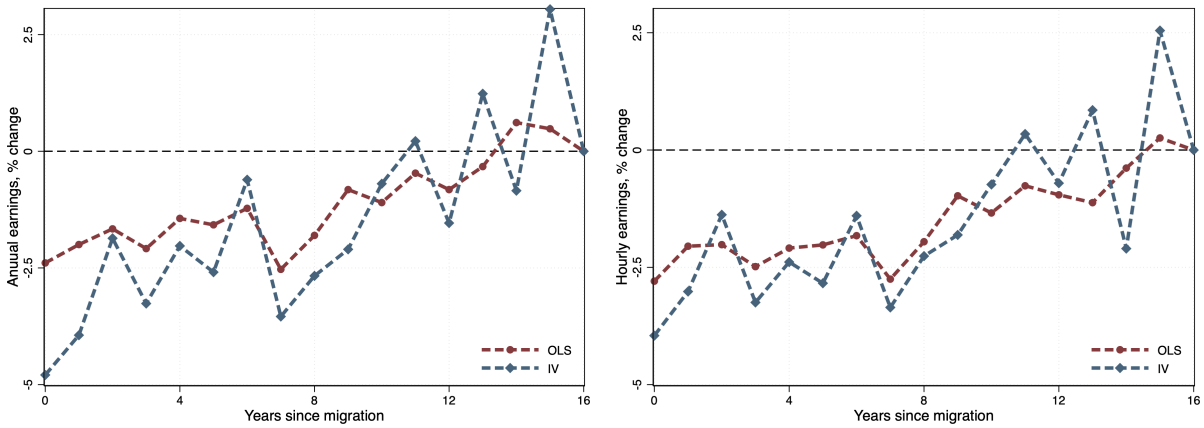
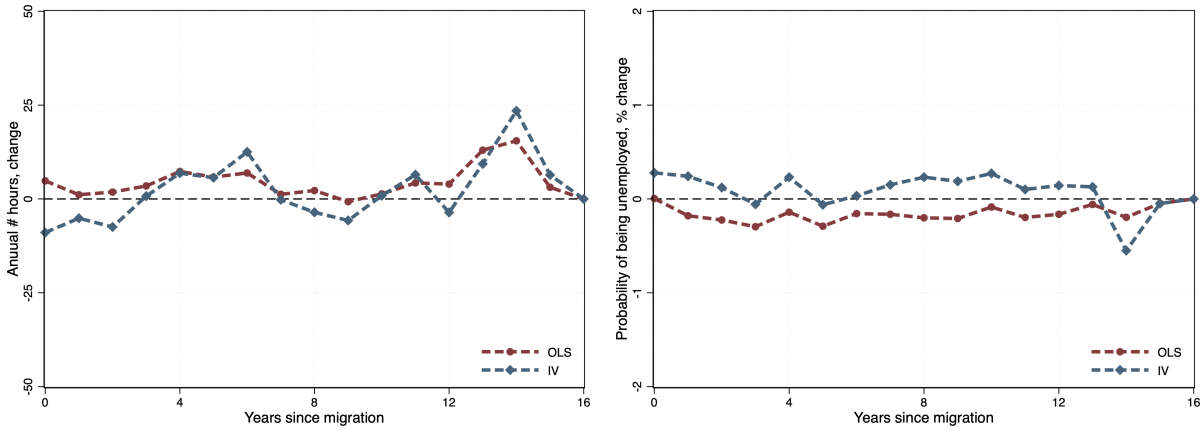


Figure 3: Unemployment at entry and labor supply assimilation of immigrants

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



Source: ACS, FRED and authors' calculation. Notes: The figures show the percent coefficients from regressing selected estimated gaps between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Panels A, B, and C are based on a sample of male workers who report to be currently employed. Panel A shows the percent change in the estimated annual earnings gap. Panel B shows the percent change in the estimated hourly earnings gap. Panel C shows the percent change in the estimated gaps in the annual number of hours worked. Panel D is based on a full sample of male workers, and it shows the percent change in the estimated gap in the probability of being unemployed. In each panel, the red lines refer to the estimates from equation (4). The blue lines refer to the estimates from equation (5).

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.

The IV estimates suggest a very similar picture as the OLS estimates do. While

the former appears to be a bit noisier than the latter, particularly in later years, and most likely because of lower identifying variation in the unemployment forecast errors, the estimated effects are aligned across specifications. Using the point estimates from column (2) in Table 2, a 1 p.p. higher unemployment rate at entry implies a drop in annual earnings of 4.9% on impact compared to the average native worker. The magnitude is twice as large as the one obtained using the OLS specification. This effect reduces with time spent in the US, although, after 8 years since migration, a 1 p.p. higher unemployment rate is still associated with an immigrant-native gap in annual earnings of about 3%.

The difference between the OLS and the IV estimates suggests there might be a correlation between national-level unemployment rates at entry and the unobserved characteristics of immigrants changing across cohorts. The IV estimates are larger in magnitude, especially in the first years following entry. This suggests that immigrants with higher potential earnings might be more likely to migrate to the U.S. during periods of high unemployment. This makes the OLS estimates downward biased, and interpretable as a lower bound for the true effect.

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 U.S. native. This effect is also long-lasting: after 8 years in the U.S. labor market, the gap with the average U.S. native is still large and amounts to 1.5 p.p., and it is fully re-absorbed only by the end of the years of analysis. Notice that these estimates are based on a selected group of immigrants, i.e. those who found jobs: to the extent that these workers are positively selected — based on their education or unobserved 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

Table 2: Effects of unemployment at entry on earnings of immigrants

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

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

Table 3: Effects of unemployment at entry on labor supply of immigrants

	Annual # Hours		Probability of Unemployment	
Years Since	OLS	IV	OLS	IV
Migration	(1)	(2)	(3)	(4)
0	-2.636	-15.21	0.001	0.003
	(-13.07,7.553)	(-35.64,4.410)	(-0.001,0.002)	(-0.000,0.006)
1-4	-4.370	-13.79	-0.001	0.002
	(-13.01,3.689)	(-30.86,2.336)	(-0.003,0.000)	(-0.001,0.005)
5-8	-2.836	-6.390	-0.001	0.002
	(-9.861,3.903)	(-21.58, 8.653)	(-0.003,0.000)	(-0.001,0.004)
9-12	-5.015	-10.17	-0.001	0.002
	(-11.87,1.447)	(-25.66,4.923)	(-0.002,0.001)	(-0.000,0.005)
N.Obs.	272	272	272	272
R-sq.	0.586	0.589	0.640	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 the probability of being unemployed between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Results in columns (1) and (2) are based on a sample of male workers reporting to be employed. Results in columns (3) and (4) are based on a full sample of male workers. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

hours worked of immigrants respond to changes in unemployment rates at the time of entry into the U.S. labor market beyond the effect experienced by the average U.S. native, see Columns (1) and (3) of Tables 3. These findings are also confirmed by the IV estimates in Columns (2) and (4), 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.

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

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

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

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

where we introduced a triple interaction between a dummy for the number of years x spent in the U.S., D^x, the unemployment rate faced by cohort c in the year of migration, u_c^0, and ι_c^0, which is an indicator function taking a value 1 if the year of entry

in the U.S. was subject to recession, 0 otherwise. We define a recession following the official NBER Business Cycle Dating. The parameter ψ_x in equation (6) 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 4 reports the OLS estimates of equation (6) for annual and hourly earnings. The estimates suggest a state-dependent response to aggregate unemployment shocks. Facing a recession in the year of entry into the U.S. labor market amplifies the negative effect on the earnings trajectories of immigrants. On impact, a 1 p.p. higher unemployment rate at that time of migration reduces annual earnings by 3.8% if migration happened during a year of recession (column 2) compared to a reduction of 2.2% otherwise (column 1). The same effect persists after 12 years since migration, causing a reduction in earnings of 1.4%, whereas it vanishes after 8 years for immigrants migrating in periods of expansion. The difference between responses is significant at a 5 percent significance level for every horizon up to 8 years since migration, as proved by the p-values (column 3). Finally, while the response of hourly earnings, which are reported in columns (4) and (5), mirrors the one of annual earnings, we find no state-dependent effects on the number of hours worked and the probability of being unemployed.[6]

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 F.

Alternative model specifications. In Tables 19 to 22 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

[6]See Table 18 in Appendix E.

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-country heterogeneity in these dimensions could bias our estimates. In Table 23 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 U.S. or in another country. If a college degree from a U.S. institution allowed immigrants to assimilate faster relative to natives, and more immigrants enrolled in college during recessions, our baseline estimates could be downward biased. To deal with this issue, we re-estimate our model using only the sample of immigrants who arrived in the U.S. when they were at least 25 years old, excluding de facto those immigrants who obtained their degree in the U.S. Table 25 reports the results from this exercise. The estimates are not statistically different from those obtained using the full sample of immigrants. For a 1 p.p. increase in the unemployment rate at entry, the annual earnings of immigrants without a U.S. college degree decreases by 2.2% relative to the average U.S. native. This effect is also as persistent as observed using the full sample: after 8 years spent in the U.S. earnings are still 1.6% lower. Similarly to the baseline estimation, the number of hours worked and the probability of being unemployed for immigrants do not react to changes in unemployment rates at the time of their migration.

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 24. 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.

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

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

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

Table 5: 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

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 5. Similar to the first robustness check, we convert the decennial probabilities in annual ones and compound them for every year since migration, separately by

education level and by deciles in the residual wage distribution. [7]

Tables 26 and 27 report the estimates for either robustness check, respectively. Accounting for selective out-migration does not alter the main results of the paper.

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 U.S. before 2001, 0.11 for immigrants who arrived between 2001 and 2010, and 0.06 for immigrants who arrived in the U.S. later than 2010. Table 28 reports the estimates for this robustness check.

4.2 Heterogeneity

Are the effects of adverse initial labor market conditions heterogeneous across immigrants? Here we leverage variations in demographic characteristics across immigrants in our data in our data to show that males without a college education from low-income countries are more adversely affected by higher initial unemployment rate conditions.

Gender. Table 29 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. The effect on earnings and hours worked of female immigrants is ambigu-

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

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

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

ous: no estimate is statistically different from zero at a 10% significance level. Taken together, the evidence indicates that, while females are immune, entering the U.S. 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 U.S. natives is modest at most for those with a high-school degree or less. In Tables 30 and 31 we focus on the role of college attainment and distinguish workers with and without a college education. The effect of entering the U.S. during a recession on the wage trajectories is large and statistically significant for immigrants with no college education. Their annual earnings reduce by 2.9% for a 1 percentage point increase in the unemployment rate at entry (column 1 of Table 30). The effect is persistent even after 12 years in the U.S. when the coefficient reduces to 1.3%. On the other hand, recessions seem not to affect the assimilation of workers with a college education: entering the U.S. when the unemployment rate increases by 1 percentage point reduces the annual wages of immigrants with a college education by 1.6% at entry, but the effect is not statistically significant. All the other estimated coefficients on earnings lack statistical significance for this group of workers.

Country of origin. The returns to experience in the U.S. are heterogeneous across workers from different countries of origin and are higher for workers migrating from high-GDP per capita countries (Lagakos et al., 2018a). We explore this dimension in Tables 32 and 33 where we report OLS estimates for the sub-samples of male immigrants from high- and low-income countries.

On the one hand, the wage trajectories of immigrants from high-income countries are not affected by adverse aggregate initial conditions. On the other hand, immigrants from low-income countries face a large and persistent loss from moving into the U.S. in periods of high unemployment: the loss goes from 6% of their hourly earnings on impact, up to 1.8% after 12 years spent in the U.S. Table 34 zooms into the pool of immigrants from low-income countries and focuses on the sample of Mexican workers, who constitute the largest group within it. Annual and hourly earnings of Mexicans migrating to the U.S. in periods of high unemployment are significantly lower than those of the average native. However, the loss is such only up to 4 years after moving to the U.S., and it is fully re-absorbed thereafter, suggesting a much faster

assimilation of Mexicans than other immigrants from comparable countries.

4.3 Re-cap.

Taken together, our results suggest that, compared to those who are not, immigrants who are unlucky to enter the U.S. labor market in periods of high unemployment face a much larger discount in earnings relative to the U.S. natives. These immigrants struggle to fully assimilate and their earnings follow a lower trajectory for at least 10 years since their migration. Slower assimilation in earnings happens to be due to lower assimilation in hourly wages, while patterns of labor supply across cohorts of migrants do not respond to differences in unemployment at entry. Finally, while women seem to be immune, male immigrants, without college education, and from low-income countries are those who bear the largest costs of recessions.

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 U.S. in a recession. In this section, we analyze one additional channel, the role of occupational attainment. Altonji et al. (2016) documents that much of the scarring effect of recessions for U.S. natives can be explained by initial employment in a low-paying occupation. Similarly, Huckfeldt (2022) finds that the earnings cost of job loss during recessions is concentrated among workers who find re-employment in lower-skill occupations. In what follows, we explore the hypothesis that shifts in the employment composition of immigrants from high- to low-paying occupations during recessions and a slow reallocation into high-paying jobs following recessions might explain their lack of assimilation.

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.[8] This choice is dictated by the large differ-

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

Table 6: Average real hourly earnings by occupation

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

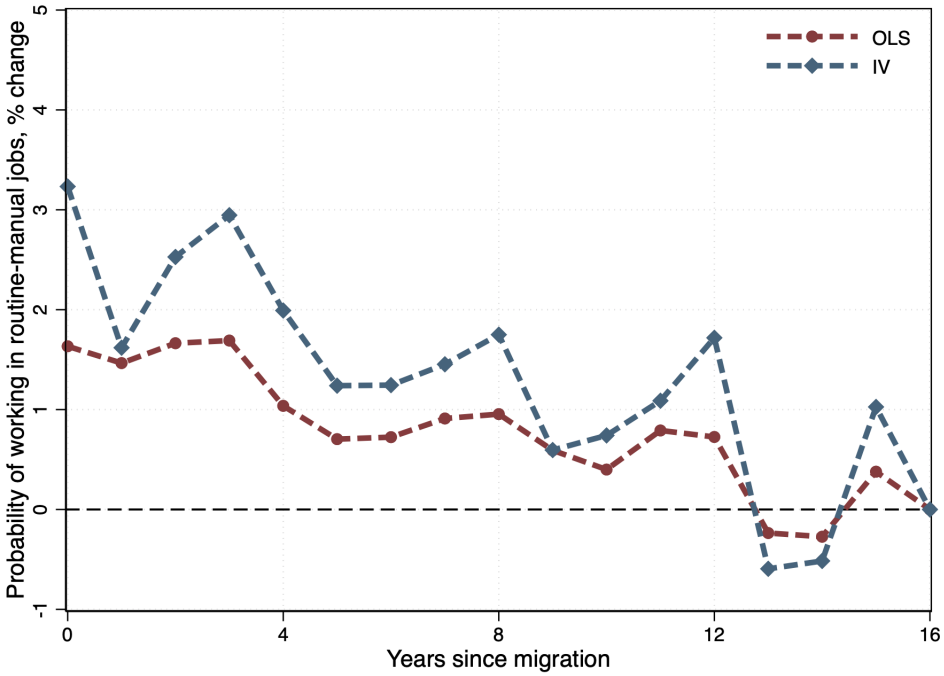
Source: ACS and authors' calculation. Notes: This table reports the average hourly wage for workers in low-paying and high-paying jobs. The former refers to jobs in routine-manual occupations. The latter to non-routine-manual occupations. The third column reports the percent wage differences across groups 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.

ence in hourly earnings between workers observed in the data (Table 6). On average workers employed in manual-routine occupations are paid almost 70% less than the rest. This is true for U.S. natives, whose earnings gap across occupations is on average 67%. And more so for immigrants, whose gap reaches 84%.

Figure 4 reports the effects of the unemployment rate at entry into the U.S. on the probability of being employed in low-skill content occupations for each year since migration. Each point estimate is obtained 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, and ii) by 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 OLS estimation. The blue line refers to the IV estimation. Table 7 summarises the estimated effects for 5 groups of experience in the U.S.

Relative to the average U.S. native, immigrants entering the U.S. during a recession have a higher probability of working in low-skill jobs, both on impact and in the following 12 years. The effect is large and long-lasting: a 1 p.p. rise in the unemployment rate increases the share of immigrants employed in routine-manual occupation by about 1.7% on the spot, and by about 0.7% after 12 years (Column 1, Table 7). Using the IV estimates in Column 2 of Table 7 the effect doubles on impact (3.52% for a 1 p.p. increase in the unemployment rate) and it is 60% larger after 12 years since migration (1.05% for 1 p.p. increase in the unemployment rate at entry). These effects

Figure 4: Probability of working in low-paying occupations



Source: ACS, FRED and authors' calculation. Notes: The figures show the estimated coefficients (times 100) from regressing the estimated immigrant-native gap in the probability of being employed in a low-paying job on the unemployment rate in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Results are based on a sample of male workers reporting to be currently employed. The red lines refer to the estimates from equation (4). The blue lines refer to the estimates from equation (5).

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:

$$\text{loss}_x = \hat{\omega}_x^{\text{RM}} \Delta \log \bar{w}_x^{\text{imm}} \tag{7}$$

where $\{\hat{\omega}_x^{\text{RM}}\}_{x \in \mathcal{X}}$ are the coefficients reported in Figure 4, while $\Delta \log \bar{w}_x^{\text{imm}}$ is the difference in average 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 4, and because $\left(\log[\bar{w}_x^{\text{non-RM}}] \geq \log[\bar{w}_x^{\text{RM}}]\right)$ — see Table 6, then

Table 7: Unemployment at entry and employment in routine-manual jobs

	OLS	IV
Years Since Migration	(1)	(2)
0	0.0171	0.0352
	(0.0091, 0.0245)	(0.0240,0.0478)
1-4	0.0154	0.0230
	(0.0086,0.0213)	(0.0127,0.0338)
5-8	0.0088	0.0145
	(0.0026,0.0148)	(0.0046,0.0254)
9-12	0.0066	0.0105
	(0.0006,0.0122)	(0.0009,0.0210)
N.Obs.	272	272
R-sq.	0.702	0.706

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

$\text{loss}_x \geq 0$. Therefore, we obtained counterfactual earnings losses $\hat{\omega}_x^{w,C}$ as:

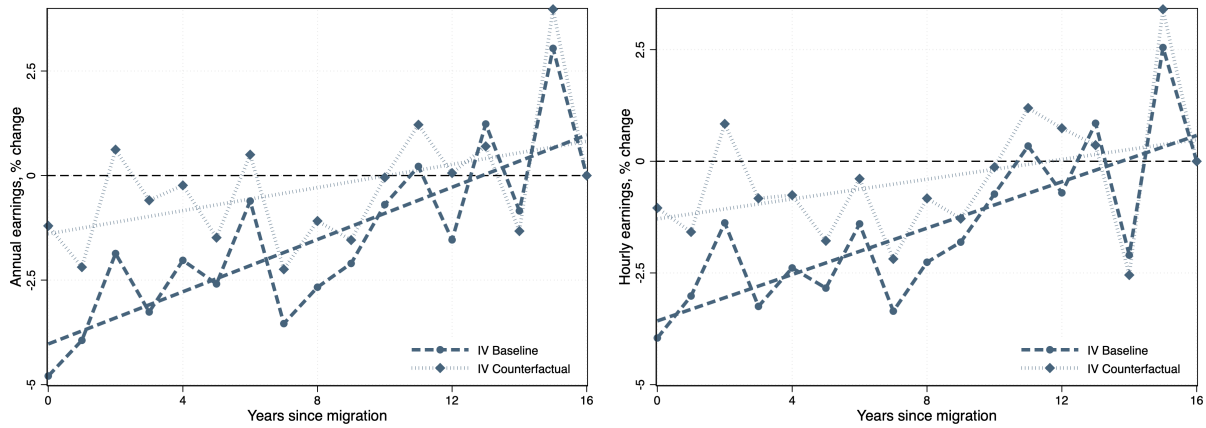
$$\hat{\omega}_x^{w,C} = \hat{\omega}_x^{w} - \text{loss}_x \tag{8}$$

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

Figure 5 reports the results of this exercise and confronts actual and counterfactual annual and hourly earnings losses, using the IV estimates from equation (5). Were occupational attainment unchanged for immigrants, annual earnings would fall on average by less than one-fourth in the year of entry in the U.S.: the counterfactual drop will be about -1.20% — instead of -4.79%, for a 1 p.p. rise in the unemployment rate (Panel A). The effect of recessions would be 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

Figure 5: Actual VS counterfactual earnings

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



Source: ACS, FRED and authors' calculation. Notes: The figures show the percent coefficients from regressing estimated annual and earnings gaps between immigrants and the average U.S. natives on the unemployment rate in the year of entering the U.S. labor market interacted with dummies for the first 16 years since migration, controlling for cohorts of entry and years since migration fixed-effects. Both panels are based on a sample of male workers who report to be currently employed. Panel A shows the percent change in the estimated annual earnings gap. Panel B shows the percent change in the estimated hourly earnings gap. In each panel, the dashed lines are constructed using estimates from equation (5), while the shaded lines are constructed using the counterfactual estimates as in equation (8).

earnings mirror the exact 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. In fact, time spent in lower-paying occupations in the first few years in the U.S. might have an impact on earnings years later, holding occupation constant, since it might drive workers on different trajectories for training and skill advancement (Altonji et al., 2016).

5.1 Discussion

Our evidence suggests that slow job mobility between low- and high-skill jobs prevents the assimilation of immigrants after an adverse initial start. This result can be interpreted through the lens of theories of job assignment, in which employers learn gradually about workers' ability and human capital is not fully portable across occupations (Gibbons and Waldman, 1999, 2006). When human capital is specific to an occupation, the state of the world in the workers' first period in the labor market influences not only current occupation assignments and wages but also, consequently,

occupation assignments and wages later in these careers. Then, a worker who spends substantial time in a given occupation at the beginning of his career can get stuck in that occupation, facing low subsequent mobility, and low wage trajectory, as long as the human capital acquired in a given occupation is of limited use in the performance of other tasks. Extensive literature supports the evidence of limited portability of human capital across occupations (Kambourov and Manovskii, 2009; Sullivan, 2010; Robinson, 2018).

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

On the other hand, while models of job search would also predict that immigrants entering the labor market in a recession might catch up through a long search process for high-paying occupations (Oreopoulos et al., 2012), the same models would be inconsistent with the evidence of no differential changes in the probability of being unemployed between natives and immigrants' entering into the U.S. in years of recessions, as documented in Section 4.

6 Welfare implications

Finally, we quantify how big is the cost of recession 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.

$$\text{NPV} = \sum_{x=0}^{15} \left(\frac{1}{1+r} \right)^x \bar{w}_x^{\text{imm}} \tag{9}$$

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.[9] 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 U.S. with a 1 pp higher unemployment rate, i.e.

$$\text{NPL} = -\bar{w}^{\text{nat}} \sum_{x=0}^{15} \left(\frac{1}{1+r} \right)^x \hat{\omega}_x^w \tag{10}$$

[9]This formula implicitly assumes that i) labor supply of immigrant entering the U.S. in recession remains unchanged relative to the average U.S. native, and ii) the difference in annual earnings between migrants and natives has decayed after 15 years since migration. Estimates in Table 2 suggest this is the case.

Table 8: Overall cost of high unemployment for immigrants

	OLS	IV
	(1)	(2)
NPV (USD)	446,083	
A.	Baseline estimates	
NPL (USD)	7,501.69	10,801.49
%	1.682	2.421
B.	Counterfactual estimates	
NPL (USD)	2,508.72	2,521.68
%	0.562	0.565

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

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

$$100 \times \frac{\text{NPL}}{\text{NPV}} \tag{11}$$

Panel A in Table 8 reports the estimated net present value losses for immigrants. The loss from starting to work in a recession is large and meaningful: depending on the estimates, it varies between 7,501 and 10,801 USD, which corresponds to 1.7 and 2.4 percent of the immigrant net present value.

Panel B of Table 8 reports the counterfactual losses that would realized had the occupational change not changed following higher unemployment at the time of entry into the U.S. We construct it using equation (10) and replacing $\hat{\omega}_x^w$ with $\hat{\omega}_x^{w,C}$, as defined in equation (8). Using both the OLS and IV estimates, the loss will amount to approximately 2,500 USD, which is about 0.5% of their net present values, and about one-third of the loss computed using baseline estimates. Therefore, changes in occupational attainment can explain up to two-thirds of the overall lifetime cost of recessions faced by immigrants in the host country.

7 Conclusions

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

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

References

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, pages 1043–1171. Elsevier.

Akee, R. and Jones, M. R. (2019). Immigrants' earnings growth and return migration from the us: Examining their determinants using linked survey and administrative data. Technical report, National Bureau of Economic Research.

Albert, C., Glitz, A., and Llull, J. (2021). Labor market competition and the assimilation of immigrants. *CEPR Discussion Paper No. DP16432*.

Altonji, J. G., Kahn, L. B., and Speer, J. D. (2016). Cashier or consultant? entry labor market conditions, field of study, and career success. *Journal of Labor Economics*, 34(S1):S361–S401.

Bandyopadhyay, S., Rodrigo, G., et al. (2017). Comparing income, education and job data for immigrants vs. those born in us. *The Regional Economist*, 25(2).

Berbée, P. and Stuhler, J. (2023). The integration of migrants in the german labor market: Evidence over 50 years. *ZEW-Centre for European Economic Research Discussion Paper*, (23-020).

Borjas, G. J. (1984). The impact of assimilation on the earnings of immigrants: A reexamination of the evidence. Technical report, National Bureau of Economic Research.

Borjas, G. J. (2000). The economic progress of immigrants. In *Issues in the Economics of Immigration*, pages 15–50. University of Chicago Press.

Borjas, G. J. (2014). *Immigration economics*. Harvard University Press.

Borjas, G. J. (2015). The slowdown in the economic assimilation of immigrants: Aging and cohort effects revisited again. *Journal of Human Capital*, 9(4):483–517.

Borjas, G. J. (2017). The labor supply of undocumented immigrants. *Labour Economics*, 46:1–13.

Borjas, G. J. and Bratsberg, B. (1996). Who leaves? the outmigration of the foreign-born.

Bratsberg, B., Barth, E., and Raaum, O. (2006). Local unemployment and the relative wages of immigrants: Evidence from the current population surveys. *The Review of Economics and Statistics*, 88(2):243–263.

Cadena, B. C. and Kovak, B. K. (2016). Immigrants equilibrate local labor markets: Evidence from the great recession. *American Economic Journal: Applied Economics*, 8(1):257–290.

Chiswick, B. R. (1978). The effect of americanization on the earnings of foreign-born men. *Journal of Political Economy*, 86(5):897–921.

Dustmann, C., Glitz, A., and Vogel, T. (2010). Employment, wages, and the economic cycle: Differences between immigrants and natives. *European Economic Review*, 54(1):1–17.

Gibbons, R. and Waldman, M. (1999). A theory of wage and promotion dynamics inside firms. *The Quarterly Journal of Economics*, 114(4):1321–1358.

Gibbons, R. and Waldman, M. (2006). Enriching a theory of wage and promotion dynamics inside firms. *Journal of Labor Economics*, 24(1):59–107.

Hainmueller, J. and Hiscox, M. J. (2010). Attitudes toward highly skilled and low-skilled immigration: Evidence from a survey experiment. *American political science review*, 104(1):61–84.

Hanson, G. H. (2006). Illegal migration from mexico to the united states. *Journal of Economic Literature*, 44(4):869–924.

Hoynes, H., Miller, D. L., and Schaller, J. (2012). Who suffers during recessions? *Journal of Economic perspectives*, 26(3):27–48.

Huckfeldt, C. (2022). Understanding the scarring effect of recessions. *American Economic Review*, 112(4):1273–1310.

Kahn, L. B. (2010). The long-term labor market consequences of graduating from college in a bad economy. *Labour economics*, 17(2):303–316.

Kambourov, G. and Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, 50(1):63–115.

Koczan, Z., Peri, G., Pinat, M., and Rozhkov, D. (2021). The impact of international migration on inclusive growth: A review.

Kwon, I. and Milgrom, E. M. M. (2005). Cohort effects and catch-ups in wages and promotions. *manuscript, University of Michigan*.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018a). Life-cycle human capital accumulation across countries: lessons from us immigrants. *Journal of Human Capital*, 12(2):305–342.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018b). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2):797–849.

Lange, F. (2007). The speed of employer learning. *Journal of Labor Economics*, 25(1):1–35.

Lee, T., Peri, G., and Viarengo, M. (2022). The gender aspect of migrants' assimilation in europe. *Labour Economics*, 78:102180.

Liu, K., Salvanes, K. G., and Sørensen, E. Ø. (2016). Good skills in bad times: Cyclical skill mismatch and the long-term effects of graduating in a recession. *European Economic Review*, 84:3–17.

Lubotsky, D. (2007). Chutes or ladders? a longitudinal analysis of immigrant earnings. *Journal of Political Economy*, 115(5):820–867.

Oreopoulos, P., Von Wachter, T., and Heisz, A. (2012). The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1):1–29.

Passel, J. S. and Cohn, D. (2018). Us unauthorized immigrant total dips to lowest level in a decade. *Pew Research Center*, 17.

Peri, G. and Rutledge, Z. (2020). Revisiting economic assimilation of mexican and central american immigrants in the united states.

Rho, D. and Sanders, S. (2021). Immigrant earnings assimilation in the united states: a panel analysis. *Journal of Labor Economics*, 39(1):37–78.

Robinson, C. (2018). Occupational mobility, occupation distance, and specific human capital. *Journal of Human Resources*, 53(2):513–551.

Rothstein, J. (2021). The lost generation? labor market outcomes for post great recession entrants. *Journal of Human Resources*.

Schoellman, T. (2012). Education quality and development accounting. *The Review of Economic Studies*, 79(1):388–417.

Schwandt, H. and Von Wachter, T. (2019). Unlucky cohorts: Estimating the long-term effects of entering the labor market in a recession in large cross-sectional data sets. *Journal of Labor Economics*, 37(S1):S161–S198.

Schwandt, H. and Von Wachter, T. (2020). Socio-economic decline and death: The life-cycle impacts of recessions for labor market entrants. Technical report, National Bureau of Economic Research, Inc.

Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. *Labour economics*, 17(3):567–580.

Toussaint-Comeau, M. (2006). The occupational assimilation of hispanic immigrants in the us: Evidence from panel data. *International Migration Review*, 40(3):508–536.

Van Hook, J., Bean, F. D., Bachmeier, J. D., and Tucker, C. (2014). Recent trends in coverage of the mexican-born population of the united states: Results from applying multiple methods across time. *Demography*, 51(2):699–726.

von Wachter, T. (2020). The persistent effects of initial labor market conditions for young adults and their sources. *Journal of Economic Perspectives*, 34(4):168–194.

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.[10]

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.

[10] 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:[11]

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

[11] 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 Instrumental variable

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

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

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

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

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 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 9 reports the OLS estimate for the second-step regression of u_{t+1} onto a constant, $\hat{F}_t$ and u_t.

Table 9: Factor 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.

Appendix D Descriptive Statistics

Table 10: Descriptive statistics of immigrants by cohorts of arrival: 1990-2005

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

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

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

Table 12: Descriptive statistics: Females

Origin	Avg. Annual Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
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	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. Annual Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
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	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. Annual Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
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	444866
	(78120.9)	(42.5)	(541.0)	(1.5)	(9.1)	

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

Table 15: Descriptive statistics: Low-Income vs Mexicans vs High-Income Immigrant workers

Origin	Avg. Annual Earnings	Avg. Hourly Earnings	Avg. Hours Worked	Avg. Years of Schooling	Avg. Potential Experience	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Low-Income	32844.9	16.2	2033.5	12.6	21.5	909289
	(45461.5)	(26.5)	(536.7)	(4.0)	(9.3)	
Mexicans	20132.7	10.3	2022.0	10.1	22.6	244097
	(21693.2)	(16.6)	(527.0)	(3.3)	(8.6)	
High-Income	67981.0	30.4	2173.1	15.6	20.5	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).

Appendix E Non-linearity

Table 18: Non-linear effects of unemployment at entry on labor supply of immigrants

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

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

Appendix F Robustness checks

Table 19: Alternative model specifications: Annual Earnings

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

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

Table 20: 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 U.S. labor market interacted with 5 dummies for the first 16 years since migration (0,1-4,5-8,9-12,13-16), controlling for cohorts of entry and years since migration fixed-effects. Hourly earnings gaps are estimated using three alternative models: column (1) refers to a model that includes a third-order polynomial for potential experience, controlling for years of schooling fixed effects and time-fixed effects; column (2) refers to a model that controls for a cubic polynomial in potential experience and time dummies while imposing linearity in the returns from schooling; column (3) refers to a model with a linear time trend while controlling for schooling and experience using a linear and a cubic polynomial, respectively. Results are based on a sample of male workers who report being currently employed. 90% confidence intervals (in parenthesis) are bootstrapped using 1000 Clustered Rademacher draws.

Table 21: Alternative model specifications: Annual # Hours

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

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

Table 22: Alternative model specifications: Probability of Unemployment

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

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

Table 23: Heterogeneous Returns to Education and Experience

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

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

Table 24: Sample of prime-age male workers (25-54 y.o.)

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

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

Table 25: Sample of immigrants with no U.S. college

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

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

Table 26: Selective outmigration weights by country of origin

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

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

Table 27: Selective outmigration weights by education and skills

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

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

Table 28: Illegal migrants weights

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

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

Appendix G Heterogeneity

Table 29: Female immigrants

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

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

Table 30: Male immigrants without college degrees

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

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

Table 31: Male immigrants with college degrees

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

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

Table 32: Immigrants from high-income countries

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

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

Table 33: Immigrants from low-income countries

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

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

Table 34: Mexicans immigrants

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

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