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Immigrating into a Recession:

Evidence from Family Migrants to the U.S

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Toman Barsbai, Andreas Steinmayr, Christoph Winter *

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ABSTRACT

IMMIGRATING INTO A RECESSION:

EVIDENCE FROM FAMILY MIGRANTS TO THE U.S

Toman Barsbai, Andreas Steinmayr, Christoph Winter ∗

We analyze the impact of economic conditions at arrival on the economic integration of family-sponsored migrants in the U.S. A one pp higher unemployment rate at arrival decreases annual wage income by four percent in the short run and two percent in the longer run. The loss in wage income results primarily from lower hourly wages due to occupational downgrading. Migrant and family networks help mitigating the negative labor market effects. Migrants who arrive during a recession take up occupations with higher concentrations of fellow countrypeople and are more likely to reside with family members, potentially reducing their geographical mobility.

Keywords: Immigrant integration, family reunification, chain migration, migrant networks, labor market, business cycle

JEL classification: E32, F22, J31, J61

Toman Barsbai
University of Bristol and
Kiel Institute for the World Economy
Email:
toman.barsbai@bristol.ac.uk

Andreas Steinmayr
University of Innsbruck, CESifo,
CReAM, IZA, and IPL
Email:
andreas.steinmayr@uibk.ac.at

Christoph Winter
EY-Parthenon

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1 Introduction

The economic integration of immigrants is key to reaping the benefits of international migration for immigrants and citizens of destination countries alike. Yet, immigrant integration is often imperfect and varies substantially across and within immigrant cohorts. A large literature has examined the economic assimilation of immigrants over time, paying particular attention to changes in immigrant characteristics and selective return migration.

This paper takes a different perspective and analyzes how economic conditions at the time of arrival shape the economic integration of immigrants over time. We introduce a new identification strategy that exploits the inability of family migrants to the U.S. to synchronize their arrival with labor market conditions in the U.S. Our focus is on key labor market outcomes, above all employment and wage income. We also provide evidence on the underlying mechanisms and coping strategies. In particular, we show that adverse economic conditions at the time of arrival can explain occupational downgrading and migrants' reliance on family and migrant networks.

Family migrants typically arrive without a job as their visas are not sponsored by an employer. Their economic integration might hence be susceptible to labor market conditions at arrival. Economic theory suggests that entering the labor market in a recession increases the odds of unemployment and job mismatch. Immigrants might also be pushed to enter occupations with larger ethnic networks. These jobs may provide fewer opportunities to accumulate destination-specific human capital and experience, thus limiting upward mobility. In addition, future employers may perceive past labor market outcomes as a signal of productivity. Unemployed or mismatched immigrants may then face persistently lower wages. We therefore hypothesize that immigrating into a recession is associated with worse labor market outcomes, even in the longer run.

Our identification strategy exploits long waiting times for family-sponsored visas to the U.S. that effectively decouple the migration decision from economic conditions at the time of immigration. Due to caps on the number of available visas and excess demand, it usually takes several years until a family-sponsored visa is granted. Once a visa becomes available, family members have a limited time window to move to the U.S. In addition, family migrants typically move to the sponsor's location in the U.S. Hence, family migrants do not choose the U.S. state based on economic conditions either. Thus, the macroeconomic conditions family migrants face at arrival in the U.S. are exogenous. Some family migrants happen to immigrate into a boom, others into a recession.

Family migrants constitute the largest group of permanent immigrants in the U.S. In

2015, 65 percent of all persons obtaining lawful permanent resident status in the U.S. were family migrants, only 14 percent were labor migrants (i.e., their visa was sponsored by their employer). Humanitarian migrants (refugees and asylees) and winners of the diversity lottery in the U.S. account for most of the remaining share. The picture looks similar for the OECD more generally. In 2015, family migrants accounted for 48 percent of all permanent immigrant arrivals in the OECD. Labor migrants accounted for only 16 percent.[1] Despite their relevance, family migrants have received little attention in economics.[2]

We base our analysis on data from the American Community Survey (ACS) and the U.S. Census for the period 2000-2019, which provide information on the year of immigration. We analyze the effect of state-level unemployment rates in the year of immigration on immigrants' labor market outcomes in the year of observation. Our econometric specification includes state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. This specification allows us to control for persistent differences in economic conditions and immigrant characteristics across states, nation-wide economic conditions at the time of observation and the year of immigration, changes in the characteristics of immigrant cohorts, and the general path of economic integration over time.

The key challenge for identification is that the migration decision is endogenous to economic conditions. If the characteristics of immigrants to a specific state differ between good and bad economic times, observed differences in economic integration may be due to differences in immigrant characteristics, not differences in initial economic conditions. As argued above, family migrants cannot choose their date of immigration based on economic conditions. And they do not choose a location within the U.S. based on economic conditions but join their sponsor's household in the U.S. As a result, the local economic conditions family migrants face at arrival are exogenous. We offer support for our identifying assumption by showing that initial unemployment rates (IURs) cannot predict the size and composition of inflows of family migrants to U.S. states. We also show that selective return migration is unlikely to bias our results. In general, rates of return migration are very low for family migrants. In addition, survival rates of migrants in our sample do not systematically differ by year of arrival and hence different initial economic conditions.

Currently available datasets do not provide information on the visa type. We are thus not able to precisely identify family migrants. In our main analysis, we therefore restrict the sample

[1] Figures for the U.S. come from the 2015 Yearbook of Immigration Statistics. Figures for the OECD come from the 2017 International Migration Outlook and exclude migration movements within areas of free circulation (mainly within the European Union).

[2] A small related literature studies migration decisions of couples and households and the resulting selection of immigrants. See, for example, Mincer (1978); Borjas and Bronars (1991); Cobb-Clark (1993); Foged (2016); Munk et al. (2022).

to immigrants from countries for which family migration is the dominant mode of migration to the U.S. We also offer alternative strategies that identify (i) family migrants from the Philippines based on administrative data from the Philippine government and (ii) subgroups of immigrants whose individual characteristics even more likely identify them as family migrants. In addition, we show that the inclusion of migrants who do not face waiting times for their visa biases our estimates towards zero. We therefore consider our results to be conservative.

We have three main findings. First, immigrating into a recession substantially worsens labor market outcomes, even in the longer run. A one pp higher IUR has a small and relatively short-lasting effect on employment rates. However, it decreases real annual wage income in the first three years by about four percent, with slow convergence to a persistent negative effect of about two percent afterwards. A five pp rise in the IUR, a typical rise in a large recession (von Wachter, 2020), would reduce the net-present-value wage income of a family migrant over a period of ten years by USD 35,5k. This is a large effect. For comparison, the equivalently estimated average earnings loss of graduating in an equally large recession is USD 23k. Second, the loss in wage income is the result of a combination of substantial occupational downgrading, leading to lower hourly wages, and a reduction in working hours. Third, family migrants rely on migrant and family networks to cope with adverse economic conditions. In regions with larger migrant networks, family migrants who arrive at times of high unemployment experience a smaller negative effect on initial employment but take up occupations with substantially higher concentrations of fellow countrypeople. They are also more likely to reside with family members, likely the sponsor of their visa. The immobile support received from the family, however, may reduce the geographic mobility of migrants. Indeed, migrants who arrive at times of high unemployment do not increase their geographical mobility. The resulting job search frictions provide a potential explanation for the observed persistence of the effects.

Our paper contributes to two strands of literature. The first strand of the literature examines how immigrant earnings evolve after their arrival in the destination country and whether immigrant earnings assimilate to native earnings over time (starting with the seminal papers by Chiswick (1978) and Borjas (1985)). This large literature typically finds that immigrants have low initial earnings relative to natives but enjoy high earnings growth over time, with the degree of catch-up depending on immigrant cohorts and destination countries.[3] We contribute to this literature by showing that initial economic conditions generate substantial heterogeneity in the evolution of earnings across immigrant cohorts. In addition, initial economic conditions constitute a key mechanism for explaining widely documented immigrant-specific phenomena

[3]For a review of the literature, see Duleep (2015).

such as downgrading (e.g., Dustmann et al., 2013, 2016) and the use of migrant and family networks (e.g., Munshi, 2003; Patel and Vella, 2013; Battisti et al., 2021). We also provide first evidence on the economic integration of family migrants who represent the most relevant group of permanent immigrants in the U.S. and the OECD more generally.

The second strand of the literature studies how entering the labor market in a recession affects labor market outcomes. Most studies focus on the labor market effects of graduating in a recession (e.g., Raaum and Røed, 2006; Kahn, 2010; Kwon et al., 2010; Oreopoulos et al., 2012; Brunner and Kuhn, 2014; Altonji et al., 2016; Schwandt and von Wachter, 2019; Rothstein, forthcoming; Stuart, 2022).[4] They find that college and school students who graduate in a recession are less likely to be employed and earn lower wage incomes in the first years of their careers, with mixed evidence on the persistence of these effects. A few studies document similar effects for immigrants and refugees who arrive at the destination country in a recession (Chiswick et al., 1997; Chiswick and Miller, 2002; Åslund and Rooth, 2007; Godøy, 2017; Mask, 2020; Fasani et al., 2021b; Aksoy et al., 2021).[5] We contribute to this literature by introducing a novel identification strategy that exploits the inability of family migrants to the U.S. to synchronize their arrival with labor market conditions in the U.S. We thus broaden the evidence that labor market outcomes are path-dependent and not only depend on current economic conditions (e.g., see Beaudry and DiNardo, 1991). It is not clear a priori that previous findings for native labor market entrants and refugees also apply to family migrants. Family migrants may enter different segments of the labor market and can draw on established networks that may cushion the effects of initial economic conditions.

2 Theoretical considerations

Recessions affect the number and types of initial job opportunities available on the labor market. Entering the labor market in a recession hence likely increases the odds of being unemployed or experiencing a job mismatch with the associated lower wages (Bowlus, 1995; McLaughlin and Bils, 2001; Devereux, 2002). This may be particularly true for immigrants as their labor market outcomes are generally more responsive to business cycle fluctuations than those of natives (Dustmann et al., 2010; Orrenius and Zavodny, 2010). If future employers perceive past spells of unemployment or low wages as a signal of low productivity, initially unemployed or mismatched individuals may then face persistently lower wages (Jacobson et al., 1993; Arulampalam, 2001;

[4] For a review of the literature, see von Wachter (2020).

[5] Going beyond economic conditions at arrival, Marbach et al. (2018) and Fasani et al. (2021a) provide evidence that the policy environment at immigration has a long-term effect on the labor market integration of refugees. Aksoy et al. (2021) and Jaschke et al. (2021) show that attitudes of natives also affect refugees' integration.

Gregg, 2001; Gregory and Jukes, 2001; Couch and Placzek, 2010; Kroft et al., 2013).

The scarring effect is likely more pronounced for immigrants than for natives. Initial unemployment and job mismatching make them less likely to accumulate destination-country specific human capital and experience. Given the limited transferability of human capital and experience from the origin to the destination country (e.g., Friedberg, 2000), it may thus be more difficult for immigrants than natives to signal their idiosyncratic productivity to future employers. Similarly, if immigrants initially enter the ethnic economy and accumulate skills that are specific to the ethnic economy, they may be more likely to remain in the ethnic economy and potentially face limited upward mobility (similar to the arguments made by Borjas, 1992; Battisti et al., 2021).

However, adverse economic conditions at arrival do not need to have persistent labor market effects. Immigrants may simply take more time to complete the job-matching process. With diminishing marginal returns to experience, immigrants may be able to recover from initial shocks over time. The ability to do so depends on the presence of search frictions and immigrants' occupational, sectoral, and geographical mobility (on the importance of mobility, see Topel and Ward, 1992).

On the one hand, due to the scarring effect and discrimination on the labor market, immigrants may face more search frictions than natives. On the other hand, due to lower degrees of geographical attachment, immigrants may have lower moving costs and could be more mobile than natives (Green, 1999; Braun and Kvasnicka, 2014; Cadena and Kovak, 2016). The mobility of family migrants, however, might be lower as they usually join their sponsor's household upon arrival and might depend on the immobile support of family members. From a theoretical perspective, it is thus not clear how persistent the negative labor market effects of immigrating into a recession are.

3 The system of family-sponsored immigration to the U.S.

The Immigration and Nationality Act of 1965 established the current system of lawful permanent immigration to the U.S. The latest major amendments occurred through the Immigration Act of 1990. The system defines four main pathways of permanent immigration: family-sponsored immigration, employer-sponsored immigration, the Diversity Immigrant Visa Program, and admission on humanitarian grounds through refugee and asylum programs.[6] U.S. immigration law has traditionally prioritized family-sponsored immigration, which remains the most important avenue for permanent immigration to the U.S.

[6] There are a few other pathways to lawful permanent resident status but they are quantitatively not important.

Table 1: Family-sponsored admission categories

Category	Sponsor	Eligible family members	Nr of visas
IR	U.S. citizen	Spouses, parents, and unmarried children under 21	unlimited
F1	U.S. citizen	Unmarried sons and daughters, and their minor children	23,400
F2A	LPR	Spouses and minor children	87,900
F2B	LPR	Unmarried sons and daughters	26,300
F3	U.S. citizen	Married sons and daughters	23,400
F4	U.S. citizen	Siblings and their minor children	65,000

Notes: LPR is short for lawful permanent resident. Unused visas from the previous year can increase the number of visas in individual categories. For more details see CSR report R43145. Source: Congressional Research Service, summary of INA §203(a) and §204; 8 U.S.C. §1153.

Family members residing in the U.S. as U.S. citizens or lawful permanent residents (LPRs a.k.a. green-card holders) can act as sponsors for family members abroad and provide legal entitlement to a visa. Sponsors need to prove that they can support their own family and the sponsored family member at an income level at or above 125 percent of the federal poverty level. They also need to sign an affidavit of financial support, which obliges them to support sponsored family members who can not support themselves for ten years or until they become U.S. citizens.

The admission categories depend on the relationship between the sponsor and the family member, the age and marital status of the family member, and on whether the sponsor is a U.S. citizen or a LPR (see Table 1). Importantly, there are caps on the number of visas available in each category per year. The only exceptions are immediate relatives of U.S. citizens, i.e., spouses, parents, and unmarried children under the age of 21 years. They are not subject to numerical limitations (Kandel, 2018b).

The Immigration Act of 1990 caps the total number of LPR visas at 675,000 per year. This number includes 480,000 family-sponsored immigrants, 140,000 employer-sponsored immigrants, and 55,000 diversity immigrants. It excludes refugees and asylees. To account for the fact that immediate relatives of U.S. citizens are not subject to numerical limitations, the annual cap of 480,000 family-sponsored immigrants is adjusted in the following way:

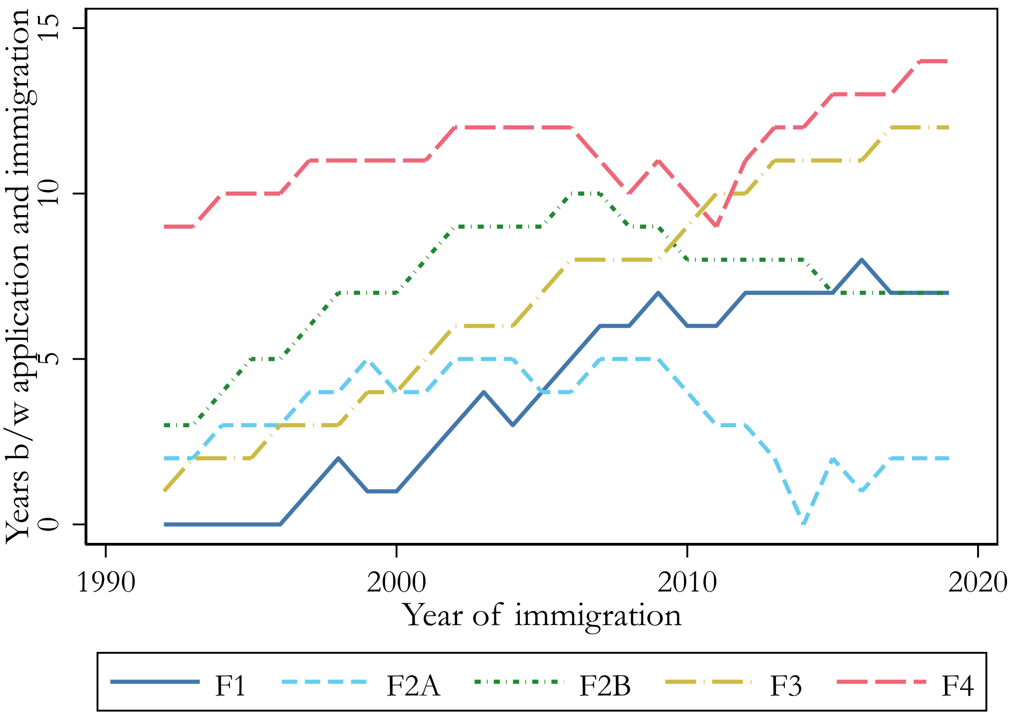
   480,000 (annual total cap on family-sponsored immigrants)
− number of immediate relatives granted LPR status in the prior year
− number of aliens paroled into the U.S. for at least a year in the prior year
+ number of unused employer-sponsored visas from the prior year

The minimum adjusted number of family-sponsored immigrants, however, is fixed at 226,000 per year. As the number of immediate relatives granted LPR status has exceeded

254,000 every year, the annual cap for other family-sponsored immigrants has effectively remained at the minimum of 226,000 for the past two decades (Kandel, 2018a). Table 1 shows the resulting number of family visas available for the different categories. In addition, per-country ceilings regulate that citizens from a single country cannot account for more than seven percent of all available visas.[7]

Demand for family migration far exceeds the number of available visas per year. As a result, the caps have created a large backlog of individuals whose LPR visa petitions have been approved by the U.S. Citizenship and Immigration Services (USCIS) but for whom visas are not available. As of November 1, 2017, 3.95 million approved LPR visa petitions in the family track were pending and waiting for visa processing (Kandel, 2018a). Within admission categories, the Department of State processes visa applications in the order in which petitions were filed. Visa applicants typically wait for several years before they receive their visa.

Figure 1: Waiting times for family migrants by admission category



Notes: The figure shows waiting times for unmarried sons and daughters of U.S. citizens and their minor children (F1), spouses and minor children of LPRs (F2A), unmarried sons and daughters of LPRs (F2B), married sons and daughters of U.S. citizens (F3) and brothers and sisters of U.S. citizens (F4). LPR is short for lawful permanent resident. Data source: U.S. Department of State Visa Bulletins (January), own calculations. Figure A.1 in the appendix shows waiting times for applicants from Mexico, China, India, and the Philippines, where the per-country ceiling is binding.

The Department of State regularly publishes the waiting times for applicants who are

[7] Exceptions are possible for category F2A (spouses and children of LPRs) and some employment-based visas. For more details, see Kandel (2018a).

currently invited for visa processing in its monthly Visa Bulletin. Figure 1 shows the waiting times, defined as the time between filing a petition and being invited for visa processing, for different categories of family migrants for the period 1992-2019. For example, in 2005, family migrants receiving F1 visas (unmarried sons and daughters of U.S. citizens and their minor children) or F2A visas (spouses and minor children of LPRs) had been in the queue for about four years, those receiving F2B visas (unmarried sons and daughters of LPRs) for more than eight years, those receiving F3 visas (married sons and daughters of U.S. citizens) for about seven years, and those receiving F4 visas (siblings of U.S. citizens and their minor children) for about twelve years. Due to the binding per-country ceilings, applicants from the most important countries of origin, Mexico, China, India, and the Philippines, have different and often considerably longer waiting times (see Figure A.1 in the appendix).

Prospective family migrants do not only face long waiting times, they also face uncertainty about the length of waiting times. At the time of filing their petition, they only know the waiting times of applicants who have just been invited for visa processing in each admission category. Their effective waiting times, however, may differ depending on how many other prospective migrants from the same and other countries have filed petitions in the same admission category. Indeed, as Figure 1 shows, waiting times have not been constant over time. They have considerably increased for most admission categories.

Once a visa becomes available, the National Visa Center informs the applicant who then has to apply for a visa within a period of twelve months. Failure to apply for the visa results in termination of the petion (Immigration and Nationality Act (INA) section 203(g)). Visas are only valid for up to six months, so migrants have to enter the U.S. within that period. Migrants receive LPR status only after arriving in the U.S.[8] Thus, family migrants have limited opportunities to time their move to the U.S.

The combination of long waiting times, uncertainty about the length of waiting times, and the short validity of their visa forces family migrants to enter the U.S. within a narrow time window that is beyond their control and not known a priori. Family migrants are thus not able to synchronize their arrival with labor market conditions in the U.S. Our identification strategy exploits this particular feature of the U.S. immigration system to overcome the problem of endogenous migration decisions.

[8] Some migrants also adjust their visa status while being in the U.S. However, relative to other types of immigrants, adjustment of status is not common among family migrants. According to the 2015 Yearbook of Immigration Statistics, only 16,783 family migrants did so in 2015. Status adjustment is particularly common for spouses of U.S. citizens and LPRs.

4 Data

4.1 Data sources and sample restrictions

We base our analysis on data from the 2000 U.S. Census and the American Community Survey (ACS) for the period 2000-2019, obtained via IPUMS. These data have two advantages over other potential data sources. First, the sample is large, even if we restrict it to immigrants with specific characteristics. Second, the data provide information on the year of immigration and country of origin as well as a wide range of labor market outcomes.[9]

Like other currently available datasets, however, our data do not provide information on the visa type. The U.S. Census and the ACS sample all types of permanent residents as well as aliens who reside in the U.S. on temporary visas or irregularly. We are hence not able to directly identify family migrants. In our main analysis, we therefore restrict the sample to immigrants from countries for which family migration is the dominant mode of migration to the U.S. In Section 6.3, we explore alternative strategies, which yield similar results.[10]

To understand the relative importance of different modes of migration to the U.S., we use data from the Yearbook of Immigration Statistics for the period 1992-2019.[11] Published every year by the U.S. Department of Homeland Security, the yearbooks provide information on the number of immigrants and aliens who were admitted to the U.S. by admission category and country of origin in that year. We only consider admission categories that are likely to be sampled by the Census and the ACS. They include LPRs, students and exchange visitors on temporary visas, and temporary workers. They exclude tourists, business travellers, and diplomats. For each country of origin, we then calculate the share of family migrants, labor migrants (permanent and temporary), and all other migrants.[12]

We define the dominant mode of migration to account for more than 50 percent of yearly admissions in a given year. We classify countries as other when neither family nor labor migration alone accounts for more than 50 percent of yearly admissions. For our estimation sample, we consider only immigrants from an origin country that was classified as *family-dominated* in

[9] We cannot use the 2010 U.S. Census as it was a short-form-only census and does not provide the relevant information.

[10] Borjas and Bronars (1991) use family relationships and the timing of immigration within a household to identify family migrants in census data. We abstain from pursuing this strategy as our results in Section 6.2 show that household formation is a function of economic conditions at immigration. Focusing on family migrants that live in the same household as the sponsor would lead to a sample selection problem.

[11] The Yearbook of Immigration Statistics was not published in 1990, 1991, and 1997. We approximate 1997 values as the average of 1996 and 1998 values.

[12] The Yearbook of Immigration Statistic does not provide information on the number of immigrants admitted to the U.S. in a given year but the number of immigrant and non-immigrant visas granted. A single individual might sequentially hold multiple non-immigrant visas, resulting in an overcount of this individual. Since multiple visas are a potential concern for non-family migrants only, our estimated share of family-migrants can be considered a lower bound.

Table 2: Main countries of origin with predominantly family migration

	Number of obs. in estimation sample	% of years family-dominated	% of migrants family-based
Philippines	41860	81.5	56.8
Vietnam	18676	77.8	61.1
Dominican Republic	18198	100	76.2
Haiti	11687	100	73.9
Guyana/British Guiana	4743	100	85.7
Bangladesh	3437	48.1	60.3
Iran	3428	33.3	58.7
Ecuador	3176	25.9	57.4
Peru	2453	22.2	53.9
Cambodia	1722	77.8	73.0
Ghana	1130	33.3	55.4
Syria	1114	51.9	54.4
Other	5351	100	62.8
Total	116975	73.5	65.7

Notes: Share of years family-dominated is the share of years between 1992 and 2018 in which a country's dominant mode of migration to the U.S. was family migration. Number of observations in estimation sample is the number of observations in our sample, i.e. individuals aged 22 to 60 years at the time of immigration and observation who were born outside the U.S. as non-U.S. citizens, did not get naturalized within the first three years of immigration, immigrated between 1992 and 2018, and had spent at most ten years in the U.S. at the time of observation. We only consider individuals who immigrated in a year in which the country was classified as family-dominated. Countries are ordered by number of observations in the estimation sample. Table A.1 in the appendix presents corresponding numbers for labor migration.

the year of immigration. Table 2 lists the main countries of origin with predominantly family migration to the U.S. Individuals from the Philippines (36% among all family migrants in our sample), Vietnam (16%), the Dominican Republic (16%), and Haiti (10%) make up for the large majority of family migrants in our sample. For these countries, family migration remains the dominant mode throughout most of the observation period. Individuals from Guyana (4%), Bangladesh (3%), Iran (3%), Ecuador (3%), Peru (2%), Cambodia (1%), Ghana (1%), and Syria (1%) play a minor role. Table A.1 in the appendix lists the main countries of origin with predominantly labor migration to the U.S. Most labor migrants in the sample come from India (48%), the United Kingdom (12%) and Japan (9%). Less important countries of origin include Germany (5%), France (4%), Argentina (3%), Australia (3%), Venezuela (2%), Italy (2%), Israel (2%), South Africa (1%), and the Netherlands (1%). We classify Mexico and countries in Central America as other countries. They have high rates of irregular migration to the U.S. (Cohn et al., 2017), which are not captured by the Yearbook of Immigration Statistics.

Table A.2 in the appendix shows that our definition of country types indeed captures meaningful differences in the composition of migrants. Family migrants account for 65 percent of migrants from countries with predominantly family migration. With 5 and 15 percent, the share of family migrants is much lower for countries with predominantly labor migration and other countries. Similarly, labor migrants account for 61 percent of migrants from countries with predominantly labor migration but only for 12 and 4 percent of migrants from countries with predominantly family migration and other countries.

In the following analysis, we hence focus on migrants from countries with predominantly family migration to the U.S. We limit the sample to individuals who were between 22 and 60 years old at the time of immigration and the time of observation. This age range captures individuals who are likely to become active in the labor market at arrival. In addition, it excludes minor children of U.S. citizens who can be sponsored without waiting times (see Table 1). It also excludes young adults who immigrate as students or exchange visitors as well as older parents of U.S. citizens. These groups do not face waiting times either. We also restrict the sample to individuals who were born outside the U.S. as non-U.S. citizens, did not get naturalized within the first three years of immigration[13], immigrated between 1992 and 2018, and had spent at most ten years in the U.S. at the time of observation. Despite these restrictions, our sample likely includes considerable numbers of non-family migrants and some family migrants could be immediate relatives who do not face long waiting times. We revisit this issue in Section 6.3 and show that the inclusion of migrants who do not face waiting times for their visa biases our estimates towards zero. For family migrants who face waiting times, the effects of immigrating into a recession are hence likely more severe than our conservative main results suggest.

4.2 Descriptive statistics

Table 3 provides summary statistics of demographic characteristics and main outcome variables. Column 1 shows statistics for family migrants. For comparison, the table also shows the same information for migrants from the Philippines who constitute the largest group of family migrants in column 2, labor migrants in column 3, refugees in column 4, natives, i.e., U.S.-born individuals, in column 5, and U.S.-born graduates (all education levels) in column 6. We restrict the sample to individuals who were between 22 and 60 years old at the time of immigration/observation and observed at most 10 years after immigration/graduation. For graduates, we follow Schwandt and von Wachter (2019) and restrict the sample to individuals who were between 19 and 33 years old at the time of observation.

On average, family migrants immigrated at the age of 35. They are disproportionally female (62%) and have on average 12.8 years of schooling. While this is about a year less than the average native, family migrants are more likely than natives to hold a college degree (36%

[13]Information on the year of naturalization is only available in the ACS starting in 2008. Therefore, we can only apply this restriction to part of the sample.

vs. 33%). By comparison, labor migrants immigrated at the age of 32. Their sex ratio is more balanced (49% female), and they have considerably higher levels of schooling (15.9 years). Family migrants are slightly younger than natives at the time of observation (40.2 years vs. 41.6 years). Labor migrants are considerably younger (36.4 years).

Family migrants faced an initial unemployment rate (IUR) of 6.21 percent.[14] This is higher than the IUR faced by labor migrants (5.87 percent) and in line with our argument that family migrants cannot synchronize their arrival with labor market conditions in the U.S.

In terms of labor market outcomes during the first ten years in the U.S., family migrants do substantially worse than natives. Their employment levels (69% vs. 84%), annual wage income conditional on being employed (USD 36k vs. USD 54k in 2019 USD), real hourly wages conditional on being employed (USD 22 vs. USD 28), and occupational income scores (USD 25 vs. 27.5), the average hourly wage of a worker in the same occupation,[15] state, and year of observation, are lower. Not surprisingly, labor migrants have a strong labor market performance. They have substantially higher wage incomes (USD 81k), hourly wages (USD 41), and occupational income scores (USD 38) than family migrants or natives.

Family migrants are about as likely to receive public welfare assistance as natives (1.6% vs. 1.3%). This can be explained by the fact that family migrants have no access to welfare benefits in their first years after arrival. Finally, family migrants are much less likely to be household heads than natives (34% vs. 54%). They are not more likely to have moved across states within the last year (2.5% vs. 2.5%). About half of family migrants also live with a family member with longer tenure in the U.S., potentially their sponsors. By contrast, labor migrants are generally more independent and mobile.

The demographic characteristics of migrants from the Philippines are comparable to those of all family migrants. However, they have significantly higher levels of schooling (14.7 vs. 12.8 years) and college graduation rates (61% vs. 36%). They also do better in the labor market than all family migrants but still worse than natives.

The table also shows characteristics of refugees and U.S.-born graduates. Like family migrants, these population groups have little control over when they enter the U.S. labor market and therefore provide an interesting comparison. Consistent with our approach for family and labor migrants, we identify refugees as coming from countries for which refugee migration

[14] State-level unemployment rates come from the Local Area Unemployment Statistics, published by the U.S. Bureau of Labor Statistics.

[15] We classify occupations following the IPUMS approach *occ1990* and using the third hierarchical level with 101 distinct occupations. We deviate from this approach only in minor instances to combine small occupations with very few observations. Specifically, (i) we combine all mining occupations, (ii) combine legislators and top executives, (iii) add funeral directors, postmasters, and mail superintendents to managers of service organizations, n.e.c., and (iv) combine managers of horticultural speciality farms and horticultural speciality farmers. Overall, we distinguish between 90 occupations in our sample.

Table 3: Summary statistics

	Family migrants		Labor migrants	Refugees	Natives	Graduates
	All	Filipinos				
Personal characteristics						
Female (0/1)	0.62	0.66	0.49	0.50	0.50	0.50
	(0.49)	(0.47)	(0.50)	(0.50)	(0.50)	(0.50)
Age at immigration	34.9	35.2	31.8	33.8	.	.
	(9.03)	(8.95)	(8.00)	(8.67)	.	.
Age at observation	40.2	40.6	36.4	39.1	41.6	24.0
	(9.17)	(9.07)	(8.28)	(8.93)	(11.1)	(4.35)
Years of schooling	12.8	14.7	15.9	12.0	13.9	13.3
	(4.15)	(2.78)	(2.92)	(4.98)	(2.54)	(2.49)
At least 4 years of college (0/1)	0.36	0.61	0.73	0.29	0.33	0.27
	(0.48)	(0.49)	(0.44)	(0.45)	(0.47)	(0.45)
Economic conditions						
Unemployment rate at immigration	6.21	6.22	5.87	6.26	.	5.95
	(2.13)	(2.11)	(2.03)	(2.27)	.	(2.04)
Labor market outcomes						
Employed (0/1)	0.69	0.74	0.70	0.68	0.84	0.68
	(0.46)	(0.44)	(0.46)	(0.47)	(0.37)	(0.47)
Real annual wage income (in 1000 USD)	36.0	43.7	81.0	33.9	54.4	31.6
	(36.7)	(38.5)	(74.5)	(35.5)	(54.3)	(34.6)
Real hourly wage	21.6	25.6	40.7	20.3	28.1	19.2
	(22.5)	(24.0)	(34.1)	(21.0)	(26.0)	(18.4)
Occupational income score (USD)	25.0	28.0	37.7	23.8	27.5	24.9
	(11.5)	(12.5)	(14.7)	(11.0)	(12.0)	(11.2)
Occupational education score	13.1	13.6	15.0	12.9	13.7	13.5
	(1.81)	(1.86)	(1.90)	(1.81)	(1.83)	(1.84)
Self employed (0/1)	0.061	0.038	0.065	0.063	0.099	0.033
	(0.24)	(0.19)	(0.25)	(0.24)	(0.30)	(0.18)
Public welfare assistance (0/1)	0.016	0.0070	0.0032	0.060	0.013	0.016
	(0.13)	(0.083)	(0.056)	(0.24)	(0.11)	(0.12)
Social outcomes						
Previous migrant in HH (0/1)	0.49	0.45	0.21	0.27	.	.
	(0.50)	(0.50)	(0.41)	(0.44)	.	.
Being hh head (0/1)	0.34	0.33	0.47	0.48	0.54	0.36
	(0.48)	(0.47)	(0.50)	(0.50)	(0.50)	(0.48)
Moved b/w states last year (0/1)	0.025	0.027	0.058	0.033	0.025	0.048
	(0.16)	(0.16)	(0.23)	(0.18)	(0.16)	(0.21)
Observations	116,975	50,520	185,761	26,686	24,889,183	8,022,205

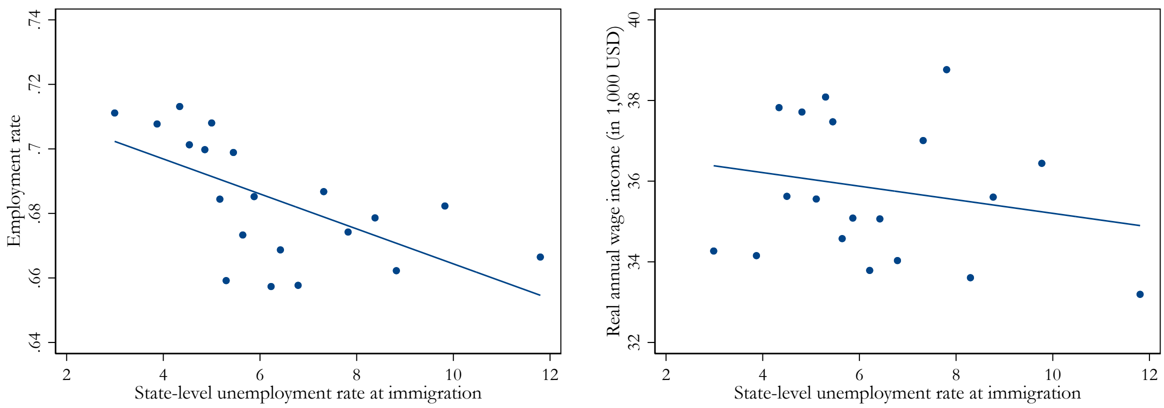
Notes: The table shows summary statistics for six different samples: Family migrants, Filipino migrants (the single largest group of family migrants), labor migrants, refugees, natives (U.S.-born individuals), and U.S.-born graduates (all education levels). Immigrant samples are restricted to individuals who were born outside the U.S. as non-U.S. citizens, did not get naturalized within the first three years of immigration, and immigrated between 1992 and 2018. In addition, the samples are restricted to individuals who were between 22 and 60 years old at the time of immigration/observation and observed at most 10 years after immigration/graduation. For graduates, the sample is restricted to individuals who were between 19 and 33 years old at the time of observation (Schwandt and von Wachter, 2019). The analysis is based on data from the 2000 U.S. Census and the 2001 to 2019 American Community Survey. Observations are weighted by the average annual sample weights to account for the fact that the census and ACS have very different sample sizes and that the sample size of the ACS is not constant over time. All wages are in 2019 USD. The occupational income score is the log average wage income of a worker in the same occupation, state, and year of observation. The occupational education score is the average number of years of schooling of a worker in the same occupation and year of observation. See Section 4 for more details.

accounts for more than 50 percent of yearly admissions. Individuals from Iraq (14.5%), Myanmar (11.4%), Ethiopia (10.5%), Ukraine (8.8%), and Somalia (6.5%) make up for most refugees in our sample. By and large, the demographic and labor market characteristics of refugees are similar to those of family migrants. Graduates are much younger (24 years vs. 40 years) as we consider graduates from all levels of education and restrict the sample to individuals who were between 19 and 33 years old at the time of observation. Graduates are close to family migrants regarding average years of schooling (13.3 vs. 12.8 years). And despite being considerably younger, they perform almost as well as family migrants on the labor market.

Before explaining our empirical approach, we explore the bivariate relationship between initial economic conditions and labor market outcomes in our sample of family migrants. Figure 2 plots average employment rates (Panel a) and real annual wage incomes (Panel b) for different IURs. As expected, higher IURs are associated with lower employment rates and lower annual wage incomes conditional on being employment in subsequent years.

Figure 2: Correlation between the initial unemployment rate and average labor market outcomes

(a) Employment **(b)** Real annual wage income



Notes: The figures show the correlation between the state-level unemployment rate in the year of immigration and the employment rate (left) and the real annual wage income (in 2019 USD) conditional on being employed (right) for our entire sample of family migrants. Binned scatter plot with 20 equally-sized bins.

5 Empirical approach

5.1 Econometric specification

We use two specifications to estimate how state-level IURs shape the economic integration of family migrants over time. The first specification takes the following form:

$$y_{i,s,t,m} = \alpha + \sum_{t=m+1}^{m+10} \beta_{(t-m)}\, IUR_{s,m} + \theta_s + \lambda_t + \chi_m + \gamma_{(t-m)} + \boldsymbol{X}_{i,t}\Delta + \epsilon_{i,t} \tag{1}$$

where $y_{i,s,t,m}$ measures the outcome of interest for family migrant i who was observed in state s in year t and immigrated in year m. Our focus is on four key labor market outcomes: Employment, log real annual wage income, log real hourly wages, and occupational quality as measured by the log occupational income score (the log average wage income of a worker in the same occupation, state, and year of observation).

The explanatory variable of interest is the state-level IUR $IUR_{s,m}$. We use a fully flexible model and allow the effect of $IUR_{s,m}$ to vary with the number of years in the U.S. $(t-m)$. We estimate the effect for the first ten years in the U.S. The coefficients $\beta_{(t-m)}$ capture the effect of the IUR plus the weighted sum of the effects of unemployment rates in subsequent years. These parameters are of interest as they capture the overall effect of initial economic conditions for a typical evolution of state-level unemployment rates afterwards (Oreopoulos et al., 2012; Schwandt and von Wachter, 2019; von Wachter, 2020). In other words, the parameters capture the full difference in labor market outcomes of family migrants who arrive at different stages of the business cycle. This qualification matters because state-level unemployment rates exhibit serial correlation, which only disappears after about five years.[16] For simplicity, we will follow the literature and only refer to the IUR in the following. However, the reader should keep in mind that the coefficient also reflects subsequent labor market conditions that are correlated with the IUR.

θ_s, λ_t, χ_m, and $\gamma_{(t-m)}$ represent a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects.[17] They control for persistent differences in economic conditions and immigrant characteristics across states (θ_s), nation-wide economic conditions at the time of observation (λ_t), nation-wide economic conditions at the time of immigration and changes in the characteristics of immigrant cohorts (χ_m), and the general path of economic integration over time ($\gamma_{(t-m)}$). $\boldsymbol{X}_{i,t}$ is a vector of migrant-level controls. It includes age, age

[16] The AR(1) coefficient is 0.81 (including state and year fixed effects). Serial correlation weakens considerably in the following years. The AR(2), AR(3), and AR(4) coefficients are 0.58, 0.36, and 0.15. Serial correlation disappears after five years. The AR(5) coefficient is close to zero (-0.01) and no longer statistically significant.

[17] As year-of-immigration, years-in-the-U.S. and year-of-observation are not separately identified, we drop two dummies from the year-of-observation instead of just one as for the other fixed effects.

squared, gender, education levels, and a full set of country-of-origin dummies. $\epsilon_{i,t}$ is an i.i.d. error term.

The second specification models the dynamic effects of the IUR with a fifth-order polynomial:

$$y_{i,s,t,m} = \alpha + \sum_{j=1}^{5} \beta_j \, IUR_{s,m}(t-m)^j + \theta_s + \lambda_t + \chi_m + \gamma_{(t-m)} + \boldsymbol{X}_{i,t}\Delta + \epsilon_{i,t} \tag{2}$$

The polynomial specification is less flexible and introduces more restrictions on the functional form. However, it generates more precise estimates as there are fewer parameters to be estimated. For the main results, we present both specifications side by side. Both specifications yield very similar results. For additional results, we therefore use the polynomial specification.

We estimate all models using OLS and cluster standard errors at the state-year-of-immigration level. We also weight observations by the average annual sample weights. Doing so accounts for the fact that the census and ACS have very different sample sizes and that the sample size of the ACS is not constant over the period 2000-2019.

5.2 Identification

Our key identifying assumption is that the immigration of family migrants is independent of state-level IURs. As we have argued above, family migrants cannot choose their date of immigration based on economic conditions. The combination of long waiting times, uncertainty about the length of waiting times, and the short validity of their visa does not allow them to synchronize their arrival with labor market condition in the U.S. In addition, family migrants typically join their sponsor's household in the U.S. Own calculations using administrative data from the Philippines on the universe of family migrants from the Philippines to the U.S. reveal that this is the case for 98.5 percent of all family migrants. Hence, family migrants do not choose the U.S. state based on economic conditions either. We therefore argue that the local economic conditions family migrants face at arrival in the U.S. are exogenous.

While migrants cannot influence waiting times, they could decide to forgo their visa when it becomes available. If this decision is correlated with migrants' characteristics, this would create a selection problem. We argue that it is unlikely that prospective migrants decide to forgo their visa to avoid temporary unfavorable conditions in the U.S. First, forgoing a visa is an extremely costly decision for family migrants. They would need to file a new application and be placed at the end of the visa queue. Second, income gains from migrating to the U.S. for migrants from lower-income countries are large (McKenzie et al., 2010; Clemens et al., 2019), which makes migration attractive even if conditions in the U.S. are not optimal.

We can conduct two indirect tests of this identifying assumption. First, if family migration is indeed exogenous to local economic conditions, the IUR should not be correlated with the composition and size of family migrant inflows to U.S. states. We test this prediction by regressing (i) the state-level IUR on individual-level migrant characteristics (including the full set of fixed effects outlined above) and (ii) the log number of family migrants arriving in a given state and year on the state-level unemployment rate in that year (including state and year-of-immigration fixed effects). Table 4 summarizes the results. The upper panel shows that individual characteristics of migrants (age, gender, years of schooling) are not correlated with the IUR. All coefficients are close to zero. This observation holds for our entire sample (column 2) as well as when we restrict the sample to migrants who were interviewed within the first three years of arrival and thus can be considered new arrivals (column 1). For the entire sample, we detect that an additional year of schooling is associated with a 0.0022 pp lower IUR. This is a very weak association and not economically significant. The lower panel shows that the size of family migrant inflows is unrelated to the IUR, too. The last two columns show the same associations for labor migrants, for whom we observe similar results.

Second, we test whether the unemployment rates before immigration are related to labor market outcomes of family migrants. If our identification strategy succeeds in decoupling the migration decision from economic conditions at the time of arrival, unemployment rates before arrival should not be correlated with labor market outcomes of family migrants. We test this prediction by using the sample specified above and regressing our four labor market outcomes on state-level unemployment rates at different points before immigration. Table A.5 in the appendix summarizes the results. It shows that unemployment rates in the years prior to immigration are not correlated with labor market outcomes. All coefficients are close to zero. Only the unemployment rate in the year of immigration has a significant and negative effect on labor market outcomes. Overall, these results support our argument that migration decisions of family migrants are exogenous to economic conditions at the time of immigration.

5.3 Internal and return migration

Measuring the unemployment rate at the state rather than the national level provides us with a more accurate measure of economic conditions at arrival. Figure A.2 in the appendix shows that there is considerable heterogeneity in unemployment rates between states over time, even after accounting for state and year fixed effects.

We do not observe the state of arrival, only the current state of residence and the state

Table 4: Correlation between the initial unemployment rate and migrant characteristics and the number of migrants

	Family migrants		Labor migrants	
	Three years	Ten years	Three years	Ten years
		Migrant characteristics		
Age at immigration (/100)	0.0237	0.0438	-0.0138	-0.0182
	(0.0442)	(0.0295)	(0.0404)	(0.0299)
Female (0/1)	0.0045	-0.0033	-0.0057	-0.0043
	(0.0081)	(0.0052)	(0.0044)	(0.0029)
Years of schooling	-0.0011	-0.0022***	-0.0029**	-0.0019**
	(0.0012)	(0.0008)	(0.0011)	(0.0008)
N	37163	116975	82109	185761
F-Test (p-value)	0.677	0.0111	0.0680	0.100
		Number of migrants		
Number of migrants (log)	-0.0086	-0.0208	0.0121	-0.0090
	(0.0186)	(0.0228)	(0.0363)	(0.0336)
N	1122	1377	1122	1377
F-Test (p-value)	0.642	0.360	0.739	0.788

Notes: The upper panel shows the coefficients from OLS regressions of the state-level unemployment rate in the year of immigration on migrant characteristics as well a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. The lower panel shows the coefficients from OLS regressions with the data collapsed by state and year of immigration. We regress the log number of family migrants observed in each state and year-of-immigration cell on the respective unemployment rate in that cell, controlling for state and year-of-immigration fixed effects. We replace missing values in empty cells with no observed migrants with zeros. In columns 1 and 3, the sample is restricted to migrants who immigrated in the three years prior to observation in order to capture recent inflows. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

of residence in the previous year. We use the earliest state of residence to proxy for the state of arrival. To the extent that migrants move between states, we measure IURs with an error. Figure A.3 in the appendix shows that family migrants are less likely to move between states than labor migrants. This is likely due to family ties. Still, in the first three years in the U.S., more than three percent of family migrants report having moved between states in the previous year. However, as we show later, family migrants do not seem to move in response to initial economic conditions. If interstate migration is independent of initial economic conditions, measurement error will increase over time. This classical measurement error would lead to attenuation bias, so we would overestimate the speed of convergence. The magnitude of our estimated effects should therefore be conservative.

Given the cross-sectional nature of our data, we are not able to track individuals over time. Selective return migration could thus potentially bias our results. For instance, we may wrongly conclude that immigrating into a recession is not associated with poor labor market outcomes if immigrants with poor labor market outcomes are more likely to leave the U.S. and disappear from our sample. However, Dustmann and Görlach (2015) document that family migrants, and those with an Asian background in particular, are least likely to return. Borjas and Bratsberg (1996) analyze the patterns of return migration and arrive at the same conclusion.

We provide additional evidence that selective return migration is unlikely to bias our estimates. Figure A.4 in the appendix plots the number of migrants observed in year t relative to the number of migrants in the year of immigration m for different years of immigration over time. There is no evidence of return migration for family migrants. If anything, the number of family migrants observed in the sample increases over time, especially for the early 2000s, potentially indicating that newly arriving family migrants were undersampled. The picture looks different for labor migrants. Their number in the sample substantially decreases over time, suggesting that many eventually return. This result is consistent with recent evidence from Akee and Jones (2019). Figure A.5 in the appendix shows that these results hold when we aggregate over all years of immigration and look at changes in cohort size of family and labor migrants over time.

6 Results

6.1 Economic conditions at arrival and labor market outcomes

Main results

Figure 3 summarizes our main regression results. It shows by how much a one pp increase in the IUR affects four key labor market outcomes: employment, log real annual wage income, log real hourly wages, and occupational quality as measured by the log occupational income score (the log average wage income of a worker in the same occupation, state, and year of observation). It plots the year-specific coefficient β for the first ten years in the U.S. Yellow diamonds refer to the flexible specification (Equation 1), blue dots to the less flexible polynomial specification including the 95 percent confidence interval (Equation 2). The results for both specifications are very similar. In the following, we therefore focus on the polynomial specification. The corresponding regression tables are in Table A.3 in the appendix.

A one pp increase in the IUR has only a small and short-lasting effect on the employment status of family migrants (Panel a of Figure 3). In the first year after arrival, family migrants are 1.0 pp less likely to be employed. Compared to a scenario where family migrants have the same labor force participation rate (LFPR) and propensity to be employed as the overall working-age population, this effect is relatively small. In that case, a one pp increase in the IUR should lower the initial employment rate by $\frac{1}{LFPR}$. With a LFPR of about 0.75 in this age group, this effect amounts to about 1.3 pp. Family migrants hence do relatively well in terms of finding a job. Consistent with this result, employment rates converge quickly and are no longer affected after five years in the U.S.

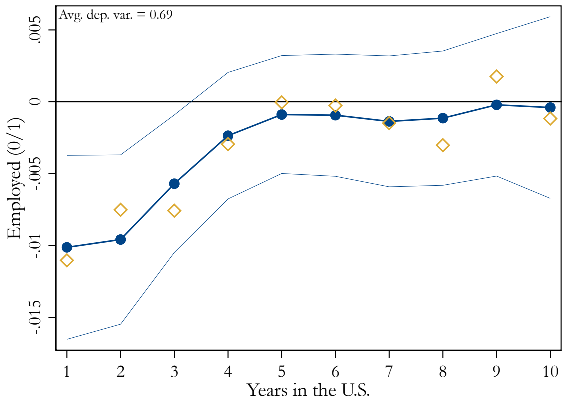
The picture looks different for real annual wage income (Panel b). Conditional on being employed, a one pp increase in the IUR decreases annual wage income in the first three years by about four percent. There is only slow convergence afterwards to a persistent negative effect of about two percent.

The negative effect on wage income is largely due to lower wage rates (Panel c). A one pp increase in the IUR decreases hourly wages by about two percent. The effect is relatively constant over time, with some convergence at the end of the ten-year period. The gap between the effect on annual wage income and the effect on hourly wages indicates that family migrants who arrive at higher unemployment rates work fewer hours.

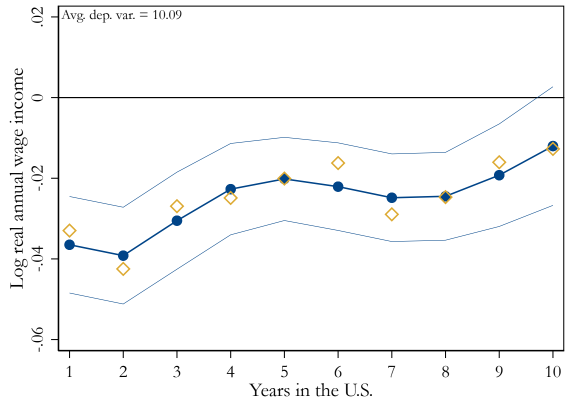
We also find evidence for occupational downgrading (Panel d). A one pp increase in the IUR persistently decreases occupational income scores by about one percent. Family migrants

Figure 3: Effect of the initial unemployment rate on labor market outcomes of family migrants

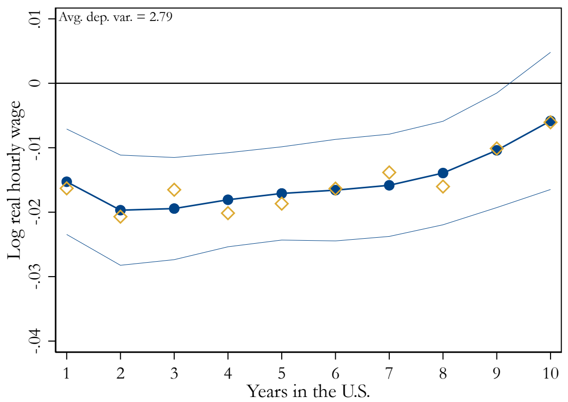
(a) Employment



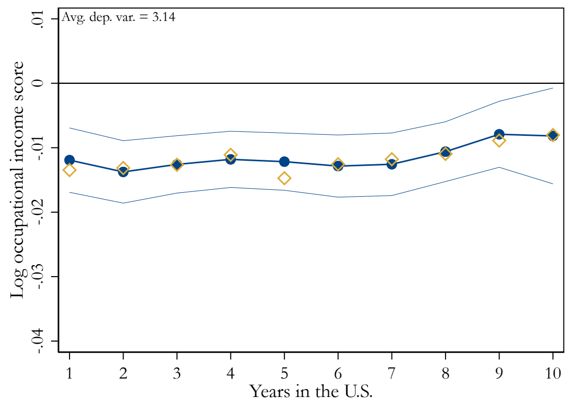
(b) Log real annual wage income



(c) Log real hourly wage



(d) Log occupational income score



Notes: The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year. Yellow diamonds refer to the flexible specification (Equation 1), blue dots including the 95 percent confidence interval to the less flexible polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. The corresponding regression tables are in Table A.3 in the appendix.

who immigrate into a recession are hence pushed into lower-paid occupations.[18]

To better understand the nature of occupational downgrading, we consider two additional outcomes: (i) an occupational education score and (ii) task measures that characterize the occupations that family migrants take up. The occupational education score is defined analogously to the occupational income score and measures the average number of years of schooling of a worker in the same occupation and year of observation. The task measures come from Acemoglu and Autor (2011) and are composite measures of O*NET (Occupational Information Network)

[18]Occupational income scores are expressed in hourly wage rates and can thus be compared to actual hourly wage rates. Interestingly, occupational income scores are substantially higher than actual hourly wage rates (the respective log values are 3.14 vs. 2.79). This is an indication that immigrants earn less than natives within occupations. It also implies that occupational downgrading accounts for almost the entire reduction in hourly wages in absolute terms (see Figure 5).

work activities. We distinguish between five different measures: (i) non-routine cognitive: analytical, (ii) non-routine cognitive: interpersonal, (iii) routine cognitive, (iv) routine manual, and (v) non-routine manual. Each measure is standardized to have a cross-occupation mean of zero and a standard deviation of one. Non-routine cognitive tasks are typical in managerial, professional, and technical occupations. Routine cognitive tasks are typical in clerical, administrative, and sales occupations. Routine manual tasks are typical in production and operative occupations. Non-routine manual tasks that require flexibility and adaptability are typical in service occupations. We provide a more detailed description of the task measures at the end of the appendix.

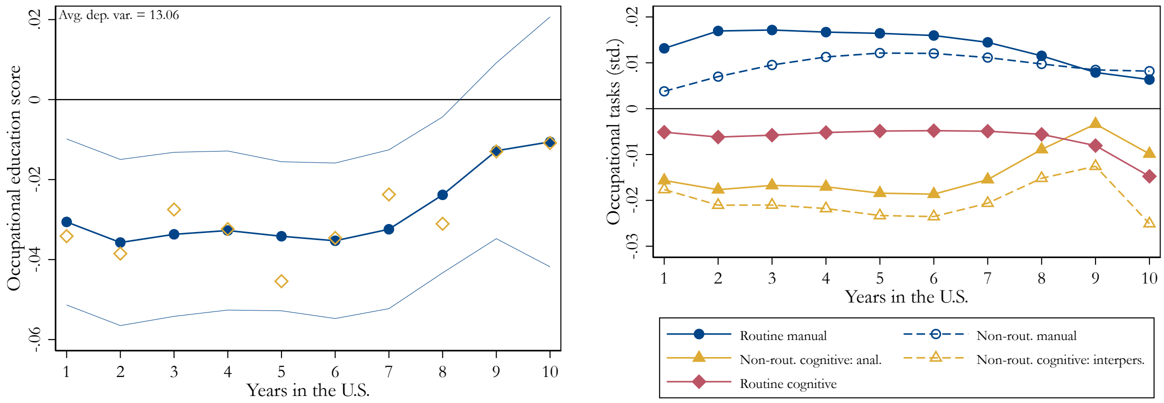
A one pp increase in the IUR decreases the occupational education score by about 0.3 years of schooling (Panel a of Figure 4). Family migrants who arrive at times of high unemployment also end up in occupations with different task profiles (Panel b). A higher IUR increases the likelihood of having an occupation with manual tasks (both routine tasks such as controlling machines and processes and non-routine tasks such as operating vehicles or mechanized devices). At the same time, a higher IUR decreases the likelihood of having an occupation with non-routine cognitive tasks (both analytical tasks such as analyzing data or thinking creatively and interpersonal tasks such as guiding and directing subordinates). The IUR has no major effect on the likelihood of having an occupation with routine cognitive tasks. Family migrants who immigrate into a recession hence experience occupational downgrading along a number of dimensions. They are more likely to enter occupations with lower average wages, lower average educational requirements, and emphasis on manual rather than non-routine cognitive tasks. This downgrading might also affect the type of human capital they accumulate on the job and explain why the effects are relatively persistent.

To more systematically understand the income loss of immigrating into a recession, we decompose the effect into four components: income loss due to occupational downgrading as measured by the occupational income score, due to a reduction in residual hourly wages (i.e., beyond the income loss due to occupational downgrading), due to a reduction in working hours (intensive margin of labor supply), and due to a lower probability of being employed (extensive margin of labor supply).

To do so, we first calculate the average employment rate, annual working hours, annual wage income, hourly wage, and occupational income score of family migrants by years in the U.S. We can now obtain the reduction in annual wage income due to occupational downgrading (a) by multiplying the effect of a one pp increase in the IUR on log occupational income scores times the average occupational income score and average hours worked. Multiplying the effect

Figure 4: Effects of the initial unemployment rate on additional occupational characteristics

(a) Occupational education score **(b)** Occupational tasks



Notes: The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year using the polynomial specification (Equation 2). The outcome in Panel a is an occupational education score, which is the average number of years of schooling of a worker in the same occupation and year of observation. The outcomes in Panel b are occupational task measures defined by Acemoglu and Autor (2011). They are standardized to have a cross-occupation mean of zero and a standard deviation of one. We describe the task measures at the end of appendix. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-since-immigration fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

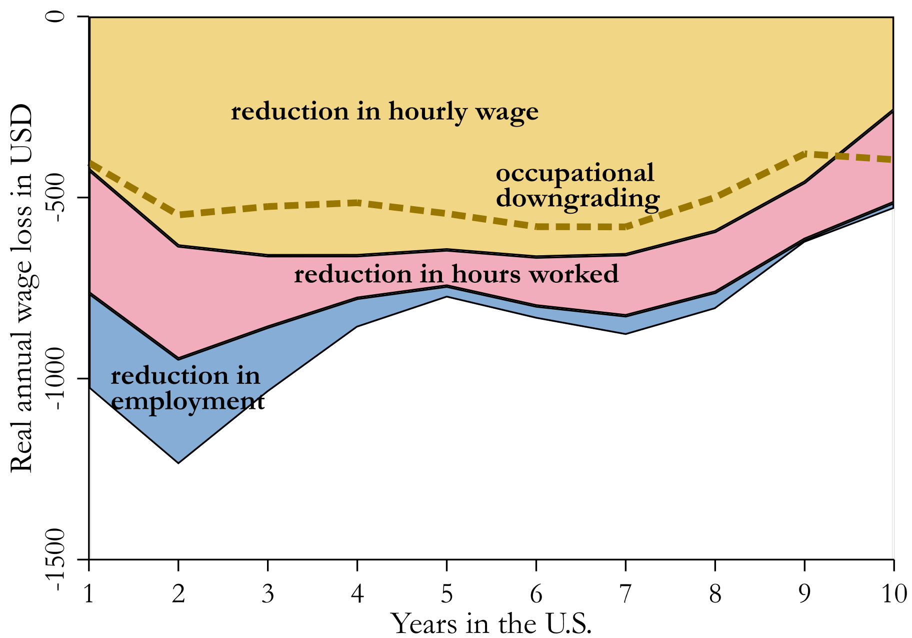
of a one pp increase in the IUR on log hourly wages times the average hourly wage rate and average working hours gives us the total effect on annual wages due to lower hourly wages (b). To obtain the effect due to a reduction of the labor supply at the intensive margin (c), we multiply the effect of a one pp increase in the IUR on annual hours worked (shown in Panel d of Figure A.14 in the appendix) times the average hourly wage rate. The sum of (b) and (c) gives us the total effect on annual wage income conditional on being employed. To obtain the effect due to a reduction of the labor supply at the extensive margin (d), we multiply the effect of a one pp increase in the IUR on being employed times the average annual wage income.

Figure 5 shows the results of the decomposition for a one pp increase in the IUR. All four components play a considerable role. Over the first ten years in the U.S., the estimated cumulative loss due to occupational downgrading is about USD 4,000, which also explains the reduction in income due to lower hourly wages that amounts to USD 4,591. The cumulative income loss due to a reduction of working hours is about USD 1,600, and due to lower employment rates USD 900 (all in 2019 USD discounted with 5%). Overall, a one pp increase in the IUR decreases annual wage income by about USD 1,100 in the first years and still more than USD 500 after ten years in the U.S.[19] The estimated loss in the net-present-value wage income over

[19]The effect on annual wage income in absolute amounts appear to be more persistent than the relative effect presented in Figure 3. This is because the relative effect translates into a fairly constant absolute effect as overall income levels rise quickly with time spent in the U.S.

the entire ten-year period amounts to about USD 7,100. A five pp rise in unemployment rates, a typical rise in a large recession (von Wachter, 2020), would hence reduce the ten-year wage income of an average family migrant by USD 35,5k (assuming linearity of the effect). This is a large effect. We can compare this earnings loss to the earnings loss of graduating in an equally large recession. We follow Schwandt and von Wachter (2019) and consider all education levels, but restrict the sample to U.S.-born graduates. We use the ACS data and our econometric specification, replacing the year of immigration with the year of graduation (also see Figure 6). A five pp rise in unemployment rates reduces the ten-year wage income of an average graduate by USD 23k. The effects are hence more severe for family migrants.

Figure 5: Decomposition of the effect of a one pp increase in the initial unemployment rate on annual wage income



Notes: The figure shows the absolute loss in real annual wage income (in 2019 USD) as a result of a one pp higher unemployment rate in the year of immigration. It decomposes the income loss into four components: (i) income loss due to a reduction in hourly wages (yellow area), (ii) the reduction in hourly wages that is due to occupational downgrading (dashed dark yellow line), (iii) income loss due to a reduction in working hours conditional on being employed (red area), and (iv) income loss due to a lower probability of being employed (blue area).

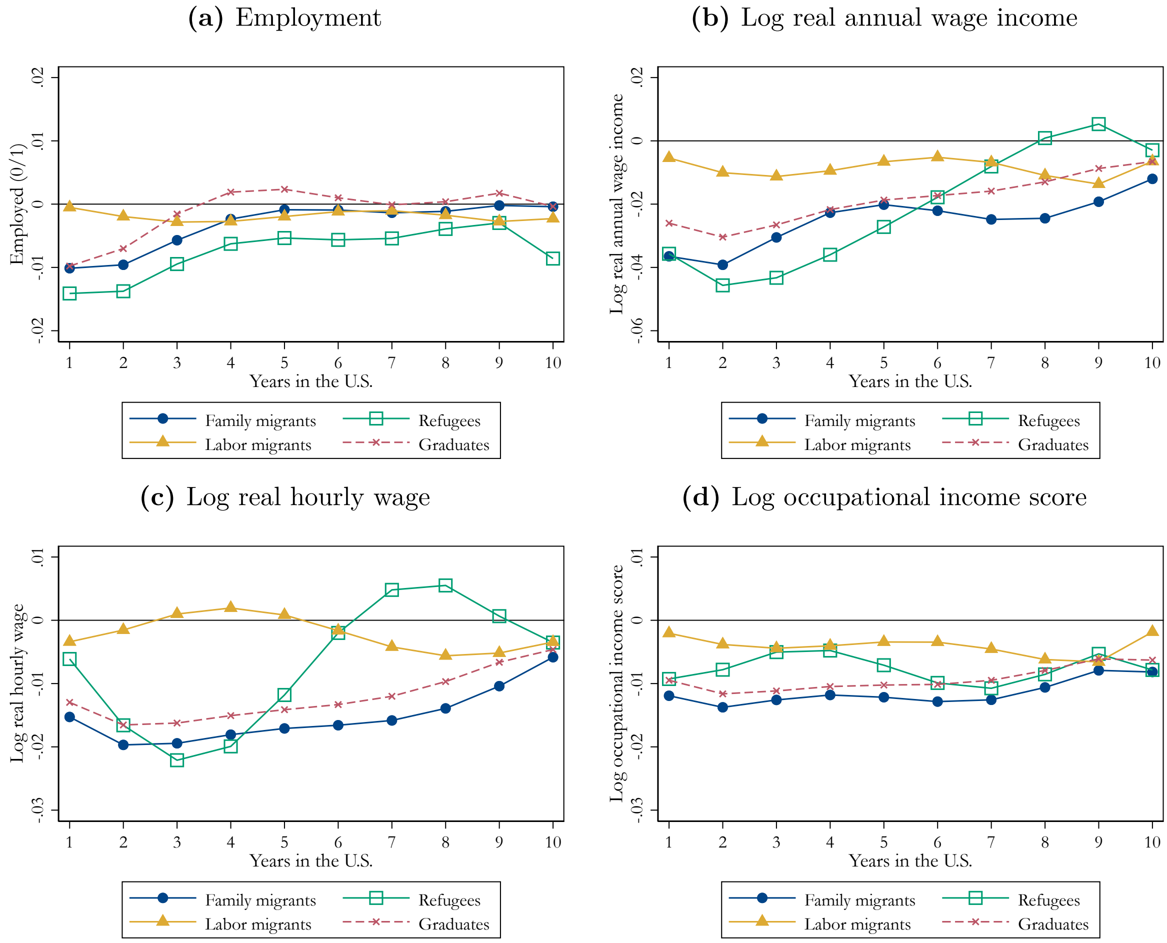
By how much does immigrating into a recession slow down the economic assimilation of family migrants? To study the convergence toward natives, we first calculate the average employment rate and annual wage income of family migrants by years in the U.S. We then use the estimated marginal effects to derive the employment rate and annual wage income for a five pp increase in the IUR. Panel a of Figure A.6 in the appendix shows that the IUR has only a relatively small and short-lasting effect on assimilation in terms of employment. The employment rate of family migrants also converges to the native employment rate after about nine years. A higher IUR, however, slows down assimilation in terms of annual wage income (Panel b). According to our estimates above, a one pp increase in the IUR decreases annual wage incomes by 2-4 percent. This relative effect translates into a fairly constant absolute effect as overall income levels rise quickly with time spent in the U.S. The figure suggests that a five pp increase in the IUR delays assimilation in terms of annual wage income by about two years. The figure also shows that the income levels of family migrants do not fully catch up with those of natives. After ten years, the average immigrant-native gap in annual wage income is about USD 12,100. A five pp increase in the IUR widens the gap by an additional USD 2,500.

How does entering the labor market in recession compare across different population groups? Figure 6 compares the effects across (i) family migrants, (ii) labor migrants, (iii) refugees, and (iv) U.S.-born graduates (all education levels). Our results are qualitatively similar for family migrants and graduates. Both groups have little control over when they enter the U.S. labor market. However, all effects are more pronounced for family migrants than for graduates. Refugees experience slightly larger and more persistent effects on employment. However, they also see more convergence in annual wage income and hourly wages. By contrast, we hardly observe any effects on the labor market outcomes of labor migrants, especially in the first years after arrival. By definition, these migrants arrive with a job. Their economic integration should hence be less susceptible to economic conditions at arrival.

We also test whether the IUR has a non-linear effect on our main outcomes by using a quadratic specification. Table A.4 in the appendix shows that the IUR has a non-linear effect on employment, which decreases as the IUR increases (column 1). Still, the effect of the IUR on employment remains small. We do not find such evidence for other outcomes (column 2-4). The coefficients on the quadratic terms are small and far from being statistically significant.

In addition, we test for effect heterogeneity by gender and level of education. Overall, we find limited effect heterogeneity for both dimensions. The employment effect is slightly more negative for female than for male family migrants (Figure A.7 in the appendix). However, the opposite is true for the effect on hourly wages. There are no major differences in annual wage income, suggesting that male family migrants work longer hours to make up for lower hourly wages. The initial labor market effects are relatively similar for family migrants with and without a college degree (Figure A.8 in the appendix). The effects on log occupational income scores are a bit more pronounced for higher-skilled family migrants though. These results also hold when we restrict the sample to individuals who were older than 30 years at the time of immigration to minimize the possibility that the level of education is potentially affected by the

Figure 6: Effect of the initial unemployment rate on labor market outcomes of family migrants, labor migrants, refugees, and U.S.-born graduates



Notes: The figure reruns the main analysis for four different samples: Family migrants, labor migrants, refugees, and U.S.-born graduates (all educational levels). Section 4 outlines the construction of these samples. The x-axis shows the years since immigration/graduation. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration/graduation on the outcome variable in the respective year using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration/graduation, and years-since-immigration/years-since-graduation fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies.

initial unemployment rate (Figure A.9 in the appendix).

Robustness checks

We check the robustness of our main results to address several potential concerns. First, our analysis of annual wage income is conditional on being employed and might therefore suffer from sample selection bias. So far, we have implicitly assumed that sorting into employment is unrelated to the IUR and annual wage income. This assumption may not be unreasonable in our case. The IUR has only a small and short-lasting effect on employment. It hence does not considerably affect the pool of individuals for whom we observe annual wage income. In addition, the analysis of effect heterogeneity does not suggest that the IUR systematically affects employment of particular groups of family migrants more strongly. Nevertheless, we address potential sample selection bias and conduct an unconditional analysis of annual wage income. We first assign zero earnings to individuals who do not report any wage income and then increase all earnings by a small amount to maintain the log specification. The effect on annual earnings depend on the amount we add (Figure A.10 in the appendix). When adding USD 1, the effect becomes much more pronounced. A one pp increase in the IUR decreases annual earnings in the first four years by about ten percent. There is quick convergence in the years that follow and the negative effect is reduced to about five percent after eight years in the U.S. When adding USD 500 and 1000, however, the effect on annual earnings is much more similar to our original estimate. The effect of a one pp increase in the IUR is slightly larger in the first years but converges to a similar negative level after eight years in the U.S. To avoid adding an arbitrary amount, we also run a similar analysis in absolute levels with the log transformation. We look at three outcomes: Annual wage income conditional on being employed, annual wage income with incomes for non-employed individuals set to zero, and total earnings (labor income and all other forms of income including transfers). Figure A.11 in the appendix shows that the effects are extremely similar across the three outcomes. It is also similar to the results of our decomposition exercise that is based on the conditional log specification but shows the wage income loss in levels (Figure 5). These exercises suggest that potential sample selection bias has no major implications for our results.

Second, economic conditions at the time of observation could also affect labor market outcomes. To the extent that current and initial economic conditions are correlated, our results reflect the effect of both initial and subsequent conditions. We use state-year-of-observation fixed effects to address this issue. The effects are qualitatively similar but smaller (Figure A.12 in the appendix). The smaller effect sizes could be due to state-year-of-observation fixed effects capturing some of the typical evolution of state-level unemployment rates after arrival (which were previously captured by the IUR).

Third, local economic conditions in the U.S. and in the country of origin might not be fully independent. For instance, migrant networks could transmit economic shocks from different U.S. states to countries of origin (via remittances, trade, or FDI links). Due to long waiting times for a visa, such links would not change the composition of new family migrants in the short run. But family migrants could potentially change their labor market behavior in the U.S. to support family members left behind through remittances. We use country-of-origin-year-of-immigration fixed effects to capture all shocks that are specific to a country of origin in the year of immigration. Our results remain unchanged (Figure A.13 in the appendix).

Fourth, we also investigate the effects on self-employment, labor income (i.e., wage, business, and farm income), and total earnings (i.e., labor income and all other forms of income including transfers). Our results are robust to these more comprehensive definitions of income (Figure A.14 in the appendix). The effect on self-employment is positive but close to zero and not statistically significant.

6.2 Coping strategies

Migrant networks

A large literature has shown that migrant networks substantially help migrants to find a job (e.g., Munshi, 2003, Patel and Vella, 2013, and Battisti et al., 2021). The support provided by migrant networks might be particularly beneficial in a recession when the scarcity of jobs makes it more difficult for recent migrants to compete in the labor market. With relatively low levels of destination-specific human capital and work experience it is difficult for migrants to signal their ability to potential employers. Migrant networks can help migrants to overcome at least part of this information asymmetry and thus increase migrants' attractiveness to employers. Network support should matter less in a boom when more jobs are available and job search is less competitive.

To test this prediction, we include an interaction in our specification and analyze whether the employment and wage effects of immigrating into a recession differ by the size of the local migrant network. We define local network size as the share of fellow countrypeople among the working-age population (defined as 22-60 years). We calculate this variable at the state level and for three points in time: for 1990 and 2000 based on census data and for 2010 based on data from the ACS waves conducted in 2009, 2010, and 2011.[20] The initial network size of each migrant in our sample is then given by the value of the network variable in the year that predates the year of immigration. For instance, a migrant who arrived in 2003 is assigned the network as measured in 2000.

We restrict the sample to migrants who had not spent more than three years in the U.S. to capture the initial integration into the labor market. We look at average effects across these years to increase the precision of our estimates. We also focus on migrants from the Philippines, Vietnam, the Dominican Republic, and Haiti. The samples of migrants from other countries with predominantly family migration are too small, especially for the analysis of ethnic occupations introduced below. For the same reason, we also exclude migrants when there are

[20]The 2010 U.S. Census was a short-form-only census and does not provide the relevant information.

Table 5: Effect of the initial unemployment rate on labor market outcomes of family migrants by network size

	Employment and wages				% of ... in occupation			
	(1) Employ-ment	(2) Log wage income	(3) Log hourly wage	(4) Log occ. inc. score	(5) Country-people	(6) Natives	(7) Mexicans	(8) Chinese
Network size x UR at immigration (/100)	0.26** (0.11)	0.02 (0.21)	0.14 (0.16)	0.01 (0.07)	3.11* (1.88)	0.27 (0.42)	-1.27 (1.78)	1.14 (1.46)
UR at immigration (/100)	-1.32** (0.54)	-2.30* (1.28)	-1.80** (0.91)	-0.72* (0.41)	-3.91 (8.27)	-2.84 (2.08)	-2.49 (8.70)	4.44 (6.85)
Network size	0.01* (0.01)	0.00 (0.02)	-0.04*** (0.01)	-0.01** (0.01)	-0.27** (0.13)	-0.04 (0.03)	0.08 (0.13)	-0.01 (0.11)
Observations	27334	17864	17864	17864	17864	17864	17864	17864
Mean outcome	0.61	9.82	2.68	3.11	4.98	2.34	3.66	3.02

Notes: The table reports OLS estimates. The column title shows the outcome variable. The outcome variables in the last four columns are the state-level shares of workers from the same country of origin that work in the same occupation (in percent). UR at immigration is the state-level unemployment rate in the year of immigration (divided by 100 to improve readability). Network size is the share of migrants from the same country of origin among all working-age adults in the state at the time of immigration. The sample is restricted to migrants who immigrated in the three years prior to observation in order to capture recent inflows. We only include observations for which we observe at least 100 migrants from the same country of origin in the same state for calculating the occupational distribution. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

fewer than 100 observations of migrants from the same country of origin in the same state to calculate the network measure and occupational distribution.

Table 5 shows the results. Consistent with our hypothesis, larger migrant networks mitigate the negative employment effect of adverse economic conditions at arrival (column 1). A one pp higher population share of fellow countrypeople weakens the employment effect of a one pp higher IUR by 0.26 pp (from -1.32 pp to -1.06 pp). However, conditional on being employed, networks are not able to cushion the effect on annual wage incomes (column 2), hourly wages (column 3), or log occupational income scores (column 4). Here, the interaction terms are not statistically or economically significant. In a recession, networks can thus help family migrants to find a job but do not improve the quality of the job found.

If networks indeed facilitate job search in a recession, they should push migrants into occupations with larger networks of fellow countrypeople. We investigate this hypothesis by following Patel and Vella (2013) and constructing a measure of the concentration of fellow countrypeople in different occupations:

$$concentration_{c,o,s,t} = \frac{100 * mig_{c,o,s,t}}{mig_{c,s,t}}$$

where $concentration_{c,o,s,t}$ measures the percent of workers from country of origin c in state

s in year t who are employed in occupation o. High values of $concentration_{c,o,s,t}$ indicate that workers from a given country of origin concentrate in these occupations. We distinguish between the same occupations as for calculating the occupational income score and again calculate the measure for the years 1990, 2000, and 2010.

Column 5 of Table 5 shows that in a recession networks indeed make family migrants more likely to enter occupations with higher concentrations of fellow countrypeople. In response to a one pp higher IUR, a one pp higher population share of fellow countrypeople increases the share of fellow countrypeople in the same occupation by 3.11 pp. Compared to the average share of fellow countrypeople (4.98%), this is a large effect amounting to a 62 percent increase. We check the robustness of this result in Table A.6 in the appendix. It holds when we base the concentration measure on industries instead of occupations or change the required minimum number of observations of migrants from the same country of origin in the same state from 100 to zero or 200. The interaction between IUR and the share of fellow countrypeople only becomes weaker when we no longer restrict the sample to recent arrivals and look at the entire ten-year period. As some migrants will have changed their jobs over that period, the initial network effects could be attenuated.

We also run a placebo regression and check whether family migrants are more likely to enter occupations in which many U.S.-born workers, i.e., generally large occupations, or other migrant groups are employed. We calculate the concentration measure for U.S.-born workers and for the two most important countries of origin of non-family migrants, Mexico and China, and use them as outcomes. The last three columns of Table 5 summarize the results. In line with the hypothesis that migrant networks should not make family migrants more likely to enter occupations with higher concentration of other population groups, all three interaction terms turn out to be insignificant. Thus, migrants do not appear to be pushed into large occupations or occupations with high concentration of migrants in general. Taken together, these results suggest that migrant networks help family migrants to find employment during periods of higher unemployment and channel them into ethnic occupations.

Family support

Family migrants are generally not entitled to welfare benefits for at least five years after arrival. Instead, sponsors are obliged to support sponsored family members for ten years or until they become U.S. citizens (Kolker, 2016). The ACS provides information on welfare receipt and the composition of household members, which we can use as a proxy for receiving support from the family.

Panel a of Figure 7 confirms that adverse economic conditions at arrival have no effect on receiving welfare assistance. Family migrants seem to rely on support from the family instead. A one pp increase in the IUR increases the likelihood of living with a family member with longer tenure in the U.S. by about 1 pp over the entire ten-year period (Panel b). At the same time, a one pp increase in the IUR decreases the likelihood of being a household head by 0.5 pp in the first years, with slow convergence afterwards (Panel c). These results are consistent with the idea that adverse economic conditions make it more difficult for recently arrived family migrants to move out of their sponsors' households because they depend on support from the family.

The immobile support received from the family could also reduce the geographic mobility of family migrants. In general, the literature has found that migrants are more mobile than natives (Green, 1999, Braun and Kvasnicka, 2014, and Cadena and Kovak, 2016). Panel d of Figure 7, however, shows that family migrants do not increase their geographical mobility in response to adverse local economic conditions at arrival. The increased dependence on family members likely increases the job search frictions of family migrants who immigrate into a recession.

Having no access to welfare benefits may also explain the small effects of a higher IUR on employment and the large effects on wages and occupational quality. Family migrants may lower their reservation wage and accept lower-paying jobs to earn own income already shortly after arrival to reduce the burden on their family.

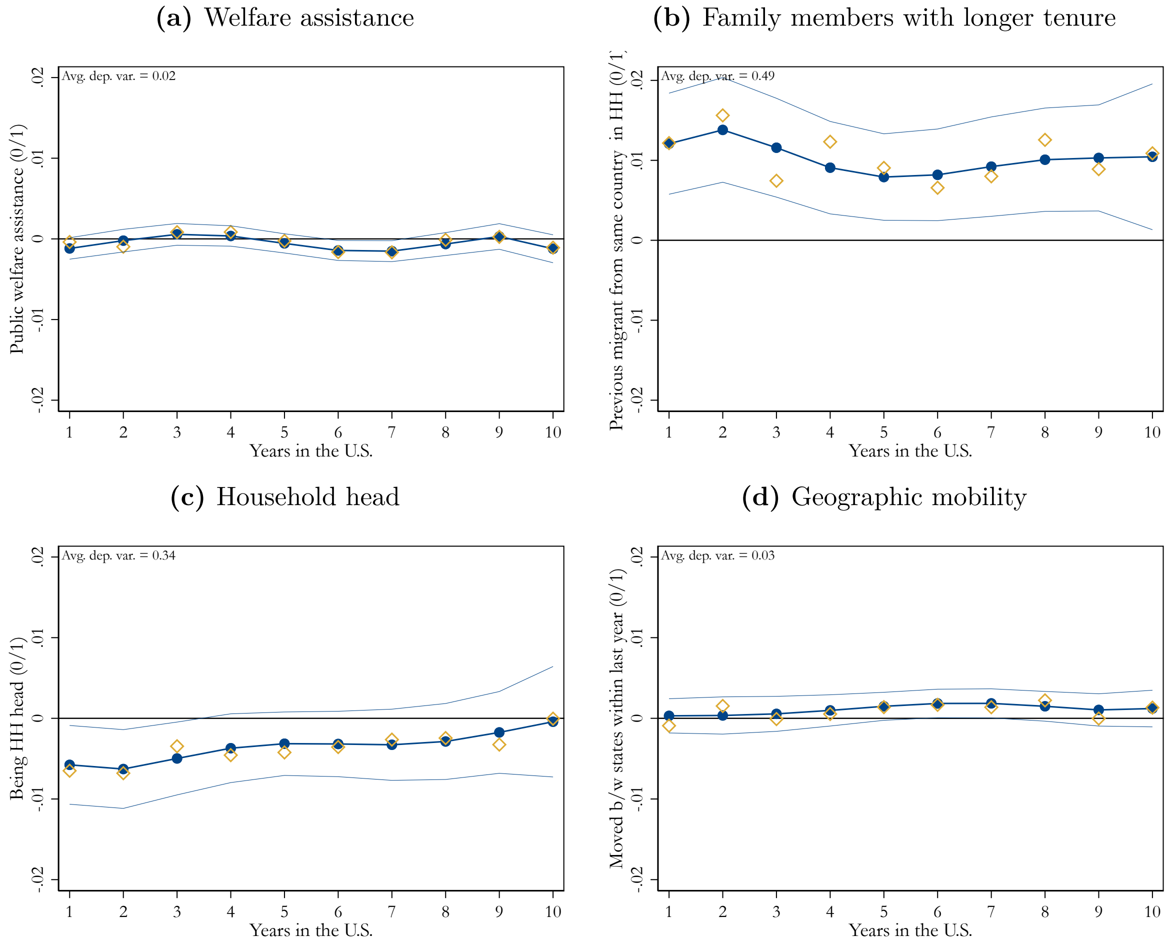
Investment in human capital

Younger family migrants might also invest in additional human capital in response to adverse economic conditions at arrival.[21] Indeed, the opportunity costs of acquiring human capital through additional formal education might be lower in times of high unemployment. We test this hypothesis by checking whether the IUR affects enrolment in tertiary education. We restrict the sample to individuals who were at most 30 years old at the time of immigration. Arguably, younger individuals should have the largest incentives to invest in human capital. We also restrict the sample to individuals who had spent at most three years in the U.S. at the time of observation to capture their initial response to the IUR. We look at average effects across these years to increase the precision of our estimates.

Table 6 shows the results. We do not find an effect of the IUR on enrolment in tertiary education (column 1), even if we further restrict the sample to individuals who were at most 25 years old at the time of immigration (column 2). As expected, we do not find an effect if

[21] Battisti et al. (2021) provide some evidence that seemingly unfavorable initial condition in the form of smaller co-ethnic networks can increase investment in human capital.

Figure 7: Effect of the initial unemployment rate on receiving welfare assistance and support from the family



Notes: The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year. Yellow diamonds refer to the flexible specification (Equation 1), blue dots including the 95 percent confidence interval to the less flexible polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

we restrict the sample to individuals who were older than 30 years at the time of immigration (column 3). Older individuals should be less likely to invest in additional human capital.

6.3 Remaining biases and alternative strategies of identifying family migrants

We cannot precisely identify family migrants who have to queue for their visa. We have therefore restricted the sample to immigrants from countries for which family migration is the dominant mode of migration to the U.S. Yet, the sample likely includes considerable numbers of non-family migrants and immediate relatives who do not face long waiting times for their visa. Their migration decisions may well be endogenous to initial economic conditions. In case of

Table 6: Effect of the initial unemployment rate on family migrants' enrolment in tertiary education

	22-30 years	22-25 years	31-60 years
UR at immigration	-0.002	-0.004	0.003
	(0.004)	(0.007)	(0.002)
Observations	13711	5944	23452
Mean outcome	0.176	0.227	0.065

Notes: The table reports OLS estimates. The column title shows the age restriction applied to the sample. The outcome variable is a binary indicator of enrolment in tertiary education at the time of the interview. UR at immigration is the state-level unemployment rate in the year of immigration. The sample is restricted to migrants who immigrated in the three years prior to observation in order to capture recent inflows. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

endogenous migration decisions, however, our estimates are likely to be biased towards zero.

Labor migrants are less susceptible to labor market conditions at the time of arrival as they arrive with a job. Indeed, as shown in Figure 6 above, IURs are hardly related to labor market outcomes of emplyoment migrants. The effects of immigrating into a recession are hence potentially more severe for family migrants than our main results suggest.

When it comes to immediate relatives who can be sponsored without waiting times, sponsors might be more likely to select more productive family members in times of high unemployment. Otherwise, they might find themselves obliged to offer financial support. A positive selection of immediate relatives would again bias our estimates towards zero. Unfortunately, our data do not allow us to test this argument. In any case, as we have shown in Table 4, IURs are not correlated with observable migrant characteristics. The potential for donors to endogenously sponsor family members might thus be limited.

To gauge the magnitude of such biases towards zero, we include an interaction between the IUR and the share of capped family migrants among all migrants moving to the U.S. from the same country and in the same year. If the above arguments are correct, the effect of the IUR should become more negative the higher the share of capped family migrants (as they face waiting times). Indeed, as Panel B of Table 7 shows, the interaction term is negative for all wage-related labor market outcomes (but not for being employed). Increasing the share of capped family migrants from 0 to 100 percent decreases the negative effect of a one pp higher IUR on annual wage incomes by an additional 8.3 percent, on hourly wages by an additional 6.6 percent, and occupational income scores by an additional 3.2 percent over the first ten

Table 7: Effect of the initial unemployment rate on labor market outcomes of family migrants by share of capped family migrants from same country of origin

	Employed (0/1)	Log real annual wage income	Log real hourly wage	Log occupational income score
Panel A: Average effect of UR at immigration for family migrants				
UR at immigration (/100)	-0.344*	-2.451***	-1.573***	-1.183***
	(0.205)	(0.452)	(0.329)	(0.207)
Observations	116975	84864	84864	84769
Panel B: Interaction between UR at immigration and share of capped family migrants				
Share capped family migrants x UR at immigration (/100)	-0.004	-0.083***	-0.066***	-0.032***
	(0.005)	(0.014)	(0.011)	(0.006)
UR at immigration (/100)	-0.623***	-0.827**	-0.166	-0.150
	(0.091)	(0.332)	(0.261)	(0.131)
Share capped family migrants	0.002***	-0.002**	-0.002***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.000)
Observations	661431	465844	465844	465419

Notes: The table reports OLS estimates. The column title shows the outcome variable. UR at immigration is the state-level unemployment rate in the year of immigration. The share of capped family migrants is the share of capped family migrants among all migrants moving to the U.S. from the same country of origin and in the same year as measured by the Yearbooks of Immigration Statistics. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

years after arrival. These effects are about three times as large as our conservative main results averaged over the same period (Panel A of Table 7).

We also offer two alternative strategies of identifying family migrants with waiting times. First, we use data from the Philippine government that provide information on the visa type for permanent migrants from the Philippines to the U.S. since 1988. The administrative data capture the universe of migrants as every permanent migrant from the Philippines needs to register with the Commission on Filipinos Overseas (CFO) for departure clearance. In addition to the exact admission category, the data include migrant-level information on age, gender, education, date of migration, and the destination state in the U.S. We use all this information to reweigh our sample of Filipino migrants in the ACS, so they resemble the characteristics of family migrants in visa categories with waiting times. Compared to Filipino migrants in the ACS sample, CFO family migrants with waiting times are on average older at the time of immigration (39 vs. 35 years), less likely to be female (53% vs. 66%), and less likely to have a college degree (55% vs. 61%). Nevertheless, as Figure A.15 in the appendix shows, the reweighted results are similar to the baseline results without such weights. Consistent with a cleaner identification of family migrants who faced waiting times, the wage effects of immigrating into a recession are even larger. The figure also shows that immigrating into a recession has generally somewhat more pronounced effects for Filipino migrants than other (non-Filipino) family migrants.

Second, we try to exclude immediate relatives who can be sponsored without waiting times from the sample. Such relatives include spouses, parents, and unmarried children under 21 years of U.S. citizens (see Table 1). Our main sample already excludes minor children and older parents as it is limited to individuals aged 22 to 60 at the time of immigration. To also exclude younger parents, we further reduce the age range to individuals aged 22 to 40. A person sponsoring parents as immediate relatives needs to be a U.S. citizen and at least 21 years old. The reduced age range hence excludes all parents who were at least 20 years old at birth of their child. To exclude spouses of U.S. citizens, we further restrict the sample to individuals who were never married (so they cannot be sponsored by their spouse) or married couples who immigrated in the same year (so none of them is likely to be U.S. citizen at the time of immigration).[22][23] Figure A.16 in the appendix shows that results for this subsample are similar to the main results. The stability of the results suggests that even family migrants without waiting times do not try to synchronize their arrival with labor market conditions in the U.S. The large income differences between countries of origin and the U.S. might explain this behavior.

7 Conclusion

We analyze how IURs affect the economic integration of immigrants in the U.S. Our identification strategy exploits long waiting times for visas that decouple the migration decision of family migrants from economic conditions at the time of arrival.

Economic conditions at arrival generate substantial heterogeneity in the economic integration of family migrants. They also help to explain immigrant-specific phenomena such as downgrading and reliance on social networks. A one pp higher IUR has a relatively small and short-lasting effect on employment but decreases annual wage income by about four percent in the short run and two percent in the longer run. These estimates are likely lower-bound estimates of the true effects as we are not able to precisely identify family migrants in the data. The negative effect on annual wage income is the result of a combination of occupational downgrading, which results in lower hourly wages, and a reduction in working hours. Migrant

[22] Information on the year of marriage and on citizenship is only available from 2008 onwards. We are thus not able to exploit this additional information for our analysis.

[23] The focus on married couples who immigrated in the same year likely also excludes spouses of LPRs (F2A visa holders). Spouses of LPRs (and U.S. citizens) are more likely than other family migrants to adjust their visa status while being in the U.S. They might hence have chosen particular economic conditions when they entered the U.S. on a non-immigrant visa. In general, adjustment of status is not common among family migrants. For instance, according to the 2015 Yearbook of Immigration Statistics, only 16,783 family migrants did so in 2015. But most of these cases were concentrated among spouses of LPRs and U.S. citizens, whom we exclude from this subsample.

networks mitigate the negative labor market effects of immigrating into a recession and channel migrants into jobs with higher concentration of fellow countrypeople. Family migrants who arrive at times of high unemployment are also more likely to continue residing with family members. The immobile support received from the family is likely associated with an increase in search frictions, which could explain the persistence of the labor market effects. Our results show that the system of family-sponsored immigration to the U.S. has important consequences for the economic integration of family migrants.

References

ACEMOGLU, D. AND D. AUTOR (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," in *Handbook of Labor Economics*, Elsevier, vol. 4, 1043–1171.

AKEE, R. AND M. R. JONES (2019): "Immigrants' Earnings Growth and Return Migration from the US: Examining Their Determinants Using Linked Survey and Administrative Data," Tech. rep., National Bureau of Economic Research.

AKSOY, C. G., P. POUTVAARA, AND F. SCHIKORA (2021): "First Time Around: Local Conditions and Multi-Dimensional Integration of Refugees," Working Paper Series 361, ifo Institute.

ALTONJI, J. G., L. B. KAHN, AND J. D. SPEER (2016): "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics*, 34, S361–S401.

ARULAMPALAM, W. (2001): "Is Unemployment Really Scarring? Effects of Unemployment Experiences on Wages," *Economic Journal*, 111, 585–606.

ÅSLUND, O. AND D.-O. ROOTH (2007): "Do When and Where Matter? Initial Labour Market Conditions and Immigrant Earnings," *Economic Journal*, 117, 422–448.

BATTISTI, M., G. PERI, AND A. ROMITI (2021): "Dynamic Effects of Co-ethnic Networks on Immigrants' Economic Success," *Economic Journal*, forthcoming.

BEAUDRY, P. AND J. DINARDO (1991): "The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from Micro Data," *Journal of Political Economy*, 99, 665–688.

BORJAS, G. J. (1985): "Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants," *Journal of Labor Economics*, 3, 463–489.

——— (1992): "Ethnic Capital and Intergenerational Mobility," *Quarterly Journal of Economics*, 107, 123–150.

BORJAS, G. J. AND B. BRATSBERG (1996): "Who Leaves? The Outmigration of the Foreign-born," *Review of Economics and Statistics*, 78, 165–176.

BORJAS, G. J. AND S. G. BRONARS (1991): "Immigration and the Family," *Journal of Labor Economics*, 9, 123–148.

Bowlus, A. J. (1995): "Matching Workers and Jobs: Cyclical Fluctuations in Match Quality," *Journal of Labor Economics*, 13, 335–350.

Braun, S. and M. Kvasnicka (2014): "Immigration and Structural Change: Evidence from Post-war Germany," *Journal of International Economics*, 93, 253–269.

Brunner, B. and A. Kuhn (2014): "The Impact of Labor Market Entry Conditions on Initial Job Assignment and Wages," *Journal of Population Economics*, 27, 705–738.

Cadena, B. C. and B. K. Kovak (2016): "Immigrants Equilibrate Local Labor Markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 8, 257–290.

Chiswick, B. R. (1978): "The Effect of Americanization on the Earnings of Foreign-born Men," *Journal of Political Economy*, 86, 897–921.

Chiswick, B. R., Y. Cohen, and T. Zach (1997): "The Labor Market Status of Immigrants: Effects of the Unemployment Rate at Arrival and Duration of Residence," *Industrial and Labor Relations Review*, 50, 289–303.

Chiswick, B. R. and P. W. Miller (2002): "Immigrant Earnings: Language Skills, Linguistic Concentrations and the Business Cycle," *Journal of Population Economics*, 15, 31–57.

Clemens, M. A., C. E. Montenegro, and L. Pritchett (2019): "The Place Premium: Bounding the Price Equivalent of Migration Barriers," *Review of Economics and Statistics*, 101, 201–213.

Cobb-Clark, D. A. (1993): "Immigrant Selectivity and Wages: The Evidence for Women," *The American Economic Review*, 83, 986–993.

Cohn, D., J. S. Passel, and A. Gonzales-Barrera (2017): "Rise in U.S. Immigrants From El Salvador, Guatemala and Honduras Outpaces Growth From Elsewhere," Report, Pew Research Center.

Couch, K. A. and D. W. Placzek (2010): "Earnings Losses of Displaced Workers Revisited," *American Economic Review*, 100, 572–589.

Devereux, P. J. (2002): "Occupational Upgrading and the Business Cycle," *Labour*, 16, 423–452.

Duleep, H. O. (2015): "The Adjustment of Immigrants in the Labor Market," *Handbook of the Economics of International Migration*, 1, 105–172.

Dustmann, C., T. Frattini, and I. P. Preston (2013): "The Effect of Immigration along the Distribution of Wages," *Review of Economic Studies*, 80, 145–173.

Dustmann, C., A. Glitz, and T. Vogel (2010): "Employment, Wages, and the Economic Cycle: Differences between Immigrants and Natives," *European Economic Review*, 54, 1–17.

Dustmann, C. and J. Görlach (2015): "Selective Outmigration and the Estimation of Immigrants' Earnings Profiles," in *Handbook of the Economics of International Migration*, vol. 1, 489–533.

Dustmann, C., U. Schönberg, and J. Stuhler (2016): "The Impact of Immigration: Why Do Studies Reach Such Different Results?" *Journal of Economic Perspectives*, 30, 31–56.

Fasani, F., T. Frattini, and L. Minale (2021a): "Lift the Ban? Initial Employment Restrictions and Refugee Labour Market oOutcomes," *Journal of the European Economic Association*, 19, 2803–2854.

——— (2021b): "(The Struggle for) Refugee Integration into the Labour Market: Evidence from Europe," *Journal of Economic Geography*, forthcoming.

Foged, M. (2016): "Family Migration and Relative Earnings Potentials," *Labour Economics*, 42, 87–100.

Friedberg, R. M. (2000): "You Can't Take It with You? Immigrant Assimilation and the Portability of Human Capital," *Journal of Labor Economics*, 18, 221–251.

Godøy, A. (2017): "Local Labor Markets and Earnings of Refugee Immigrants," *Empirical Economics*, 52, 31–58.

Green, D. A. (1999): "Immigrant Occupational Attainment: Assimilation and Mobility over Time," *Journal of Labor Economics*, 17, 49–79.

Gregg, P. (2001): "The Impact of Youth Unemployment on Adult Unemployment in the NCDS," *Economic Journal*, 111, 626–653.

Gregory, M. and R. Jukes (2001): "Unemployment and Subsequent Earnings: Estimating Scarring Among British Men 1984–94," *Economic Journal*, 111, 607–625.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993): "Earnings Losses of Displaced Workers," *American Economic Review*, 685–709.

Jaschke, P., S. Sardoschau, and M. Tabellini (2021): "Scared Straight? Threat and Assimilation of Refugees in Germany," Discussion Paper Series 36/21, CReAM.

Kahn, L. B. (2010): "The Long-term Labor Market Consequences of Graduating from College in a Bad Economy," *Labour Economics*, 17, 303–316.

Kandel, W. A. (2018a): *Permanent Legal Immigration to the United States: Policy Overview*, [Library of Congress public edition]. [Washington, D.C.] : Congressional Research Service, 2018.

——— (2018b): *U.S. Family-based Immigration Policy*, [Library of Congress public edition]. [Washington, D.C.] : Congressional Research Service, 2018.

Kolker, A. (2016): *Noncitizen Eligibility for Federal Public Assistance: Policy Overview*, [Library of Congress public edition]. [Washington, D.C.] : Congressional Research Service, 2016.

Kroft, K., F. Lange, and M. J. Notowidigdo (2013): "Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment," *Quarterly Journal of Economics*, 128, 1123–1167.

Kwon, I., E. M. Milgrom, and S. Hwang (2010): "Cohort Effects in Promotions and Wages Evidence from Sweden and the United States," *Journal of Human Resources*, 45, 772–808.

Marbach, M., J. Hainmueller, and D. Hangartner (2018): "The Long-term Impact of Employment Bans on the Economic Integration of Refugees," *Science Advances*, 4, eaap9519.

Mask, J. (2020): "Consequences of Immigrating During a Recession: Evidence from the US Refugee Resettlement Program," *IZA Journal of Development and Migration*, 11.

McKenzie, D., S. Stillman, and J. Gibson (2010): "How Important is Selection? Experimental vs. Non-experimental Measures of the Income Gains from Migration," *Journal of the European Economic Association*, 8, 913–945.

McLaughlin, K. J. and M. Bils (2001): "Interindustry Mobility and the Cyclical Upgrading of Labor," *Journal of Labor Economics*, 19, 94–135.

Mincer, J. (1978): "Family Migration Decisions," *Journal of Political Economy*, 86, 749–773.

Munk, M., T. Nikolka, and P. Poutvaara (2022): "International Family Migration and the Dual-Earner Model," *Journal of Economic Geography*, forthcoming.

Munshi, K. (2003): "Networks in the Modern Economy: Mexican Migrants in the US Labor Market," *Quarterly Journal of Economics*, 118, 549–599.

Oreopoulos, P., T. Von Wachter, and A. Heisz (2012): "The Short-and Long-term Career Effects of Graduating in a Recession," *American Economic Journal: Applied Economics*, 4, 1–29.

Orrenius, P. M. and M. Zavodny (2010): "Mexican Immigrant Employment Outcomes over the Business Cycle," *American Economic Review*, 100, 316–320.

Patel, K. and F. Vella (2013): "Immigrant Networks and Their Implications for Occupational Choice and Wages," *Review of Economics and Statistics*, 95, 1249–1277.

Raaum, O. and K. Røed (2006): "Do Business Cycle Conditions at the Time of Labor Market Entry Affect Future Employment Prospects?" *Review of Economics and Statistics*, 88, 193–210.

Rothstein, J. (forthcoming): "The Lost Generation? Labor Market Outcomes for Post Great Recession Entrants," *Journal of Human Resources.*

Schwandt, H. and T. von Wachter (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, S161–S198.

Stuart, B. A. (2022): "The Long-Run Effects of Recessions on Education and Income," *American Economic Journal: Applied Economics*, 14, 42–74.

Topel, R. H. and M. P. Ward (1992): "Job Mobility and the Careers of Young Men," *Quarterly Journal of Economics*, 107, 439–479.

von Wachter, T. (2020): "The Persistent Effects of Initial Labor Market Conditions for Young Adults and Their Sources," *Journal of Economic Perspectives*, 34, 168–194.

Appendix

A Additional tables and figures

Table A.1: Main countries of origin with predominantly labor migration

	Number of obs. in estimation sample	% of years labor-dominated	% of migrants labor-based
India	86754	81.5	69.8
United Kingdom	21051	100	70.7
Japan	16584	100	63.9
Germany	9911	77.8	58.6
France	6821	96.3	60.9
Argentina	5513	96.3	58.7
Australia	4584	100	69.0
Venezuela	4451	40.7	59.0
Italy	4094	85.2	56.8
Israel	4005	100	57.4
South Africa	3841	100	58.8
Netherlands	2119	85.2	64.7
Other	16033	52.3	58.6
Total	185761	68.6	61.7

Notes: Share of years labor-dominated is the share of years between 1992 and 2018 in which a country's dominant mode of migration to the U.S. was labor migration. Number of observations in estimation sample is the number of observations in our sample, i.e. individuals aged 22 to 60 years at the time of immigration and observation who were born outside the U.S. as non-U.S. citizens, did not get naturalized within the first three years of immigration, immigrated between 1992 and 2018, and had spent at most ten years in the U.S. at the time of observation. We only consider individuals who immigrated in a year in which the country was classified as labor-dominated. Countries are ordered by number of observations in the estimation sample. Table 2 presents corresponding numbers for family migration.

Table A.2: Composition of admission categories by country type (in %)

	Country type		
	Family	Labor	Other
Family migrants	65.0	4.9	14.9
Family-capped	23.5	0.8	2.9
Immediate relatives	41.5	4.1	12.0
Labor migrants	12.2	60.8	4.0
Other	22.9	34.3	81.1
Total	100.0	100.0	100.0

Notes: Countries are classified according to their dominant mode of migration to the U.S., where the dominant mode of migration is defined to account for more than 50 percent of admissions from that country to the U.S. We classify countries as other when neither family nor labor migration alone accounts for the majority of admissions. See Section 4 for more details. Rows show the share of migrants considered family migrants, labor migrants, or other migrants, averaged over the period 1992-2019. Note that the share of capped family migrants in our sample is considerably higher as it is limited to individuals aged 22 to 60 at the time of immigration. It hence excludes minor children and older parents who can be sponsored as immediate relatives without waiting times. Data come from the Yearbook of Immigration Statistics, published by the U.S. Department of Homeland Security.

Table A.3: Effect of the initial unemployment rate on labor market outcomes of family migrants

	Employed (0/1)	Log real annual wage income	Log real hourly wage	Log occupational income score
Panel A: Effects by years in the U.S. (x 100)				
Year 1	-1.013***	-3.649***	-1.528***	-1.192***
	(0.327)	(0.610)	(0.417)	(0.255)
Year 2	-0.959***	-3.918***	-1.969***	-1.375***
	(0.301)	(0.612)	(0.436)	(0.247)
Year 3	-0.570**	-3.052***	-1.944***	-1.258***
	(0.244)	(0.614)	(0.404)	(0.227)
Year 4	-0.236	-2.270***	-1.807***	-1.180***
	(0.225)	(0.578)	(0.372)	(0.222)
Year 5	-0.089	-2.016***	-1.709***	-1.216***
	(0.209)	(0.526)	(0.369)	(0.227)
Year 6	-0.093	-2.208***	-1.658***	-1.285***
	(0.217)	(0.554)	(0.402)	(0.246)
Year 7	-0.136	-2.483***	-1.583***	-1.257***
	(0.232)	(0.554)	(0.405)	(0.248)
Year 8	-0.114	-2.447***	-1.392***	-1.061***
	(0.238)	(0.556)	(0.410)	(0.237)
Year 9	-0.021	-1.924***	-1.040**	-0.791***
	(0.253)	(0.648)	(0.453)	(0.261)
Year 10	-0.040	-1.201	-0.584	-0.817**
	(0.323)	(0.750)	(0.543)	(0.379)
Panel B: Polynomial coefficients (x 1000)				
1st order	-18.950***	-63.920***	-23.561***	-20.474***
	(6.708)	(13.176)	(8.353)	(5.303)
2nd order	10.953**	33.841***	10.006*	10.739***
	(4.609)	(10.110)	(5.929)	(3.802)
3rd order	-2.342**	-7.022**	-1.877	-2.422**
	(1.161)	(2.803)	(1.608)	(1.012)
4th order	0.218*	0.633**	0.162	0.244**
	(0.124)	(0.321)	(0.184)	(0.113)
5th order	-0.007	-0.021	-0.005	-0.009**
	(0.005)	(0.013)	(0.007)	(0.004)
Observations	116975	84864	84864	84769

Notes: The table reports OLS estimates that correspond to Figure 3. It shows by how much a one pp increase in the IUR affects four key labor market outcomes: employment, log real annual wage income, log real hourly wages, and occupational quality as measured by the log occupational income score (the log average wage income of a worker in the same occupation, state, and year of observation). The column title shows the outcome variable. The upper panel shows the year-specific coefficients β for the first ten years in the U.S. using the flexible specification (Equation 1). The lower panel shows the coefficients using polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level. The American Community Survey uses different reference periods for employment status and wage income. Employment status refers to the week preceding the survey, whereas wage income refers to the past twelve months. The share of employed individuals (0.69 as printed in panel a of Figure 3) therefore slightly differs from the share of individuals with a wage income (0.73 based on the number of observations in columns 1 and 2 of this table). Our results are robust to defining being employed as reporting a wage income (available upon request).

Table A.4: Testing for non-linear effects of the initial unemployment rates on labor market outcomes of family migrants

	Employed (0/1)	Log real annual wage income	Log real hourly wage	Log occupational income score
UR at immigration (/100)	-1.471**	-2.271*	-2.161**	-1.453***
	(0.620)	(1.300)	(0.956)	(0.497)
UR at immigration (/100) squared	7.061**	-1.141	3.729	1.706
	(3.216)	(7.268)	(4.957)	(3.007)
Observations	116975	84864	84864	84769

Notes: The table reports OLS estimates. The column title shows the outcome variable. Coefficients shows the effect of a one pp higher state-level unemployment rate at immigration on the outcome variable. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

Table A.5: Average effect of the initial and preceding unemployment rates on labor market outcomes of family migrants

	Employed (0/1)	Log real annual wage income	Log real hourly wage	Log occupational income score
UR in years 4-5 before immigration	0.001	0.001	-0.001	-0.002
	(0.004)	(0.007)	(0.006)	(0.003)
UR in years 2-3 before immigration	0.002	0.004	-0.005	-0.003
	(0.004)	(0.008)	(0.006)	(0.003)
UR in year of immigration	-0.004	-0.026***	-0.014***	-0.011***
	(0.003)	(0.006)	(0.004)	(0.003)
Observations	116975	84864	84864	84769

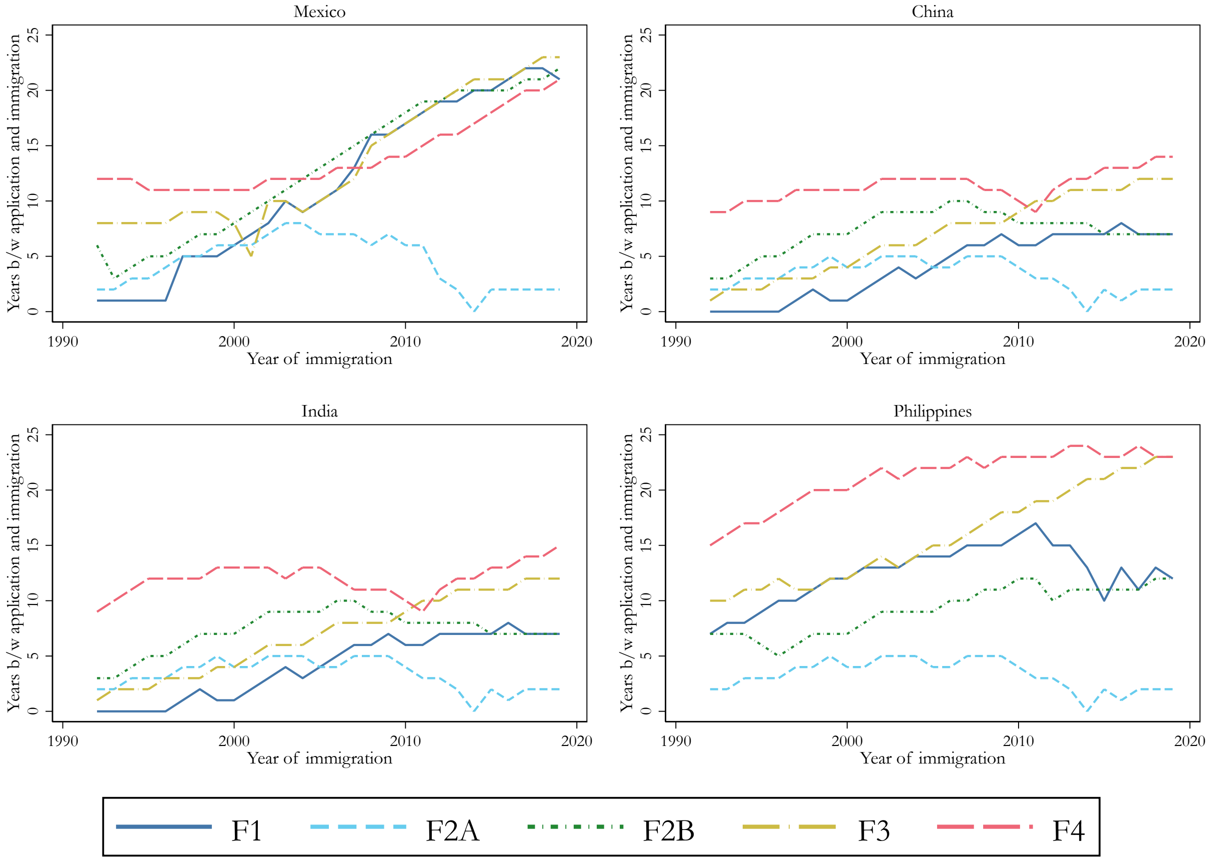
Notes: The table reports OLS estimates. The column title shows the outcome variable. Coefficients shows the effect of a one pp higher state-level unemployment rate in the respective year(s) on the outcome variable. UR in years 4-5 before immigration is the average state-level unemployment rate in years 4 and 5 before immigration (analogous for UR in years 2-3 before immigration). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

Table A.6: Effect of the initial unemployment rate on labor market outcomes of family migrants by network size (robustness)

	(1) Industries	(2) Ten years	(3) No threshold	(4) Threshold 200
UR at immigration	5.94**	1.46	3.50*	4.39**
(/100) × Network size	(2.61)	(1.33)	(1.81)	(1.95)
UR at immigration	-25.55*	-7.47	-10.74	-7.50
(/100)	(13.84)	(5.19)	(7.80)	(8.76)
Network size	-0.88***	-0.11	-0.24*	-0.49***
	(0.22)	(0.10)	(0.13)	(0.16)
Observations	17864	62198	19248	16667
Mean outcome	11.84	4.80	4.98	4.97

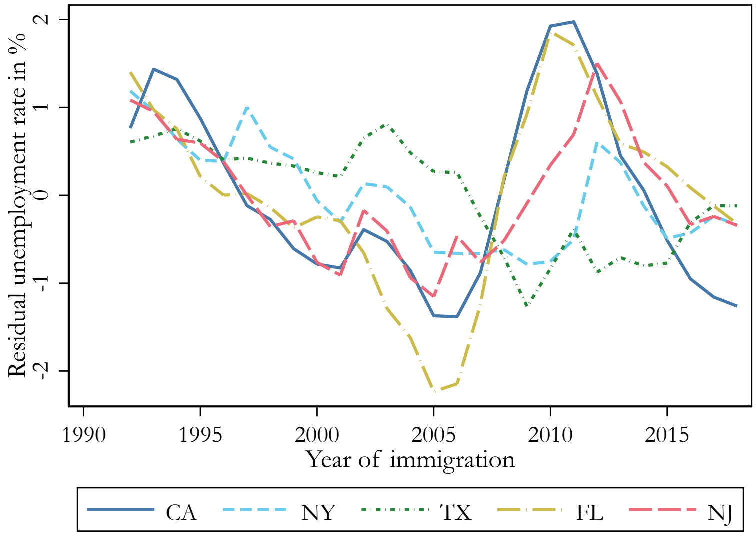
Notes: The table reports OLS estimates. The outcome variables are the state-level shares of workers of the same origin that work in the same occupation/industry (in percent). UR at immigration is the state-level unemployment rate in the year of immigration (divided by 100 to improve readability). Network size is the share of migrants from the same country of origin among all working-age adults in the state at the time of immigration. Column 1 uses industries instead of the narrow occupation categories used in Table 5. Column 2 uses the entire ten-year period instead of three-year period used in Table 5. Columns 4 and 5 change the required minimum number of observations of migrants from the same country of origin in the same state from 100 to zero and 200. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level. */**/*** denote statistical significance at the 10/5/1 percent level.

Figure A.1: Waiting times for family migrants from countries in which per-country ceiling is binding by admission category



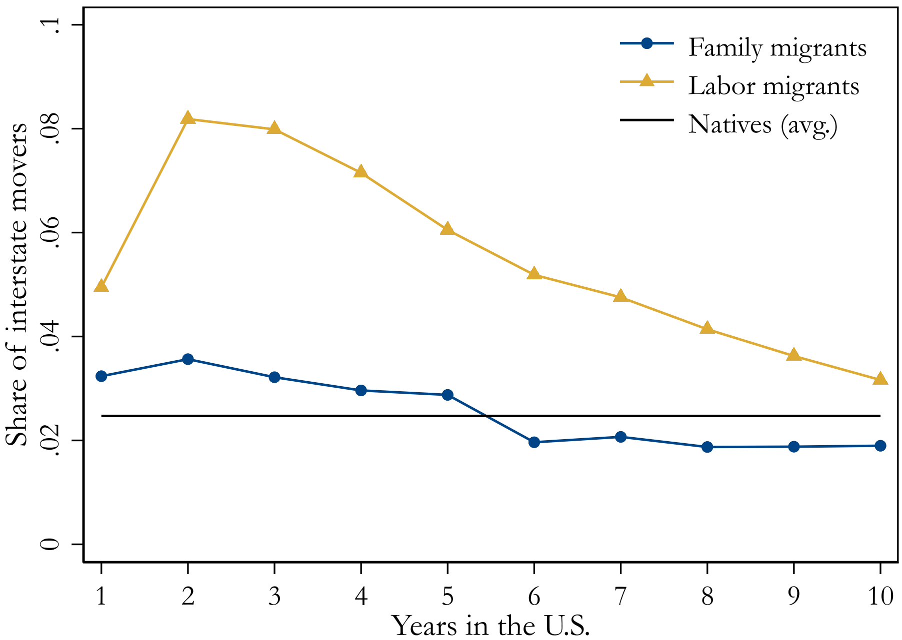
Notes: The figure shows waiting times for unmarried sons and daughters of U.S. citizens and their minor children (F1), spouses and minor children of LPRs (F2A), unmarried sons and daughters of LPRs (F2B), married sons and daughters of U.S. citizens (F3) and brothers and sisters of U.S. citizens (F4). LPR is short for lawful permanent resident. Data source: U.S. Department of State Visa Bulletins (January), own calculations.

Figure A.2: Residual state-level unemployment rate for most important U.S. destination states of family migrants



The figure shows the residual unemployment rate for the five most important U.S. destination states of family migrants: California (CA), New York (NY), Texas (TX), Florida (FL), and New Jersey (NJ). The residual unemployment rate is estimated using state and year fixed effects. State-level unemployment rates come from the Local Area Unemployment Statistics, published by the U.S. Bureau of Labor Statistics.

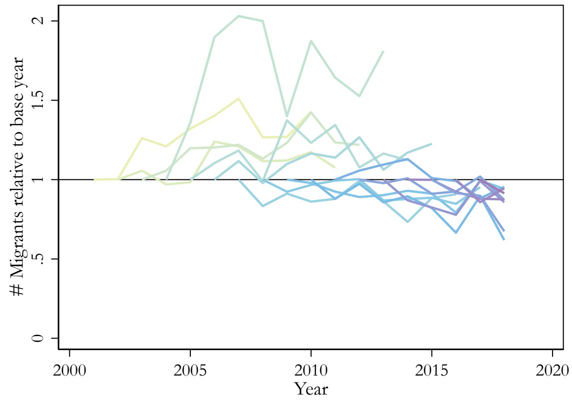
Figure A.3: Share of individuals that moved between U.S. states within the last year



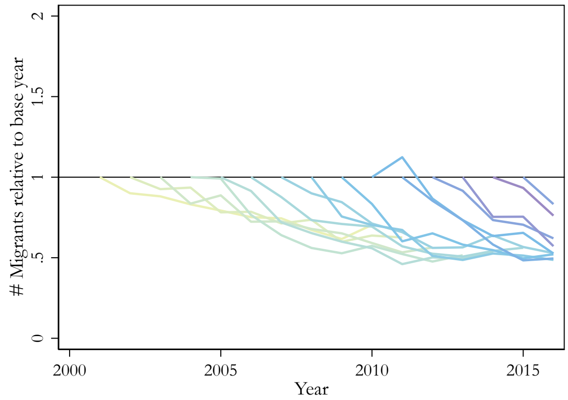
Notes: The figure shows the share of individuals that moved between U.S. states within the year preceding the survey. Immigrant samples are restricted to individuals who were born outside the U.S. as non-U.S. citizens, did not get naturalized within the first three years of immigration, immigrated between 1992 and 2018, and had spent at most ten years in the U.S. at the time of observation. Native refers to U.S.-born individuals. In addition, the samples are restricted to individuals who were between 22 and 60 years old at the time of immigration and observation. The analysis is based on data from the 2000 U.S. Census and the 2001 to 2019 American Community Survey.

Figure A.4: Cohort size by years since immigration (individual years)

(a) Family migrants

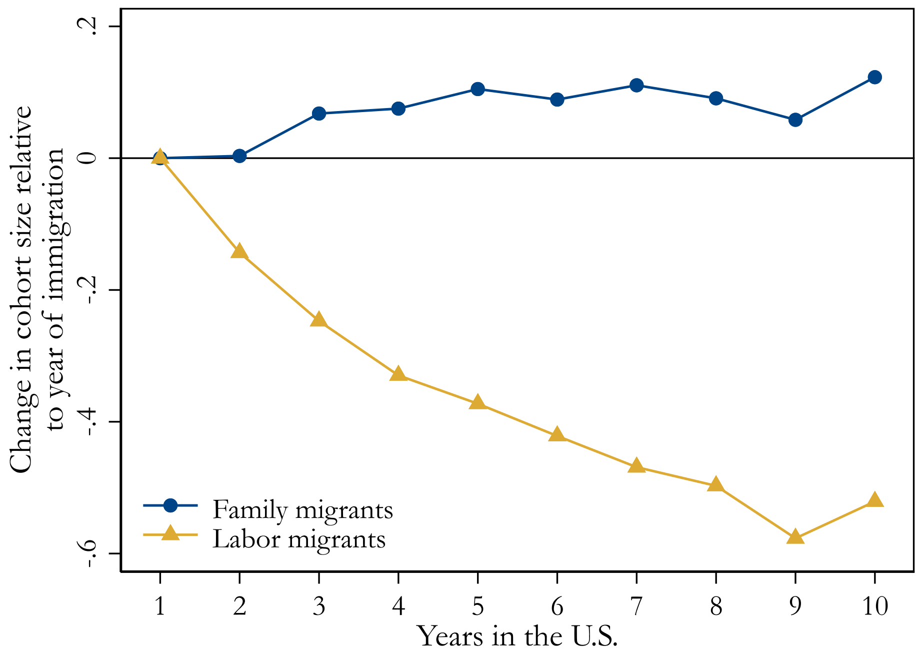


(b) Labor migrants



Notes: The figures shows how many migrants who immigrated in a given year are observed in subsequent years relative to the number observed in the year of immigration. The samples are restricted to individuals who were between 22 and 50 years old at the time of immigration because these individuals remain in our sample for the full observation period. The analysis is based on data from the 2000 U.S. Census and the 2001 to 2019 American Community Survey. Observations are weighted by the average annual sample weights to account for the fact that the census and ACS have very different sample sizes and that the sample size of the ACS is not constant over time.

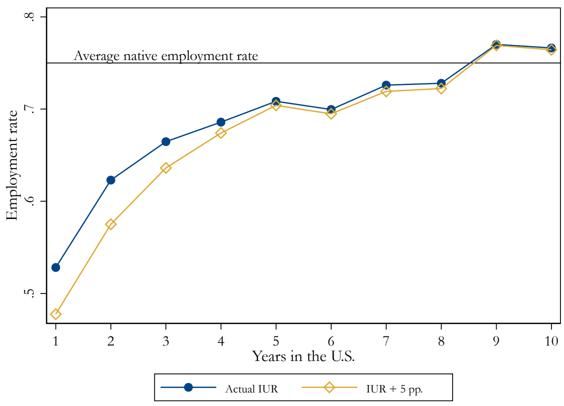
Figure A.5: Cohort size by years since immigration (aggregated)



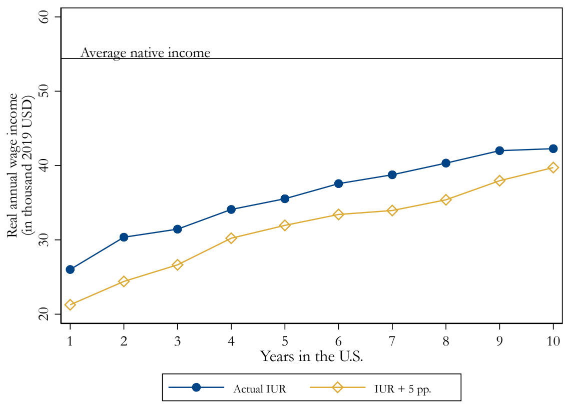
Notes: The figure plots the coefficients from an OLS regression of the log number of immigrants observed in year-of-immigration and years-in-the-U.S. cells on a full set of year-of-immigration and years-in-the-U.S. dummies. The coefficients of the years-in-the-U.S. dummies reflect the number of migrants observed in year t relative to the year of immigration and thus capture potential return migration. The sample is restricted to individuals who were between 22 and 50 years old at the time of immigration because these individuals remain in our sample for the full observation period. The analysis is based on data from the 2000 U.S. Census and the 2001 to 2019 American Community Survey. To account for differences in sample size over time, observations are weighted by the average annual sample weights.

Figure A.6: Effects of the initial unemployment rate on the economic assimilation of family migrants

(a) Employment rate



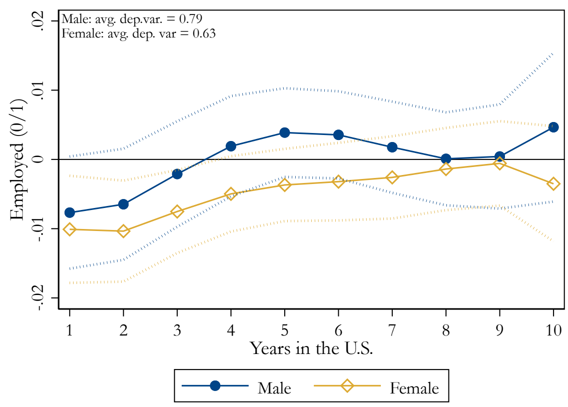
(b) Annual wage income



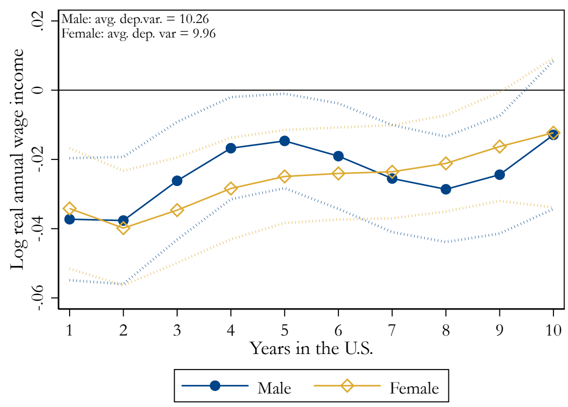
Notes: The x-axis shows the years since immigration. The y-axis shows employment rates (Panel a) and real annual wage income (Panel b). Average native outcomes are based on the sample described in Table 3. For family migrants, we first calculate the average employment rate and annual wage income of family migrants by years in the U.S. We then use the estimated marginal effects from Table A.3 to derive the employment rate and annual wage income for a five pp increase in the IUR.

Figure A.7: Effect of the initial unemployment rate on labor market outcomes of family migrants by sex

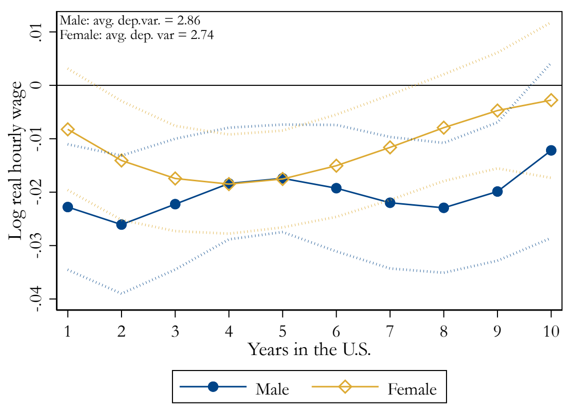
(a) Employment



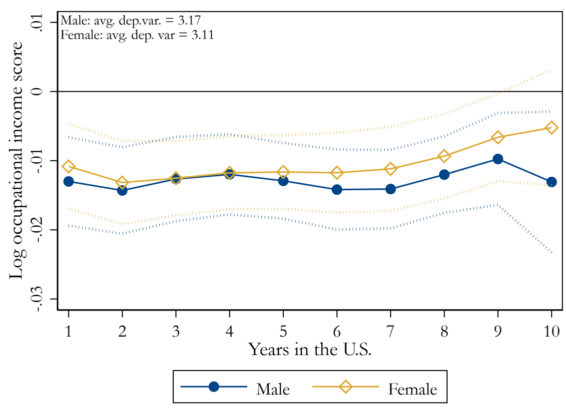
(b) Log real annual wage income



(c) Log hourly wage



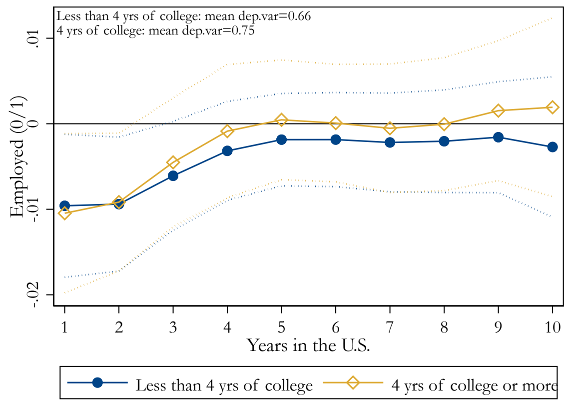
(d) Log occupational income score



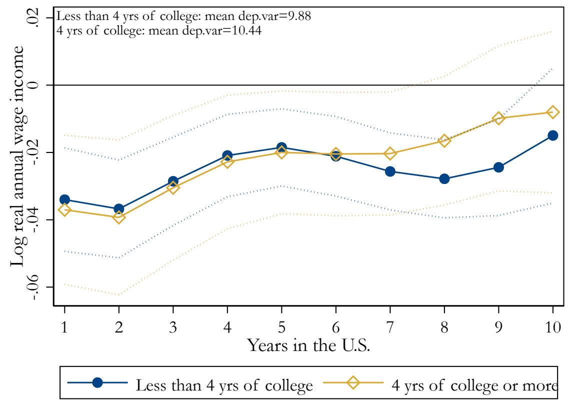
Notes: The figure reruns the main analysis separately for men and women. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year including the 95 percent confidence interval using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

Figure A.8: Effect of the initial unemployment rate on labor market outcomes of family migrants by education

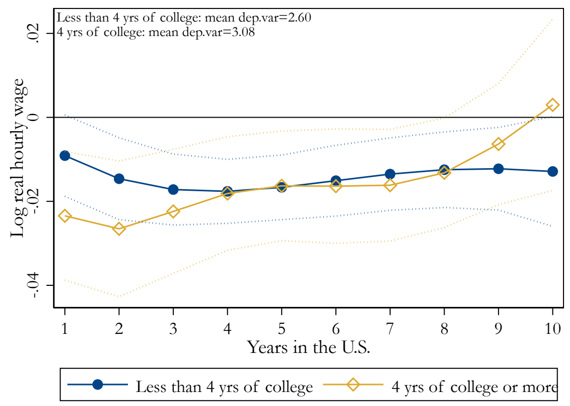
(a) Employment



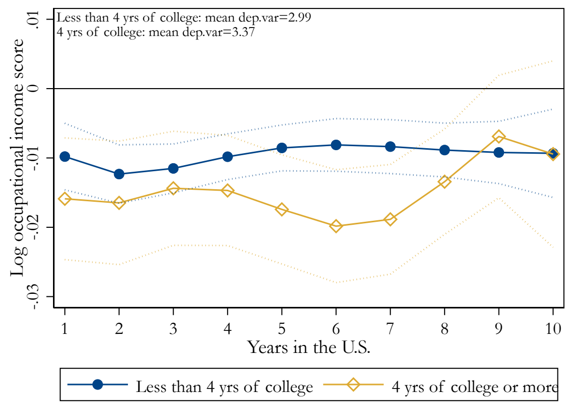
(b) Log real annual wage income



(c) Log hourly wage



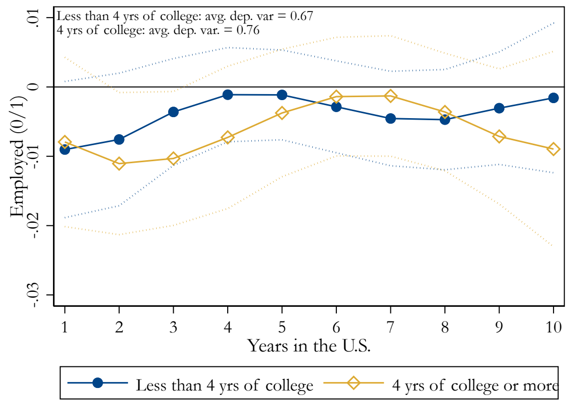
(d) Log occupational income score



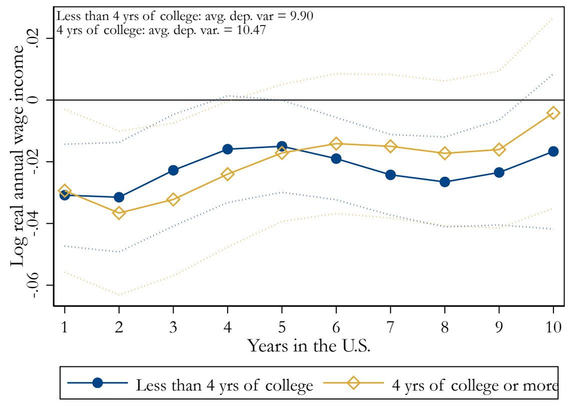
Notes: The figure reruns the main analysis separately for individuals with and without at least four years of college education. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year including the 95 percent confidence interval using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

Figure A.9: Effect of the initial unemployment rate on labor market outcomes of family migrants by education (conditional on being older than 30 years at immigration)

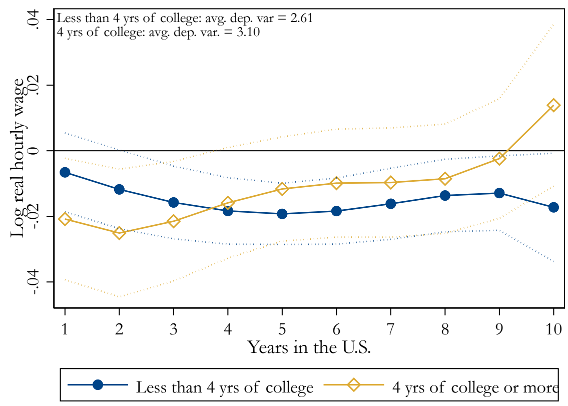
(a) Employment



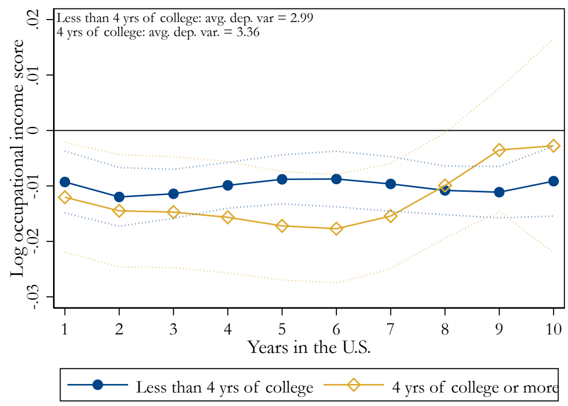
(b) Log real annual wage income



(c) Log hourly wage

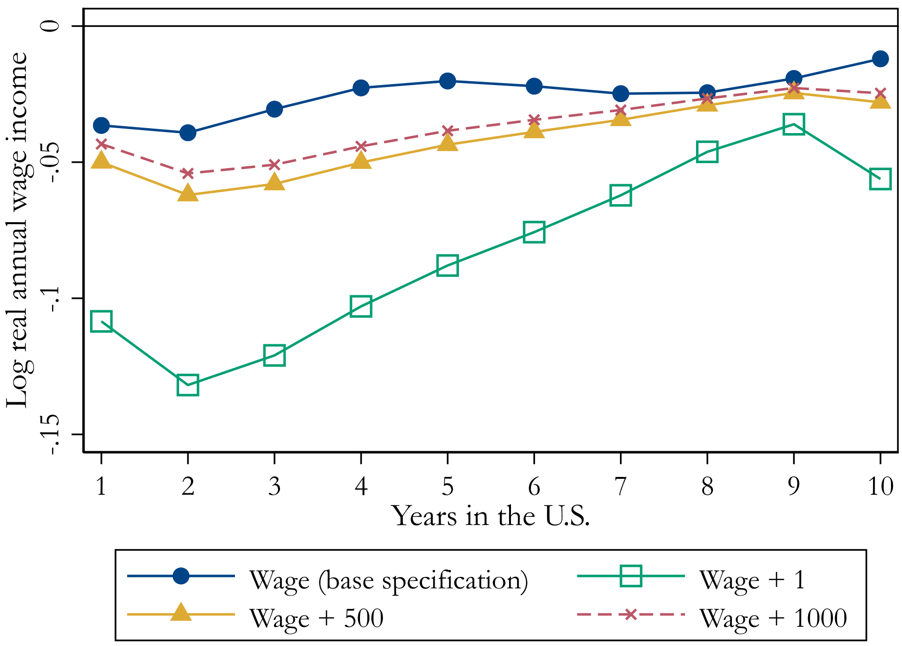


(d) Log occupational income score



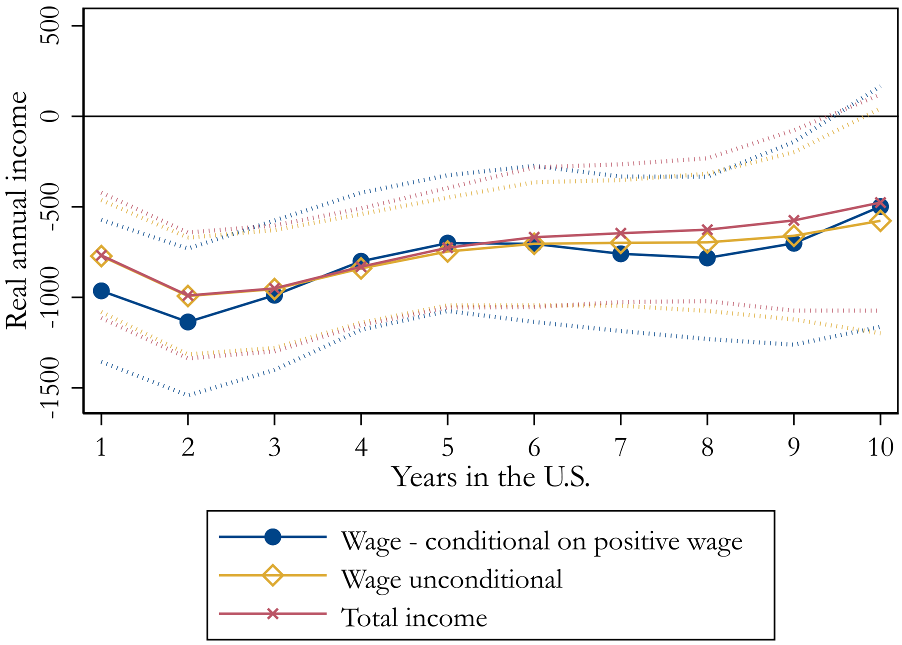
Notes: The figure reruns the main analysis separately for individuals with and without at least four years of college education. In contrast to Figure A.8, the sample is restricted to individuals who were older than 30 years at the time of immigration to minimize the possibility that the level of education is potentially affected by the initial unemployment rate. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year including the 95 percent confidence interval using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

Figure A.10: Effect of the initial unemployment rate on annual earnings of family migrants, including individuals with no wage income



Notes: The figure reruns the main analysis for annual earnings, including individuals with no wage income. We first assign zero earnings to individuals who do not report any wage income and then add USD 1/500/1000 to maintain the log specification. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on annual earnings in the respective year using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies.

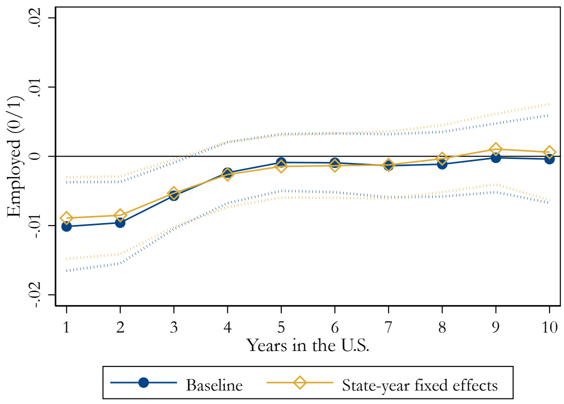
Figure A.11: Effect of the initial unemployment rate on annual earnings of family migrants in absolute levels



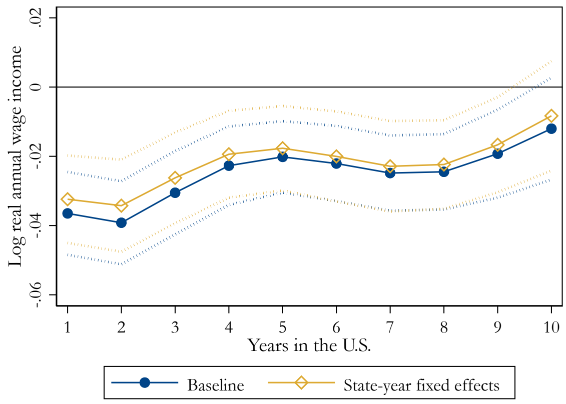
Notes: The figure reruns the main analysis for annual earnings in absolute levels (not logged). We use three different outcomes: Annual wage income conditional on being employed (our baseline outcome), annual wage income with incomes for non-employed individuals set to zero, and total earnings (labor income and all other forms of income including transfers). The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on annual earnings in the respective year including the 95 percent confidence interval using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies.

Figure A.12: Effect of the initial unemployment rate on labor market outcomes of family migrants controlling for current economic conditions

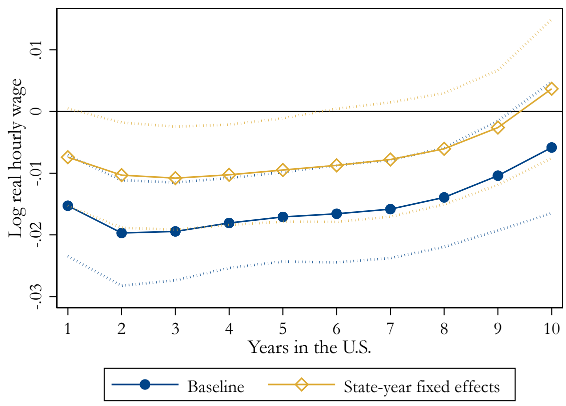
(a) Employment



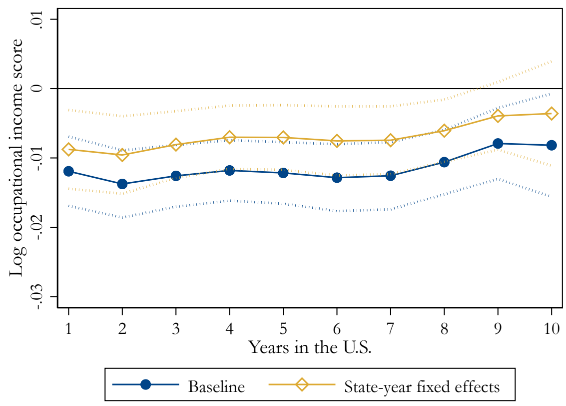
(b) Log real annual wage income



(c) Log hourly wage



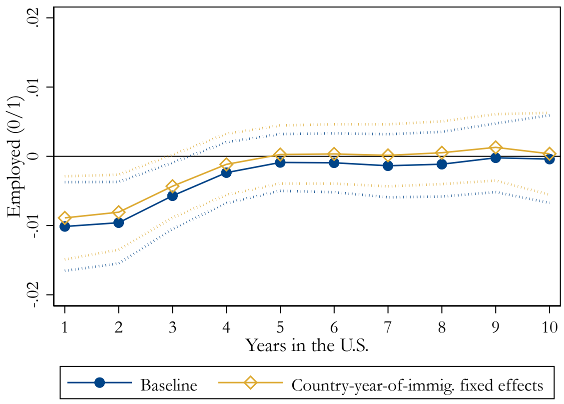
(d) Log occupational income score



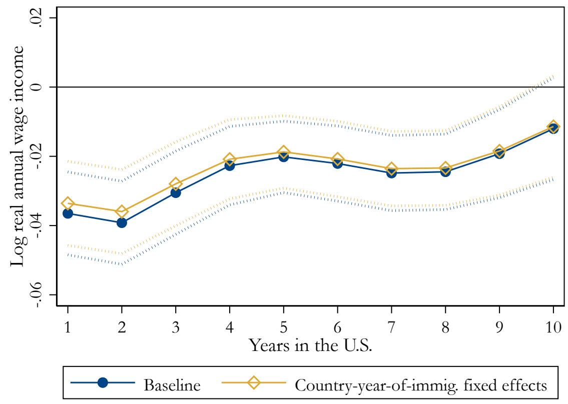
Notes: The figure shows how our main results change when we add state-year-of-observation fixed effects to control for economic conditions at the time of observation. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year including the 95 percent confidence interval using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

Figure A.13: Effect of the initial unemployment rate on labor market outcomes of family migrants controlling for country-of-origin-year-of-immigration fixed effects

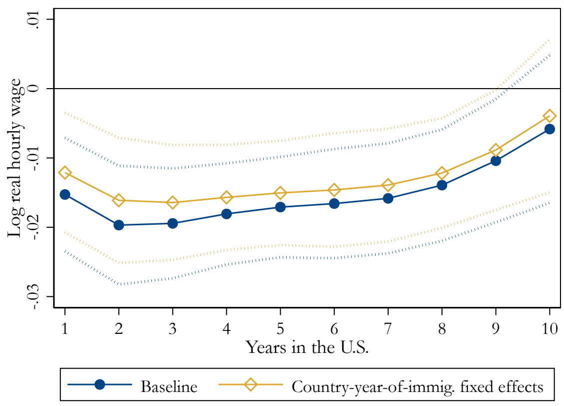
(a) Employment



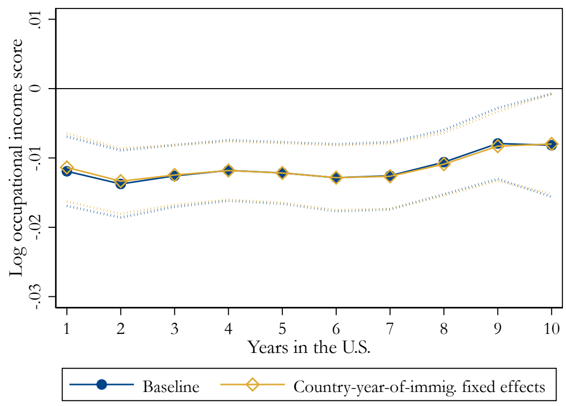
(b) Log real annual wage income



(c) Log hourly wage



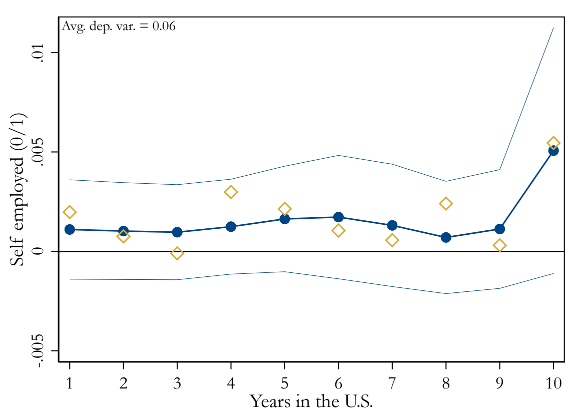
(d) Log occupational income score



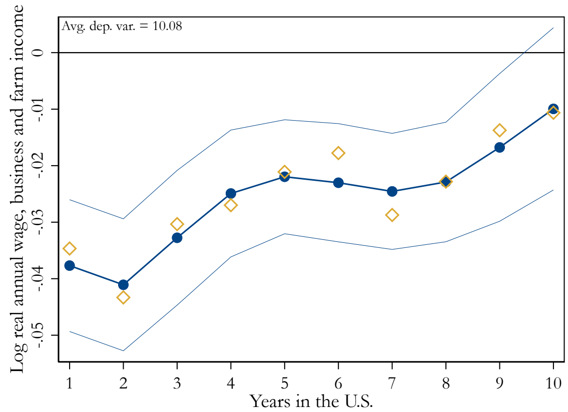
Notes: The figure shows how our main results change when we add country-of-origin-year-of-immigration fixed effects to control for shocks that are specific to a country of origin in the year of immigration. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year including the 95 percent confidence interval using the polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

Figure A.14: Effect of the initial unemployment rate on self-employment, annual labor income, annual total earnings, and hours worked of family migrants

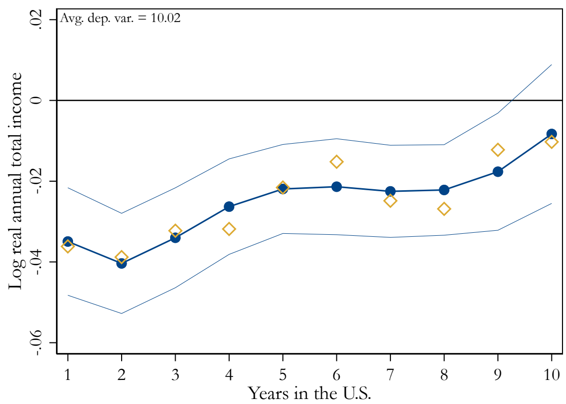
(a) Self-employment



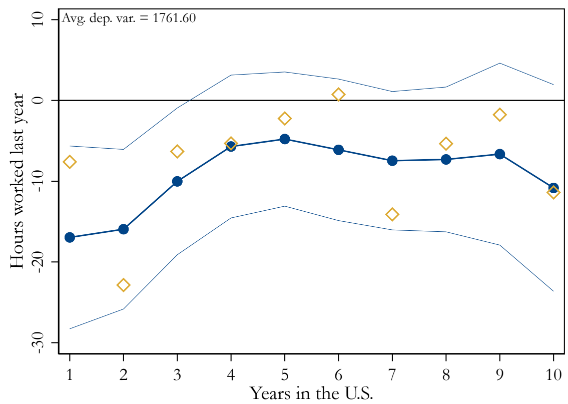
(b) Log of annual labor income



(c) Log real annual total income

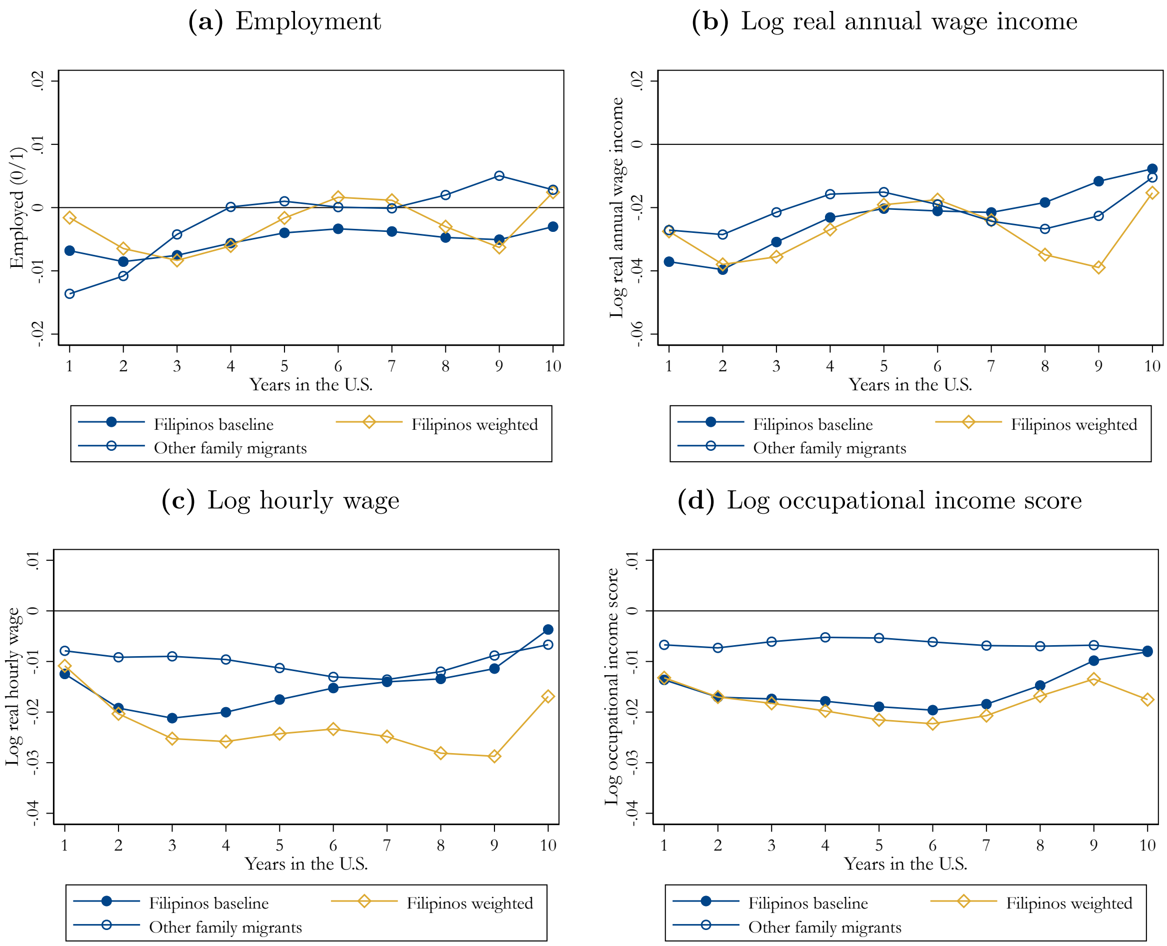


(d) Hours worked last year



Notes: The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year. Labor income includes wage, business, and farm income. Total earnings include labor income and all other forms of income including transfers. Yellow diamonds refer to the flexible specification (Equation 1), blue dots including the 95 percent confidence interval to the less flexible polynomial specification (Equation 2). All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

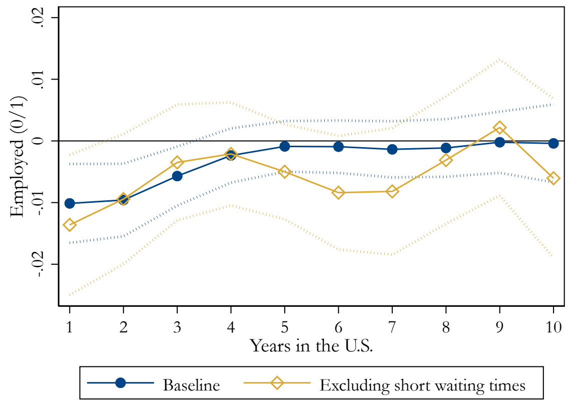
Figure A.15: Effect of the initial unemployment rate on labor market outcomes separately for Filipino and other (non-Filipino) family migrants



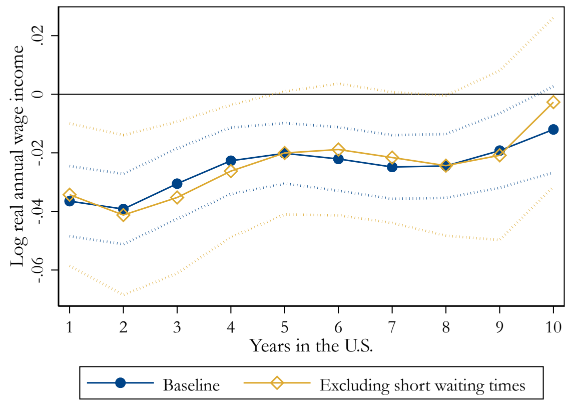
Notes: The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year using the polynomial specification (Equation 2) with different weights. Blue dots and red circles show coefficients for our baseline specification, in which we weigh observations by the average annual sample weights (to account for the fact that the census and ACS have very different sample sizes and that the sample size of the ACS is not constant over the period 2000-2019). Yellow diamonds show effects using weights based on administrative data on the universe of Filipino emigrants, which we obtained from the Commission on Filipinos Overseas. The data provide migrant-level information on the exact admission category, age, gender, education, date of migration, and the destination state in the U.S. We use this information to reweigh our sample of Filipino migrants in the American Community Survey, so they resemble the characteristics of family migrants in visa categories with waiting times. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies (the latter only for other family migrants).

Figure A.16: Effect of the initial unemployment rate on labor market outcomes of family migrants with long waiting times

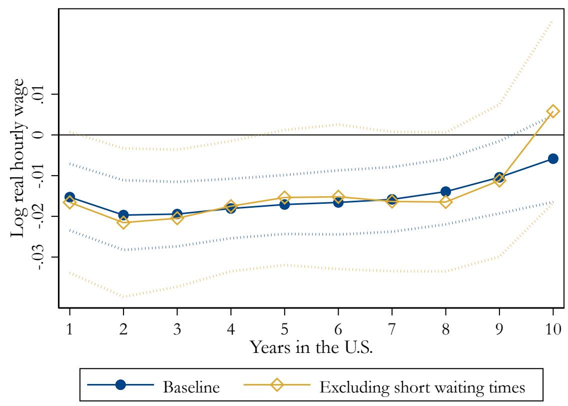
(a) Employment



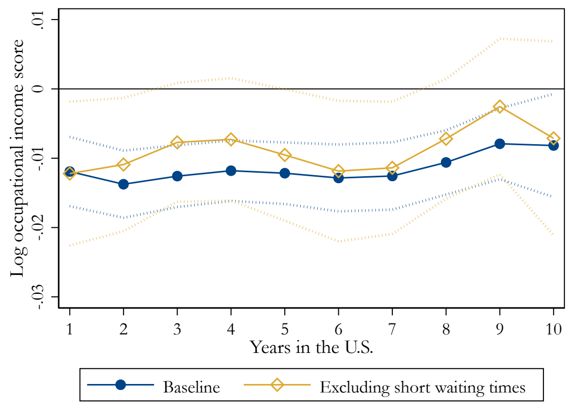
(b) Log real annual wage income



(c) Log hourly wage



(d) Log occupational income score



Notes: The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year using the polynomial specification (Equation 2). Blue dots show coefficients for our baseline sample including the 95 percent confidence interval. Yellow diamonds including the 95 percent confidence interval refer to restricted sample that tries to exclude immediate relatives who can be sponsored without waiting times (i.e., minor children, parents, and spouses of U.S. citizens). It is based on individuals aged 22 to 40 who were never married and married couples of the same age who immigrated in the same year. All regressions include a full set of state, year-of-observation, year-of-immigration, and years-in-the-U.S. fixed effects. They also include age, age squared, gender, education, and country-of-origin dummies. Standard errors are clustered at the state-year-of-immigration level.

B O*NET-based task measures

Our task measures come from Acemoglu and Autor (2011) and are composite measures of O*NET (Occupational Information Network) work activities and work context importance scales. We distinguish between five different task measures: (i) non-routine cognitive: analytical, (ii) non-routine cognitive: interpersonal, (iii) routine cognitive, (iv) routine manual, and (v) non-routine manual. Each task measure is standardized to have a cross-occupation mean of zero and standard deviation of one. Non-routine cognitive tasks are typical in managerial, professional, and technical occupations. Routine cognitive tasks are typical in clerical, administrative, and sales occupations. Routine manual tasks are typical in production and operative occupations. Non-routine manual tasks require flexibility and adaptability and are typical in service occupations. The following description of the construction of the measures is taken from Acemoglu and Autor (2011) and included for readers' convenience. Please consult Acemoglu and Autor (2011) for more details.

Non-routine cognitive: Analytical

4.A.2.a.4 Analyzing data/information
4.A.2.b.2 Thinking creatively
4.A.4.a.1 Interpreting information for others

Non-routine cognitive: Interpersonal

4.A.4.a.4 Establishing and maintaining personal relationships
4.A.4.b.4 Guiding, directing and motivating subordinates
4.A.4.b.5 Coaching/developing others

Routine cognitive

4.C.3.b.7 Importance of repeating the same tasks
4.C.3.b.4 Importance of being exact or accurate
4.C.3.b.8 Structured v. unstructured work (reverse)

Routine manual

4.C.3.d.3 Pace determined by speed of equipment
4.A.3.a.3 Controlling machines and processes
4.C.2.d.1.i Spend time making repetitive motions

Non-routine manual physical

4.A.3.a.4 Operating vehicles, mechanized devices, or equipment
4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls
1.A.2.a.2 Manual dexterity
1.A.1.f.1 Spatial orientation