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Immigrating into a Recession: Evidence from Family Migrants to the U.S.

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Abstract

We analyze how economic conditions at the time of arrival affect the economic integration of family-sponsored migrants in the U.S. Our identification strategy exploits long waiting times for family-sponsored immigration visas that decouple the migration decision from economic conditions at the time of arrival. 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 is the result of substantial occupational downgrading, lower hourly wages, and a reduction in working hours. Family migrants who immigrate into a recession draw on migrant and family networks to mitigate the negative labor market effects. As a result, they take up occupations with higher concentrations of fellow countrypeople. They are also more likely to reside with family members, potentially reducing their geographical mobility.

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

JEL classification: E32, F22, J31, J61

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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-based migrants, only 14 percent were employment-based migrants. 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-based migrants accounted for 48 percent of all permanent immigrant arrivals in the OECD. Employment-based 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

[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).

sample to immigrants from countries for which family-based 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, would reduce the net-present-value wage income of a family migrant over a period of ten years by USD 36k. This is a large effect. For comparison, while college graduates on average have about 30% higher wage income than family migrants, the equivalently estimated average earnings loss of graduating in an equally large recession is USD 29k (von Wachter, 2020). 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 builds on and contributes to two strands of literature. One strand of the literature has examined 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]

The other strand of the literature has studied how entering the labor market in a recession

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

affects labor market outcomes. A few studies have focused on immigrants. Chiswick et al. (1997) find that immigrants to the U.S. who arrive in a recession have lower initial employment rates but quickly catch up with natives. By contrast, Chiswick and Miller (2002) find that immigrants to the U.S. who arrive in a recession have substantially lower earnings and take about 30 years to close this gap. These studies, however, do not address the potential endogeneity of migration decisions. Differences in observed labor market outcomes may therefore be due to differences in immigrant characteristics, not differences in initial economic conditions.

Åslund and Rooth (2007) explicitly address this issue. They exploit a placement policy that exogenously assigns refugees to initial locations in Sweden. They find that arriving in a recession reduces refugees' earnings and employment rates for at least ten years. Godøy (2017) and Mask (2020) also exploit refugee placement policies and report similar but less long-lasting effects for refugees in Norway and the U.S. Fasani et al. (2021) show that adverse economic conditions at immigration decrease refugees' short-term labor market outcomes in Europe and Aksoy et al. (2021) report a similar finding using data from Germany.[4]

A number of studies have investigated the labor market effects of graduating in a recession.[5] Raaum and Røed (2006) find that Norwegian secondary school students who graduate in a recession are less likely to be employed during the first ten years of their work careers. Kahn (2010) shows that U.S. college students who graduate in a recession persistently earn lower wage incomes and work in lower-level occupations but do not see changes in their working hours. Oreopoulos et al. (2012) document similar effects for Canadian college graduates. More recently, Altonji et al. (2016) find that U.S. college students who graduate in a recession see a substantial reduction in initial earnings through less full-time work and lower wages. They document, however, only small persistent effects on wages. Similarly, Rothstein (forthcoming) shows that unlucky U.S. college graduates experience persistently lower employment rates.

A few studies have gone beyond graduates and extend the set of workers under study to include school leavers at all levels. Kwon et al. (2010) show that Swedish white-collar workers who enter the labor market during a boom earn higher wages and are promoted more quickly. Brunner and Kuhn (2014) find that high unemployment rates at the time of labor market entry have a persistent negative effect on the wage income of Austrian men. This effect is more pronounced for blue-collar workers who may be permanently locked into low-paying jobs. Most recently, Schwandt and von Wachter (2019) show that entering the labor market at times of high unemployment substantially reduces earnings of U.S. workers. The effect is driven by

[4]Going beyond economic conditions at arrival, Marbach et al. (2018) and Fasani et al. (2021) 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.

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

a reduction in working hours and hourly wages and persists for about ten years. The effect for high-school graduates is about twice the size of the effect for college graduates and more persistent. Stuart (2022) shows that experiencing a recession during childhood has strong effects on college graduation and subsequent income.

We contribute to these two strands of literature in three ways. First, we introduce a novel identification strategy and show that initial economic conditions can generate substantial heterogeneity in the evolution of earnings across immigrant cohorts. Thus, we 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. Second, we show that adverse economic conditions at the time of arrival constitute a key mechanism for explaining widely documented immigrant-specific phenomena such as downgrading (e.g., see Dustmann et al., 2016) and the use of migrant and family networks. Third, we 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.

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 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; 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 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, employment-based 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.

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.

[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.

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 employment-based 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:

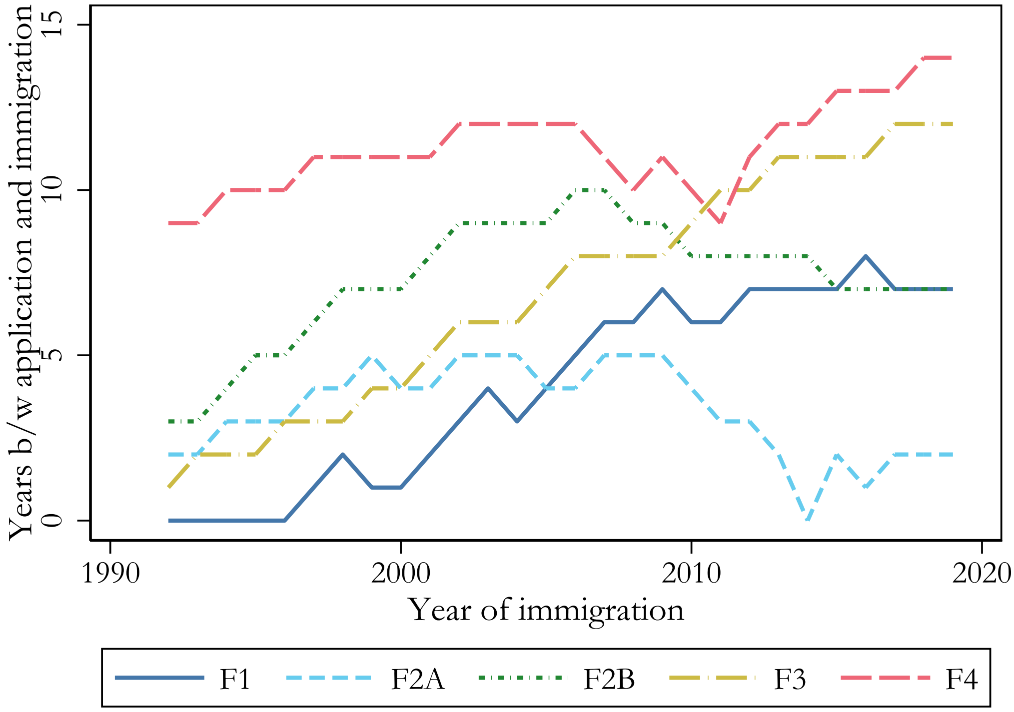
480,000 (annual total cap on family-sponsored immigrants)
− number of immediate relatives granted LPR status in the prior year
− number of aliens paroled into the U.S. for at least a year in the prior year
+ number of unused employment-based visas from the prior year

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]

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

Demand for family-based 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 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.

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

[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.

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-based 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 admissions, employment admissions (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 mixed when neither family-based nor employment-based 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 the year of immigration. Table 2 lists the main countries of origin with predominantly family-based 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-based 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

[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-based 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-based 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 at most spent 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 predominantly family-based. Countries are ordered by number of observations in the estimation sample. Table A.1 in the appendix presents corresponding numbers for employment-based migration.

main countries of origin with predominantly employment-based migration to the U.S. according to this classification. Most employment 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%). Other countries have mostly mixed modes of migration to the U.S. We also classify Mexico and countries in Central America as mixed 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-based migration. With 11 and 15 percent, the share of family migrants is much lower for countries with predominantly employment-based migration and mixed countries. Similarly, employment migrants account for 60 percent of migrants from countries with predominantly employment-based migration but only for 8 and 9 percent of migrants from countries with predominantly family-based migration and mixed countries.

In the following analysis, we hence focus on migrants from countries with predominantly family-based 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 at most spent 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 A.3 in the appendix 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), employment migrants in column (3), natives, i.e., U.S.-born individuals, in column (4), and U.S.-born college graduates in column (5). For all populations, we restrict the sample to individuals who were between 22 and 60 years old at the time of immigration/graduation and observed at most 10 years after immigration/graduation.

On average, family migrants immigrated at the age of 35 and faced an initial unemployment rate (IUR) of 6.2 percent.[14] They are disproportionally female (62%) and have on average 12.8 years of schooling. While this is almost a year less than the average native, family migrants are more likely than natives to hold a college degree (36% vs. 31%). By comparison, employment migrants immigrated at the age of 32 and faced an IUR of 5.85 percent on average. 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

[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.

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

years vs. 42 years). Employment migrants are considerably younger (36 years).

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. 75%), 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), the mean hourly wage of a worker in the same occupation,[15] state, and year of observation, are lower. Not surprisingly, employment 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-based migrants or natives.

Family migrants are not more likely to receive public welfare assistance than natives (1.6% vs. 1.7%). 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, employment migrants are generally more independent and mobile.

The demographic characteristics of migrants from the Philippines are comparable to 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.

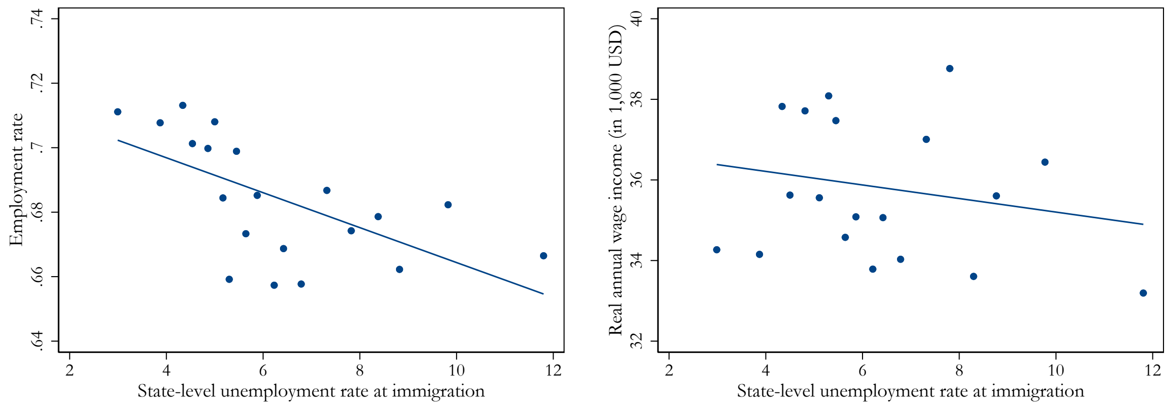
By definition, college graduates have the highest level of education. They are also much younger on average and, conditional on their younger age and limited experience, perform relatively well on the labor market. Out of the different groups, they are most likely to have moved across states within the last year (7.0%).

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.

[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.

Figure 2: Correlation between 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 mean 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). 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.[16] 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 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:

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

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 mean 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

[16] 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.

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 would decide to forgo their to avoid tempory 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-based 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 3 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 column shows the same associations for employment migrants. Here, we see a weak association between the IUR and years of schooling but overall no indication that migrant characteristics systematically vary by IUR. However, the number of employment migrants is positively associated with the IUR.

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

Table 3: Correlation between the initial unemployment rate and migrant characteristics and the number of family migrants

	Family migrants		Employment 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)	-0.0033	0.0279	0.1136***	0.0546***
	(0.0317)	(0.0230)	(0.0337)	(0.0188)
N	2381	7520	2799	8632
F-Test (p-value)	0.916	0.224	0.000785	0.00372

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, year-of-immigration, and year-of-observation. We regress the log number of family migrants observed in each cell on the state-level unemployment rate in the year of immigration, controlling for state, year-of-observation, and year-of-immigration fixed effects. 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 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 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 employment migrants. This is likely due to strong 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 decide 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 employment 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 employment 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 mean 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.4 in the appendix.

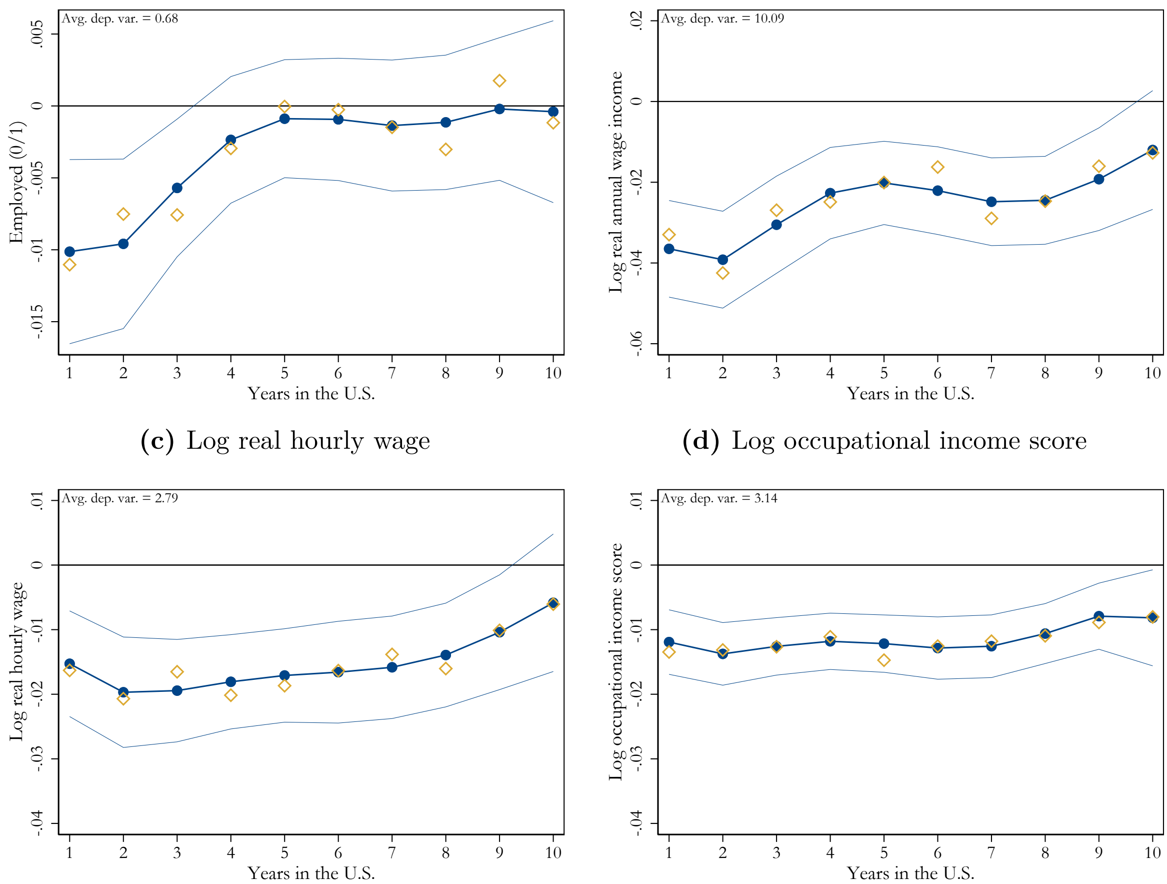
Figure 3: Effect of the initial unemployment rate on labor market outcomes of family migrants

(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.4 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 who immigrate into a recession are hence pushed into lower-paid occupations.[17]

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).

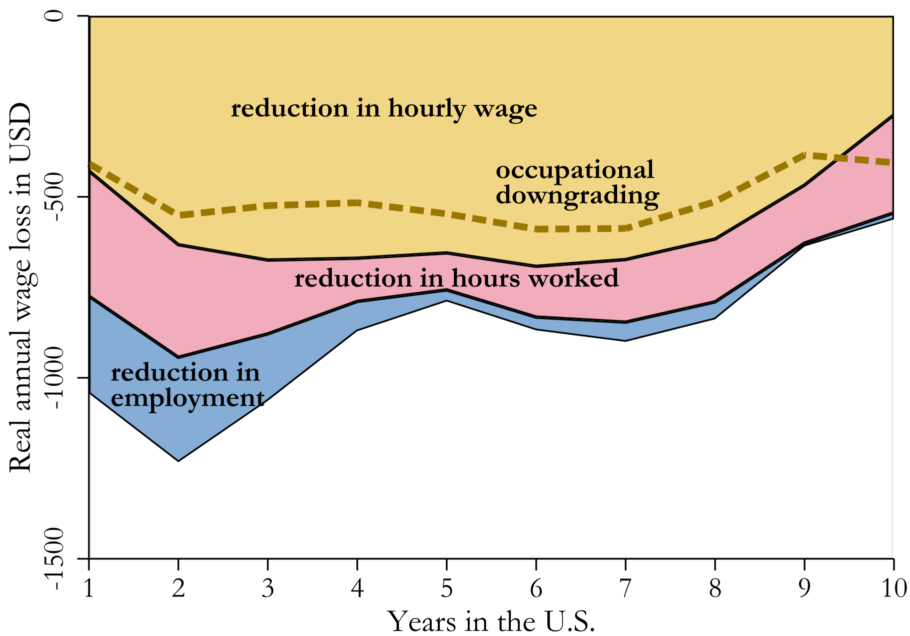
To do so, we first calculate the average annual employment rate, annual working hours, annual wage income, hourly wage, and occupational income score of family migrants by years in the U.S. We can now obtain the reduction in annual wage income due to occupational downgrading (a) by multiplying the effect 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 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.11 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

[17]Mean 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 acoounts for almost the entire reduction in hourly wages in absolute terms (see Figure 4).

of a one pp increase in the IUR on being employed times the average annual wage income.

Figure 4 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 USD 4,050, which also explains the reduction in income due to lower hourly wages that amounts to USD 4,690. The cumulative income loss due to a reduction of working hours is USD 1,645, and due to lower employment rates USD 927 (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 by about USD 600 after ten years in the U.S.[18] The estimated loss in the net-present-value wage income over the entire ten-year period amounts to USD 7,260. A 5 pp rise in unemployment rates, a typical rise in a large recession (von Wachter, 2020), would hence reduce the ten-year wage income of a family migrant by USD 36k. This is a large effect. While college graduates on average have about 30% higher wage income than family migrants, the equivalently estimated average earnings loss of graduating in an equally large recession is USD 29k (von Wachter, 2020).

Figure 4: 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).

[18] The effects on annual wage income in absolute amounts appear to be more persistent than the relative effects presented in Figure 3. This observation is misleading as family migrants experience strong increases in average annual wage incomes over their first years in the U.S.

Figure 5 compares the labor market effects of entering the labor market in a recession across different population groups. Our results are similar when we focus on Filipino migrants who constitute the largest group of family migrants. The effects on annual wage income and log occupational income scores do not differ between all family migrants and the subsample of Filipino migrants. The effects on employment and hourly wages, however, are slightly more pronounced for Filipino migrants.

We also compare the effects to college graduates, who might serve as a natural benchmark. To do so, we replicate the results for college graduates using the ACS data and our econometric specification. We restrict the sample to U.S.-born college graduates and replace the year of immigration with the year of graduation. As Figure 5 shows, the results obtained using our specification are similar to the results in Kahn (2010), Oreopoulos et al. (2012), and Altonji et al. (2016). However, consistent with the evidence presented above, the effects for immigrating into a recession are considerably more adverse than for graduating in a recession.

Figure 5 also shows the effects for employment migrants. By definition, these migrants arrive with a job. Their economic integration should hence be less susceptible to economic conditions at arrival. Indeed, we hardly observe any effects on their labor market outcomes, especially in the first years after arrival.

We also test for effect heterogeneity by gender and level of education. Overall, we find limited effect heterogeneity for both dimensions. The employment effect is a bit more negative for female than for male family migrants (Figure A.6 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.7 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 at least 30 years old at the time of immigration to minimize the possibility that the level of education is potentially affected by the initial unemployment rate (Figure A.8 in the appendix).

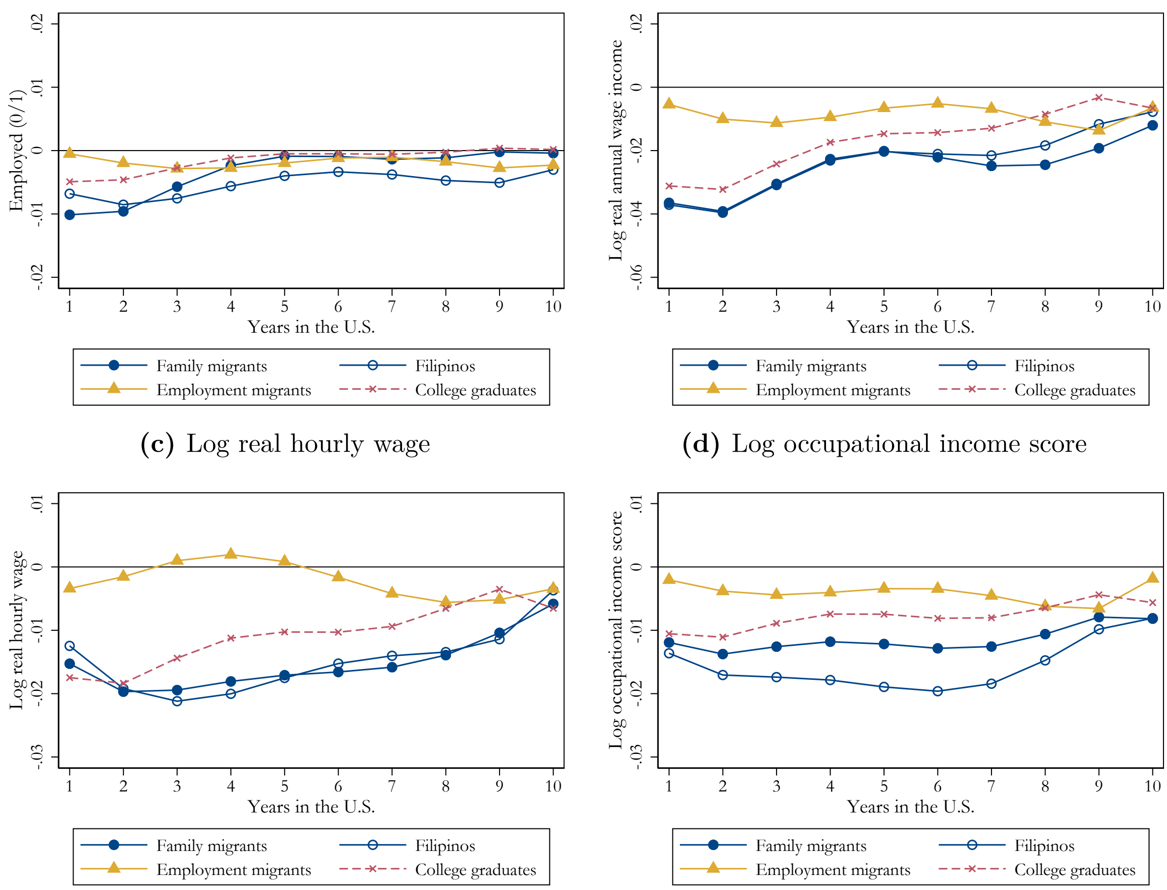
Robustness checks

We check the robustness of our main results to address several potential concerns. First, 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.9 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).

Second, 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.10 in the appendix).

Third, 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.11 in the appendix). The effect on self-employment is positive but close to zero and not statistically significant.

Figure 5: Comparison of the effects of initial unemployment rates across family migrants, employment migrants, and U.S. college graduates



(a) Employment

(b) Log real annual wage income

(c) Log real hourly wage

(d) Log occupational income score

Notes: The figure reruns the main analysis for four different samples: Family migrants, Filipino migrants (the largest group of family migrants), employment migrants, and U.S. college graduates. 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) for the different samples. 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.

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, or Patel and Vella, 2013). 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 their attractiveness to employers. Network support should be relatively less important 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.[19] 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 have 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-based migration are too small, especially for the analysis of ethnic occupations introduced below. For the same reason, we also exclude migrants when there are 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 4 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

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

Table 4: 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**	0.02	0.14	0.01	3.11*	0.27	-1.27	1.14
	(0.11)	(0.21)	(0.16)	(0.07)	(1.88)	(0.42)	(1.78)	(1.46)
UR at immigration (/100)	-1.32**	-2.30*	-1.80**	-0.72*	-3.91	-2.84	-2.49	4.44
	(0.54)	(1.28)	(0.91)	(0.41)	(8.27)	(2.08)	(8.70)	(6.85)
Network size	0.01*	0.00	-0.04***	-0.01**	-0.27**	-0.04	0.08	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)	(0.13)	(0.03)	(0.13)	(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 of the same 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.

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 4 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 4 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

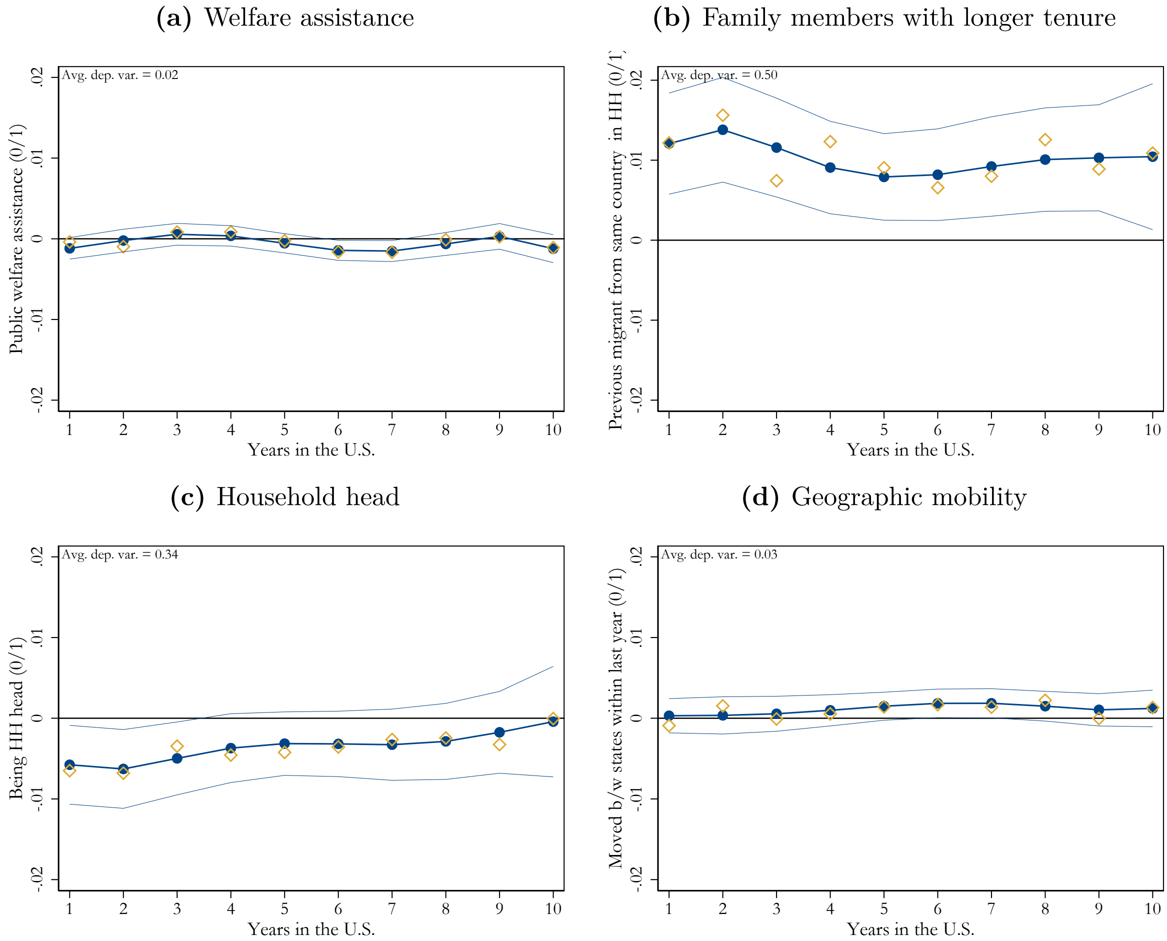
Family migrants are generally not entitled to welfare benefits for at least five years after arrival. Instead, sponsors are obliged to support sponsored family members for ten years or until they become U.S. citizens (Kolker, 2016). The ACS provides information on welfare receipt and the composition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

Panel a of Figure 6 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 6, 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.

Figure 6: 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.

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

Employment migrants are less susceptible to labor market conditions at the time of arrival as they arrive with a job. Indeed, as shown in Figure 5 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 3, 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 5 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 7.2 percent, on hourly wages by an additional 5.7 percent, and occupational income scores by an additional 2.8 percent over the first ten 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 5).

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 7 shows, the reweighted results are similar to the previous 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

Table 5: 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*	-2.439***	-1.579***	-1.183***
	(0.205)	(0.451)	(0.329)	(0.207)
Observations	116975	84769	84769	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***	-0.831**	-0.171	-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	465419	465419	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.

even larger.

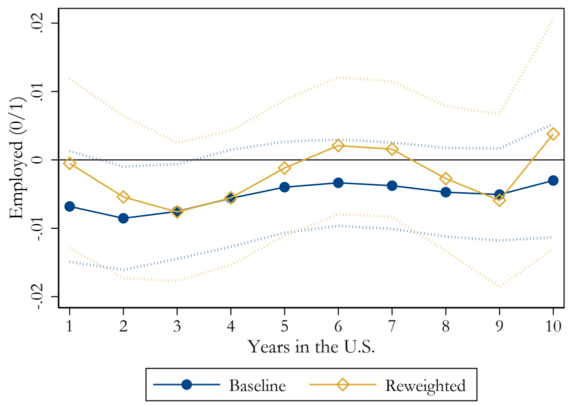
Second, we try to exclude immediate relatives who can be sponsored without waiting times from the sample. Such relatives include spouses, parents, and unmarried children under 21 years of U.S. citizens (see Table 1). Our main sample already excludes minor children and older parents as it is limited to 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).[20][21] Figure 8 shows that results for this subsample are similar to the main results.

[20]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.

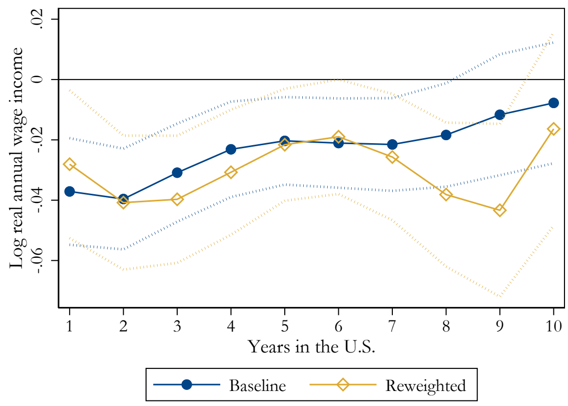
[21]The focus on married couples who immigrated in the same year likely also excludes spouses of LPRs (F2A visa holders). Spouses of LPRs (and U.S. citizens) are more likely than other family migrants to adjust their visa status while being in the U.S. They might hence have chosen particular economic 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.

Figure 7: Effect of the initial unemployment rate on labor market outcomes of Filipino migrants

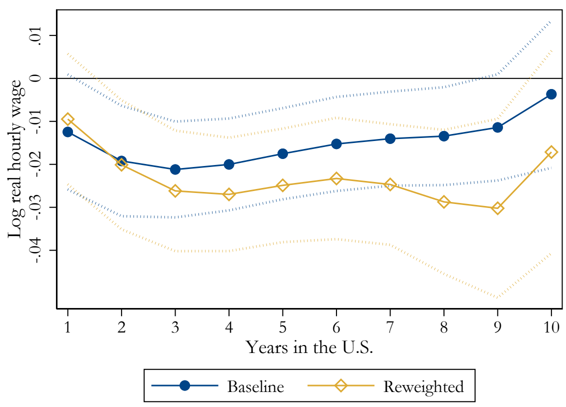
(a) Employment



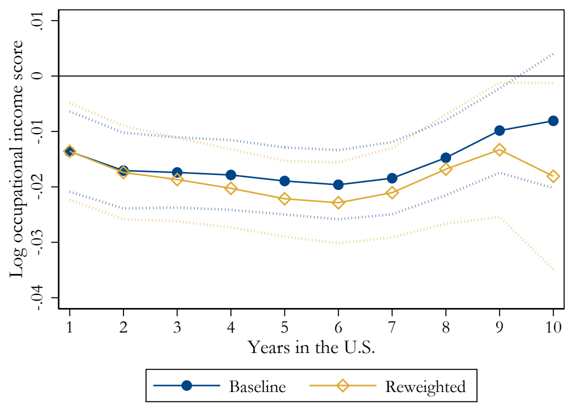
(b) Log real annual wage income



(c) Log hourly wage

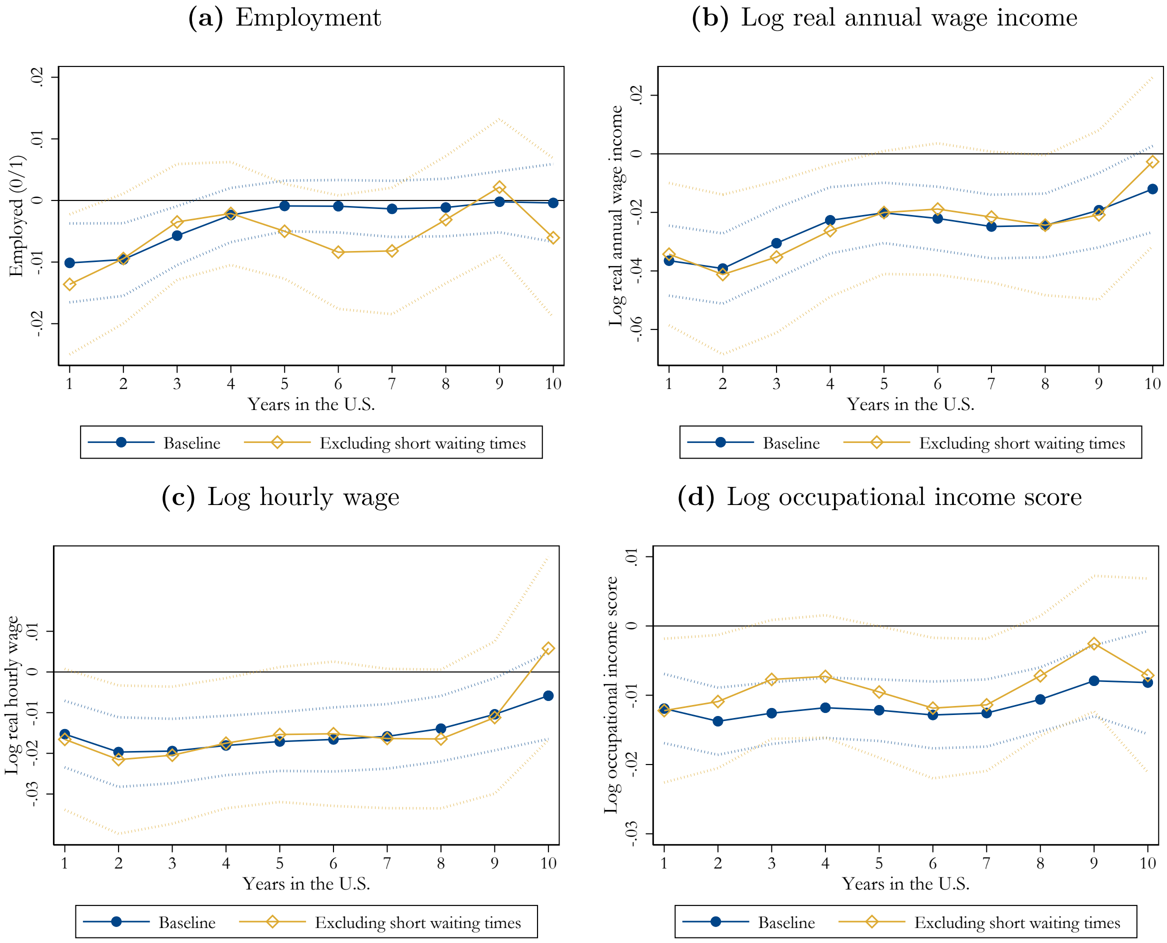


(d) Log occupational income score



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) with different weights. Blue dots including the 95 percent confidence interval show coefficients for our baseline specification, in which we weigh observations by the mean 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 including the 95 percent confidence interval show coefficients 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. Standard errors are clustered at the state-year-of-immigration level.

Figure 8: Effect of the initial unemployment rate on labor market outcomes of family migrants with long waiting times



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.

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 that results in lower hourly wages, and a reduction in working hours. Migrant networks mitigate the negative labor market effects of immigrating into a recession and also 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. Allowing family-sponsored visa holders to delay their immigration might improve their ability to synchronize their arrival with labor market conditions in the U.S. and integrate into the U.S. economy. However, family migrants might not be willing to do so. The typically large income differences between the U.S. and their countries of origin might still make it optimal for family migrants to enter the U.S. as soon as they obtain their visa.

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Appendix

A Additional tables and figures

Table A.1: Main countries of origin with predominantly employment-based migration

	Number of obs. in estimation sample	% of years employment-dominated	% of migrants employment-based
Indida	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 employment-dominated is the share of years between 1992 and 2018 in which a country's dominant mode of migration to the U.S. was employment-based 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 at most spent 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 predominantly employment-based. Countries are ordered by number of observations in the estimation sample. Table 2 presents corresponding numbers for family-based migration.

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

	Country type		
	Family	Employment	Mixed
Family migrants	65.0	4.9	14.9
Family-capped	23.5	0.8	2.9
Immediate relatives	41.5	4.1	12.0
Employment 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 mixed when neither family-based nor employment-based migration alone accounts for the majority of admissions. Table 2 shows the main countries of origin for the different modes of migration to the U.S. See Section 4 for more details. Rows show the share of migrants considered family migrants, employment 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: Summary statistics

	Family migrants		Employment migrants	Natives	College graduates
	All	Filipinos			
Personal characteristics					
Female (0/1)	0.62	0.66	0.49	0.51	0.56
	(0.49)	(0.47)	(0.50)	(0.50)	(0.50)
Age at immigration	34.9	35.2	31.8	.	.
	(9.03)	(8.95)	(8.00)	.	.
Age at observation	40.2	40.6	36.4	41.9	27.3
	(9.17)	(9.07)	(8.28)	(11.2)	(2.81)
Years of schooling	12.8	14.7	15.9	13.7	16
	(4.15)	(2.78)	(2.92)	(2.65)	(0)
At least 4 years of college (0/1)	0.36	0.61	0.73	0.31	1
	(0.48)	(0.49)	(0.44)	(0.46)	(0)
Economic conditions					
Unemployment rate at immigration	6.21	6.22	5.87	.	5.99
	(2.13)	(2.11)	(2.03)	.	(2.03)
Labor market outcomes					
Employed (0/1)	0.69	0.74	0.70	0.75	0.87
	(0.46)	(0.44)	(0.46)	(0.43)	(0.34)
Real annual wage income (in 1000 USD)	36.0	43.7	81.0	54.4	47.2
	(36.7)	(38.5)	(74.5)	(54.1)	(36.6)
Real hourly wage	21.6	25.6	40.7	28.0	25.1
	(22.5)	(24.0)	(34.1)	(25.9)	(19.3)
Occupational income score (USD)	25.0	28.0	37.7	27.4	30.3
	(11.5)	(12.5)	(14.7)	(12.0)	(11.0)
Self employed (0/1)	0.061	0.038	0.065	0.088	0.041
	(0.24)	(0.19)	(0.25)	(0.28)	(0.20)
Public welfare assistance (0/1)	0.016	0.0070	0.0032	0.017	0.0052
	(0.13)	(0.083)	(0.056)	(0.13)	(0.072)
Social outcomes					
Previous migrant in HH (0/1)	0.49	0.45	0.21	.	.
	(0.50)	(0.50)	(0.41)	.	.
Being hh head (0/1)	0.34	0.33	0.47	0.54	0.48
	(0.48)	(0.47)	(0.50)	(0.50)	(0.50)
Moved b/w states last year (0/1)	0.025	0.027	0.058	0.025	0.070
	(0.16)	(0.16)	(0.23)	(0.16)	(0.26)
Observations	116,975	50,520	185,761	28,023,040	1,518,218

Notes: The table shows summary statistics for five different samples: Family migrants, Filipino migrants, employment migrants, U.S. natives, and U.S. college graduates. 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 at most spent ten years in the U.S. at the time of observation. The sample of U.S. college graduates is restricted to U.S.-born individuals who graduated from college 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/graduation and observation. 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 mean 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 mean wage income of a worker in the same occupation, state, and year of observation. See Section 4 for more details.

Table A.4: 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)	(0.555)	(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. The column title shows the outcome variable. Coefficients 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 after arrival. The upper panel shows results for the flexible specification (Equation 1), the lower panel results for 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. */**/*** 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

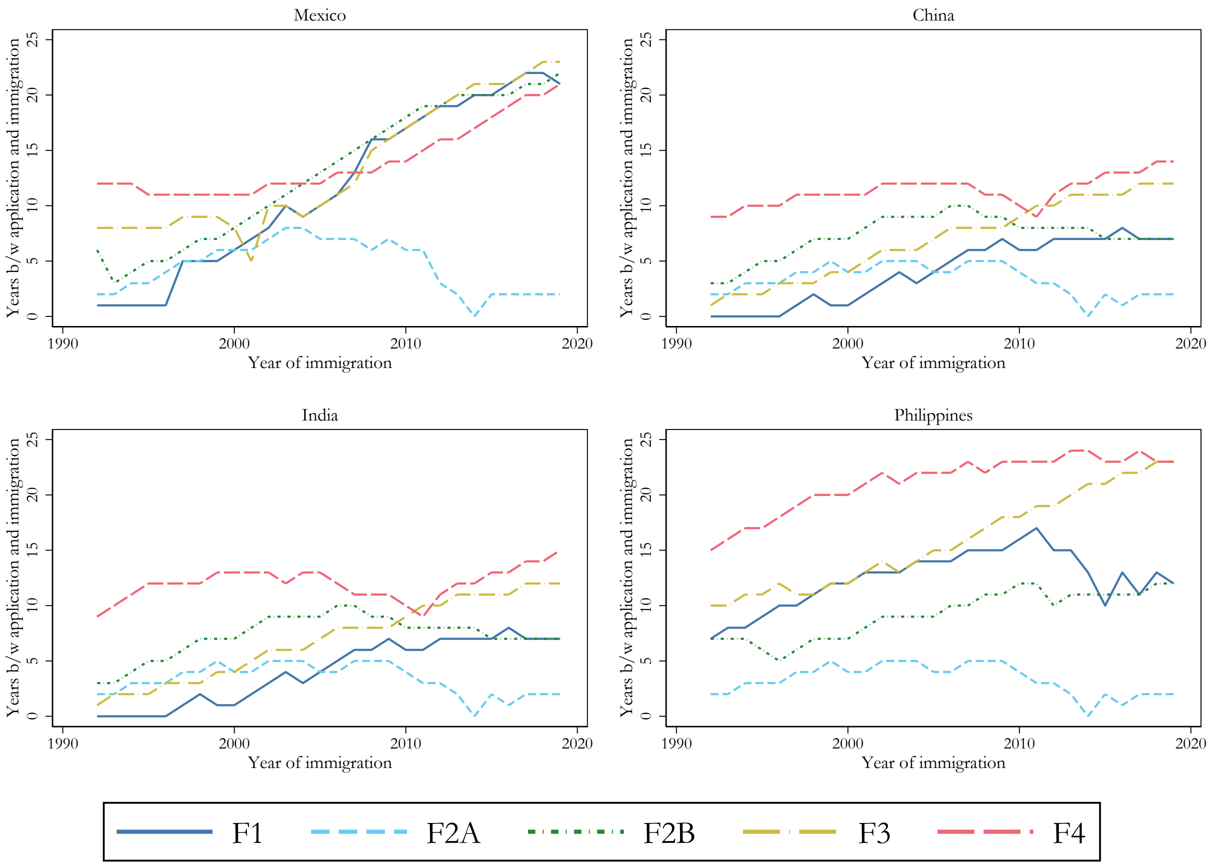
Notes: The table reports OLS estimates. The column title shows the outcome variable. Coefficients shows the effect of a one pp higher state-level unemployment rate in the respective year(s) on the outcome variable. UR in years 4-5 before immigration is the average state-level unemployment rate in years 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

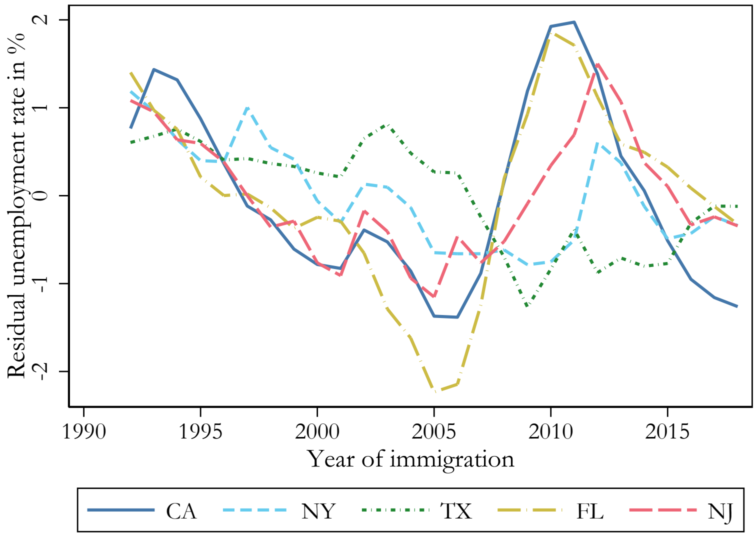
Notes: The table reports OLS estimates. The outcome variables are the state-level shares of workers of the same origin that work in the same occupation/industry (in percent). UR at immigration is the state-level unemployment rate in the year of immigration (divided by 100 to improve readability). Network 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 4. Column 2 uses the entire ten-year period instead of three-year period used in Table 4. 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



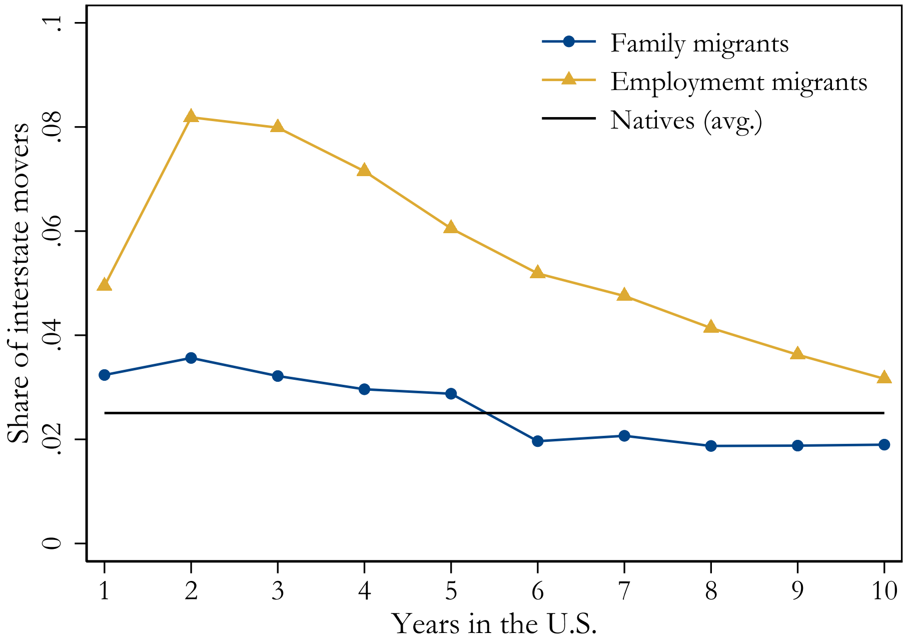
Notes: The figure shows waiting times for unmarried sons and daughters of U.S. citizens and their minor children (F1), spouses and minor children of LPRs (F2A), unmarried sons and daughters of LPRs (F2B), married sons and daughters of U.S. citizens (F3) and brothers and sisters of U.S. citizens (F4). 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.

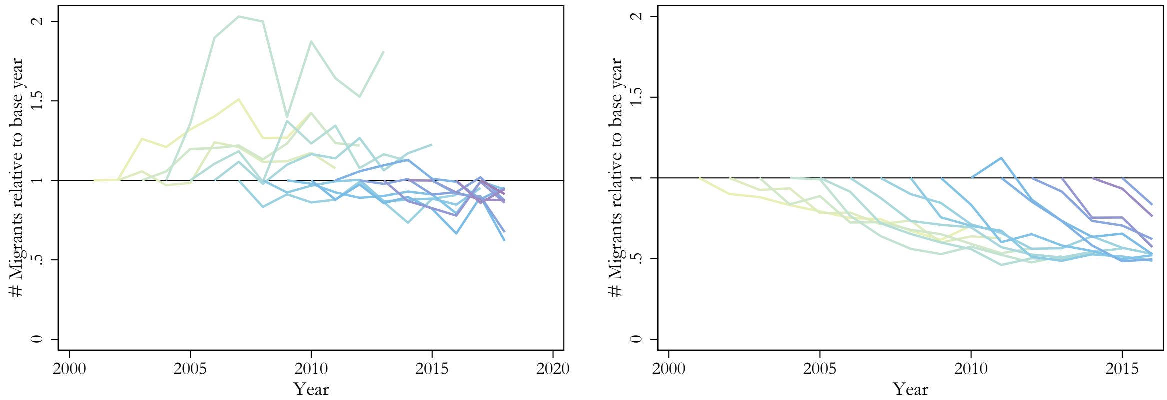
Figure A.3: Share of individuals that moved between U.S. states within the last year



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 at most spent 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.

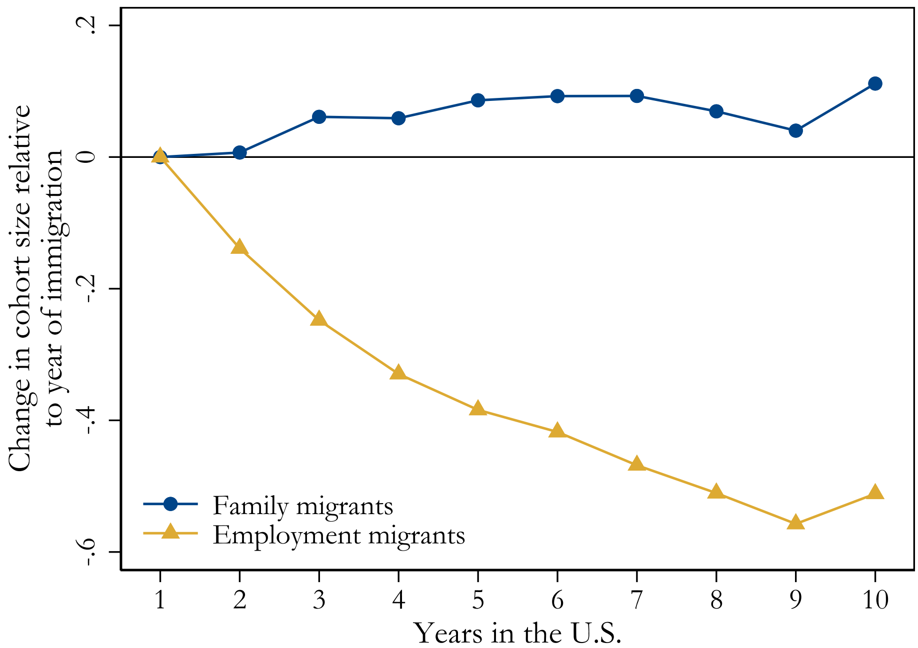
Figure A.4: Cohort size by years since immigration (individual years)

(a) Family migrants **(b)** Employments 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 mean 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.

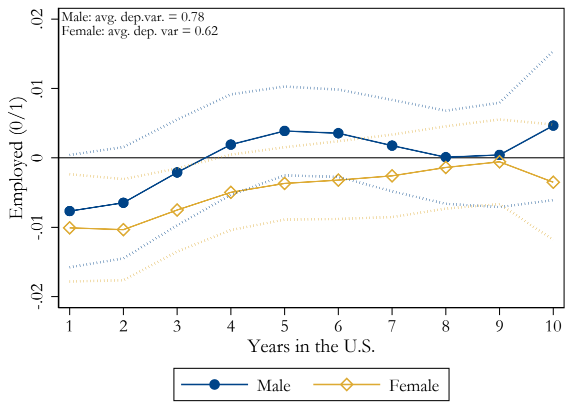
Figure A.5: Cohort size by years since immigration (aggregated)



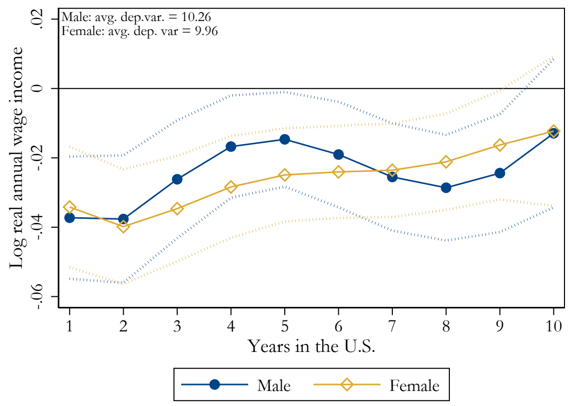
Notes: The figure plots the coefficients from an OLS regression of the log number of immigrants observed in year-of-immigration and years-in-the-U.S. cells on a full set of year-of-immigration and years-in-the-U.S. dummies. The coefficients of the years-in-the-U.S. dummies reflect the number of migrants 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 mean annual sample weights.

Figure A.6: Effect of the initial unemployment rate on labor market outcomes of family migrants by sex

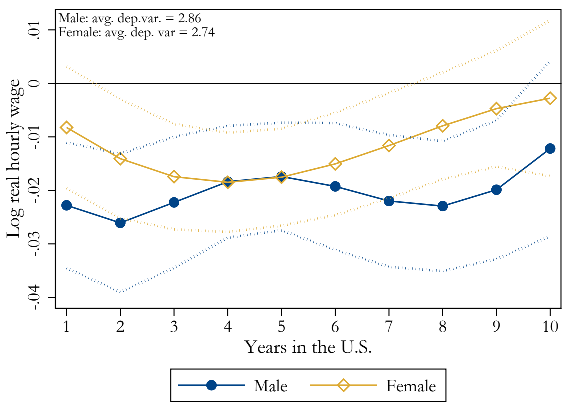
(a) Employment



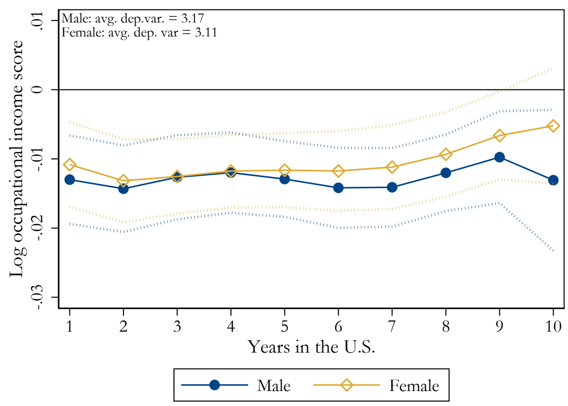
(b) Log real annual wage income



(c) Log hourly wage



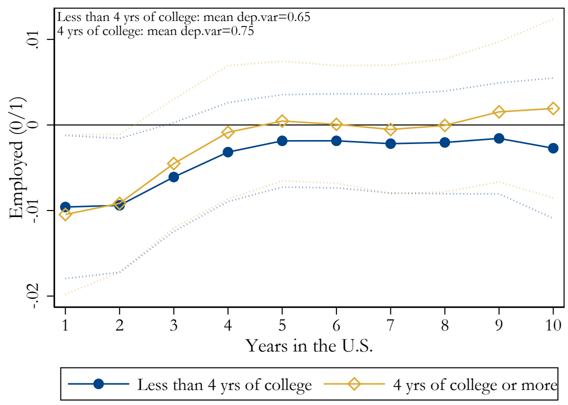
(d) Log occupational income score



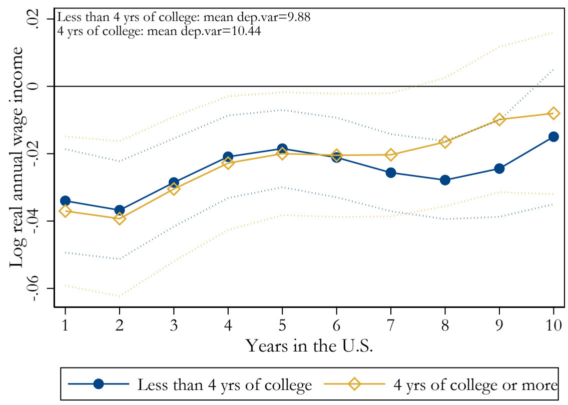
Notes: The figure reruns the main analysis separately for men and women. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable in the respective year including the 95 percent confidence 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.7: Effect of the initial unemployment rate on labor market outcomes of family migrants by education

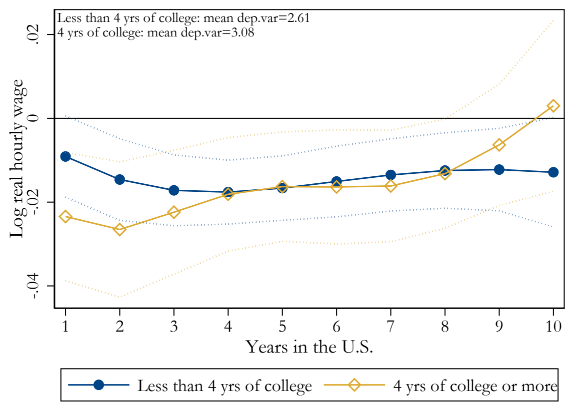
(a) Employment



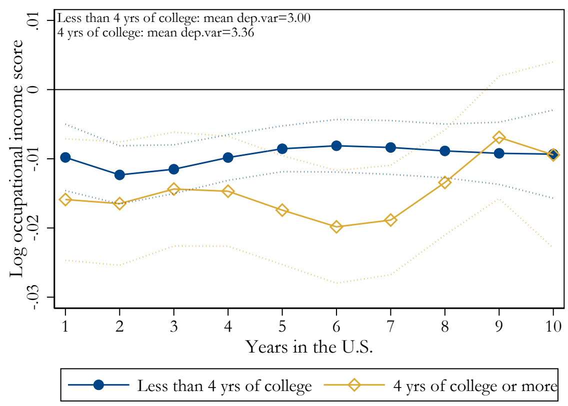
(b) Log real annual wage income



(c) Log hourly wage



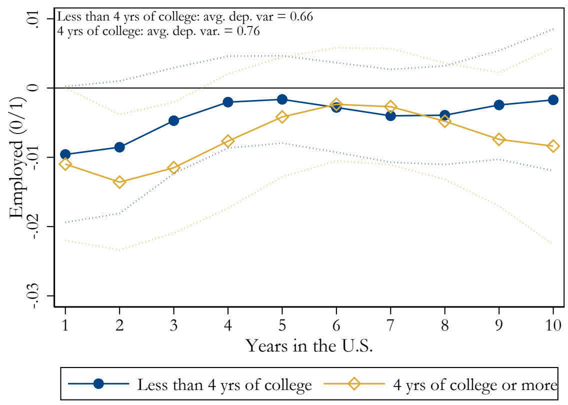
(d) Log occupational income score



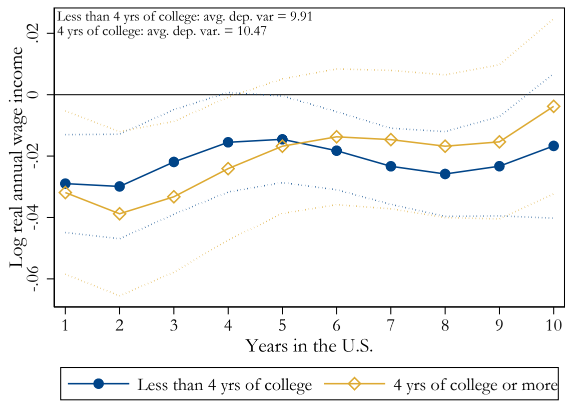
Notes: The figure reruns the main analysis separately for individuals with and without at least four years of college education. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level unemployment rate in the year of immigration on the outcome variable 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.8: Effect of the initial unemployment rate on labor market outcomes of family migrants by education (conditional on being older than 30 years at immigration)

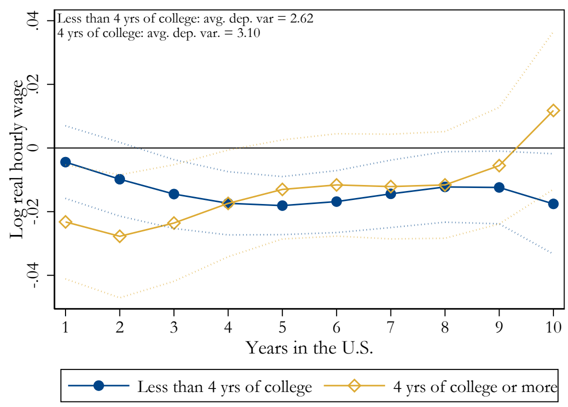
(a) Employment



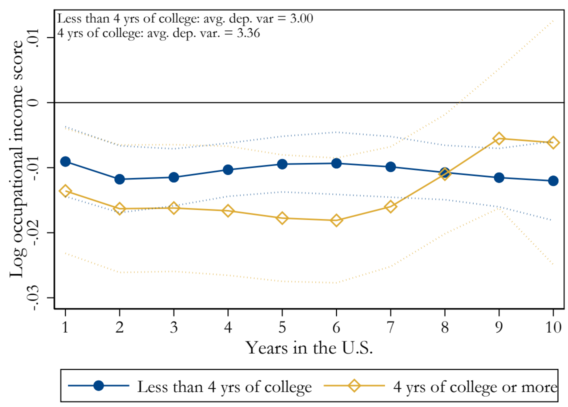
(b) Log real annual wage income



(c) Log hourly wage

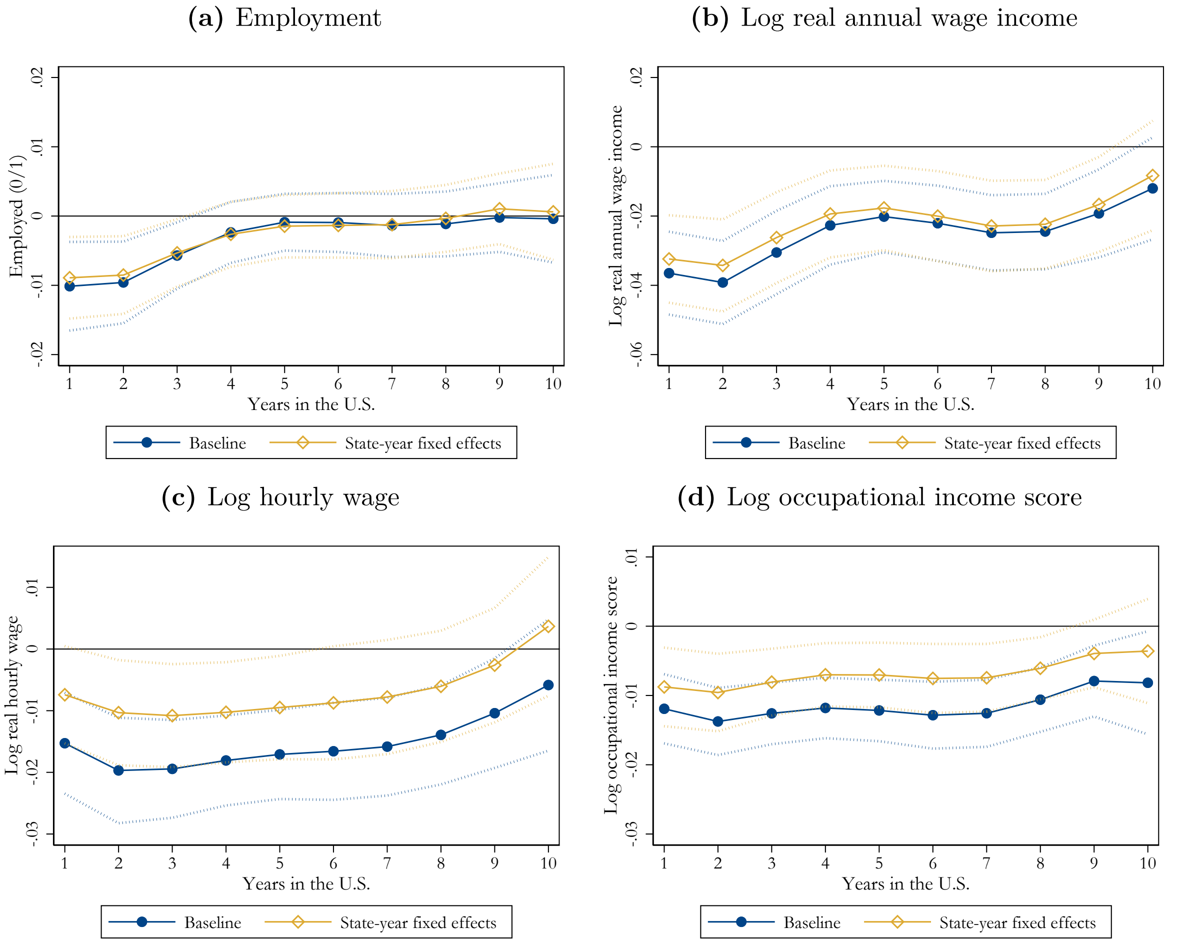


(d) Log occupational income score



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.7, the sample is restricted to individuals who were at least 30 years old 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.

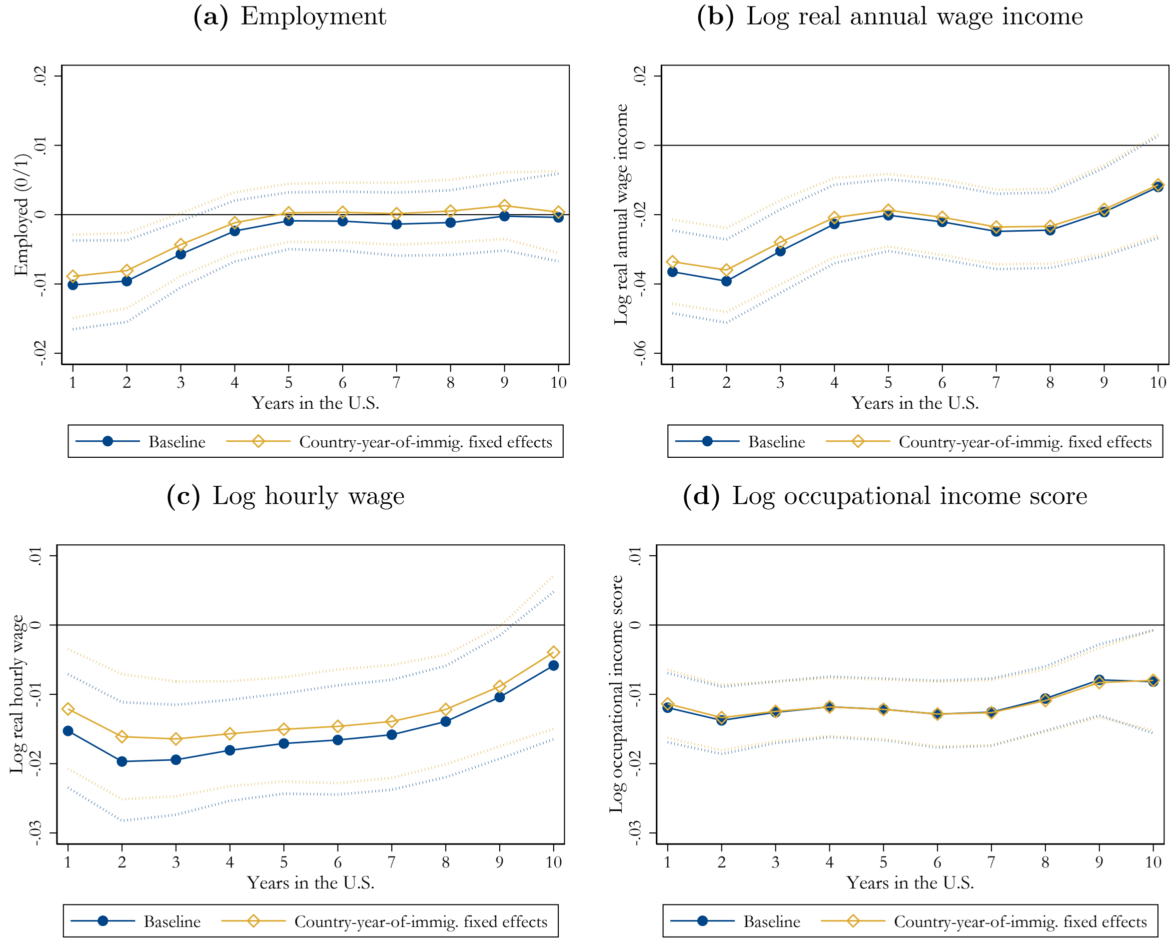
Figure A.9: Effect of the initial unemployment rate on labor market outcomes of family migrants controlling for current economic conditions



(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.

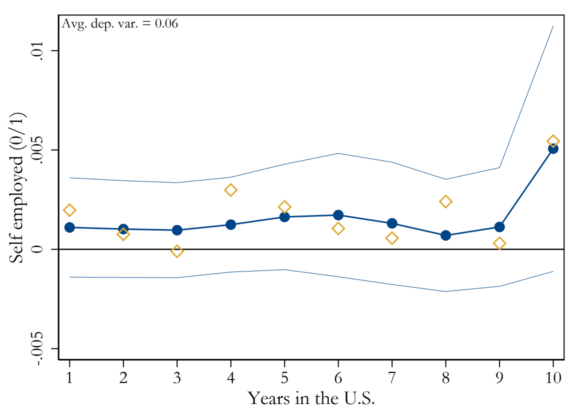
Figure A.10: Effect of the initial unemployment rate on labor market outcomes of family migrants controlling for country-of-origin-year-of-immigration fixed effects



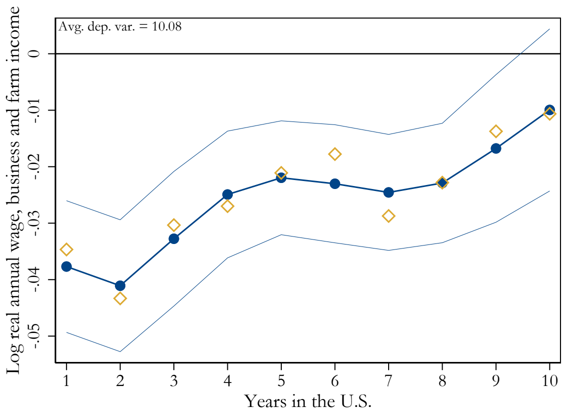
Notes: The figure shows how our main results change when we add country-of-origin-year-of-immigration fixed effects to control for shocks that are specific to a country of origin in the year of immigration. The x-axis shows the years since immigration. The y-axis shows the effect of a one pp higher state-level 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.11: Effect of the initial unemployment rate on self-employment, annual labor income, annual total earnings, and hours worked of family migrants

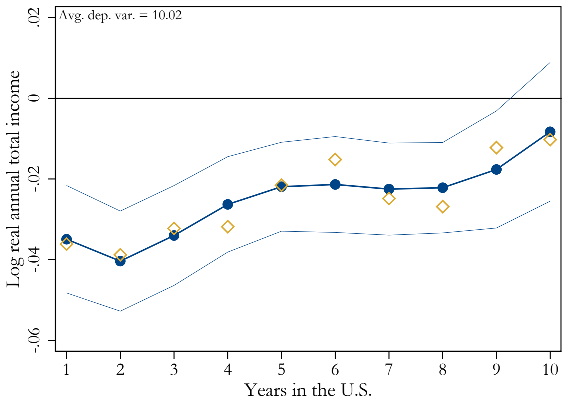
(a) Self-employment



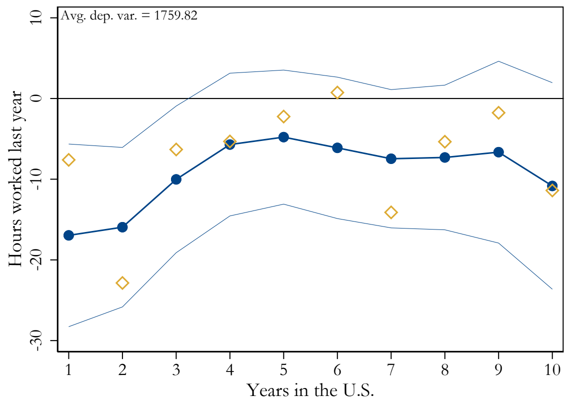
(b) Log of annual labor income



(c) Log real annual total earnings



(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.