LIS
Working Paper Series

No. 899

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May 2025

Luxembourg Income Study (LIS), asbl

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May 15, 2025
Forthcoming at *Population Research & Policy Review*

Word Count (excl. title page, abstract, references, tables, figures & supplement): 8358

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THE HETEROGENEITIES OF IMMIGRANT POVERTY IN THE U.S.

ABSTRACT

Immigrants are now more than one-fifth of the poor in the U.S. Yet, despite some valuable literature, immigrant poverty remains arguably understudied. This study builds on the larger literatures on immigrant attainment and poverty, and the smaller literature on immigrant poverty. Using the Luxembourg Income Study (LIS), we provide an improved descriptive demographic portrait of immigrant poverty from 1993-2023, across 51 states (including D.C.), and within 2019-2024 (N=760,026). There is considerable heterogeneity over time. After declining for several decades, immigrant poverty increased substantially in recent years. Immigrant poverty also varies enormously across states. States' immigrant poverty rates are moderately negatively correlated with states' immigrant share of the population and strongly positively correlated with states' non-immigrant poverty. There are large heterogeneities by nation of origin as well. While immigrants from India have among the lowest poverty of any group in the U.S., Honduran immigrant poverty is 6-7 times higher. While especially being a non-citizen immigrant increases poverty, heterogeneities in immigrant poverty are driven more by the major risks of poverty than the immigrant characteristics of being a citizen, years of residence, or mixed status households. That said, heterogeneities by nation of origin are explained by varying mixes of risks, immigrant characteristics and educational selectivity. Ultimately, we demonstrate immigrant poverty is not one coherent phenomenon. Indeed, the heterogeneities within immigrant poverty are perhaps even more important than the heterogeneities in poverty between immigrants and non-immigrants.

Key words: Poverty; Immigration; Immigrants; Citizenship; Assimilation; Ethno-Racial Inequality

INTRODUCTION

In recent years, a growing share of the poor in the U.S. are immigrants. As Figure 1 displays, only 14.1% of the poor were immigrants in 1993. In 1994, only 11% of the poor were non-citizen immigrants. The immigrant share has grown steadily since, partly due to a rising share of immigrants in the population. By 2020, more than one-fifth (20.2%) of the poor were immigrants and more than one-tenth (10.6%) of the poor were non-citizen immigrants. By 2023, fully 22.3% of the poor were immigrants and 13.2% were non-citizen immigrants.

[FIGURE 1 ABOUT HERE]

Because immigrants are a growing share of the poor, understanding the lives of immigrants is increasingly essential to understanding poverty in the U.S. (Card and Raphael 2013; Raphael and Smolensky 2009). Indeed, Parolin and Brady (2019) demonstrate that the largest group of children in extreme poverty are in households (HHs) headed by immigrants. Poverty matters to immigrant health and well-being, and is relevant to long-standing literatures on immigrant economic attainment (e.g. Flippen 2012; Florian 2023; Hagan et al. 2015; Ortiz and Telles 2017; Portes and Zhou 1993; Potochnick et al. 2017; Waldinger and Lichter 2003). Poverty also bears on immigrant marginalization from other institutions, such as the housing market (Pedroza 2022). As we explain below, immigrant poverty is also important to public policy debates. Further, understanding immigrant poverty is essential to understanding the enduring large ethno-racial inequalities in poverty (Baker et al. 2022; Ortiz and Telles 2017).

Despite the increasing salience of immigrant poverty, immigrant poverty remains arguably understudied. This article aims to provide a deeper understanding of immigrant poverty, and in the process, address gaps between and within relevant literatures. The present study aims to make three main contributions. First, we provide a uniquely updated and comprehensive demographic portrait of immigrant poverty in the U.S. We use the better measures of poverty available in the Luxembourg Income Study Database (LIS) and more rigorously investigate immigrant poverty over time, across states, and by citizenship, nations of origin, immigrant characteristics, and poverty risks. Second, integrating the literatures on immigrant attainment and poverty, we provide the first assessment comparing the roles of both immigrant characteristics versus poverty risks for immigrant poverty. Third, as a result of the first two, we provide novel evidence to demonstrate a variety of salient heterogeneities in immigrant poverty. Immigrant poverty is not one coherent phenomenon. Indeed, the heterogeneities within immigrant poverty are perhaps even more important than the heterogeneities in poverty between immigrants and non-immigrants.

BACKGROUND

Literatures on immigrant attainment, poverty and immigrant poverty all inform this study. While there are large literatures on both immigrant attainment and poverty, there are often disconnects between these literatures. Moreover, the literature specifically on immigrant poverty is much smaller than either of those two larger literatures.

In what we broadly call immigrant “attainment”, there are extensive literatures on immigrant employment, income, and socio-economic standing (Card and Raphael 2013; Flippen 2012; Florian et al. 2023; Hagan et al. 2015; Kandel and Parrado 2005; Portes and Rumbaut 2014; van Tubergen et al. 2004; Villarreal and Tamborini 2018; Waldinger and Lichter 2003). This literature is so vast, we can only summarize a few major themes in broad strokes. Scholars have devoted considerable attention to origin and destination effects (van Tubergen et al. 2004). Many show substantial roles for immigrant characteristics like citizenship/documentation status, years of residence in the host country, mixed status HHs, nation of origin and the related modes of incorporation (Bean et al. 2015; Bostic and Hyde 2023; Canizales 2022; Portes and Zhou 1993; Rosales 2022; Zhou and Gonzales 2019). The field often emphasizes how immigration enforcement severely constrains attainment (Amuedo-Dorantes et al. 2018; Bohn et al. 2015). Of course, classic human capital factors like education and demographic characteristics also play a role in immigrant attainment (Flippen 2012; Florian et al. 2023; Park and Myers 2010; Portes and Zhou 1993; Villarreal and Tamborini 2018; Zhou and Gonzales 2019).

Much of the immigrant attainment literature focuses on intra- and intergenerational mobility (Ortiz and Telles 2017; Portes and Zhou 2003; Waldinger and Feliciano 2004; Zhou and Gonzales 2019). An ongoing debate has occurred regarding how immigrants and their children experience segmented assimilation and mobility. Indeed, the literature on segmented assimilation has been animated by how the factors above interact with discrimination and blocked opportunity to result in low attainment of the children of immigrants. At the other end, immigration scholars have highlighted the role of educational selectivity – and "hyper-selectivity" – in the high attainment of immigrants from certain nations of origin (Tran et al. 2018; Zhou and Gonzales 2019). Throughout, this literature has always highlighted the heterogeneities of attainment between immigrants, including the many at the low end of the income distribution. Because poverty is essentially a measure of low economic attainment, this extensive literature certainly must guide any study of immigrant poverty.

The poverty literature is also vast and we only focus on a few key aspects that are most relevant here. Poverty research has long been animated by thoroughly describing how and why certain groups are more likely to be poor than others (Brady 2023; Laird et al. 2018). Considerable research has long investigated which demographic and labor market characteristics most predict poverty (Madrick 2020; O'Connor 2001; Rainwater and Smeeding 2004). The observable, non-ascriptive and at least partially malleable, individual- and HH-level demographic and labor market characteristics more common among the poor than non-poor are called the "risks" of poverty (Brady et al. 2017). In the past decade, the field has converged on four major risks that are the most commonly studied and carry the largest "penalties" (i.e. coefficients): joblessness, young headship, low education and single motherhood (Baker et al. 2022; Brady 2023; Brady et al. 2024; Burciu and Parolin 2024; Laird et al. 2018; Rothwell and McEwen 2017; Thiede et al. 2021; Zagel et al. 2021). These four risks capture the most important "behaviors" that predict poverty.

Many study how structural or political contexts influence the prevalence of these behaviors. Yet, the poverty literature increasingly emphasizes the role of power resources, social policies and institutions in how poverty varies across time and place even net of risks and behaviors (Brady 2023; Bostic and Hyde 2023; Zagel et al. 2021). Such political explanations emphasize the substantial heterogeneity in poverty across countries (Bostic and Hyde 2023; Brady 2023) and U.S. states (Baker et al. 2022), and how social policies have substantially reduced poverty over time even within the U.S. (Jones and Ziliak 2022; Parolin and Brady 2019; Parolin and Filauro 2023). Within the U.S. context, this literature encourages scrutiny of interstate and temporal heterogeneity in poverty beyond simply studying heterogeneities in poverty between individuals (Baker et al. 2022; Brady 2023; Laird et al. 2018).

While the literatures on immigrant attainment and poverty are vast, the two fields are often disconnected.[1] Within both the poverty and immigration literatures, there is less research

[1] Of course, certain threads in the immigrant literature have been in dialogue with the poverty literature. For instance, the segmented assimilation literature that arose in the 1990s was obviously influenced by the underclass and culture of poverty literatures of the 1980s (e.g. Portes

on immigrant poverty than many other topics. To some extent, immigrant poverty has fallen through the cracks between these fields. For the immigration literature, there has been greater attention on intra- and intergenerational mobility rather than immigrants' current economic deprivation. For the poverty literature, the field has traditionally disproportionately focused on upper Midwestern cities versus Sun Belt cities where immigrants are more prevalent. While literature on ethno-racial inequalities in poverty considers the role of Latino and Asian immigrants, the poverty literature has focused far more on the Black-white divide (Baker et al. 2022). Data limitations have probably also constrained the study of immigrant poverty. It is well known that Census data cannot cover immigrant as well as native populations. Also, datasets like the Panel Study of Income Dynamics that have long been workhorses of poverty research were constructed decades before recent immigrants arrived and have long been known to underrepresent immigrants. At the same time, despite being quite valuable for studying immigrants for other purposes, surveys with strong coverage of immigrants tend to lack the precise income, tax and welfare transfers data needed for leading poverty measures (e.g. Add Health, The Children of Immigrants Longitudinal Study).

Partly due to this confluence of factors, immigrant poverty remains arguably understudied. Brady (2023) even argues: "Immigrants could be the most understudied population in poverty in the United States." In turn, the literature specifically concentrating on immigrant poverty is far smaller. As a result, it is important to highlight the valuable contributions that have been made.

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and Zhou 1993; Waldinger and Feliciano 2004). Broadly speaking and unfortunately given Figure 1, it does not appear the poverty literature has as fully incorporated the immigration literature. Moreover, the segmented assimilation literature was grounded in a poverty literature that is now almost four decades old.

First, typically based on the official poverty measure, some show that immigrants and especially non-citizen immigrants are more likely to be poor (Amuedo-Dorantes et al. 2018; Card and Raphael 2013; De Trinidad Young et al. 2018; Raphael and Smolensky 2009). Only a few analyze immigrant poverty with the superior and relative Supplemental Poverty Measure (SPM) (Batalova and Fix 2023; Thiede et al. 2021), and only one study we are aware of uses a relative income poverty measure (Garcia 2011). Second, there are several ethnographies analyzing immigrant poverty (Rendon 2019; Rosales 2022). For instance, Dohan (2003) contrasts immigrant poverty in an established Los Angeles destination against a then new destination in San Jose, California. Dohan demonstrates that many classic accounts of urban poverty do not fit immigrant poverty very well. Third, a few cross-national studies demonstrate generous welfare states tend to be more inclusive of immigrants than less generous welfare states (Bostic and Hyde 2023; Roemer 2017; Sainsbury 2012). As the U.S. has a weak welfare state and has maintained systemically high poverty for many decades (Brady 2023), immigrant poverty is likely to be especially high in the U.S. (Sainsbury 2012). At the same time, there is dualization because immigrants receive disproportionately less benefit from generous welfare states (Bostic and Hyde 2023). Finally, several studies scrutinize poverty among Hispanics and/or Asian Americans with a focus on immigration (Garcia 2011; Iceland 2019; Lichter et al. 2005; Ludwig-Dehm and Iceland 2017; Mattingly and Pedroza 2018; Orrenius and Zavodny 2013; Sullivan and Ziegert 2008; Takei and Sakamoto 2011; Thiede et al. 2017). For instance, Baker and colleagues (2022) show that immigrant status and citizenship account for the largest share of the Latino-white and Asian-white poverty gaps.

Across the literature on immigrant poverty, two key themes have emerged. First, several show immigrant poverty is predicted by similar individual and HH risks that predict poverty among non-immigrants (Amuedo-Dorantes et al. 2018; Bostic and Hyde 2023; Garcia 2011; Thiede et al. 2021). Mattingly and Pedroza (2018) even call these the "usual suspects." For instance, Thiede and colleagues (2021) show the major risks of poverty account for variations in immigrant child poverty. Using the SPM, they also show poverty is quite high among first-generation children (32.2%) and second-generation children with foreign-born parents (32.1%), compared to second-generation children with one foreign-born parent and third+ immigrant generation children.

Second, the literature shows how immigrants – especially non-citizen immigrants – are particularly vulnerable to being excluded from social policies (Portes and Zhou 1993; Zhou and Gonzales 2019). Social policy in the U.S. is increasingly "fiscalized" using tax credits (McCabe 2018) and social policies have always had substantial administrative burdens (Herd and Moynihan 2019). Both tax credits and administrative burdens undermine immigrants' access to social policies (Jones and Ziliak 2022; Parolin and Brady 2019). Further, immigration enforcement and lack of legal status discourage accessing welfare programs (Amuedo-Dorantes et al. 2018; Alsan and Yang 2024; Bitler and Hoynes 2013; Cruz et al. 2018; Perreira and Pedroza 2019). The inability of many immigrants to access social policies is particularly critical because welfare programs do reduce immigrant poverty and would do so more if immigrants had greater access (Bollinger and Hagstrom 2011; Stimpson and Wilson 2018).

Building on these three literatures, the present study aims to make three contributions. First, we provide an updated and comprehensive demographic portrait of immigrant poverty in the U.S. Guided by the immigrant attainment literature, we provide novel evidence of how poverty varies by key immigrant characteristics. Guided by the poverty literature, we assess the influence of the four major risks. Also, building on the poverty literatures, we scrutinize how immigrant poverty varies over time and across states. There have been substantial changes to social policies in recent years, which could contribute to temporal changes in immigrant poverty. For instance, Batalova and Fix (2023) describe a substantial decline in immigrant child poverty from 2009 to 2019 and even more in 2021. However, no study has investigated 2022-2023 after the historically low poverty rates of 2021 (Parolin and Filauro 2023). There are also substantial differences in policies, institutions and poverty across states (Laird et al. 2018; VanHeuvelen and Brady 2022), which could contribute to variation in immigrant poverty by state (Bostic and Hyde 2023). Further building on the poverty literature, we incorporate leading international standards in poverty measurement. Building on the immigrant poverty literature's emphasis on the inaccessibility of social policies, it is essential to incorporate transfers, taxes and tax credits. If non-immigrants are receiving generous tax credits and transfers that immigrants cannot access, immigrant poverty must reflect this relative deprivation.

Second, we integrate the literatures on immigrant attainment and poverty by assessing the comparative explanatory role of both immigrant characteristics and poverty risks for immigrant poverty. To the best of our knowledge, this is the first study to explicitly compare and contrast how much these two matter conditional on each other. We conduct this comparison between non-immigrants and immigrants, among immigrants, and among nations of origin. When comparing nations of origin, we also incorporate the immigrant attainment literature's specific emphasis on educational selectivity.

Third, as a result of the first two contributions, we are able to demonstrate a variety of salient heterogeneities in immigrant poverty. While the poverty and immigrant poverty literatures have certainly studied heterogeneities, this contribution is particularly inspired by a longstanding emphasis in the immigrant attainment literature on the variation within immigrants (Portes and Zhou 1993; Waldinger and Feliciano 2004).

DATA AND METHODS

We use the LIS, an archive of internationally harmonized individual-level nationally representative datasets. The LIS provides high quality and standardized measures of income as well as several immigration variables. The LIS is publicly available to registered users. For transparency, we provide our LIS code in the Supplemental File, which enables any registered user to replicate our entire analysis.

We analyze annual waves of LIS data for the U.S., which are drawn from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC). The LIS adds a suite of standardized income variables that incorporate taxes, tax credits and transfers. This "lissification" is essential for valid and reliable measurement of income and poverty. Hence, the key advantage of the LIS over the CPS ASEC is this critical step of lissification.

The immigrant identifier begins in 1993, and the citizenship identifier begins in 1994. After analyzing 1993/1994-2023, we pool five recent years (2019-2023) to scrutinize recent immigrant poverty (N=760,026).[2] Pooling five years ensures quite large samples of immigrant (N=115,990) and even non-citizen immigrants (N=53,383) (see e.g. Tran et al. 2018; Waldinger and Feliciano 2004). The unit of the analysis is individuals nested in HHs.

[2] This sample includes one pre- and two post-COVID years (collected March 2023 and 2024). It is particularly important that we include two years after 2021. This is because 2021 featured the anomalously generous expanded child tax credit and the lowest child poverty ever. In other analyses, we replicated Tables 1-2 on 2016-2020. The results and conclusions were very similar.

Of course, the CPS ASEC and LIS trigger understandable concerns about coverage and measurement of immigrants in Census data (see Chen et al. 2004; Jones and Ziliak 2022; Puente 2022; Van Hook and Bachmeier 2013). The CPS ASEC only counts foreign-born individuals who take the survey voluntarily. It seems reasonable to presume that especially unauthorized immigrants are undercounted, and this is exacerbated when multiple individuals and families reside in one housing unit. Especially undocumented immigrants are understandably disinclined to report accurate information on income, immigration status and HH composition. These problems might be even more pronounced in the CPS ASEC because of its lack of language questions (vs. the American Community Survey (ACS) [Van Hook and Bachmeier 2013]).[3]

While we concede this limitation, the CPS ASEC provides very large samples and the LIS provides far better income and poverty measurement. Moreover, the Census' limitations likely lead to an underestimation of immigrant poverty and immigrant populations. It seems plausible that the biases consistently result in conservative/lower-bound estimates of immigrant poverty. Because we show quite high rates of immigrant poverty, and very high rates for certain groups, immigrant poverty could be even worse. If so, we hope this encourages tolerance of our data limitations in the spirit that immigrant poverty is an even more pressing problem.[4]

Poverty

We define poverty as relative to the prevailing standards of living and consumption within each year (Fremstad 2020). Poverty is a shortage of resources compared to needs, and

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[3] This might lead one to prefer the ACS. However, the ACS lacks critical tax and transfer variables like the benefit amount from SNAP and tax credits. Moreover, the ACS is not available before 2005 and one could only analyze the Census decennially before.

[4] That said, we are forced to assume that Census-based limitations are similarly distributed across groups, characteristics, states and nation of origin (net of controls). We concede this could be a strong assumption (Van Hook and Bachmeier 2013).

both resources and needs are defined in the context of a time and place (Smeeding 2016). Following the vast majority of international poverty research (e.g., Bostic and Hyde 2023; Brady 2023; Brady et al. 2017; Burciu and Parolin 2024; Fremstad 2020; Garcia 2011; Rainwater and Smeeding 2004; Smeeding 2016), we operationalize *relative poverty* as a binary indicator for those residing in HHs with less than 50% of the median equivalized disposable HH income (reference=not poor). In addition to this approach prevailing in international poverty research, relative measures: (a) have better predictive validity for well-being, health and life chances; (b) are more reliable over time; (c) are more consistent with leading conceptualizations of poverty; and because (d) absolute measures with fewer problems have not been developed (Brady 2023; Brady et al. 2017; Fremstad 2020; Rainwater and Smeeding 2004; Smeeding 2016).

We also show analyses of recent years with a binary indicator for anchored poverty. *Anchored poverty* fixes the poverty threshold in the first year (i.e. 2019) and only adjusts the threshold for inflation. Anchored poverty is a well-established more "absolute" alternative that locks in the threshold even if HH income rises or falls with economic development and business cycles (Smeeding 2016; VanHeuvelen and Brady 2022).

Both measures are based on the LIS's high-quality measure of disposable HH income (DHI), which incorporates taxes, tax credits (e.g. the Child Tax Credit [CTC] and Earned Income Tax Credit [EITC]), and cash (e.g. Temporary Assistance to Needy Families [TANF]) and near-cash (e.g. the Supplemental Nutritional Assistance Plan [SNAP]) transfers. We equivalize income by dividing by the square root of the number of HH members. The poverty thresholds are established with population weights in the entire sample in each year.

Unlike much prior research on immigrant poverty, we expressly avoid the deeply flawed official poverty measure (OPM) because it has overwhelming validity and reliability problems

(Brady 2023; Fremstad 2020; Madrick 2020; O'Connor 2001; Rainwater and Smeeding 2004; Smeeding 2016). The OPM thresholds are widely considered to be too low and the family size adjustments are incoherent. The OPM ignores taxes, tax credits, and near cash transfers that play an increasingly critical role in reducing poverty. Cash transfers like TANF (counted by the OPM) have declined dramatically over time, while near cash transfers like SNAP and tax credits like the EITC or CTC (omitted by the OPM) have grown over time (Bitler and Hoynes 2013). While most benefits during COVID were omitted by the OPM (Batalova and Fix 2023), those benefits were only temporary (Parolin and Filauro 2023). As a result of these over-time changes, the OPM is particularly unreliable. The OPM is also particularly invalid for immigrants because they often distinctively do not have access to near cash transfers like SNAP, tax credits like the EITC/CTC, and even many cash transfers. Hence, the OPM critically underestimates the particular economic disadvantages that immigrants actually experience and this biases comparisons with non-immigrants.[5]

Measures of Immigrants

[5] An obvious alternative is the relative SPM (Batalova and Fix 2023; Thiede et al. 2021). Unfortunately, the SPM is not available in the LIS. Also, we cannot construct the SPM in the LIS because it requires unavailable fine-grained geographic identifiers to calibrate local housing costs. Our measures share the SPM's comprehensive definition of income including taxes, cash and near cash transfers, and tax credits and both are relative. Thus, both are a clear advance beyond the OPM. That said, there are actually several underappreciated limitations to the SPM. Prior to 2021, the SPM threshold was based at the 33rd percentile of consumption expenditures. Since 2021, the SPM threshold was changed to be near 80% of the median consumption expenditures. Hence, 2021 introduced a discontinuity that makes before/after comparisons uncertain. The SPM is also far more complicated and requires trustworthy data on consumption expenditures, geographically precise information about housing costs, and details on out of pocket medical expenses. It is often not appreciated that the SPM sets the threshold quite low – even lower than the OPM for some – and it is dubious a HH can make ends meet at the SPM threshold (Fremstad 2020). Finally, the SPM is not available prior to 2010.

Our analyses first use binary indicators for *immigrants* and *non-immigrants* based on self-reported foreign born. We then break up immigrants with binary indicators for *citizen immigrants* and *non-citizen immigrants*. All our immigrant groups have at least some heterogeneity by citizenship. This means that we ultimately decided to treat Puerto Rican origin people as non-immigrants. This is of course a debatable decision, and we report the high poverty rate of Puerto Ricans below. However, as all Puerto Ricans who migrate to the mainland U.S. are citizens, this makes them less comparable to other immigrants. Of course, we stress that the high poverty rate of Puerto Ricans deserves attention alongside the high poverty rates of ethno-racial groups like Latinos and African Americans (Baker et al. 2022).

We also analyze immigrants by *state of residence* and according to the 12 largest *nations of origin*. Further, we measure the *number of years in the U.S.* We also identify *mixed status HHs* for individuals residing in HHs with variation by citizenship. Combining these measures with individuals being the unit of analysis, this means we do not define U.S.-born children in immigrant-led HHs as immigrants themselves. Those children still contribute to the HH-level characteristics that influence the poverty of any immigrants in those HHs, but we define U.S.-born children as non-immigrants.

Individual and HH Characteristics

Our analyses incorporate a standard set of individual- and HH-level predictors of poverty (see e.g. Baker et al. 2022; Brady et al. 2024; Rainwater and Smeeding 2004; Thiede et al. 2021; VanHeuvelen and Brady 2022; Zagel et al. 2021). We include the “four major risks”. Instead of the often arbitrary “head”, we identify the HH “lead” as the adult with the highest labor market earnings (with ties broken by higher age, and chosen randomly if tied on age). *Single motherhood* is defined as those in a HH led by an unmarried/unpartnered female who resides with her own children under 18 years-old.[6] *Young lead* includes those in HHs with a lead under 25 years old. Low education is measured as residing in a HH where the lead has *less than a high school* degree. *Jobless* is measured as living in a HH where no one is employed.

The models also adjust for: a *female* binary (reference: male); HH *lead 25-34 years old*, *55-64 years old, 65-74 years old*, and *75+ years old* (reference: lead 35-54); the *number of children* and *number over 65* in the HH; whether the lead has *some college* or a *post-graduate degree* (reference: high school); whether there are *multiple earners* in the HH (reference: one employed person); family structure including *female head no child HH*, *male head no child HH*, and *single father HH* (reference: coupled HH); and indicators for *Black*, *Latino*, or *Other* Race (reference: white). In most analyses, we also include fixed effects for states and years.

Analytical Techniques

We use several different techniques beyond simple descriptive analyses. All analyses use population weights. All regression and decomposition analyses cluster the standard errors by HH. We use logistic regression models to predict poverty based on immigrant, individual and HH characteristics (i.e. Tables 2-3). From those models, we estimate average marginal effects (AMEs). Because we compare AMEs across models, we also use the KHB technique (and "average partial effects" from KHB [Kohler et al. 2011]). Finally, we use the Fairlie decomposition technique to estimate the relative contributions of poverty risks, immigrant characteristics, and educational selectivity for differences in poverty by nation of origin (Fairlie 2005; see e.g. Baker et al. 2022). For the Fairlie decompositions, we employ random ordering of variables, each nation of origin's coefficients, and the default 100 replications.

[6] This follows other LIS and CPS ASEC analyses (e.g. Baker et al. 2022; Brady et al. 2017). In the LIS data, cohabitors are in the reference. In other analyses, cohabitors do not have significantly different poverty versus married couples.

Throughout the results, we organize our presentation by highlighting the most important heterogeneities that emerge from our analyses. Several analyses include all available years of LIS/CPS ASEC data (i.e. 1993-2023 or 1994-2023). Other analyses concentrate on the five most recent years (2019-2023).

RESULTS

Table 1 shows descriptive statistics for the five most recent years (2019-2023). We show descriptives for the immigrant, non-citizen immigrant, non-immigrant and total sample. As the first rows show, relative and anchored poverty are highest among non-citizen immigrants, followed by immigrants, and lowest among non-immigrants. About 15.8% of the sample are immigrants and about 45.5% of immigrants are non-citizen immigrants.

[TABLE 1 ABOUT HERE]

Heterogeneity by Citizenship

Table 2 shows logistic regression and KHB models based on the five most recent years (2019-2023). We estimate models with immigrant indicators omitting and adjusting for the full set of predictors. The key heterogeneity regarding immigration is by citizenship.

[TABLE 2 ABOUT HERE]

First, being an immigrant is robustly associated with a 4.4-5.1 or 4.3-4.9 percentage point increase in relative or anchored poverty (cf. average marginal effects [AMEs] models 1-4). For context, the overall relative and anchored poverty rates are 16.1 and 15.5% (see Table 1).

Being an immigrant has an AME that is about 60% as large as the AME for being in a single mother HH, slightly less than half as large as residing in a HH led by someone lacking a high school degree, and about a quarter as large as residing in a HH with a young lead. Further, being an immigrant has an AME about one-eighth as large as being in jobless HH. Thus, the magnitude of the effect of being an immigrant is smaller than the effects of the four major risks. The second and fourth models also show the effect of being an immigrant modestly attenuates with controls. This partly reflects that immigrants are disadvantaged especially in terms of lead education (see Table 1).

The next models show that being a non-citizen or citizen immigrant robustly increases the probability being poor versus non-immigrants. Being a non-citizen immigrant increases poverty by about 6-9 percentage points. The AME for non-citizen immigrants is about two-thirds as large after adjusting for controls, which suggests some share of the non-citizen immigrant disadvantage is due to other predictors (see Table 1: lead education, and # >65 and children in HH). The adjusted AMEs for being a non-citizen immigrant are slightly smaller than the AME for a single mother HH. As single motherhood has the smallest AME of the four major risks, being a non-citizen immigrant has a smaller effect than the four major risks.

Being a citizen immigrant has a much smaller AME than being a non-citizen immigrant. Being a citizen immigrant increases the probability of poverty by about 1.5-2.5 percentage points. This AME is much smaller than the four major risks and is among the smallest significant predictors of poverty. The AME for citizen immigrants is even smaller than the AME for being in a male head no child HH (vs. coupled; See Appendix II). Notably, the AME gets larger after adjusting for controls. This is partly because citizen immigrants are advantaged versus non-immigrants (e.g. in lead education). Given immigrant poverty is far higher among non-citizens, subsequent analyses focus more on immigrants and non-citizen immigrants.

Heterogeneity Over Time

Figure 2 displays the relative poverty trends over time.[7] For the overall U.S. population, non-immigrants, and even citizen immigrants, there is only modest over-time variation. For non-immigrants and citizen immigrants, poverty is fairly stable at about 16% from 1993-2023. That said, it is important to keep in mind that the level of non-immigrant and citizen immigrant poverty is high compared to most other rich democracies (Brady 2023).

[FIGURE 2 ABOUT HERE]

From the early 1990s until 2021, immigrant and non-citizen immigrant poverty declined. In 1993-1994, about 25% of immigrants and 31% of non-citizen immigrants were poor. In 2021, about 18% of immigrants and 21% of non-citizen immigrants were poor. The decline to this lowest overall poverty rate in recent U.S. history (i.e. 14.2%) (Parolin and Filauro 2023) was partly driven by substantial declines in immigrant and especially non-citizen immigrant poverty (Batalova and Fix 2023). For instance, non-citizen immigrant poverty was about 25% as recently as 2019 and fell to 20.8% in 2021.

Since that low point in 2021 however, poverty and especially immigrant poverty have increased substantially. This is partly driven by the retrenchment of social policies like the expanded CTC. However, the magnitude of increased poverty is especially pronounced among immigrants. Immigrant poverty rose from 18.2 in 2018 to 22.4% in 2024. Non-citizen immigrant poverty rose from 22.8% in 2021 to 28.4%. For both groups, these were the highest poverty rates since 2008.

[7] Of course, we could apply the anchored threshold over time as well. However, stretching the 2019 relative threshold all the way back to 1993/1994 would make the strong, and probably indefensible, assumption that prevailing standards and needs were identical 26-27 years earlier (Fremstad 2020; Smeeding 2016). Using a relative measure assumes instead that prevailing standards and needs are defined in a given time and place.

Altogether, what looked like a long-term decline in immigrant poverty before and during the pandemic (Batalova and Fix 2023) ended with a sharp increase in immigrant poverty since. As a result, immigrant poverty is better characterized by its substantial over-time heterogeneity rather than a clear trend in one direction.

Heterogeneity by State of Residence

It is well known that there are substantial heterogeneities in poverty across the U.S. states. Yet, only a few assess spatial (Ellis et al. 2013) or interstate heterogeneities in immigrant poverty (De Trinidad Young et al. 2018) and such studies use the OPM.

Figure 3 shows immigrant poverty across the 50 U.S. states and D.C. (2019-2023). For reference, Appendix I shows the immigrant share of states' populations. The average state immigrant poverty rate is 20.3%. The median (Montana) has an immigrant poverty rate of 20%, and the largest immigrant state (California) has slightly lower immigrant poverty. There is enormous interstate variation. Mississippi and New Mexico have immigrant poverty rates above 36%, while New Hampshire has an immigrant poverty rate less than 8.8%.

[FIGURE 3 ABOUT HERE]

Figure 4 shows vast interstate variation in non-citizen immigrant poverty rates as well. For non-citizen immigrant poverty, the average rate is 24.2% and the median is 23.1% (i.e. Iowa). Although the largest immigrant state (California) has a below average non-citizen immigrant poverty rate (22.7%), many have higher rates in Figure 4 vs. Figure 3. Again, Mississippi, New Mexico, and New Hampshire are the extremes. Mississippi has a more than 55% non-citizen immigrant poverty rate and New Mexico is above 44% whereas even non-citizen immigrants have a poverty rate below 10% in New Hampshire.

[FIGURE 4 ABOUT HERE]

To investigate this interstate variation in immigrant poverty further, we can address two common questions (e.g. Card and Raphael 2013). First, we assess if immigrant poverty is more common where there are more immigrants. Figure 5 shows states with higher immigrant shares of the population tend to have lower immigrant poverty rates. This applies to both immigrant and non-citizen immigrant poverty, though the correlations are only a moderate r=-0.23. The immigrant share is low in states like Mississippi and Louisiana, and where immigrant poverty rates are very high. By contrast, New Jersey and Massachusetts have high immigrant shares and low immigrant poverty. States like California and New York, with high immigrant shares of the population, have moderate immigrant poverty rates.

[FIGURE 5 ABOUT HERE]

States that deviate from the pattern in Figure 5 also warrant attention. Both Arizona and Maryland have moderate immigrant shares, but Arizona has high immigrant poverty and Maryland has low immigrant poverty. Also, note the low immigrant share, low immigrant poverty states of Maine, New Hampshire and Vermont.

Second, many ask if immigrant poverty corresponds with non-immigrant poverty (Bostic and Hyde 2023; Sainsbury 2012). On one hand, there could be a negative correlation if low non-immigrant poverty is accomplished through chauvinistic social policies that protect non-immigrants and exclude immigrants. On the other hand, there could be a positive correlation if higher social equality settings protect immigrants alongside non-immigrants (Roemer 2017).

[FIGURE 6 ABOUT HERE]

Figure 6 shows there is a strong positive correlation between a state's non-immigrant poverty rate and the immigrant (r>0.76) or non-citizen immigrant poverty (r>0.69). Again, states like Mississippi and Louisiana stand out for their high poverty for everyone – non-immigrants,

immigrants and non-citizen immigrants. New Hampshire has strikingly low poverty for all as well. States like Hawaii and Massachusetts are also low poverty states for both immigrants and non-immigrants. By contrast, states like Arkansas, Georgia and especially West Virginia stand out for fairly high non-immigrant poverty and relatively moderate immigrant poverty.

Heterogeneities by Risks and Immigrant Characteristics

We estimate regression models in Table 3 comparing the role of risks and immigrant characteristics as predictors of non-immigrant, immigrant, and non-citizen immigrant relative and anchored poverty. Again, we report AMEs.

[TABLE 3 ABOUT HERE]

First, the four risks have robust AMEs. Indeed, the magnitudes of the AMEs for the four risks are similar across non-immigrants, immigrants, and non-citizen immigrants for both relative and anchored poverty. Being in a jobless HH has the largest AME by a considerable margin. Being in a jobless HH increases the probability of poverty by about 36 percentage points. For immigrant and non-citizen immigrant relative and anchored poverty, lead with less than high school degree is the second most important risk. Being in a young led or single mother HH increases the probability of poverty by about 7-8 percentage points for immigrants and non-citizen immigrants. At the same time, the AMEs for young led and less than high school led HHs are slightly smaller for immigrants and non-citizen immigrants versus non-immigrants.

Second, the key immigrant characteristics are robustly significant for both citizen and non-citizen immigrants and both relative and anchored poverty. Being a non-citizen immigrant increases the probability of poverty by 2 percentage points compared to citizen immigrants. Being in a mixed status HH reduces the probability of poverty by 2 percentage points among immigrants and 4 percentage points among non-citizen immigrants. The standard deviation in years in the U.S. is 16 for immigrants and 12.4 for non-citizen immigrants (see Table 1). For a standard deviation increase in years in the U.S., the probability of poverty declines by 3.2 percentage points for immigrants and by 3.7 percentage points for non-citizen immigrants. Thus, the three immigrant characteristics do meaningfully influence immigrant poverty net of risks.

Third, risks matter more than immigrant characteristics. This is the case because joblessness has a far greater impact on immigrant poverty than any of the three characteristics. However, the greater influence of risks is also illustrated by the fact that the three other risks have larger AMEs than any of the three immigrant characteristics. For instance, single motherhood HH and young led HH have the smaller AMEs of the four risks. Yet, the magnitude of their AMEs is more than twice as large as the magnitude of the AMEs for being a non-citizen immigrant or residing in a mixed HH and nearly twice as large as the AME for a standard deviation in year in the U.S. Thus, while immigrant characteristics do matter, the standard risks are the paramount drivers of immigrant poverty.

Heterogeneities by Nation of Origin

Next, we estimate the poverty rates of immigrants by nation of origin. We concentrate on the 12 largest nations of origin to ensure our samples from each are sufficiently large to estimate reliable poverty rates.[8] Because the results are similar between relative and anchored poverty, we only report relative poverty. Figure 7 shows there are very large heterogeneities in immigrant poverty by nation of origin.

[FIGURE 7 ABOUT HERE]

[8] As we show in Table 4, each has more than 2,195 respondents. Moving to 13th or 14th largest (Jamaica and Haiti) would be about 15-20% smaller than the twelfth largest (Korea).

Immigrants from certain nations have extremely high poverty rates.[9] For instance, Honduran (38.2%), Guatemalan (34.6%), and Mexican (27.6%) immigrants have poverty rates near or above 30%. At the same time, immigrants from some nations have very low poverty rates. Immigrants from India (6%), the Philippines (8.9%) and Korea (14.8%) all have poverty rates lower than non-immigrants (15.4%). Indeed, Indian immigrants have poverty rates lower than any other ethno-racial group in the U.S. (Baker et al. 2021) and as low as any demographic group in the U.S. (Brady 2023). There is also a clear region of origin pattern. All seven of the Latin American origin groups have higher poverty than all five of the Asian origin groups. That is, no Asian immigrant group has as high of poverty as Colombians (i.e. the lowest Latin American). Among Asian origin immigrants, only immigrants from China and Vietnam have poverty rates higher than non-immigrants. Immigrants from Honduras are more than six times as likely to be poor as immigrants from India.

Figure 8 examines nation of origin for non-citizens. The same patterns hold despite higher poverty rates, and despite El Salvador surpassing the Dominican Republic, Cuba and Mexico (unlike Figure 7). All four Central American origin countries exhibit very high poverty rates above 30%. Indeed, almost 42% of Honduran non-citizen immigrants are poor. Again, all five Asian origin countries remain below all seven Latin American origin countries. Even though Figure 8 only includes non-citizens, Indian-origin (5.9%) and Philippines-origin (11.1%) non-citizen immigrants continue to have much lower poverty rates than non-immigrants. Among non-citizen immigrants, the poverty rate for Honduras is more than seven times as high as for India.

[FIGURE 8 ABOUT HERE]

[9] Again, we treat Puerto Ricans as non-immigrants as they are U.S. citizens. If we included them, they would have the third highest relative poverty rate of 28%. Again, we acknowledge it would be reasonable to compare Puerto Ricans with immigrants.

To understand why there is so much heterogeneity in poverty by nation of origin, we use the Fairlie decomposition technique to assess the role of three major factors: (i) poverty risks (joblessness, low education, young headship, and single motherhood), (ii) immigrant characteristics (non-citizen, mixed status, and years in residence), and (iii) educational selectivity (lead with college degree and lead with post-graduate degree). We also report how much of the gap between nations of origin can be explained by all predictors. We compare each nation of origin against all other immigrants. Hence, this analysis focuses on heterogeneities between immigrants (not versus non-immigrants).

[TABLE 4 ABOUT HERE]

Between these heterogeneous nations of origin, heterogenous mixes of the three sets of factors account for differences in poverty rates. To highlight the most important contributing factor (among risks, characteristics and selectivity), we shade the cell for the one that plays the largest role in the gap between a given nation of origin and other immigrants.

For five of the nations of origin, the most important factor was poverty risks. This includes Mexico, Cuba and the Dominican Republic, where a disadvantage in poverty risks explains why those nations of origin were more likely to be poor than other immigrants. This also includes India and the Philippines, where an advantage in poverty risks explains why those nations of origin were less likely to be poor than other immigrants.

For four of the nations of origin, the most important factor was immigrant characteristics. For El Salvador, Guatemala and Honduras, disadvantaged immigrant characteristics most account for being more likely to be poor than other immigrants. For Vietnam, advantaged immigrant characteristics most account for being less likely to be poor than other immigrants.

For three nations of origin, educational selectivity has the largest influence. For all three of China, Colombia and Korea, advantages in educational selectivity best account for being less likely to be poor than other immigrants.

Altogether, the mix of risks, characteristics, selectivity and controls can explain the majority of the gap for nine of twelve countries. Indeed, accounting for these three sets of factors explain more than 100% of the gaps for immigrants from China, Vietnam, the Dominican Republic, and Colombia. This means their poverty advantage/disadvantage would be reversed if they had the risks, characteristics, selectivity and controls of other nations of origin. For Cuba and Korea however, these factors and controls explain only 39% and 18% of the gap compared to other nations of origin. Something besides these factors and controls must account for why Cuba has a distinctive disadvantage, and Korea has a distinctive advantage in poverty.

DISCUSSION AND CONCLUSION

At least since 1993 when data becomes available, immigrants have always been more likely to be poor than non-immigrants in the U.S. However, immigrants have become an increasingly large share of the poor in the U.S. By 2023, more than 22% of the poor were immigrants. Partly for this reason, understanding immigrant poverty is increasingly important to understanding poverty in general. As well, understanding poverty is clearly essential to understanding the lives of immigrants in the U.S. Unfortunately, and despite some valuable contributions, immigrant poverty has been arguably understudied.

Building on literatures on immigrant attainment, poverty, and immigrant poverty, this article aims to make three contributions. First, we provide an updated and comprehensive demographic portrait of immigrant poverty in the U.S. Being an immigrant, and especially a non-citizen immigrant, robustly increases the probability of being poor. That said, being even a non-citizen immigrant has a smaller effect on poverty than the standard risks of poverty.

Second, we provide the first assessment comparing the roles of immigrant characteristics versus poverty risks for immigrant poverty. Like considerable prior research on immigrant attainment, we find that the immigrant characteristics of citizenship, mixed status HHs, and years in the U.S. do certainly matter to immigrant poverty. Nevertheless, the major risks matter more to immigrant poverty than immigrant characteristics. Moreover, the major risks have similar effects on poverty across non-immigrants, immigrants and non-citizen immigrants. Just like non-immigrants, immigrant poverty is strongly driven by the four major risks. This buttresses other research emphasizing the role of risks for immigrant poverty (e.g. Bostic and Hyde 2023; Mattingly and Pedroza 2018; Thiede et al. 2021). This also tempers an emphasis on under- vs. unemployment for immigrant attainment (e.g. Dohan 2003). Further, this implies that interventions aiming to reduce immigrant poverty should focus on the same risks that matter most to non-immigrant poverty. In some ways, this also suggests that immigrant poverty can be folded into our general understanding of poverty.

Third, as a result of the first two, we demonstrate a variety of salient heterogeneities in immigrant poverty. There is considerable heterogeneity within immigrant poverty by citizenship, over time, between states, by risks, and by immigrant characteristics, and by nation of origin. While immigrant and non-citizen immigrant poverty declined substantially from the early 1990s until 2021, they have increased substantially since.

We find very large heterogeneities in immigrant poverty by state. Further, we show that a state's immigrant poverty is moderately negatively correlated with the immigrant share of the population and strongly positively correlated with the non-immigrant poverty rate. These two findings undermine the seemingly common view that there are necessary tradeoffs. State can have many immigrants without having higher immigrant poverty. States also do not rely on higher immigrant poverty to accomplish lower non-immigrant poverty.

We also find large and meaningful heterogeneities in immigrant poverty by nation of origin. All five major Asian origin immigrant groups have lower poverty rates than all seven major Latin American origin immigrant groups. A few Asian origin groups – even among non-citizen immigrants – have lower poverty rates than non-immigrants. By contrast, Central American immigrants have some of the highest poverty rates of any group in the U.S. and exhibit extremely high poverty among non-citizen immigrants. For instance, while immigrants from India have one of the lowest poverty rates of any group in the U.S., immigrants from Honduras have a poverty rate 6-7 times higher. This large heterogeneity by nation of origin illustrates how it can limit our understanding to focus on one immigrant group at a time. The economic lives of immigrants from Central American are remarkably different than those from India and the Philippines. We also provide a novel decomposition that shows heterogenous mixes of immigrant characteristics, risks, and educational selectively account for different poverty rates by nations of origin.

While we explicitly build on the aforementioned valuable literatures, the present study advances beyond what are perhaps the most similar prior studies. Our study is different than studies that focus on ethno-racial inequalities while emphasizing the important role of immigration (e.g. Baker et al. 2022; Ludwig-Dehm and Iceland 2017; Mattingly and Pedroza 2018). For instance, while Thiede and colleagues (2021) demonstrate how the prevalences and penalties of the four major risks shape Latino children's poverty across immigrant generations and the native born, we concentrate exclusively on foreign born immigrants of all nations of origin and age. Unlike many prior demographic descriptions of immigrant poverty, we avoid the flawed OPM and incorporate leading international standards in poverty measurement. Unlike the one exemplary study that uses the relative SPM (Batalova and Fix 2023) and the one using relative income poverty (Garcia 2011), we critically update to include the two most recent years of substantially increasing immigrant poverty and conduct a much wider array of analyses.

Our study also can inform relevant international literatures. Generous welfare states tend to have lower poverty, more generous welfare programs for immigrants, and lower immigrant poverty (Bostic and Hyde 2023; Brady 2023; Roemer 2017; Sainsbury 2012). Nevertheless, immigrants appear to be more likely to be poor in nearly every country. Therefore, rising immigration is likely to result in greater overall poverty even in egalitarian welfare states. The present study suggests two major strategies to alleviate immigrant poverty and maintain lower poverty overall. First, because immigrant poverty is driven more by the four major risks and less by immigrant characteristics, reducing the penalties to joblessness, single motherhood, low education and young headship is essential for immigrant poverty just like non-immigrant poverty. Second, countries will need to redouble efforts to incorporate immigrants into social policies. To reduce immigrant poverty, less reliance on tax credits, fewer administrative burdens, less dualization between immigrants and non-immigrants, and less connections between immigration enforcement and welfare programs are key. Our study therefore underlines the importance of measuring how generous and accessible welfare programs are to immigrants. Fortunately, Roemer and colleagues (2023) have developed a robust database that should prove pivotal for future research.

Beyond those mentioned above, the present study has a few limitations that call for future research. First, our within-state samples of immigrants are unfortunately small for some states. This constrains us from testing if the interstate heterogeneity corresponds with state policies regarding immigration enforcement (e.g. De Trinidad Young 2018; Perreira and Pedroza 2019; Potochnick et al. 2017) or welfare programs (e.g. Bostic and Hyde 2023). However, our improved state-level description is a first step in facilitating such research. At first glance, interstate heterogeneity does not correspond obviously to interstate variation in social policies, labor unionization or other egalitarian institutions (Laird et al. 2018; VanHeuvelen and Brady 2022). Second, it would be valuable to test if the relationships with immigrant characteristics and risks have changed over time – especially as the LIS now provides 30 years of data on immigrant poverty. Third, as mentioned above, existing panel datasets tend to lack sufficient numbers of immigrants (e.g. PSID) or sufficient information on income to measure poverty properly (e.g. e.g. Add Health, The Children of Immigrants Longitudinal Study). While the PSID previously incorporated more immigrants, the present study encourages a renewal of such efforts. In addition, this study shows how valuable it would be to incorporate more income, tax and transfer variables in panels that have comparatively large samples of immigrants.

We conclude that immigrant poverty is not one coherent phenomenon because the heterogeneities within immigrant poverty are quite substantial. Indeed, we show that some immigrant groups exhibit very low poverty rates while others exhibit very high poverty rates. Although common discourse often implies the shared economic experiences of all immigrants, there appear to be as large of heterogeneities within immigrant poverty as there is between non-immigrant and immigrant poverty. Partly because of these heterogeneities, understanding immigrant poverty bears on a wide variety of other salient topics, including racial inequality, social policy, and labor markets.

DECLARATIONS

Funding and/or Conflicts of interests/Competing interests

This article has no potential conflicts of interest. There was no funding related to this project. The data is archival, anonymized and publicly provided and available. It therefore did not require that informed consent be secured separately by the researchers. The LIS Database also requires users to sign pledges for ethical and non-commercial use of the data, which we signed. As noted in the Methods section, the data is publicly available to registered users. In the Supplemental File, we provide the entire code that enables anyone to replicate our analyses.

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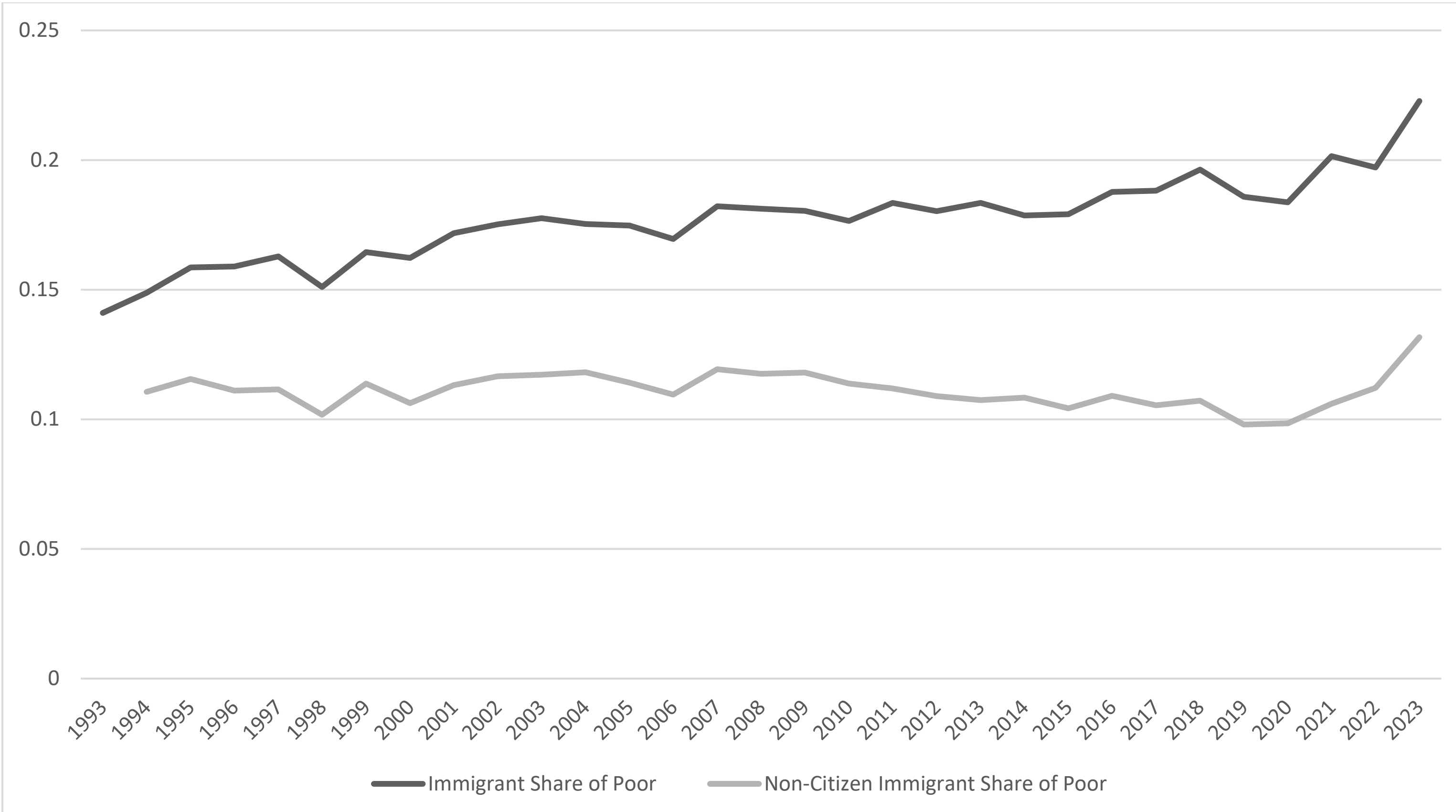
Table 1. Descriptive Statistics in the U.S., 2019-2023: Means and Standard Deviations in Parentheses.

	Immigrant	*Non-Citizen Immigrant*	*Non-Immigrant*	*All*
Relative Poverty	0.202	0.246	0.154	0.161
	(0.402)	(0.430)	(0.361)	(0.368)
Anchored Poverty	0.194	0.236	0.148	0.155
	(0.396)	(0.425)	(0.355)	(0.362)
Immigrant	--	--	--	0.158
				(0.365)
Non-Citizen Immigrant	0.455	--	--	0.072
	(0.498)			(0.258)
Years in U.S.	22.463	14.542	--	22.463
	(16.042)	(12.427)		(16.042)
Mixed Status HH	0.536	0.263	--	0.259
	(0.499)	(0.440)		(0.438)
Jobless HH	0.116	0.063	0.164	0.156
	(0.321)	(0.243)	(0.370)	(0.363)
Lead < High School	0.179	0.260	0.068	0.086
	(0.384)	(0.439)	(0.252)	(0.280)
Single Mother HH	0.056	0.071	0.082	0.078
	(0.230)	(0.256)	(0.275)	(0.268)
Young Lead	0.044	0.061	0.046	0.045
	(0.205)	(0.239)	(0.208)	(0.208)
Female	0.523	0.499	0.511	0.513
	(0.499)	(0.500)	(0.500)	(0.500)
Multiple Earner HH	0.565	0.595	0.531	0.536
	(0.496)	(0.491)	(0.499)	(0.499)
Lead High School	0.249	0.265	0.269	0.266
	(0.432)	(0.441)	(0.443)	(0.442)
Lead Some College	0.167	0.134	0.265	0.250
	(0.373)	(0.340)	(0.441)	(0.433)
Lead College	0.226	0.185	0.241	0.239
	(0.419)	(0.388)	(0.428)	(0.427)
Lead Post-Graduate	0.178	0.156	0.156	0.160
	(0.383)	(0.363)	(0.363)	(0.366)
Lead 25-34	0.175	0.225	0.180	0.179
	(0.380)	(0.418)	(0.384)	(0.384)
Lead 55-64	0.163	0.123	0.160	0.160
	(0.369)	(0.329)	(0.366)	(0.367)
Lead 65-74	0.082	0.040	0.104	0.101
	(0.274)	(0.196)	(0.305)	(0.301)
Lead 75+	0.061	0.022	0.078	0.075
	(0.239)	(0.147)	(0.268)	(0.264)
Single Father HH	0.037	0.049	0.039	0.039
	(0.188)	(0.215)	(0.194)	(0.193)
Female Head No Child HH	0.116	0.089	0.136	0.133
	(0.320)	(0.285)	(0.343)	(0.340)
Male Head No Child HH	0.112	0.115	0.113	0.112
	(0.316)	(0.320)	(0.317)	(0.316)
# >65 in HH	0.383	0.206	0.371	0.373
	(0.697)	(0.535)	(0.682)	(0.685)
# Children in HH	0.909	1.139	1.015	0.998
	(1.183)	(1.263)	(1.332)	(1.310)
N	115,990	53,383	644,036	760,026



<u>Figure 1.</u> Trends in the Immigrant and Non-Citizen Immigrant Share of People in Poverty in the U.S., 1993-2023. See Supplemental File for Replication Code.

Table 2. Average Marginal Effects for Predictors of Relative and Anchored Poverty from Logistic Regression and KHB Models in the U.S., 2019-2023.

	Relative: Bivariate	*Relative: Controls Included*	*Anchored: Bivariate*	*Anchored: Controls Included*	*Relative: Bivariate*	*Relative: Controls Included*	*Anchored: Bivariate*	*Anchored: Controls Included*
Immigrant	0.051** (0.002)	0.044** (0.002)	0.049** (0.002)	0.043** (0.002)				
Non-Citizen Immigrant					0.090** (0.003)	0.063** (0.003)	0.087** (0.003)	0.061** (0.003)
Citizen Immigrant					0.012** (0.002)	0.024** (0.003)	0.011** (0.002)	0.023** (0.003)
Jobless HH		0.320** (0.004)		0.364** (0.004)		0.363** (0.004)		0.364** (0.004)
Lead < High School		0.106** (0.004)		0.103** (0.004)		0.104** (0.004)		0.100** (0.004)
Single Mother HH		0.081** (0.004)		0.075** (0.004)		0.081** (0.004)		0.075** (0.004)
Young Lead		0.134** (0.005)		0.132** (0.005)		0.134** (0.005)		0.131** (0.005)
% Mediated by Controls								
Immigrant		12.87%		12.40%				
Non-Citizen Immigrant						30.10%		29.93%
Citizen Immigrant						-108.82%		-113.65%

Notes: N=574,454; ** p<0.001, * p<0.01; Cells show AMEs and standard errors (clustered by HH) in parentheses; the models also adjust for (not shown) sex, race (Black, Latino, Asian, Other), multiple earners, lead education (some college, college, post-graduate), lead age (25-34, 55-64, 65-74, 75+), family structure (single father, female head no child, male head no child), # >65, # <18, and state and year fixed effects. See Appendix II for results for all variables.

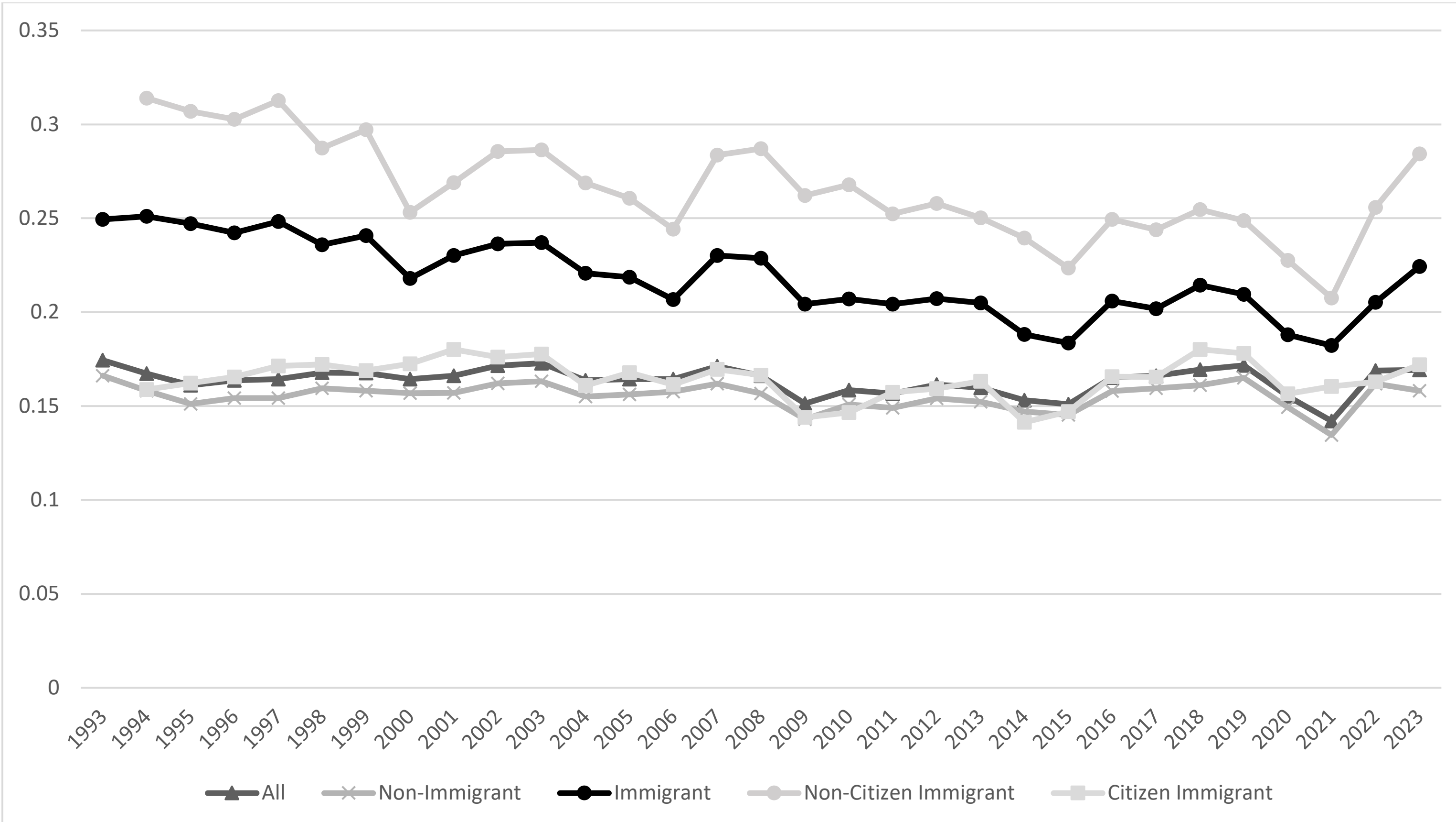


Figure 2. Trends in Poverty for All, Non-Immigrant, Immigrant, Non-Citizen Immigrant and Citizen Immigrant People in the U.S., 1993-2020. See Supplemental File for Replication Code.

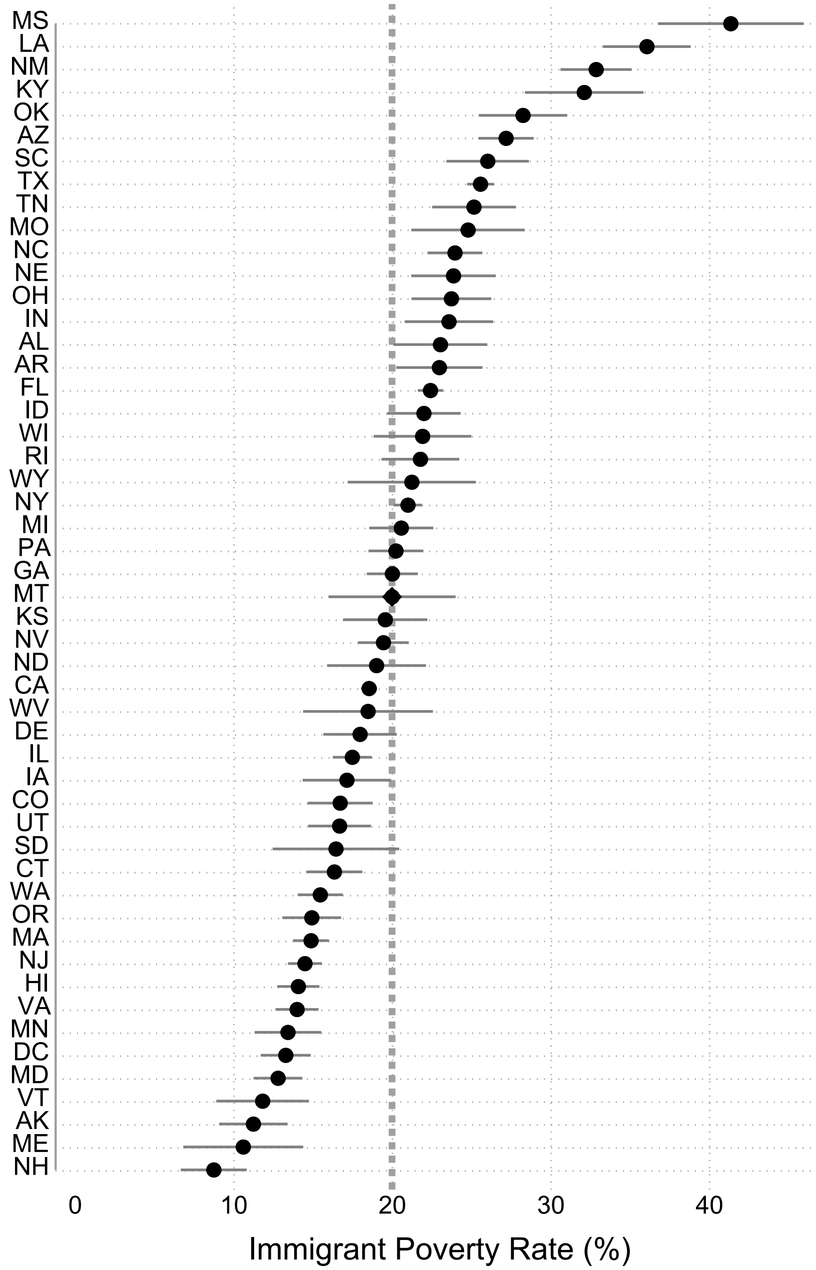
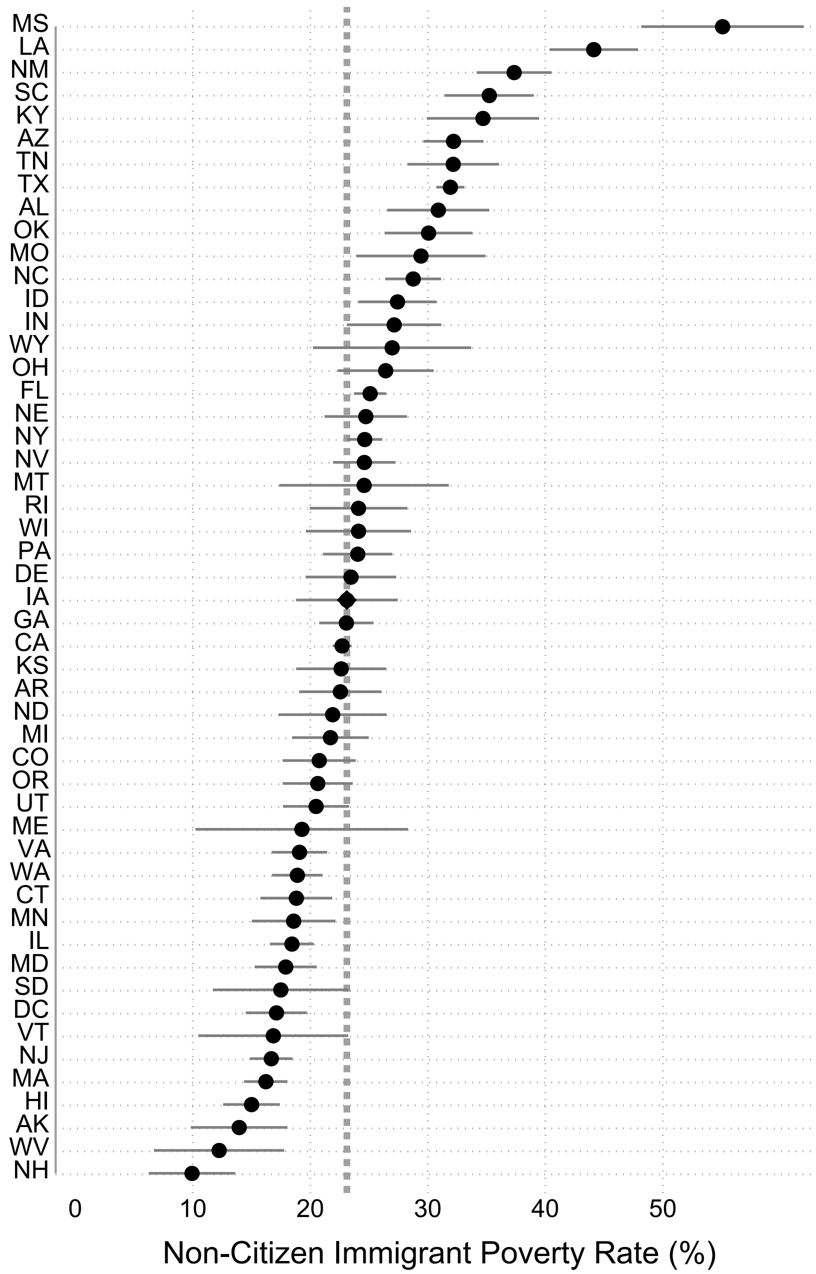


Figure 3. Immigrant Poverty Rates by State in the U.S., 2016-2020 (point estimates and bands with 95% confidence intervals; vertical line=median state). See Supplemental File for Replication Code.



<u>Figure 4.</u> Non-Citizen Immigrant Poverty Rates by State in the U.S., 2016-2020 (point estimates and bands with 95% confidence intervals; vertical line=median state). See Supplemental File for Replication Code.

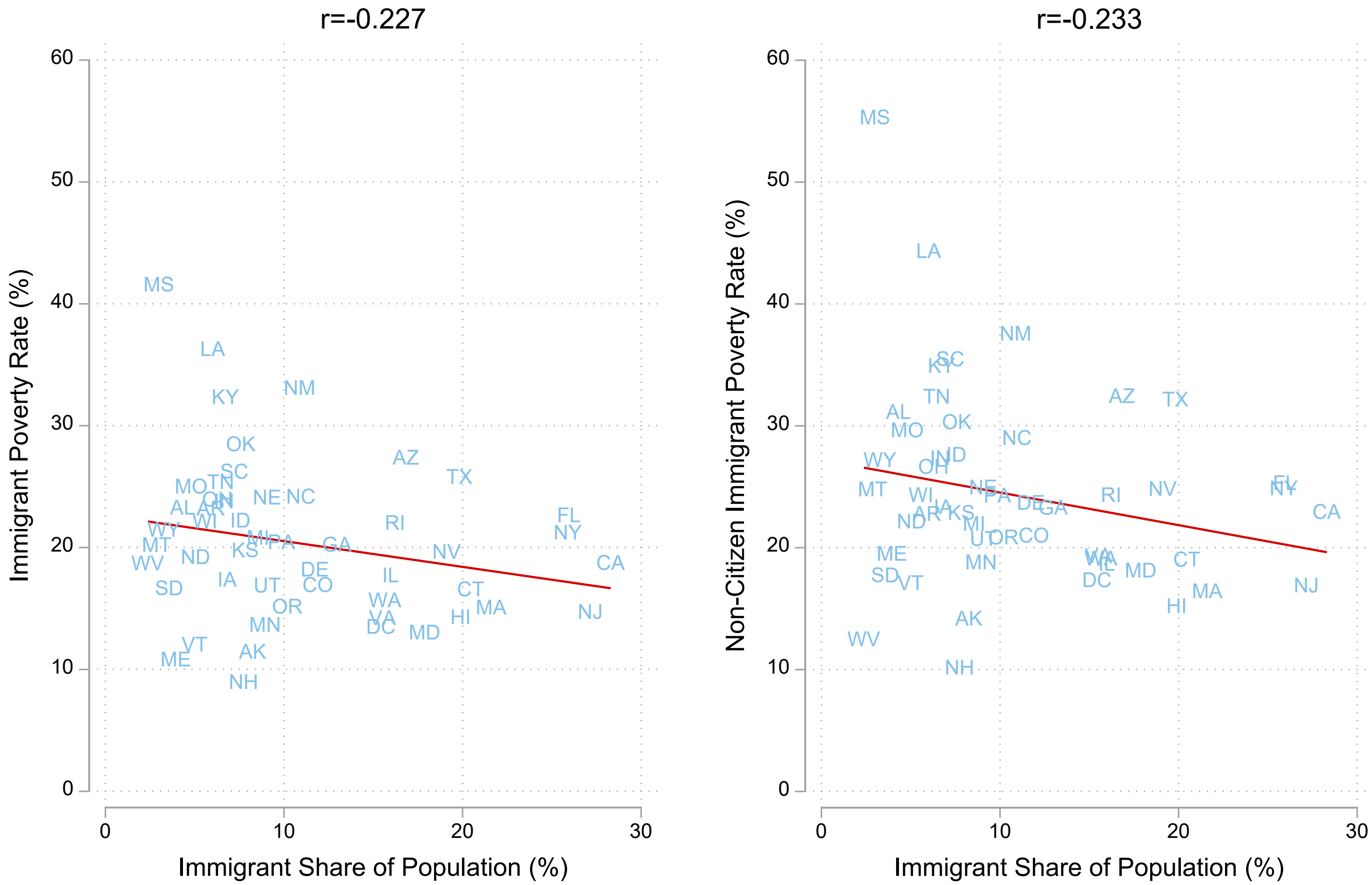


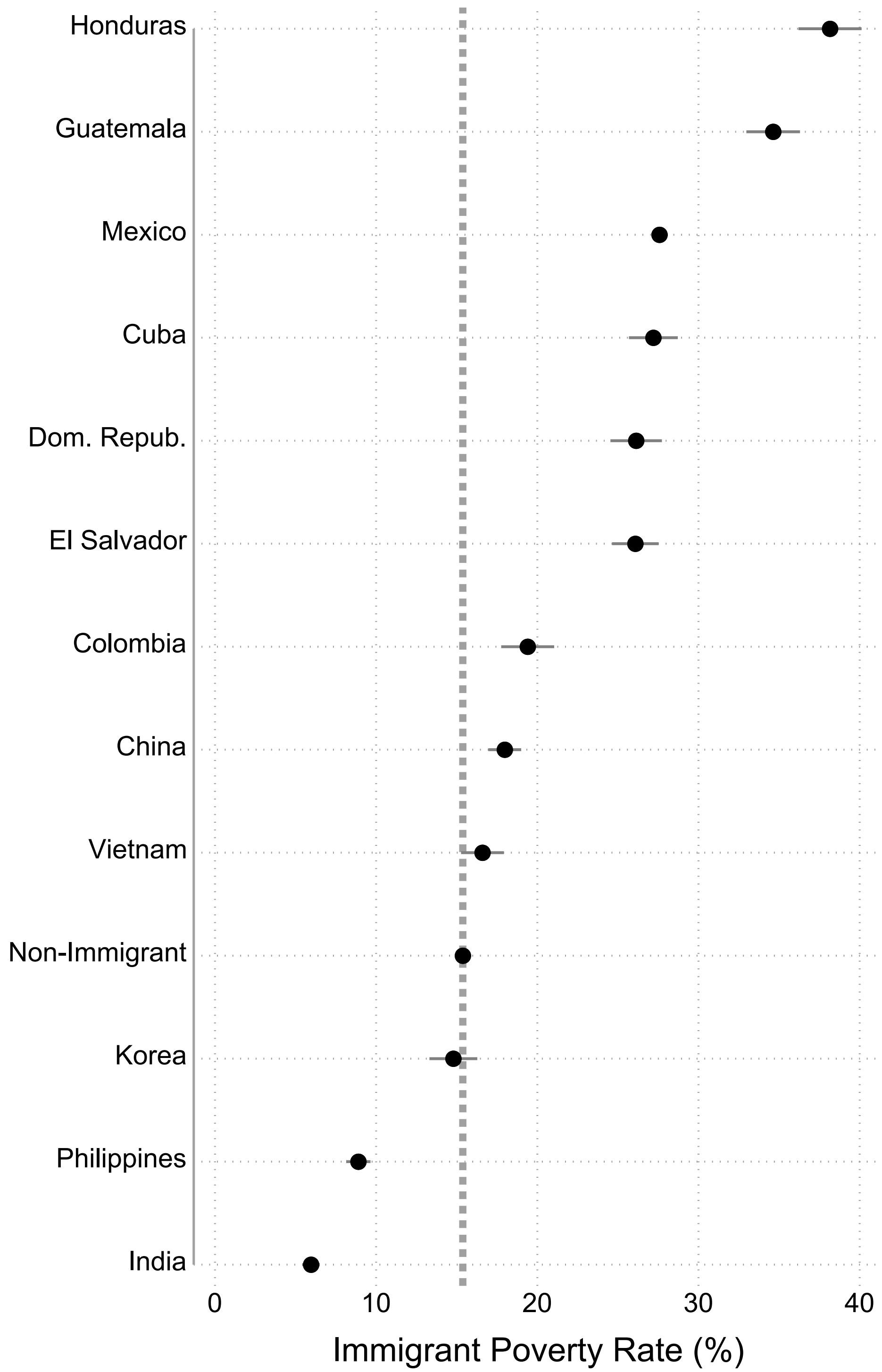
Figure 5. Interstate Correlations Between Immigrant Shares of the Population and Immigrant and Non-Citizen Immigrant Poverty Rates in the U.S., 2016-2020. See also Appendix I and Supplemental File for Replication Code.

Figure 6. Interstate Correlations Between Non-Immigrant Poverty Rates and Immigrant and Non-Citizen Immigrant Poverty Rates in the U.S., 2016-2020. See Supplemental File for Replication Code.

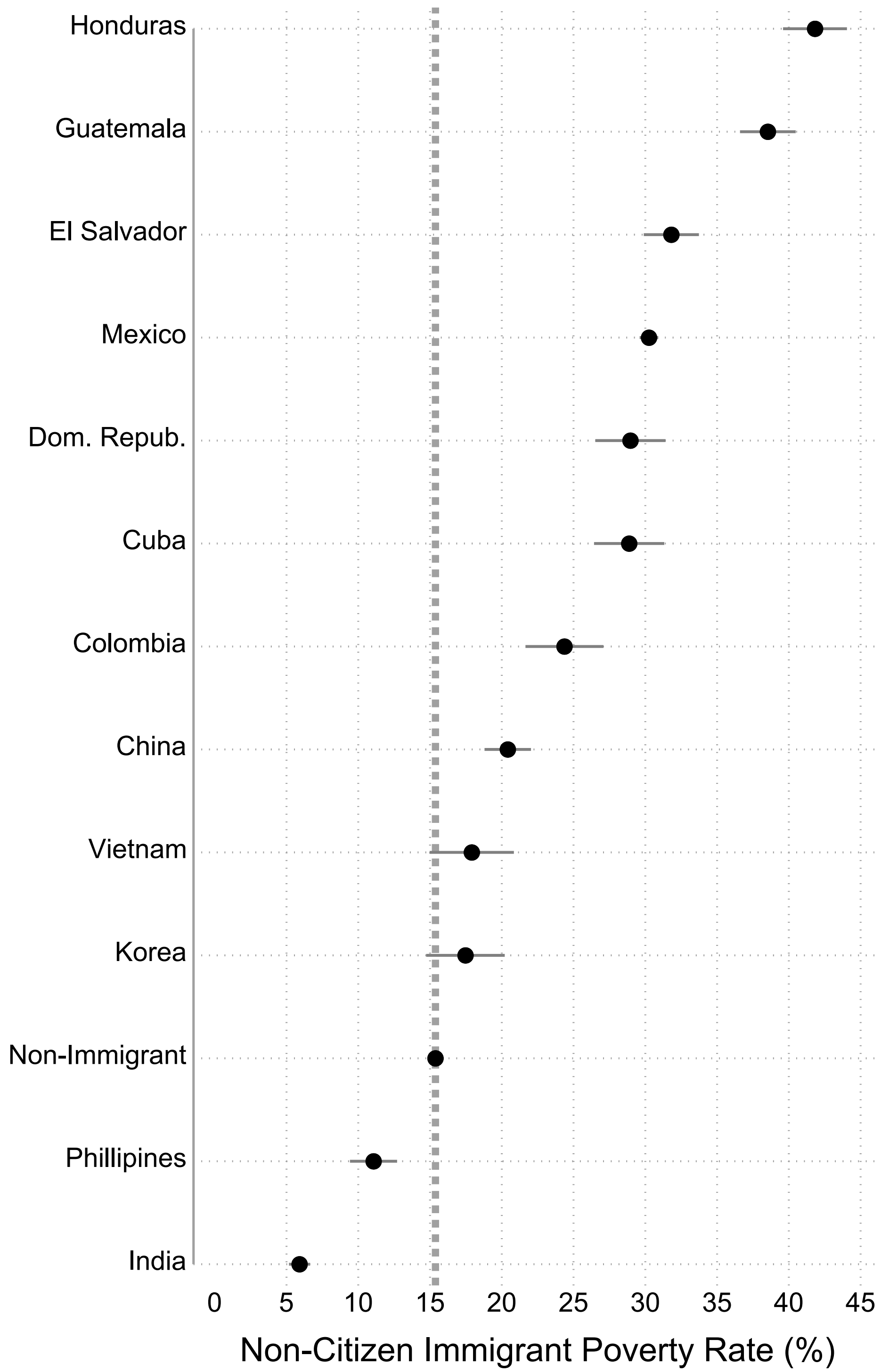
Table 3. Average Marginal Effects for Predictors of Relative and Anchored Poverty from Logistic Regression Models in the U.S., 2019-2023.

	Non-Immigrant: Relative	***Immigrant: Relative***	***Non-Citizen Immigrant: Relative***	***Non-Immigrant: Anchored***	***Immigrant: Anchored***	***Non-Citizen Immigrant: Anchored***
Non-Citizen Immigrant		0.026** (0.004)			0.023** (0.004)	
Mixed Status HH		-0.023** (0.005)	-0.040** (0.007)		-0.025** (0.005)	-0.044** (0.007)
Years in U.S.		-0.002** (0.0002)	-0.003** (0.0003)		-0.002** (0.0001)	-0.003** (0.0003)
Jobless HH	0.364** (0.005)	0.356** (0.010)	0.355** (0.015)	0.365** (0.005)	0.358** (0.011)	0.363** (0.015)
Lead < High School	0.107** (0.004)	0.092** (0.006)	0.097** (0.009)	0.103** (0.004)	0.087** (0.006)	0.088** (0.009)
Single Mother HH	0.079** (0.004)	0.079** (0.009)	0.086** (0.012)	0.073** (0.004)	0.075** (0.009)	0.079** (0.012)
Young Lead	0.140** (0.005)	0.080** (0.011)	0.072** (0.015)	0.137** (0.005)	0.079** (0.011)	0.070** (0.014)
N	485,242	89,176	43,298	485,242	89,176	43,298

Notes: ** p<0.001, * p<0.01; Cells show AMEs and standard errors (clustered by HH) in parentheses; the models also adjust for (not shown) sex, race (Black, Latino, Asian, Other), multiple earners, lead education (some college, college, post-graduate), lead age (25-34, 55-64, 65-74, 75+), family structure (single father, female head no child, male head no child), # >65, # <18, and state and year fixed effects. See Appendix III for results for all variables.



<u>Figure 7.</u> Immigrant Relative Poverty Rates for 12 Largest Nations of Origin in the U.S., 2019-2023 (point estimates and bands with 95% confidence intervals; vertical line=non-immigrant poverty rate). See Supplemental File for Replication Code.



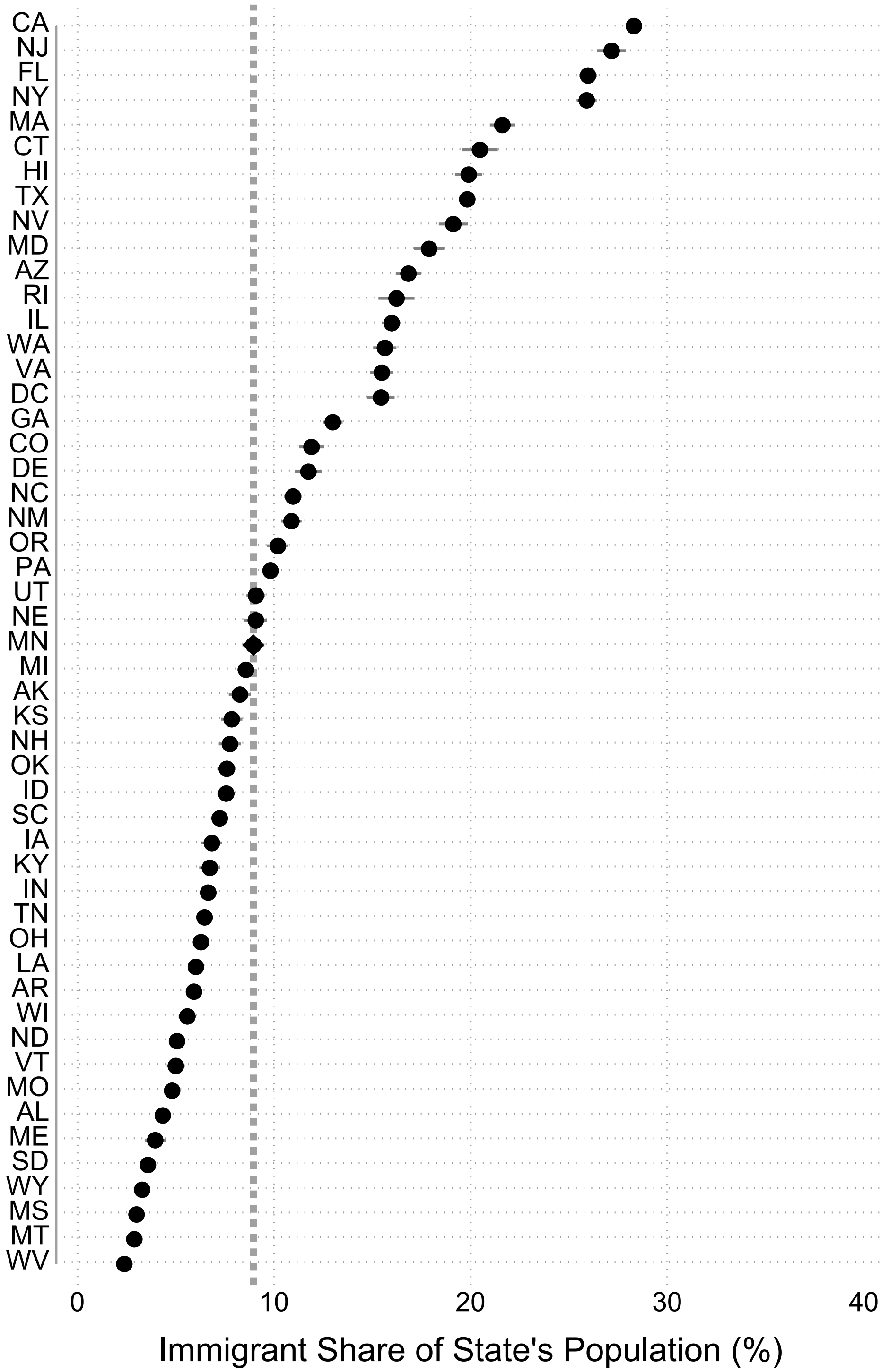
<u>Figure 8.</u> Non-Citizen Immigrant Relative Poverty Rates for 12 Largest Nations of Origin in the U.S., 2019-2023 (point estimates and bands with 95% confidence intervals; vertical line=non-immigrant poverty rate). See Supplemental File for Replication Code.

<u>Table 4.</u> Fairlie Decompositions of Predictors of Poverty Between Each Major Nation of Origin and All Other Immigrants in the U.S., 2019-2023 (shaded cells=largest contributing factor).

Nation of Origin	***Gap: Other Immigrant Poverty Rate Minus Group Poverty Rate***	***Explained by All Factors (% of Gap Explained)***	***Explained by Poverty Risks***	***Explained by Immigrant Characteristics***	***Explained by Educational Selectivity***	***N***
Mexico	-.095	-.066 (69.5%)	-.048***	-.010***	-.014***	29,722
India	.153	.111 (72.5%)	.070***	-.015***	0.046***	7,390
Philippines	.118	.102 (86.4%)	.039***	0.019***	0.011*	5,457
China	.024	.027 (112.5%)	-.001	-.001	.032***	5,431
El Salvador	-.060	-.039 (65%)	-.022*	-.028***	-.011	3,543
Cuba	-.072	-.028 (38.9%)	-.026***	0.002	0.002	3,310
Guatemala	-.148	-.076 (51.4%)	-.009	-.061***	-.025***	3,140
Vietnam	.037	.047 (127.0)	-.006**	.019***	-.008*	3,015
Dominican Republic	-.061	-.065 (106.6%)	-.032***	-.003	.003	2,905
Honduras	-.183	-.131 (71.6%)	-.066**	-.079***	.018	2,361
Colombia	.008	.045 (562.5%)	.008***	-.004	.016**	2,222
Korea	.055	.010 (18.2%)	-.017**	.012**	.035**	2,196

Notes: * $p<0.05$, ** $p<0.01$, *** $p<0.001$. A positive sign indicates a group advantage versus other immigrants, and a negative sign indicates a group disadvantage versus other immigrants. Fairlie decompositions based on logistic regressions with random ordering of variables and the group's coefficients. Models also adjust for (not shown) sex, multiple earners, lead some college, lead age (25-34, 55-64, 65-74, 75+), family structure (single father, female head no child, male head no child), # >65, and # <18. The replication code yields the full estimates for these models.

Appendix I. Immigrant Share (%) of the Population Across U.S. States, 2019-2023 (point estimates and bands with 95% confidence intervals; vertical line indicates median state). Supplemental File for Replication Code.



Appendix II. Full Table of Average Partial and Marginal Effects Corresponding to Table 2.

	Relative: Bivariate	***Relative: Controls Included***	***Anchored: Bivariate***	***Anchored: Controls Included***	***Relative: Bivariate***	***Relative: Controls Included***	***Anchored: Bivariate***	***Anchored: Controls Included***
Immigrant	0.050	0.043	0.049	0.041				
	(0.002)	(0.002)	(0.002)	(0.002)				
Non-Citizen Immigrant					0.089	0.060	0.086	0.058
					(0.002)	(0.002)	(0.002)	(0.002)
Citizen Immigrant					0.016	0.025	0.015	0.025
					(0.002)	(0.002)	(0.002)	(0.002)
Jobless HH		0.360		0.360		0.359		0.359
		(0.004)		(0.004)		(0.004)		(0.004)
Lead < High School		0.102		0.098		0.099		0.095
		(0.004)		(0.003)		(0.004)		(0.003)
Single Mother HH		0.073		0.068		0.074		0.068
		(0.003)		(0.003)		(0.003)		(0.003)
Young Lead		0.129		0.126		0.129		0.126
		(0.004)		(0.004)		(0.004)		(0.004)
Female		0.028		0.003		0.003		0.003
		(0.001)		(0.001)		(0.001)		(0.001)
Lead 25-34		.021		0.021		0.021		0.021
		(0.002)		(0.002)		(0.002)		(0.002)
Lead 55-64		-0.003^		-0.003^		-0.002^		-0.001^
		(0.002)		(0.002)		(0.002)		(0.002)
Lead 65-74		-0.023		-0.024		-0.023		-0.024
		(0.004)		(0.004)		(0.004)		(0.004)
Lead 75+		-0.037		-0.039		-0.037		-0.039
		(0.004)		(0.004)		(0.004)		(0.004)
Lead Some College		-0.046		-0.044		-0.046		-0.043
		(0.002)		(0.002)		(0.002)		(0.002)
Lead College		-0.107		-0.102		-0.107		-0.101
		(0.002)		(0.002)		(0.002)		(0.002)
Lead Post-Graduate		-0.134		-0.127		-0.134		-0.127
		(0.002)		(0.002)		(0.002)		(0.002)
Single Father		0.031		0.029		0.031		0.029
		(0.004)		(0.004)		(0.004)		(0.004)
Female Head No Child		0.059		0.057		0.060		0.058
		(0.002)		(0.002)		(0.002)		(0.002)
Male Head No Child		0.032		0.031		0.032		0.031
		(0.002)		(0.002)		(0.002)		(0.002)

Multiple	-0.146	-0.139	-0.146	-0.139
Earners	(0.002)	(0.002)	(0.002)	(0.002)
Black	0.047	0.045	0.047	0.045
	(0.002)	(0.002)	(0.002)	(0.002)
Latino	0.051	0.049	0.050	0.048
	(0.002)	(0.002)	(0.002)	(0.002)
Asian	0.036	0.035	0.038	0.037
	(0.004)	(0.004)	(0.004)	(0.004)
Other Race	0.036	0.037	0.037	0.037
	(0.004)	(0.004)	(0.004)	(0.004)
# >65	-0.047	-0.046	-0.046	-0.045
	(0.002)	(0.002)	(0.002)	(0.002)
# <18	0.020	0.019	0.020	0.019
	(0.001)	(0.001)	(0.001)	(0.001)

Notes: N=747,079; For immigration variables, cells shows average partial effects from KHB models; For other variables, cells show average marginal effects from logit models; The numbers in parentheses are standard errors (clustered by HH); All coefficients are statistically significant $p<0.01$, so only the insignificant coefficients for lead 55-64 are marked with ^; The models also adjust for state and year fixed effects (not shown).

<u>Appendix III.</u> Full Table of Average Marginal Effects Corresponding to Table 3.

	Non-Immigrant: Relative	***Immigrant: Relative***	***Non-Citizen Immigrant: Relative***	***Non-Immigrant: Anchored***	***Immigrant: Anchored***	***Non-Citizen Immigrant: Anchored***
Non-Citizen Immigrant		0.022 (0.004)			0.020 (0.004)	
Mixed Status HH		-0.021 (0.004)	-0.036 (0.006)		-0.023 (0.004)	-0.040 (0.006)
Years in U.S.		-0.002 (0.0001)	-0.003 (0.0002)		-0.002 (0.0001)	-0.003 (0.0002)
Jobless HH	0.357 (0.005)	0.366 (0.010)	0.378 (0.014)	0.357 (0.005)	0.367 (0.010)	0.383 (0.015)
Lead < High School	0.103 (0.004)	0.088 (0.006)	0.093 (0.009)	0.099 (0.004)	0.082 (0.006)	0.085 (0.009)
Single Mother HH	0.071 (0.003)	0.076 (0.008)	0.081 (0.011)	0.066 (0.003)	0.072 (0.008)	0.074 (0.011)
Young Lead	0.134 (0.005)	0.083 (0.010)	0.078 (0.014)	0.130 (0.005)	0.081 (0.010)	0.077 (0.014)
Female	0.003 (0.001)	0.004 (0.002)	0.010 (0.003)	0.002 (0.001)	0.004 (0.002)	0.010 (0.003)
Lead 25-34	0.023 (0.002)	0.003^ (0.002)	-0.006^ (0.007)	0.022 (0.002)	0.0003^ (0.005)	-0.002^ (0.007)
Lead 55-64	-0.003^ (0.002)	0.016 (0.006)	0.014^ (0.009)	-0.004^ (0.002)	0.019 (0.006)	0.017^ (0.009)
Lead 65-74	-0.018 (0.004)	-0.014^ (0.009)	-0.004^ (0.016)	-0.019 (0.004)	-0.010^ (0.009)	-0.0004^ (0.016)
Lead 75+	-0.031 (0.004)	-0.020^ (0.010)	-0.040^ (0.019)	-0.034 (0.004)	-0.022^ (0.010)	-0.038^ (0.018)
Lead Some College	-0.045 (0.002)	-0.046 (0.006)	-0.035 (0.009)	-0.042 (0.002)	-0.045 (0.005)	-0.037 (0.009)
Lead College	-0.106 (0.002)	-0.108 (0.005)	-0.118 (0.009)	-0.102 (0.002)	-0.101 (0.005)	-0.110 (0.009)
Lead Post-Graduate	-0.131 (0.002)	-0.108 (0.005)	-0.161 (0.010)	-0.125 (0.002)	-0.141 (0.005)	-0.153 (0.009)
Single Father	0.033 (0.004)	0.0122^ (0.009)	0.018^ (0.013)	0.031 (0.004)	0.014^ (0.009)	0.017^ (0.013)
Female Head No Child	0.060 (0.002)	0.063 (0.006)	0.073 (0.011)	0.058 (0.002)	0.060 (0.006)	0.066 (0.011)

Male Head No	0.034	0.023	0.021^	0.033	0.022	0.020^
Child	(0.002)	(0.006)	(0.010)	(0.002)	(0.006)	(0.010)
Multiple Earners	-0.135	-0.201	-0.263	-0.128	-0.195	-0.257
	(0.002)	(0.004)	(0.006)	(0.002)	(0.004)	(0.006)
Black	0.047	0.021	0.011^	0.045	0.021	0.014^
	(0.002)	(0.008)	(0.013)	(0.002)	(0.008)	(0.013)
Latino	0.046	0.058	0.086	0.045	0.054	0.084
	(0.002)	(0.005)	(0.010)	(0.002)	(0.005)	(0.010)
Asian	0.049	0.009^	0.009^	0.047	0.008^	0.008^
	(0.005)	(0.006)	(0.011)	(0.005)	(0.006)	(0.010)
Other Race	0.035	0.015^	0.038^	0.036	0.022^	0.064^
	(0.004)	(0.017)	(0.036)	(0.004)	(0.018)	(0.043)
# >65	-0.051	-0.021	-0.007^	-0.050	-0.021	-0.004^
	(0.002)	(0.005)	(0.008)	(0.002)	(0.005)	(0.008)
# <18	0.019	0.021	0.022	0.019	0.021	0.022
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
N	633,448	113,585	52,407	633,448	113,585	52,407

Notes: cells show average marginal effects from logit models; The numbers in parentheses are standard errors (clustered by HH); Most coefficients are statistically significant p<0.01, so only the insignificant coefficients are marked with ^; The models also adjust for state and year fixed effects (not shown). State and Year FEs not shown.

Supplemental File: LIS Code for Dataset Construction and All Analyses.

*Analyses conducted December 2024 – April 2025 using LISSY.
*The following code can be submitted to the LISSY interface of the Luxembourg Income Study Database (LIS)
*(www.lisdatacenter.org) by registered users. LISSY is a publicly available server and interface for analyzing the LIS data.
*Analyses conducted using STATA.
*For [username], we submit the folder of the first author.

*All US waves 1993-2023 Since Immigrant Variable Becomes Available Starting in 1993

```
global c " us93 us94 us95 us96 us97 us98 us99 us00 us01 us02 us03 us04 us05 us06 us07 us08 us09 us10 us11 us12 us13 us14
us15 us16 us17 us18 us19 us20 us21 us22 us23"

foreach x of global c {
*HH file
use $`x'h, clear
*drop missing
drop if dhi==.
drop if dhi==0
drop if hwgt==.
drop if hwgt==0
*equivalize and top and bottom-code income
gen wt=hwgt*nhhmem
gen ey=dhi/(sqrt(nhhmem))
qui sum ey [w=wt]
gen botlin=0.01*_result(3)
replace ey=botlin if ey<botlin
quietly sum dhi [w=wt], de
gen toplin=10*_result(10)
replace ey=(toplin/(nhhmem^0.5)) if dhi>toplin
*Median and Poverty thresholds
quietly sum ey [w=wt], de
generate medey=_result(10)
generate povl5=_result(10)*.5
*Define poverty
gen poor5=.
replace poor5=0 if ey>= povl5 & ey!=.
replace poor5=1 if ey< povl5 & ey!=.
*Add anchored poverty measure for most recent five years, anchored to 2019 threshold
gen anchpov=0 if ey!=. & year>2018 & year <2024
replace anchpov=1 if poor5==1 & year ==2019
*use https://www.bls.gov/data/inflation_calculator.htm for inflation adjustment of 2019 threshold
*Median equivalized hh income in 2019 is 41359.21, so threshold is 20679.61
replace anchpov=1 if ey< (20679.61*1.01)  & year ==2020
replace anchpov=1 if ey< (20679.61*1.06)  & year ==2021
replace anchpov=1 if ey< (20679.61*1.15) & year ==2022
replace anchpov=1 if ey< (20679.61*1.19) & year ==2023
replace anchpov=. if year<2019
*HH employment variables
gen multearn=.
replace multearn=0 if nearn==0 | nearn==1
replace multearn=1 if nearn>1 & nearn!=.
gen unemphh=.
replace unemphh=0 if nearn>0 & nearn!=.
replace unemphh=1 if nearn==0
*combined employment variable
recode nearn (0 = 0 "Unemp HH") (1 = 1 "One Earn") (2/max = 2 "Multi Earn"), gen(emphh)
label define earnlab 0 "Non-Employed" 1 "One Earner" 2 "Multiple Earners", replace
label val emphh earnlab
*use b1 as reference
sort hid
keep hid did year dname cname hwgt hhtype hpartner nhhmem nhhmem65 nhhmem17 nearn ey dhi hitotal hifactor hitransfer
hi33 hiprivate poor5 anchpov unemphh multearn emphh region_c
```

```
save $mydata/[username]/`x'h, replace

*Person File
use $`x'p, clear

*Head and Sex for single parent variables later*
gen head=.
replace head=1 if relation==1000
replace head=0 if relation>1000 & relation!=.
recode sex (1=0)(2=1)(.=.), gen(female)
recode sex (1=1)(2=0)(.=.), gen(male)

sort hid
keep hid pid did year relation partner parents nchildren ageyoch age sex marital immigr citizen yrsresid ethnic_c immigr_c educ
educ_c emp head male female pilabour pi11 hourstot weeks
save $mydata/[username]/`x'p, replace

merge m:1 hid using $mydata/[username]/`x'h, keep(match) nogen

*create citizen variable
gen citimmig=0 if immigr!=.
replace citimmig=1 if immigr==1 & citizen<2000
gen noncitimmig=0 if immigr!=.
replace noncitimmig=1 if immigr==1 & citizen==2000
*mixed status HH
egen sdcitizen= sd(citimmig), by(hid)
gen mixed=1 if sdcitizen!=0
replace mixed=0 if sdcitizen==0
*create variable for lead earner*
replace pilabour = pi11 if pilabour<0
egen double maxinc=max(pilabour) if pilabour!=., by(hid)
gen lead=pilabour==maxinc
egen maxage=max(age) if lead & age!=., by(hid)
replace lead=0 if age!=maxage
egen numlead = sum(lead), by(hid)
gen rlead = runiform()
egen maxrlead = max(rlead) if lead, by(hid)
replace lead = 0 if numlead>1 & rlead<maxrlead
*create variables for education*
gen leadeduc_a=educ_c*lead
egen leadeduc=max(leadeduc_a), by(hid)
gen postgrad=0 if leadeduc!=.
replace postgrad=1 if leadeduc>43 & leadeduc!=.
gen college=0 if leadeduc!=.
replace college=1 if leadeduc==43
gen somecoll=0 if leadeduc!=.
replace somecoll=1 if leadeduc>39 & leadeduc<43
gen highsch=0 if leadeduc!=.
replace highsch=1 if leadeduc==39
gen lesshs=0 if leadeduc!=.
replace lesshs=1 if leadeduc<39
*create age of head variables
gen agelead_a=age*lead
egen agelead=max(agelead_a), by(hid)
gen leadu25=0 if agelead!=.
replace leadu25=1 if agelead<25 & agelead!=.
gen lead2534=0 if agelead!=.
replace lead2534=1 if agelead>24 & agelead<35
gen lead5564=0 if agelead!=.
replace lead5564=1 if agelead>54 & agelead<65
gen lead6574=0 if agelead!=.
replace lead6574=1 if agelead>64 & agelead<75
```

```
gen lead75plus=0 if agelead!=.
replace lead75plus=1 if agelead>74 & agelead!=.
*create family structure variables*
gen married=.
replace married=0 if marital>=200 & marital!=.
replace married=1 if marital<200 | partner==110
gen marriedhh_a=married*head
egen marriedhh=max(marriedhh_a), by(hid)
recode marriedhh (1=0)(0=1)(.=.), gen(single)
recode nchildren 2/17=1, gen(nchild)
replace nchild=0 if ageyoch>17 & ageyoch!=.
gen sing_mom_a=head*female
gen sing_mom_b=sing_mom_a*single
gen sing_mom_c=sing_mom_b*nchild
egen singmom=max(sing_mom_c), by(hid)
replace singmom=1 if singmom>1 & singmom!=.
gen sing_dad_a=head*male
gen sing_dad_b=sing_dad_a*single
gen sing_dad_c=sing_dad_b*nhhmem17
egen singdad =max(sing_dad_c), by(hid)
replace singdad=1 if singdad>1
gen fhnk_a=0
replace fhnk_a=1 if sing_mom_b ==1 & nhhmem17==0
egen fhnk=max(fhnk_a), by(hid)
gen mhnk_a=0
replace mhnk_a=1 if sing_dad_b ==1 & nhhmem17==0
egen mhnk=max(mhnk_a), by(hid)
*combined lead age categorical variable
gen agehh=1 if leadu25==1
replace agehh=2 if lead2534==1
replace agehh=3 if agelead>34 & agelead<54
replace agehh=4 if lead5564==1
replace agehh=5 if lead6574==1
replace agehh=6 if lead75plus==1
label define agelab 1 "Under 25" 2 "a2534" 3 "a3554" 4 "a5564" 5 "a6574" 6 "a75plus", replace
label val agehh agelab
*use b3 as reference
*combined education variable
gen educhh=1 if lesshs==1
replace educhh=2 if highsch==1
replace educhh=3 if somecoll==1
replace educhh=4 if college==1
replace educhh=5 if postgrad==1
label define edulab 1 "lesshs" 2 "highsch" 3 "somecoll" 4 "college" 5 "postgrad", replace
label val educhh edulab
*use b2 as reference
*combined family variable
gen famHH = 1
replace famHH = 2 if singmom==1
replace famHH = 3 if singdad==1
replace famHH = 4 if fhnk==1
replace famHH = 5 if mhnk==1
label define famlab 1 "Couple" 2 "Single Mom" 3 "Single Dad" 4 "FHNK" 5 "MHNK", replace
label val famHH famlab
*use b1 as reference
*generate race variable, other is coded as zero
*code “other race” as zero
gen race=0 if ethnic_c!=.
*white=1
replace race=1 if ethnic_c==1 & year<2002
*black=2
replace race=2 if ethnic_c==3 & year<2002
```

```
*latino=3
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10) & year<2002
*Asian=4
replace race=4 if ethnic_c==7 & year<2002
*2002, new race coding available
replace race=1 if ethnic_c==1 & year>2001 & year!=.
replace race=2 if ethnic_c==3 & year>2001 & year!=.
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10 | ethnic_c==12) & year>2001 & year!=.
replace race=4 if (ethnic_c==7 | ethnic_c==9) & year>2001 & year!=.
label define racelab 0 "Other" 1 "white" 2 "Black" 3 "Latino" 4 "Asian", replace
label val race racelab
*use b1 as reference

save $mydata/[username]/`x', replace
}

*** append country files
global c "us94 us95 us96 us97 us98 us99 us00 us01 us02 us03 us04 us05 us06 us07 us08 us09 us10 us11 us12 us13 us14 us15
us16 us17 us18 us19 us20 us21 us22 us23"

use $mydata/[username]/us93, clear
foreach x of global c {
append using "$mydata/[username]/`x'"
}

tabstat did, by(dname)

save XXX, replace

*Figure 1 Analyses
*Level and Trend in Immigrant Share of Poor
tabstat immigr if poor5 [w=hwgt], by(year) stats (mean semean n)
tabstat noncitimmig if poor5 [w=hwgt], by(year) stats (mean semean n)
tabstat immigr if anchpov [w=hwgt], by(year) stats (mean semean n)
tabstat noncitimmig if anchpov [w=hwgt], by(year) stats (mean semean n)

*Descriptive Statistics for Table 1
tabstat poor5 anchpov noncitimmig yrsresid mixed unemphh lesshs singmom leadu25 female multearn highsch somecoll college
postgrad lead2534 lead5564 lead6574 lead75plus singdad fhnk mhnk nhhmem65 nhhmem17 if immigr==1 & year>2018 &
year<2024  [w=hwgt], stats (mean sd n)
tabstat poor5 anchpov yrsresid mixed unemphh lesshs singmom leadu25 female multearn highsch somecoll college postgrad
lead2534 lead5564 lead6574 lead75plus singdad fhnk mhnk nhhmem65 nhhmem17 if immigr==1 & year>2018 & year<2024
[w=hwgt], stats (mean sd n)
tabstat poor5 anchpov noncitimmig yrsresid mixed unemphh lesshs singmom leadu25 female multearn highsch somecoll college
postgrad lead2534 lead5564 lead6574 lead75plus singdad fhnk mhnk nhhmem65 nhhmem17 if noncitimmig==1 & year>2018 &
year<2024  [w=hwgt], stats (mean sd n)
tabstat poor5 anchpov unemphh lesshs singmom leadu25 female multearn highsch somecoll college postgrad lead2534 lead5564
lead6574 lead75plus singdad fhnk mhnk nhhmem65 nhhmem17 if immigr==0 & year>2018 & year<2024  [w=hwgt], stats
(mean sd n)
tabstat poor5 anchpov immigr noncitimmig yrsresid mixed unemphh lesshs singmom leadu25 female multearn highsch somecoll
college postgrad lead2534 lead5564 lead6574 lead75plus singdad fhnk mhnk nhhmem65 nhhmem17 if year>2018 & year<2024
[w=hwgt], stats (mean sd n)

*Table 2 Models of Poverty & Details in Appendix II
*Create hhid by wave
gen hid2 = 1000*hid + did

*KHB gives APE for immigr without and with controls
*Models 1-2
khb logit poor5 immigr || female i.agehh i.educhh i.famHH i.emphh i.race nhhmem65 nhhmem17 i.region_c i.year if year>2018
& year<2024  [pw=hwgt], sum verbose ape vce(cluster hid2)
*logit model gives AMEs for risks & other independent variables
```

```
logit poor5 immigr female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c i.year if
year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Models 3-4
khb logit anchpov immigr || female i.agehh i.educhh i.famHH i.emphh i.race nhhmem65 nhhmem17 i.region_c i.year if
year>2018 & year<2024  [pw=hwgt], sum verbose ape vce(cluster hid2)
logit anchpov immigr female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c i.year if
year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Models 5-6
khb logit poor5 noncitimmig citimmig || female i.agehh i.educhh i.famHH i.emphh i.race nhhmem65 nhhmem17 i.region_c i.year
if year>2018 & year<2024  [pw=hwgt], sum verbose ape vce(cluster hid2)
logit poor5 noncitimmig citimmig female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c
i.year if year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Models 7-8
khb logit anchpov noncitimmig citimmig || female i.agehh i.educhh i.famHH i.emphh i.race nhhmem65 nhhmem17 i.region_c
i.year if year>2018 & year<2024  [pw=hwgt], sum verbose ape vce(cluster hid2)
logit anchpov noncitimmig citimmig female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c
i.year if year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)

*Figure 2 Analyses
**Levels and Trends in Poverty Rates for All, Non-Immigrants, Immigrants, Citizen Immigrants, and Non-Citizen Immigrants by
Years*
tabstat poor5 anchpov [w=hwgt], by(year) stats (mean semean n)
tabstat poor5 anchpov if immigr==0 [w=hwgt], by(year) stats (mean semean n)
tabstat poor5 anchpov if immigr==1 [w=hwgt], by(year) stats (mean semean n)
tabstat poor5 anchpov if citimmig [w=hwgt], by(year) stats (mean semean n)
tabstat poor5 anchpov if noncitimmig [w=hwgt], by(year) stats (mean semean n)

*Figures 3-6 Analyses
*Immigrant poverty by state, pooling most recent five years 2019-2023
tabstat poor5 anchpov if year>2018 & year<2024 [w=hwgt], by(region_c) stats (mean semean n)
tabstat poor5 anchpov if immigr==1 & year>2018 & year<2024 [w=hwgt], by(region_c) stats (mean semean n)
tabstat poor5 anchpov if noncitimmig==1 & year>2018 & year<2024 [w=hwgt], by(region_c) stats (mean semean n)
tabstat poor5 anchpov if immigr==0 & year>2018 & year<2024 [w=hwgt], by(region_c) stats (mean semean n)
*Immigrant Share of state’s populations
tabstat immigr if year>2018 & year<2024 [w=hwgt], by(region_c) stats (mean semean n)

*Table 3 Models
*Create hhid by wave
gen hid2 = 1000*hid + did
*Model 1
logit poor5 female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c i.year if immigr==0 &
year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
tabstat yrsresid mixed if immigr==1 & year>2018 & year<2024 [pw=hwgt], by(noncitimmig) stats (min p25 p50 mean p75 max
sd n)
*Model 2
logit poor5 noncitimmig yrsresid mixed female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17
i.region_c i.year if immigr==1 & year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Model 3
logit poor5 yrsresid mixed female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c i.year if
noncitimmig==1 & year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Model 4
logit anchpov female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c i.year if immigr==0 &
year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Model 5
```

```
logit anchpov noncitimmig yrsresid mixed female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17
i.region_c i.year if immigr==1 & year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)
*Model 6
logit anchpov yrsresid mixed female b3.agehh b2.educhh b1.famHH b1.emphh b1.race nhhmem65 nhhmem17 i.region_c i.year if
noncitimmig==1 & year>2018 & year<2024 [pw=hwgt], cluster(hid2)
margins, dydx(*)

***NATION OF ORIGIN ANALYSES
*Identify Most Common Nations of Origin for Immigrants in Recent Five Years
tab immigr_c if immigr==1 & year>2018 & year<2024 [aw=hwgt]
*Most Common Nations of Origin: 1) Mexico, 2) India, 3) China, 4) Philippines, 5) Cuba, 6) El Salvador, 7) Vietnam, 8)
Dominican Republic, 9) Guatemala, 10) Honduras, 11) Colombia 12) combined Koreas
gen mexico=0 if immigr==1
replace mexico = 1 if immigr==1 & immigr_c==2246
gen india=0 if immigr==1
replace india = 1 if immigr==1 & immigr_c==2334
gen china=0 if immigr==1
replace china = 1 if immigr==1 & immigr_c==2321
gen philip=0 if immigr==1
replace philip = 1 if immigr==1 & immigr_c==2357
gen cuba=0 if immigr==1
replace cuba = 1 if immigr==1 & immigr_c==2215
gen elsalv=0 if immigr==1
replace elsalv = 1 if immigr==1 & immigr_c==2243
gen vietnam=0 if immigr==1
replace vietnam = 1 if immigr==1 & immigr_c==2362
gen domrep=0 if immigr==1
replace domrep = 1 if immigr==1 & immigr_c==2217
gen guatem=0 if immigr==1
replace guatem = 1 if immigr==1 & immigr_c==2244
gen hondur=0 if immigr==1
replace hondur = 1 if immigr==1 & immigr_c==2245
gen colomb=0 if immigr==1
replace colomb = 1 if immigr==1 & immigr_c==2265
gen korea=0 if immigr==1
replace korea = 1 if immigr==1 & (immigr_c==2324|immigr_c==2327)

*Non-immigrant poverty in recent 5 years for benchmark
tabstat poor5 anchpov if immigr==0 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Mexico (1)
tabstat poor5 anchpov if mexico==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: India (2)
tabstat poor5 anchpov if india==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: China (3)
tabstat poor5 anchpov if china==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Philipines (4)
tabstat poor5 anchpov if philip==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Cuba (5)
tabstat poor5 anchpov if cuba==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: El Salvador (6)
tabstat poor5 anchpov if elsalv==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean var n)
*Origin: Viet Nam (7)
tabstat poor5 anchpov if vietnam==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Domincan Republic (8)
tabstat poor5 anchpov if domrep==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Guatemala (9)
tabstat poor5 anchpov if guatem==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Honduras (10)
tabstat poor5 anchpov if hondur==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Columbia (11)
tabstat poor5 anchpov if colomb==1 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean n)
```

```
*Origin: Koreas (combined 12)
tabstat poor5 anchpov if korea==1 & year>2018 & year<2024  [w=hwgt], by(citizen) stats (mean semean n)
*Origin: Puerto Rico for comparison
tabstat poor5 anchpov if immigr==1 & immigr_c==2225 & year>2018 & year<2024 [w=hwgt], by(citizen) stats (mean semean
n)

*Table 4: Fairlie decompositions for each of nations of origin
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(mexico) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(india) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(china) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(philip) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(cuba) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(elsalv) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(vietnam) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(domrep) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(guatem) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(hondur) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(colomb) ro ref(1)
fairlie poor5 (risk: unemphh lesshs leadu25 singmom) (imm: noncitimmig yrsresid mixed) (highed: college postgrad) female
multearn highsch somecoll singdad fhnk mhnk nhhmem65 nhhmem17 lead2534 lead5564 lead6574 lead75plus if immigr==1 &
year>2018 & year<2024  [pw=hwgt], by(korea) ro ref(1)
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