UNAUTHORIZED IMMIGRATION AND LOCAL GOVERNMENT FINANCES*

Jess Cornaggia[a], Kimberly J. Cornaggia[a], Ryan D. Israelsen[b,†]

[a] Smeal College of Business, Penn State University, University Park, PA 16802
[b] Broad College of Business, Michigan State University, East Lansing, MI 48824

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Abstract

This paper examines how unauthorized immigration affects the fiscal health of local governments. We isolate immigration to the U.S. driven by social, economic, and political conditions in countries of origin. We predict destination county immigration using a shift-share instrument based on pre-existing population distributions. In areas with structurally tight labor markets, unauthorized immigration explains lower municipal bond yields. Areas with typical labor market conditions experience higher yields, as do areas with "sanctuary" status. These effects accompany increased unemployment rates and expenditures on public amenities, including welfare assistance, construction, education, and law enforcement. These expenditures are not offset by higher tax revenues.

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† Corresponding author. Tel: 517.353.1705; E-mail address: israels4@broad.msu.edu.

1. Introduction

Prior literature documents historical economic benefits of (primarily legal) immigration – especially high skilled immigration – to the U.S. economy and the local communities where legal immigrants settle; e.g. Peri (2012), Bernstein, et al. (2022), Burchardi et al. (2024), Zimmerschied (2024). Less is known about the fiscal effects of the unprecedented levels of unauthorized immigration in recent years to the United States and other developed nations.[1] By late 2023, U.S. Border Patrol agents apprehended over 10,000 unauthorized immigrants daily, a figure that underscores the magnitude of current immigration flows and the urgency of understanding their economic implications.[2] We examine how unauthorized immigration influences local government fiscal health through the lens of municipal bond markets, providing insights into how communities adapt financially to immigrant inflows.

The relationship between unauthorized immigration and local economic conditions is theoretically ambiguous. Similar to legal immigration, unauthorized immigration may stimulate economic growth by increasing labor supply, creating new businesses, and generating demand for local goods and services. These positive effects should strengthen local government finances through expanded tax bases and economic vitality. Alternatively, if immigrants face barriers to formal economic participation or require substantial public support then unauthorized immigration strains public resources and services without generating corresponding revenue. These competing possibilities highlight the importance of empirical evidence for understanding the fiscal impact of unauthorized immigration.

[1] Rhetoric surrounding this type of immigration is controversial. Advocates of deportation typically describe such immigrants as “illegal aliens” or “illegal immigrants”. Opponents of deportation typically use the term “undocumented immigrants”. We use “unauthorized immigrants” because the U.S. Department of Homeland Security uses this term. Unauthorized immigrants enter the U.S. without inspection or were admitted temporarily and stayed past the date they were required to leave (https://ohss.dhs.gov/topics/immigration/unauthorized-immigrants). We provide a precise definition of the type of immigration we measure in the data section.

[2] Source: Reuters: https://www.reuters.com/world/us/biden-restricts-asylum-access-mexico-border-title-42-ends-2023-05-10/

A fundamental challenge in studying economic effects of immigration lies in disentangling treatment from selection effects. We expect that immigrants choose locations with strong economies and abundant employment opportunities, creating endogeneity that complicates causal inference. Previous immigration studies address this challenge through various methodological approaches, but the specific context of unauthorized immigration presents unique identification challenges. We address these challenges through a novel approach that combines detailed administrative data with economic indicators from immigrants' countries of origin.

We analyze aggregate unauthorized immigration flows using the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) database, which provides comprehensive data on immigration enforcement actions. We develop measures of predicted country-year immigration based on "push" factors including social, economic, and political conditions in immigrants' countries of origin. Drawing on World Bank data for the top 20 source countries of U.S. immigration, we examine factors such as death rates, GDP growth, inflation, labor force participation, and political stability. This model explains between 70% and 89% of the variation in aggregate unauthorized immigration flows, depending on specification, suggesting that country-level factors are crucial determinants of immigration patterns.

Our identification strategy builds on established literature showing that immigrants tend to settle in areas with existing populations from their home countries. Using detailed Census data on pre-existing foreign-born populations by U.S. county and immigrant country of origin, we construct a shift-share (Bartik) instrument that interacts these historical settlement patterns with predicted immigration flows from our first-stage analysis. This approach generates county-level predictions of unauthorized immigration that strongly correlate with actual patterns – a one percent increase in predicted immigration explains a 0.91% increase in actual immigration, with an R-squared of 0.87. The strength of this relationship provides confidence in our ability to identify plausibly exogenous variation in local immigration patterns.

Our analysis reveals that unauthorized immigration's effects on municipal bond yields depend on local labor market conditions, a finding that helps reconcile seemingly contradictory results in previous research. In areas with structurally tight labor markets – characterized by low unemployment and low labor force participation – unauthorized immigration explains lower municipal bond yields, suggesting that markets view immigration as beneficial in these contexts. This effect is particularly pronounced for general obligation bonds, which depend on the overall fiscal health of the issuing jurisdiction. However, in areas with typical labor market conditions, unauthorized immigration associates with higher yields, indicating that market participants perceive increased fiscal risk.

The role of local institutions emerges as another significant factor in our analysis. We find that "sanctuary" jurisdictions – those that limit cooperation with federal immigration enforcement – experience higher yields as unauthorized immigration increases, despite having lower baseline borrowing costs. This pattern suggests that while sanctuary policies might signal positive attributes to bond markets, they also affect how communities absorb and respond to immigrant inflows.

These yield effects reflect underlying economic mechanisms rather than merely market perceptions. In structurally tight labor markets, unauthorized immigration predicts future increases in labor force participation and reduced labor market tightness, suggesting that immigration helps address labor shortages and promotes economic dynamism. These positive labor market effects offer explanation for why bond markets view immigration more favorably in such contexts. Conversely, in sanctuary jurisdictions, unauthorized immigration predicts much higher future unemployment without corresponding changes in labor force participation, indicating limited economic stimulus and potential fiscal strain.

To better understand the mechanisms driving these market responses, we analyze local government finances. We find that unauthorized immigration correlates with increased expenditures across multiple categories, including welfare assistance, construction, education, and law enforcement. The magnitude of these effects increases with immigration intensity, suggesting non-linear responses in public service demands. Importantly, these higher expenditures are not offset by corresponding increases in tax revenues or other government income sources. This imbalance helps explain the observed effects on municipal bond yields and provides insight into how unauthorized immigration affects local government fiscal sustainability.

Our study makes several contributions to the literature on immigration's economic effects and local public finance. First, while previous research documents the impact of (primarily legal) immigration on various economic outcomes, we provide the first comprehensive analysis of unauthorized immigration and its effects on municipal bond markets, offering new insights into how financial markets price this risk. Second, our findings highlight the role of local economic conditions, particularly labor market characteristics, in determining whether unauthorized immigration strengthens or strains local government finances. Third, our analysis of expenditure and revenue patterns reveals specific channels through which immigration affects local fiscal outcomes, informing both academic understanding and policy discussions.

These results have implications for both immigration policy and municipal finance. They suggest that the fiscal impact of unauthorized immigration varies substantially across localities, depending on economic conditions and institutional characteristics. This heterogeneity implies that uniform immigration policies may have disparate local effects and that complementary policies addressing labor market conditions and fiscal capacity might be necessary for communities to successfully absorb immigrant inflows. Furthermore, our findings indicate that municipal bond markets serve as a useful lens for understanding how immigration affects local fiscal health, providing real-time feedback on the economic implications of immigration patterns and policies.

2. Related Literature

Many prior studies highlight the generally beneficial effects of immigration. Immigrants to the U.S. have not historically harmed labor market opportunities of less-educated natives (Card, 2005). Rather, immigrants act more as "job creators" than "job takers" and play a significant role in increasing entrepreneurship (Azoulay, et al. 2022), innovation (Bernstein, et al. 2022), total factor productivity (Peri, 2012), and long-run economic prosperity (Blau and Mackie, 2017; Sequeira, et al. 2020). Using Census data from 1980 to 2000, Hong and McLaren (2015) find that immigrants create demand for labor in consumer services; each immigrant creates 1.2 local jobs, most of which go to native workers. Burchardi, et al. (2024) show a positive impact of immigration on local innovation and wages at the 5-year horizon. A structural model estimates that immigration to the U.S. since 1965 increased innovation and wages by 5%. Burchardi, et al. (2019) and Cohen, Gurun, and Malloy (2017) show that immigration encourages foreign direct investment and trade with immigrants' countries of origin. Borjas (1995) argues that immigration can generate economic gains because of production complementarities between immigrant workers and other factors of production. He argues that the economic benefits to the U.S. from immigration are low but can be increased by pursuing an immigration policy that attracts more skilled immigrants. Edwards and Ortega (2017) employ a theoretical framework and conclude that unauthorized workers in the U.S. contribute 3.1% of GDP annually. We contribute to this literature empirical analysis of the effects of unauthorized immigration on local governmental fiscal health.

Our paper builds on contemporaneous work from Zimmerschied (2024) that uses U.S. Census data to analyze total immigration, including legal immigration. That analysis finds that increased immigration inflows are associated with lower municipal bond yields, on average. The conclusion from that paper is that immigration stimulates economic growth enough to outweigh the costs associated with increased demand for local public resources. Our paper uses Notice to

Appear (NTA) data from the Syracuse Transactional Records Access Clearinghouse (TRAC) immigration database. These data allow us to study unauthorized immigration apart from benefits of legal immigration, and to more accurately measure the time and location of unauthorized immigrants entering the U.S.

We hypothesize that the net effects of economic growth and increased demand for public assistance on municipal bond yields depend on the type of immigration. We expect that legal immigration, particularly of highly educated people, most likely stimulates economic growth. We expect that unauthorized immigration of less educated people stimulates comparatively less economic growth and more likely drives increased demand for public assistance. Given the exponential growth in unauthorized immigration (Figure 1), we hypothesize that public assistance costs outweigh economic growth for this type of immigration.

Indeed, we find that unauthorized immigration is associated with an increase in municipal bond yields, on average. This contrasts with the primary result in Zimmerschied (2024), where the offsetting positive effects of legal immigration result in an average reduction in municipal bond yields. We further provide novel evidence that the economic effects of unauthorized immigration vary based on local labor market conditions. Unauthorized immigration is associated with a reduction in municipal bond yields only in U.S. counties with tight labor markets. Areas with typical labor markets face higher borrowing costs as unauthorized immigration increases. Areas with sanctuary status in particular face higher borrowing costs, and unemployment rates increase as unauthorized immigrants enter sanctuary areas. The magnitude of the strain on sanctuary areas is more than twice the loosening benefits to areas with tight labor markets.

The channels for increased borrowing costs include higher expenditures on local public amenities including welfare assistance, construction, education, and law enforcement. Because these expenditures are not offset by higher tax revenues, on average, we observe higher costs of local government borrowing.

These findings contribute to the literature on economic challenges associated with immigration. For example, Borjas (2015) warns that estimated gains from unrestricted immigration may be oversold. Lewis and Peri (2015) and Hanson (2009) discuss evidence on the economic consequences of global labor mobility and Card (2007) describes the effects of immigration on city characteristics, including population, skill composition, rents, housing prices, and neighborhood and school compositions.

Several papers examine the effects of immigration on natives' wages. Card (1990) and Saiz (2003) study the Mariel Boatlift and find that it had little effect on wages in Miami but that home rental prices increased. Peri and Yasenov (2019) find similar non-results on wages. Card (2001) finds that intercity mobility rates of natives and earlier immigrants are insensitive to immigrant flows. However, immigrant inflows over the 1980s reduced wages and employment rates of low-skilled natives in gateway cities like Los Angeles and Miami by 1 to 3 percentage points. Likewise, Cortes (2008) finds that immigration reduces wages associated with immigrant-intensive services. Consistent with this finding, Bertoli, et al. (2013) show that expected earnings are a significant determinant of immigrants' destination choices. Dustmann, et al. (2013) show that immigrants depress (increase) wages of ex-ante low-wage (high-wage) natives. Ottaviano and Peri (2012) find similar depressive effects on wages for natives without high school degrees, but positive average effects. Foged and Peri (2016) show that refugees to Denmark pushed less-educated native workers to pursue less manual-intensive occupations, thus increasing wages and employment. Doran, et al. (2022) show that one additional H-1B visa crowds out 1.5 other workers at visa-winning firm. Piyapromdee (2021) estimates a spatial equilibrium model with U.S. Census data and shows substantial variation in wages, internal migration, and welfare due to immigration across and within cities. Smith (2012) finds that low-skilled immigration reduces native youth employment.

Beyond broad economic effects, a substantial literature examines the impact of immigration on specific local public services. For example, Borjas (1999) finds that immigrants who receive welfare cluster in states that provide high welfare benefits. Borjas (2003) provides a foundational analysis of immigration's fiscal effects, showing that the net impact depends on immigrants' skill levels and local labor market conditions. Dustmann and Frattini (2014) study the UK context and find that European immigrants made positive net fiscal contributions to tax and welfare systems, while the impact of non-European immigrants varies by arrival cohort. Speciale (2012) finds that increased immigration leads to reduced per-pupil education spending in European countries. Our paper contributes to this literature by examining how unauthorized immigration affects local governments' revenues and tax receipts, as well as expenditures on welfare, construction, education, and law enforcement.

Immigration requires the amalgamation of cultures, and this process is not always smooth. Alesina, et al. (2023) conduct surveys and experiments in six countries to study perceptions of immigrants and redistributive policies. These authors find that respondents overestimate the total number of immigrants and believe immigrants' culture, religion, and economic status are more different than they actually are. Tabellini (2020) studies European immigration to the U.S. between 1910 and 1930 and finds that immigration triggered hostile political reactions even though immigration increased natives' employment, spurred industrial production, and did not generate losses among natives working in exposed sectors. He concludes that immigration presents social challenges even when it is economically beneficial. Hainmueller and Hopkins (2014) survey literature on natives' attitudes toward immigration and find little correlation with economic circumstances. Instead, immigration attitudes are more shaped by concerns about culture. Our results do not speak directly to the social consequences of immigration, but they raise the possibility of tension stemming from economic consequences.

Our analysis is timely given policy debates about immigration enforcement. Chalfin (2015) examines crime resulting from Mexican immigration. Fasani, et al. (2019) survey the literature on immigration and crime and suggest policy and political economy considerations. Mayda, et al. (2022) show that the political impact of immigration varies with immigrants' skill levels and voting rights. Cascio and Lewis (2012) show that low-skilled immigration reduces native demand for public education. Allen, et al. (2024) examine how border wall expansion from 2006 to 2010 affected migration patterns and wages of U.S. workers. Amuedo-Dorantes and Puttitanum (2014) examine how immigration enforcement affects remittance flows to developing countries. Our results on municipal borrowing costs provide an additional consideration to these policy discussions.

Our findings also connect to a growing literature on the determinants of municipal borrowing costs. Butler, et al. (2009) show that political connections affect municipal bond yields, suggesting that local governance factors influence borrowing costs. Gao, Lee, and Murphy (2019) find that state-level policies for distressed municipalities affect borrowing costs, highlighting the importance of institutional frameworks. Cornaggia, et al. (2018) examine how credit ratings affect municipal bond pricing. Gao, Murphy, and Qi (2019) and Gao, et al. (2022) study the effects of gubernatorial political uncertainty and the Affordable Care Act, respectively. Painter (2020) and Goldsmith-Pinkham et al. (2023) study the effects of seal level rise. Cornaggia and Iliev (2024a and 2024b) study the effects of local energy resources and state mandates to consume renewable energy in net-zero emissions targets, respectively. Cornaggia, et al. (2022a) study the effects of the opioid crisis. Cornaggia, et al (2022b and 2024) examine the role of investor attention and insurance in municipal bond pricing, respectively. Our results suggest that demographic changes through unauthorized immigration represent another important factor affecting municipal borrowing costs.

3. Data

3.1. Immigration Data

We collect unauthorized immigration data from the Syracuse Transactional Records Access Clearinghouse (TRAC) database.[3] Figure A1 in the appendix provides a screenshot demonstrating the granularity of these data. TRAC includes data from each Notice to Appear (NTA) document issued by the Department of Homeland Security (DHS) to a noncitizen who the DHS believes to have violated immigration laws and should thus be deported. NTAs are filed with an immigration court which begins removal proceedings, though immigrants may appeal and defensively seek asylum.[4] If the court agrees to hear an appeal, then the immigrant may become eligible to work in the U.S. while waiting for the case to be heard. Case backlogs are often years long.

From the NTA we capture country of origin, current state and county of residence, and the time since the immigrant initially entered the country, as well as the year and month the NTA was filed. We use this information to construct and validate our instrument. Figure 1 shows the total number of unauthorized immigrants entering the U.S. by month according to this database. For comparison, Figure 2 shows the total number of legal immigrants to the U.S. by year.

[Insert Figure 1 here.]

[Insert Figure 2 here.]

We collect the foreign-born country of origin and population for each county each year between 2009 and 2022 from the Census American Community Survey 5-Year Database (ACS5). The ACS5 publishes county-level statistics for each county in the U.S. based on the previous 60-month period ending each year in June. We use the current foreign-born population distribution for a given country of origin in our instrument to predict where incoming immigrants likely settle.

[3] See https://trac.syr.edu/immigration/.

[4] Immigrants seeking asylum at a port of entry (affirmative asylum) do not receive a NTA unless they eventually violate an immigration law, and are, thus, not generally in the data.

Figure A2 in the appendix presents three panels examining the geographic distribution of foreign-born populations from specific countries. These panels show distinct spatial patterns in immigrant settlement that help explain variation in local effects. Panel A focuses on Mexican immigration, showing a broad distribution pattern across the U.S. We observe concentration in the Southwest and certain metropolitan areas, but with significant presence across many regions. This widespread pattern suggests that Mexican immigration may have diffuse effects on local government finances. Panel B reveals a notably different pattern for Haitian immigration, with strong coastal concentration in the Southeast and Northeast. This concentrated distribution suggests that Haitian immigration effects may be more localized and potentially more intense in specific jurisdictions. Nicaraguan immigration patterns in Panel C indicate regional clustering distinct from both Mexican and Haitian patterns. The clustering appears more pronounced in different metropolitan areas and regions.

The contrast among these three panels highlights the importance of considering country-specific patterns when analyzing immigration's fiscal effects. Different origin countries show distinct geographic preferences. We predict variation in effects on local government finances based on the predominant source countries in each area.

3.2. Municipal Bond Data

We collect municipal bond issuance and yield data from three sources. Our sample is from the Mergent Municipal Bond database. We augment identifiers with data from the S&P IPREO iDeal database and the MSRB EMMA database. We identify each U.S. issuer of municipal bonds between 2010 and 2023 and drop State issuers. We use the IPREO database to identify the county of each issuer. For cases where the county is missing or the name of the county or city is not explicitly included in the issuer name, we query the OPENAI GPT-3.5 Turbo model to identify the county. We then drop any issuers that cover multiple counties. These are typically special districts.

The remaining issuers are mostly counties, cities, and school districts. For each new bond issue, we retain the issuer type and collect issue characteristics including sale date, offer yield, issuance size, coupon rate, whether the bond is callable, or insured, and whether the bond is a General Obligation or a Revenue bond.

3.3. Treasury Yields

From Bloomberg and Refinitiv, we collect yields on treasury strips from 2010 - 2023 which allow us to create a zero-coupon risk-free yield curve each trading day during that period. We interpolate the yields between maturities. For each municipal bond, we calculate duration and match to the interpolated yield curve to generate spreads to treasuries.

3.4. County Level Data

From the Census ACS5 data, we collect additional county-level statistics including median household income, poverty rate, Gini coefficient, college graduation rate and population. From the Bureau of Labor Statistics, we collect monthly unemployment rate and labor force population statistics by county. We collect local-level government revenues and expenditures data from the Government Finance Database curated by Willamette University which is a standardized version of the annual census of local governments conducted by the U.S. Census Bureau.[5] This census covers every county, city, township, school district and special district every year ending in "2" or "7" as well as large issuers and every school district on the other years. We linearly interpolate values for issuers too small to be included in the "off" years based on non-missing years. Then, we aggregate up to the county level for each variable. We exclude special districts and any issuer with a presence in more than a single county.

For each county, we identify those designated as a "sanctuary county" using data from the

[5] https://my.willamette.edu/site/mba/public-datasets

Center for Immigration Studies.[6] We define an issuer in a county as belonging to a sanctuary county if the state, county, or any city in the county has such a designation. Bonds issued after the first date of such a designation are given this status. By the end of our sample period, 545 counties have "sanctuary" designation.

3.5. Country Level Data

From the World Bank we collect annual country level data on GDP growth, inflation, death rate, labor force participation, and a measure of political stability. We use these "push" variables to predict aggregate immigration to the U.S. from specific countries. Table I displays summary statistics of the bond sample (Panel A), the unemployment data sample (Panel B) and the local government financial data sample (Panel C).

[Insert Table I here.]

4. Methods and the Immigration Instrument

We use the distribution of existing county-level foreign-born population across the U.S. from a given country of origin to predict the likely settlement locations of incoming unauthorized immigrants. For example, if 3% of the U.S. population that was born in Armenia lives in Los Angeles County, then we would predict a 3% chance that a given new immigrant from Armenia goes to Los Angeles County. To check whether this prediction is reasonably accurate, we use the NTA documents issued within one year of arrival to unauthorized immigrants by country of origin.[7] Specifically, from the TRAC data, we count the total number of immigrants from each country to the U.S. within the previous year and apply the foreign-born county shares by country of birth to

[6] https://cis.org/Full-Screen-Map-Sanctuary-Cities

[7] While most NTAs are issued within the first year, some unauthorized immigrants are not identified for a few or many years after they have arrived. We know when they entered the country, but we cannot be sure that they were in the same location the entire time. Accordingly, we initially focus on NTAs issued within a year of arrival to verify that incumbent immigrant population distributions predict new immigration. Later, in the main analysis, having validated the use of the instrument in predicting immigrant location, we use the total immigration from a specific country in a given month based on all NTAs since we no longer need to rely on the disclosed location in the NTA.

the new immigrant totals from the same country. So, the variation in immigration comes from the total number arriving from a specific country. For instance, if there are an unexpectedly high number of immigrants from Venezuela, then the counties that happen to have large existing populations of people born in Venezuela would expect a larger inflow of immigrants to those counties. Panel A of Figure 3 shows the distribution of total foreign-born people (irrespective of source country) by county in the U.S. relative to total population by county. We measure this for each county and form deciles. The figure shows that certain counties have relatively high numbers of foreign-born people.

[Insert Figure 3 here.]

Panel B of Figure 3 shows an analogous distribution of new unauthorized immigrants (irrespective of source country) based on the NTA filings during the same period. While the patterns are not exactly the same, they are correlated. Given this similarity, we create a predicted immigration measure using distributions of foreign-born populations by specific countries of origin and apply those to the total population of unauthorized immigrants from the same country. Going back to Los Angeles County, if 1,000 immigrants from Armenia are identified in the NTA data, we predict 30 immigrants (3%) from Armenia to L.A. County that month. We do the same for the hundred-plus countries of origin in the Census and NTA data and sum up across all countries for each county. Figure 4 shows the predicted value for each year and county pair during the sample, as well as the actual value. We log and demean these values and display the results in Panel B. There is a strong positive correlation between the two series. We compute the shift-share measure as follows:

$$Shiftshare\ prediction_{j,t} = \sum_i Unauthorized\ immigration_{i,t} \times FBShare_{i,j,t-1} \qquad (1)$$

where j is U.S. county, t is year-month, and i is source country. $Unauthorized\ immigration_{i,t}$ is the total number of unauthorized immigrants entering the U.S. from country i over the previous twelve months. $FBShare_{i,j,t-1}$ is foreign-born share, the percentage of county *j*'s population that was born in country i, lagged one calendar year. County foreign born population data are from the Census ACS 5-year survey. Table II shows that a line fitted through this panel has a statistically significant coefficient of 0.9 and explains a large amount of the variation.

[Insert Figure 4 here.]

[Insert Table II here.]

Our identification strategy builds on recent methodological advances in the shift-share literature. Goldsmith-Pinkham, et al. (2020) provide a formal examination of shift-share instruments, showing that identification relies on the exogeneity of initial shares. Jaeger, et al. (2018) highlight the importance of accounting for dynamic adjustments when using shift-share instruments in immigration research. Borusyak, et al. (2022) develop new tools for assessing the validity of shift-share research designs.

The evidence in Figure 4 and Table II shows that counties' foreign-born populations are a good predictor of where unauthorized immigrants who receive an NTA within one year of entering the U.S. will appear. However, this approach does not take full advantage of the rich information in the NTA database on when immigrants enter the U.S. because it only counts newly arrived and identified immigrants. We refine the measure by using all immigrants from specific countries in the NTA database, regardless of whether they arrived in the past year or not. Specifically, we infer when they arrived based on the NTA filing, which allows us to get a better estimate of the total number of immigrants to the U.S. in a given month from a specific country. At this point, we do not rely on the stated county of residence since we are only using these data to infer the total number of immigrants from a country, which we then use to predict likely state and county where the immigrants first settle.

We focus on immigration driven by "push" factors from each country of origin to address the concern that the total flow of immigrants from countries endogenously move in anticipation of economic conditions in counties where others from their country have previously moved. Specifically, we regress (log) $Unauthorized\ immigration_{i,t}$ on recent conditions in country i that may encourage citizens to leave. Columns 1 and 2 use independent variables measured in the same year as the dependent variable. Columns 3 and 4 use independent variables lagged one year. Columns 5 and 6 (7 and 8) use lagged two-year (three-year) rolling averages of independent variables. If (log) $Unauthorized\ immigration_{i,t}$ is measured in year t, the independent variables in columns 5 and 6 (7 and 8) are averages over years t-1 and t-2 (t-1, t-2, and t-3). Table III shows the results for the top twenty countries supplying immigrants to the U.S. These countries represent more than 93% of total unauthorized immigration in our sample.

[Insert Table III here.]

Table III shows that death rates have a consistently positive relationship with immigration to the U.S., with coefficients ranging from 0.18 to 0.60 depending on specification. GDP growth demonstrates a positive correlation with immigration, with coefficients ranging from 0.07 to 0.21. This somewhat counterintuitive relationship may indicate that immigrants typically need a minimum foundation of wealth before they can afford to emigrate. This finding is consistent with Bertoli, Fernandez-Huertas, and Ortega (2013), who estimate that the cost of immigrating to the U.S. for a typical low-educated Ecuadorian is about nine times the worker's annual salary. Inflation shows a consistent positive relationship with immigration, with coefficients between 0.04 and 0.10. These results suggest that macroeconomic instability in source countries may drive migration decisions. Labor force participation in source countries generally shows a negative relationship with immigration, though the significance varies across specifications. The coefficients range from -0.07 to -0.23, suggesting that weaker labor markets in source countries may encourage emigration to the US. The political stability percentile consistently shows a negative relationship with emigration, with coefficients between -0.04 and -0.08. This indicates that less stable countries tend to generate more population outflows. The specifications include both country and year fixed effects in various combinations, helping to isolate the impact of time-varying country characteristics from broader temporal trends and country-specific factors. The adjusted R-squared values are consistently high, ranging from 0.70 to 0.89, indicating that these factors explain a substantial portion of the variation in immigration flows.

Going forward, we use the approach in column 7 to model unauthorized immigration explained by "push" factors. This approach omits year fixed effects. We use this approach because our goal at this stage is to explain immigration with sending-country characteristics. The results in Table III show that year fixed effects are helpful in boosting the explanatory power of the specifications. (The adjusted R-squared values in columns 2, 4, 6, and 8 are higher compared to their analogs in columns 1, 3, 5, and 7, respectively.) However, time effects are common across countries and potentially absorb explanatory power from country-specific characteristics. We also focus on the approach in column 7 because it uses three-year trailing averages of independent variables. Averaging the independent variables over three years provides more stable measures of sending-country characteristics that are less affected by transient conditions that may have less influence on immigration patterns. Ultimately, the results that follow are robust using any specification from Table III. We define the predicted values from this approach as $Push\ immigration_{i,t}$ and use that to predict unauthorized immigration as follows:

$$Predicted\ immigration_{j,t} = \sum_i Push\ immigration_{i,t} \times FBShare_{i,j,t-1} \qquad (2)$$

where $Push\ immigration_{i,t}$ is the total predicted amount of push immigration from country i to the U.S. during trailing year *t*. $FBShare_{i,j,t-1}$ is foreign-born share, the percentage of county j's population that was born in country i, lagged one calendar year. We use a trailing one-year window to measure the total predicted immigration to the county during the previous 12 months and scale the number by the county population to measure the intensity of predicted immigration.

We create predicted immigration quintiles each month and use those quintiles as our measure of predicted immigration intensity in most of our regressions. We use this approach because immigration enforcement likely varies through time. This within-month design holds constant U.S. immigration enforcement efforts, allowing us to test whether variation in unauthorized immigration within time periods explains local government financial conditions.

5. Results

5.1. Unauthorized Immigration and Municipal Bond Yields

Table IV presents the central analysis of how predicted unauthorized immigration affects municipal bond yields. The specifications are organized across nine columns, examining three issuer categories (All Issuers, City Issuers, and County Issuers) and three bond types (All Bonds, General Obligation, and Revenue). This structure allows for examination of how immigration effects vary across different segments of the municipal bond market.

[Insert Table IV here.]

For All Issuers (columns 1-3) in Panel A, the results show at most modest adverse effects of immigration on bond yields. City Issuers (columns 4-6) show marginally significant effects; the fifth quintile coefficient for city issuers reaches 0.0334 (significant at 10%) for all bonds, indicating that cities in high-immigration areas face marginally higher borrowing costs. County Issuers (columns 7-9) show insignificant effects.

Coefficients on control variables are consistent with existing results documented in the literature. For example, competitive issuance consistently reduces yields, with effects ranging from -0.0432 to -0.0870 for GO bonds. Bond characteristics such as duration and callable status show consistent effects across specifications, with longer duration and callable features associated with higher yields. Issuer characteristics also play important roles. Population size generally shows negative coefficients, suggesting economies of scale in borrowing costs. Higher household income levels are associated with lower yields, consistent with the importance of tax base strength for municipal credit quality.

Table IV Panel B examines immigration effects using continuous measures rather than quintile-based categorization. The continuous immigration measure shows varying effects across issue type and bond categories, with stronger results for county GO bonds, where the coefficient reaches 27.94 (significant at 1% level). For city issuers, the continuous measure shows insignificant effects. The R-squared values are high across specifications, indicating that control variables explain a substantial portion of yield variation. Overall, Table IV shows, at most, a weak and adverse relation between unauthorized immigration and municipal bond yields, on average. Next, we test whether this relation varies with local labor market conditions.

5.2. Unauthorized Immigration in Structurally Tight Labor Markets

Barnichon and Shapiro (2022) provide a comparison of common measures of labor market tightness, commending the ratio of job vacancies to unemployment (V-U ratio) and the rate of employee job switching as useful measures for forecasting inflation. Absent granular county-year data on numbers of job vacancies or employee job-switching rates, we classify a county as having a structurally tight labor market when its labor force per capita and unemployment rate are simultaneously below sample means.[8] This dual condition identifies areas facing a distinctive economic situation: Despite having relatively few people participating in the labor force, those who do participate find employment at high rates. This combination suggests markets where there

[8] Labor force per capita is the number of people in a county-year who are employed or seeking employment divided by total population. Unlike the labor force participation rate, this measure accounts for residents who generate demand for public services, irrespective of whether they are of working age. The mean labor force per capita in our sample is 46.8%. The mean unemployment rate is 5.6%.

may be a low supply of labor alongside high demand for labor.

Figure 5 provides a visualization of labor market conditions across U.S. counties, identifying areas with structurally tight labor markets during the period 2016-2023. The map employs a color gradient to display the number of months each county meets the criteria for "structurally tight" classification. Some regions show persistent structural tightness, experiencing many months that meet both criteria, while others rarely or never exhibit these conditions.

[Insert Figure 5 here.]

Labor market tightness may be correlated with other economic characteristics that explain municipal bond yields. For example, counties with tight labor markets could have higher concentrations of retirees. Retirees tend to be wealthy and provide a robust tax base. On the other hand, counties with tight labor markets could have higher concentrations of physically unhealthy or disabled persons who cannot work. In this case, labor market tightness would capture a county's unproductive tax base and weak fundamentals. Our main analysis includes issuer fixed effects, meaning any explanatory power in labor market tightness on municipal bond yields will derive from within-county time series variation in tightness. To the extent that the presence of, for example, retirees or disabled persons are stable through time, these alternative characteristics will not explain our results. Panel A of Table I shows that 21.6% of observations satisfy the criteria for being associated with structurally tight labor markets.

Table V examines how immigration interacts with local labor market conditions to explain municipal bond yields. The table's structure is like that of Table IV but adds interaction terms between immigration quintiles and an indicator for structurally tight labor markets.

[Insert Table V here.]

Panel V.A presents the base coefficients and interactions. The coefficients on the immigration quintiles indicate that for issuers in most counties, unauthorized immigration increases bond spreads. For All Issuers, spreads are 3.94 basis points wider for the highest predicted unauthorized immigration quintile relative to the lowest. Columns 4 through 9 indicate that this result is driven primarily by City Issuers where the impact on spreads in the highest quintile varies from 5.75 basis points for GO bonds to 10 basis points for Revenue bonds.

The structurally tight indicator shows a positive coefficient for the base effect (0.0555 for all bonds and All Issuers), suggesting that tight labor markets are generally associated with higher borrowing costs. However, the interactions between tight labor markets and predicted unauthorized immigration quintiles show increasingly negative coefficients as immigration intensity increases. For All Issuers, the interaction coefficients become progressively more negative across quintiles, reaching -0.0961 for the highest quintile. This pattern suggests that immigration alleviates borrowing cost pressure in areas with tight labor markets. The effect is pronounced for city issuers, where the highest quintile interaction reaches -0.130.

Panel V.B presents F-tests of the summed coefficients, examining the total effect of immigration in tight labor markets. The results show that the adverse base effect of immigration evident in the majority of counties is largely offset by the negative interaction terms in tight labor markets, particularly for higher immigration quintiles. This finding suggests that tight labor market conditions mitigate any adverse relationship between unauthorized immigration and higher borrowing costs.

5.3. Unauthorized Immigration in Sanctuary Jurisdictions

Table VI examines how sanctuary status interacts with unauthorized immigration to explain municipal bond yields. The analysis provides insight into how local immigration policies influence the fiscal impacts of unauthorized immigration.

[Insert Table VI here.]

The baseline effect of sanctuary status is negative (-0.0950 for all bonds and All Issuers), suggesting that areas with sanctuary policies are generally associated with lower borrowing costs. However, this advantage diminishes with higher levels of unauthorized immigration, as shown by the positive interaction terms. For city issuers, the sanctuary effect is pronounced with a baseline coefficient of -0.160 and increasingly positive interaction terms across immigration quintiles. This pattern suggests that while sanctuary areas may have certain attributes that reduce municipal bond yields (e.g., large and highly educated populations), these benefits are diminished as unauthorized immigration intensity increases.

The analysis also reveals differences between GO and revenue bonds. For City Issuers, GO bonds show stronger sanctuary effects and interactions. We infer a market view that sanctuary policies have broader implications for the general creditworthiness of the city rather than specific revenue-generating projects. Panel VI.B provides F-tests of summed coefficients, combining those for predicted immigration quintiles with predicted immigration quintiles interacted with the sanctuary status indicator. The results indicate that within sanctuary areas, unauthorized immigration significantly increases municipal borrowing costs, with differences in spreads as high as 25.3 basis points for City issued GO bonds.

5.4. Employment Outcomes following Unauthorized Immigration

Table VII presents analysis of how unauthorized immigration affects local labor markets over the following two years. The analysis examines three dependent variables: future unemployment rates, labor force per capita, and the likelihood of structurally tight labor markets. The results are presented separately for different categorical variables (tight labor markets and sanctuary status), providing insight into how institutional and economic conditions moderate employment effects.

[Insert Table VII here.]

Panel VII.A presents the coefficient estimates. For unemployment rates (column 1), the results show increasingly adverse effects across immigration quintiles, with the highest quintile showing a coefficient of 0.0853 (significant at 5% level) in the base specification. This pattern suggests that higher levels of unauthorized immigration are associated with increases in future unemployment rates.

The interaction effects in columns 2 and 3 highlight the importance of tight labor markets and sanctuary jurisdiction status in explaining future employment outcomes. In tight labor markets, the effect of unauthorized immigration on unemployment becomes more pronounced for higher quintiles, with the interaction coefficient reaching 0.285 for the highest quintile. This amplification effect suggests that tight labor markets are particularly sensitive to immigration-induced changes in labor supply. Specifically, an influx of immigrants allows employers to find workers. However, if the number of immigrants exceeds the demand for workers, then they pressure unemployment rates. The coefficient on "tight" is not statistically significant suggesting that unemployment rates are not generally increasing over time without increased immigration. In sanctuary jurisdictions, unemployment increases by about 0.16 percent on average over the subsequent year. This effect amplifies with unauthorized immigration, where unemployment rates in areas in the highest quintile of unauthorized immigration increase by an additional 0.615%. Moreover, as shown in the F-tests of summed coefficients in Panel VII.B, the combined impact in sanctuary counties is an increase in unemployment rates of 0.656% - more than twice as large as the increase in "tight" counties.

The labor force analysis (columns 4-6) shows generally negative but statistically weak effects of immigration on participation rates. However, the interaction terms with tight labor markets show positive coefficients, particularly for higher immigration quintiles. This pattern suggests that immigration may help activate the labor force in areas with tight markets.

Analysis of future labor market tightness (columns 7-9) reveals that immigration reduces the probability of structurally tight conditions, particularly in areas that are already tight. The negative interaction coefficients become larger in magnitude for higher immigration quintiles, suggesting that immigration alleviates labor market tightness. A similar effect obtains for sanctuary jurisdictions in the highest quintile of unauthorized immigration. Panel VII.B confirms that the impact of immigration on employment outcomes varies significantly with local conditions, with stronger effects in tight labor markets and sanctuary jurisdictions.

5.5. Unauthorized Immigration and Municipal Revenues

Table VIII examines how unauthorized immigration affects various components of local government revenue. The analysis considers outcome variables in the future, both one and two years ahead, providing insight into short- to medium-term effects.

[Insert Table VIII here.]

The results for total revenue show minimal direct effects, with coefficients generally small and statistically insignificant. The effects of unauthorized immigration on total taxes and property taxes are also insignificant. However, significant results appear in the analysis of selective sales taxes, where higher immigration quintiles show progressively more negative coefficients. The fifth quintile shows coefficients of -0.101 and -0.124 for one-year and two-year horizons respectively, both statistically significant. These results suggest that areas with higher unauthorized immigration may experience challenges in sales tax collection (e.g., increased cash transactions) or changes in consumption patterns that affect this revenue source. The high R-squared values (ranging from 0.935 to 0.996) indicate that the models capture most of the variation in revenue outcomes.

5.6. Unauthorized Immigration and Municipal Expenditures

Table IX presents an extensive analysis of how unauthorized immigration affects various categories of local government expenditure. The table is divided into five panels, each focusing on different types of spending. Panel IX.A examines welfare expenditures excluding capital outlays and construction. The results show increasing expenditures across immigration quintiles. The highest quintile shows coefficients of 0.103 for public welfare cash assistance and 0.103 for welfare categorical total expenditures, and both are statistically significant. These results suggest that areas with higher unauthorized immigration face increased demands for welfare services. Column 5 shows a similar effect for welfare categorical cash assistance, although the coefficient for the highest quintile is only marginally significant. Columns 7 and 8 show that areas in the highest quintile of unauthorized immigration transfer significantly more cash to state governments in exchange for welfare services, particularly in the following year.

[Insert Table IX here.]

Panel IX.B focuses on expenditures by welfare institutions and federal cash assistance. The coefficients show fiscal strain for higher immigration quintiles, with large increases in welfare institutional spending. Intuitively, these results show that unauthorized immigration creates the most pressure on welfare institutions that provide direct assistance to these immigrants.

Panel IX.C examines construction and capital outlays, revealing patterns in infrastructure spending. General construction shows positive coefficients for higher immigration quintiles, reaching 0.127 for the highest quintile. The coefficient remains similar in magnitude at a two-year horizon, indicating construction projects to accommodate growing populations are not short-lived. Coefficients for the highest quintile of unauthorized immigration likewise show marginally significant effects at a two-year horizon for welfare construction, capital outlays for welfare institutions, and public welfare capital outlays. Overall, these results suggest that areas with more unauthorized immigration face increased public infrastructure demands over the medium term.

Panel IX.D focuses on education expenditures, showing generally that expenditures increase with unauthorized immigration intensity. The effects are similar across categories: total education expenditures, total direct expenditures on education, and total current expenditures on education. Each of the coefficients for the highest quintile of unauthorized immigration is positive and significant at a two-year horizon, suggesting that immigration creates ongoing rather than one-time public education costs.

Finally, Panel IX.E examines law enforcement expenditures. We examine intergovernmental transfers from local to state governments for policing services, as well as capital outlays for police protection. Both have positive coefficients with unauthorized immigration at a one-year horizon. These results suggest that areas with higher unauthorized immigration spend more on law enforcement services in the near term.

Across panels in Table IX, the analysis reveals that the effects of unauthorized immigration on local government expenditures become stronger at higher quintiles. The results also show important differences between immediate and lagged effects, with some expenditure categories showing stronger responses over longer horizons. These effects contrast with those for municipal government revenues in Table VIII, where we saw insignificant or negative effects. In combination, Tables VIII and IX indicate that demand for public services increases with unauthorized immigration, but local tax receipts do not keep up with the higher expenditures.

6. Conclusion

This study provides the first comprehensive analysis of how unauthorized immigration affects local government fiscal health through its impact on municipal bond markets. Our findings reveal that the economic consequences of unauthorized immigration are not uniform but depend on local labor market conditions and institutional characteristics.

Using a novel identification strategy that combines detailed data on unauthorized immigration along with source country push factors, we demonstrate that areas with tight labor markets experience reduced borrowing costs when exposed to unauthorized immigration. This beneficial effect appears to operate through labor market channels, as immigration alleviates worker shortages and stimulates economic activity in these areas. The reduction in municipal bond yields suggests that market participants recognize these benefits and price them into local government debt.

However, the story is different for areas with typical labor market conditions and those with sanctuary status. In these jurisdictions, unauthorized immigration explains higher borrowing costs, reflecting increased fiscal strain. Our analysis of local government finances helps explain this pattern: unauthorized immigration drives higher expenditures across multiple categories – including welfare assistance, construction, education, and law enforcement – without generating offsetting increases in tax revenues.

The divergent effects across different local contexts have implications for both immigration and municipal finance policy. They suggest that the success of immigration absorption depends crucially on local economic conditions, particularly labor market characteristics. This finding challenges one-size-fits-all approaches to immigration policy and suggests that complementary policies addressing labor market conditions are necessary for communities to successfully integrate immigrant populations.

Our results also highlight the role of municipal bond markets as an important mechanism for understanding immigration's fiscal impacts. These markets convey investors' perceptions of the risks associated with unauthorized immigration across different local contexts, reflecting variation in how immigration patterns affect local government fiscal health.

These findings commend several avenues for future research. Further investigation of the specific channels through which labor market conditions mediate immigration's fiscal effects could provide additional insights for policy design. Similarly, further analysis of how different types of public expenditures respond to immigration could help local governments better prepare for demographic changes. Finally, our methodology for isolating exogenous variation in unauthorized immigration flows could be applied to study economic outcomes of interest beyond municipal financing costs.

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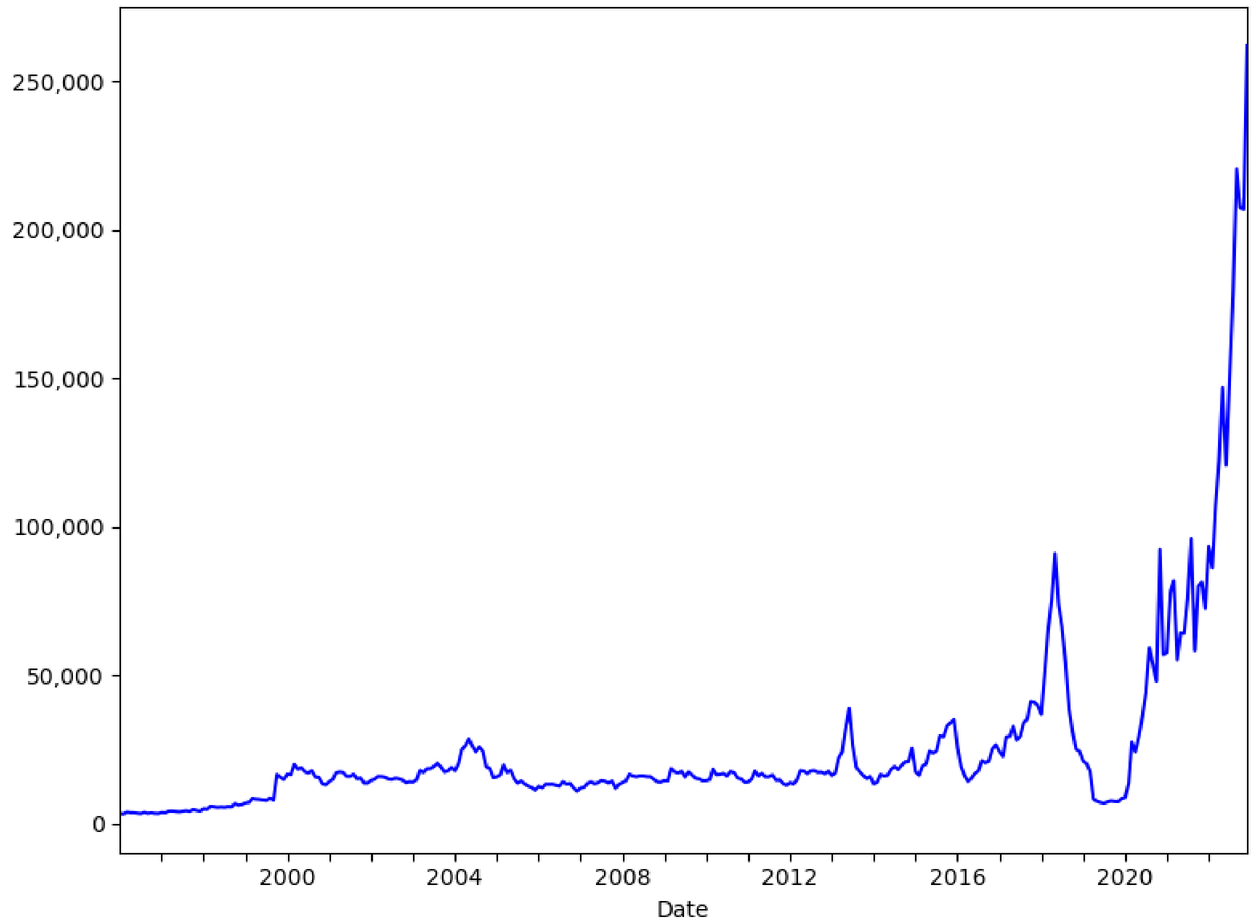


Figure 1. Monthly Unauthorized Immigration to the United States

This figure displays the number of known unauthorized immigrants entering the United States each month. Data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) database. Numbers include those with a Notice to Appear (NTA) in immigration court and are backdated to the disclosed time of initial entry into the United States.

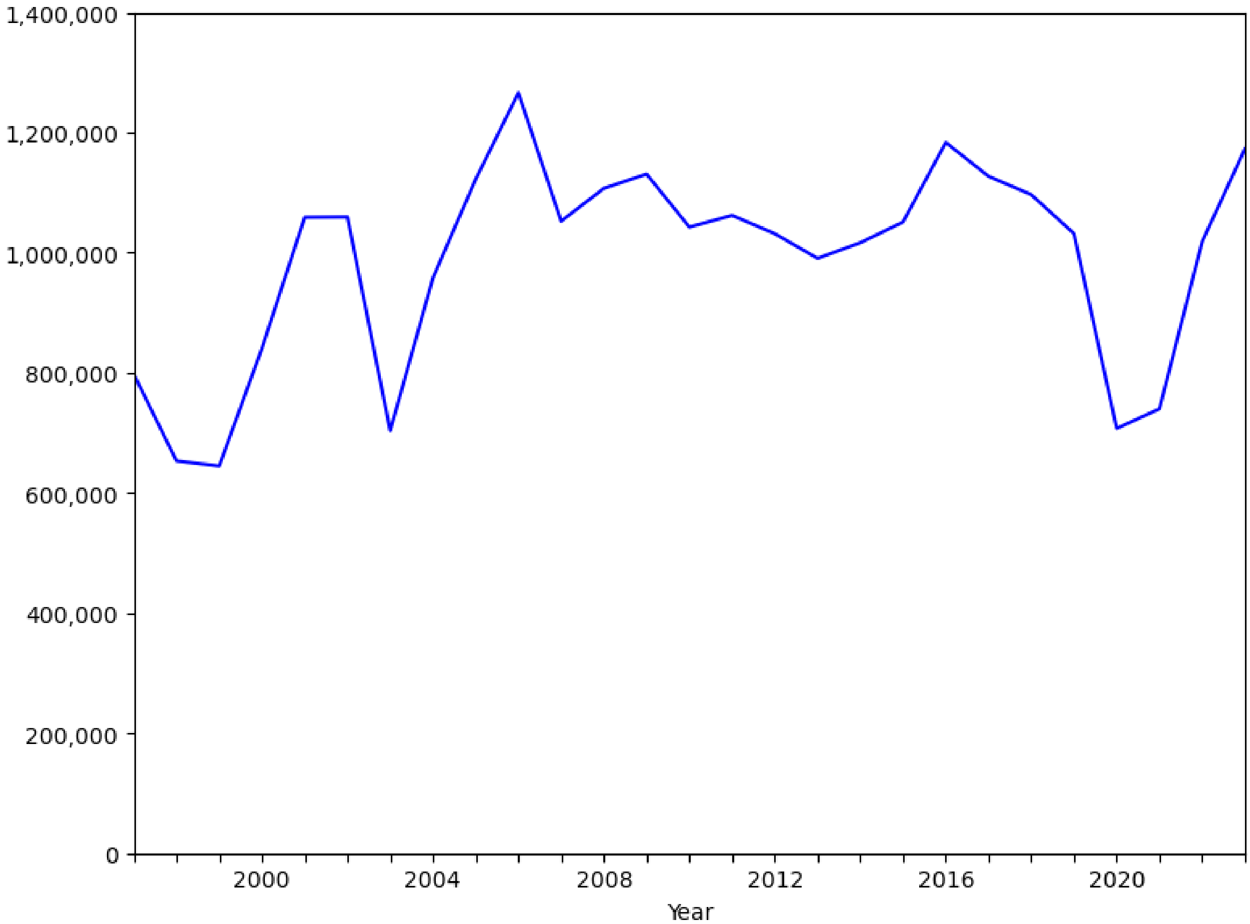
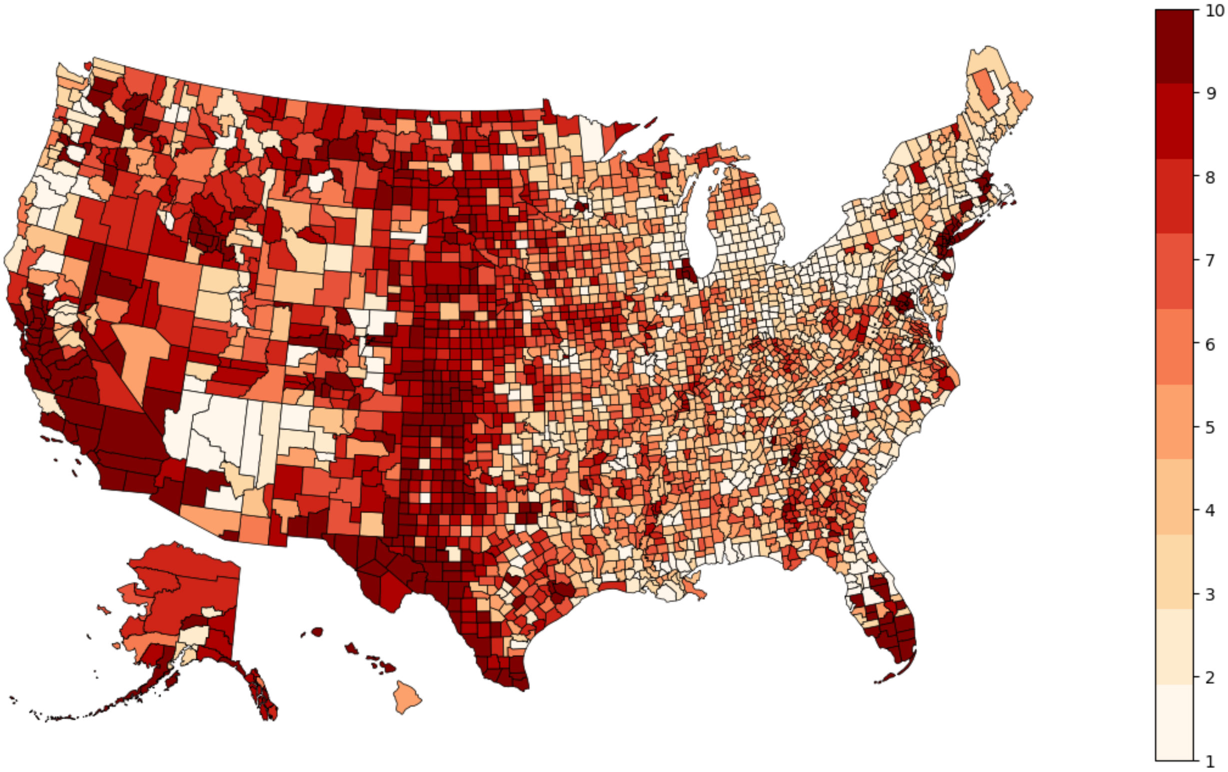
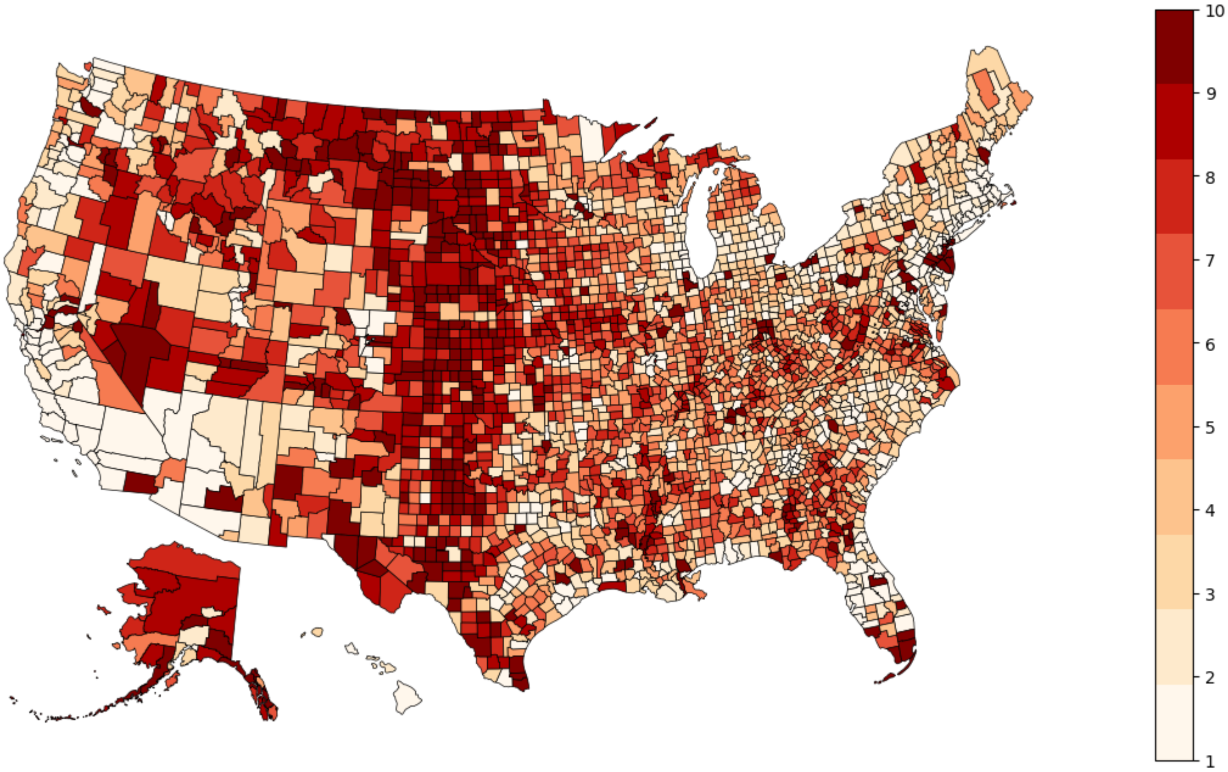


Figure 2. Annual Legal Immigration to the United States

This figure displays the number of persons obtaining lawful permanent resident status in the United States each year. Data are from the Department of Homeland Security 2023 Yearbook of Immigration Status.



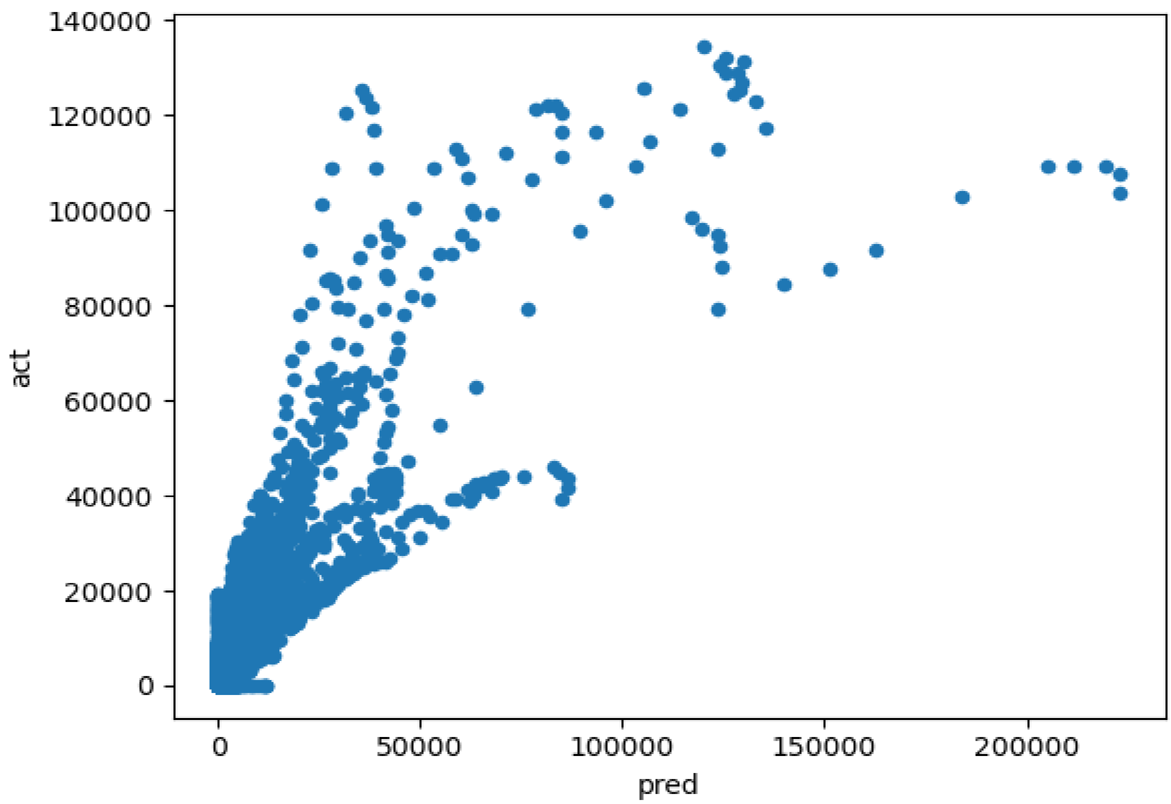
Panel A – Data from U.S. Census ACS 5-year Surveys



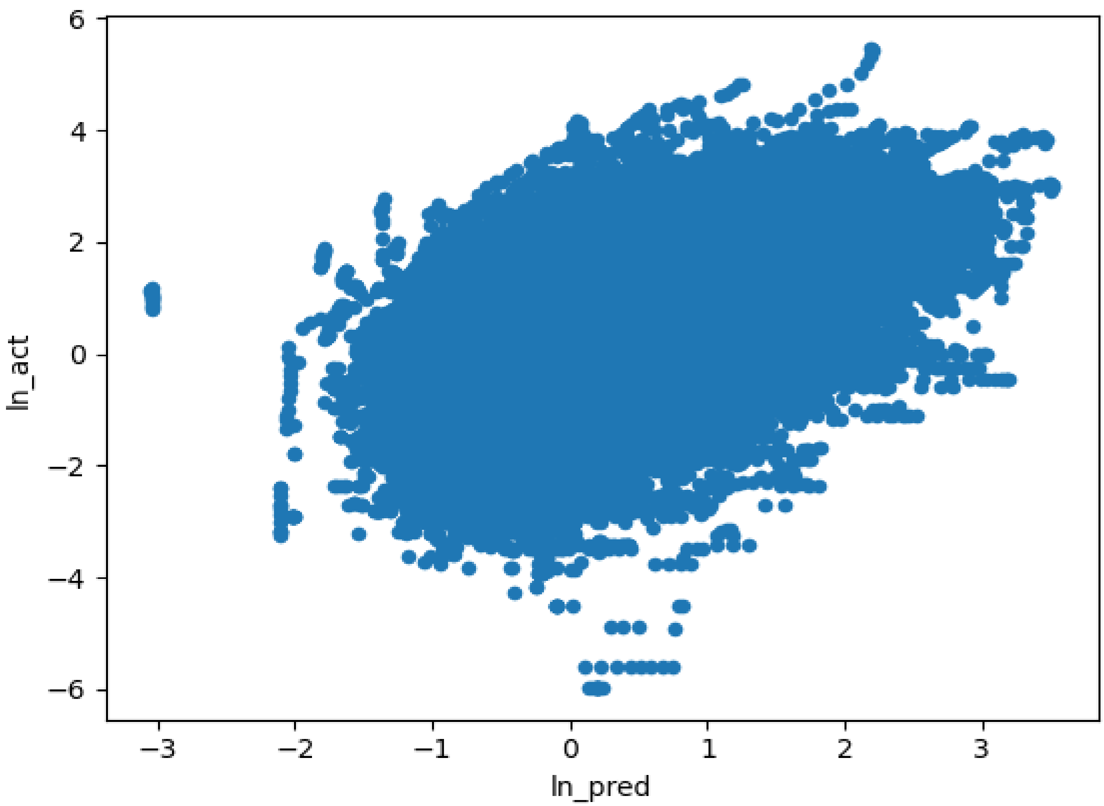
Panel B – Data from Syracuse Transactional Records Access Clearinghouse (TRAC) database

Figure 3. Foreign-born Population Distributions

This figure displays counties' decile ranks of foreign-born populations. Panel A displays deciles formed using the average foreign born population rate of a county from the Census ACS 5-year survey for the years 2010 – 2022. Panel B displays deciles formed using the unauthorized immigration rate (relative to population) by county for the years 2010 - 2022. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) database using the number of new Notices to Appear (NTA) by county for those arriving in the country during the previous 12 months.



Panel A – Raw Data



Panel B – Data Demeaned by Country

Figure 4. Unauthorized Immigration versus Shift-share Prediction

This figure displays scatter plots of actual unauthorized immigration to the United States (y axis) versus unauthorized immigration predicted by a shift-share measure (x axis). Each observation represents a U.S. county and year-month. Actual unauthorized immigration is the number of individuals with a Notice to Appear (NTA) in immigration court for unauthorized entry into the United States over the previous 12 months. We compute the shift-share measure as follows:

$$Shiftshare\ prediction_{j,t} = \sum_i Unauthorized\ immigration_{i,t} \times FBShare_{i,j,t-1}$$

where j is US county, t is year-month, and i is source country. $Unauthorized\ immigration_{i,t}$ is the total number of unauthorized immigrants entering the U.S. from country i over the previous twelve months. $FBShare_{i,j,t-1}$ is foreign-born share, the percentage of county j's population that was born in country i, lagged one calendar year. County foreign born population data are from the Census ACS 5-year survey. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Panel A presents raw numbers while Panel B presents the demeaned (by source country) natural logarithm.

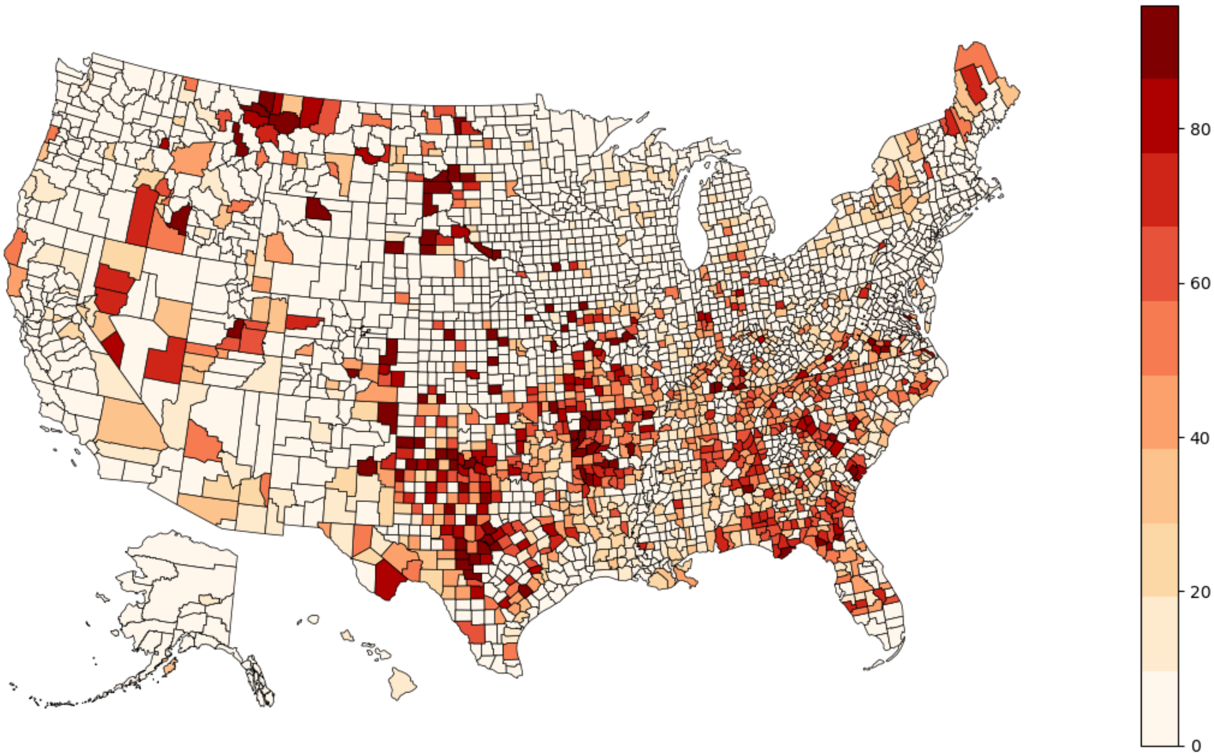


Figure 5. Structurally Tight Labor Market Counties

This figure displays the number of months between 2016 and 2023 that each US county's labor market is considered "structurally tight". Counties are considered structurally tight if (a) the labor force per capita is below the sample mean (46.8%) and (b) the unemployment rate is below the sample mean (5.6%).

Table I – Summary Statistics

This table displays summary statistics of the bond issuance sample (Panel A), the employment data sample (Panel B) and the local government finance sample (Panel C). The unit of observation is a municipal bond issue (Panel A), a county-month (Panel C), or a county-year (Panel C).

In Panels A and B, *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a country and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. *Unemployment* (*Labor force per capita*) is the average unemployment rate (labor force per capita) over the previous two years. *Structurally tight* is an indicator variable taking a value of one if *Unemployment* and *Labor force per capita* are both below sample means in the employment sample. Unemployment and labor force data are from the Bureau of Labor Statistics. *Sanctuary* is an indicator variable taking a value of one in years during which a county designates itself as a sanctuary county, and zero before. Data on sanctuary status are from the Center for Immigration Studies.

In Panel A, *Spread* is the difference between a bond's offer yield and the yield on a duration-matched treasury security. Offer yields are from the Mergent Municipal Bond database and zero-coupon treasury yields are from Bloomberg and Refinitiv. *Competitive* is an indicator taking a value of one if the bond is issued through a competitive process, and zero if it issued through a negotiated process or other process. *Coupon* is the bond's coupon. *Amount* is the bond's issue size in millions of dollars. We take the natural log of this variable. *Duration* is the bond's duration measured in years. *Callable* is an indicator variable taking a value of one if the bond is callable and zero otherwise. *Insured* is an indicator variable taking a value of one if the bond is wrapped with third party insurance and zero otherwise. *GO* is an indicator variable if a bond is a general obligation bond, and zero if it is a revenue bond or other type. *Refunding* is an indicator variable taking a value of one if the bond is issued to refund an existing bond and zero otherwise. Bond characteristics are from the Mergent Municipal Bond database and the S&P IPREO iDeal database. *Population* is county population measured in millions of people. We take the natural log of this variable. *Household income* is the county median household income measured in thousands of dollars. *Gini* is the county's gini coefficient. *Poverty* is the percentage of households living below the poverty line. *College educated* is the percentage of adults over the age of 25 in a county with at least a four-year college degree. Data on population, household income, gini coefficients, poverty rates, and education are from U.S. Census ACS 5-year surveys.

In Panel C, *Total revenue* is the sum of local government revenues not arising from utilities, liquor stores, or social insurance. *Total taxes* is the sum of tax revenue from all tax categories. *Property tax* is all taxes on property that use its value as a basis. *Total select sales tax* is the sum of the eight selective sales tax categories, including alcoholic beverages, amusement, insurance premiums, motor fuel, pari-mutuels, public utilities, tobacco, and other selective sales taxes. *Total other capital outlays* is outlays on equipment other than construction with at least a one-year durability. *Total assist subsidies* is total assistance and subsidies. *Total educ total exp* is total education expenditures, including elementary, secondary, and higher education. *Total educ direct exp* is total direct expenditures on education, such as salaries, supplies, etc., including elementary, secondary, and higher education. *Total educ current exp* is total current education expenditures, including elementary, secondary, and higher education. *Public welf cash asst* is aggregate public welfare cash assistance (sum of all welfare categories). *Public welf cap outlay* is aggregate public welfare capital expenditures. *Welfare categ total exp* is federal categorial expenditure from three programs: Supplementary Security Income (SSI), Temporary Assistance for Needy Family (TANF), and Medicaid. *Welfare categ cash assist* is federal categorical cash assistance. *Welfare categ ig to state* is federal categorical payments to the state. *Welfare ins total exp* is public welfare institutions expenditures, including public nursing homes, veterans' homes, orphanages, homes for the elderly or aged, and indigent care institutions. It excludes hospitals or privately operated welfare institutions. *Welfare ins cap outlay* is capital outlays for public welfare institutions. *Welfare ins current exp* is current expenditures for public welfare institutions. *Welfare ins construction* is construction for public welfare institutions. *General construction* is construction of general public buildings (e.g., county offices, city halls, etc.). It excludes schools, police buildings, and libraries. *General construction capital outlay* other is capital outlays for general public use. *Police prot cap outlay* is capital outlays for police. *Police prot ig to sta* is payments to the state for police services. Variables in Panel C are from the Government Finance Database curated by Willamette University.

Panel I.A – Bond Sample

Variable	Obs	Mean	Std. dev.	P25	P50	P75
Predicted immigration	1,035,486	0.044%	0.060%	0.009%	0.024%	0.055%
Unemployment	1,035,486	4.878	1.699	3.708	4.613	5.733
Labor force per capita	1,035,486	51.179	5.236	48.358	51.388	54.387
Structurally tight	1,035,486	0.216	0.412	0.000	0.000	0.000
Sanctuary	1,035,486	0.332	0.471	0.000	0.000	1.000
Spread	1,035,486	0.166	0.692	-0.233	0.145	0.556
Competitive	1,035,486	0.528	0.499	0.000	1.000	1.000
Coupon	1,035,486	3.505	1.303	2.500	3.625	5.000
Amount	1,035,486	13.483	1.547	12.468	13.353	14.425
Duration	1,035,486	7.888	4.491	4.244	7.532	11.231
Callable	1,035,486	0.481	0.500	0.000	0.000	1.000
Insured	1,035,486	0.198	0.398	0.000	0.000	0.000
GO	1,035,486	0.592	0.492	0.000	1.000	1.000
Refunding	1,035,486	0.462	0.499	0.000	0.000	1.000
Population	1,035,486	12.679	1.625	11.599	12.874	13.763
Household income	1,035,486	69.563	20.561	54.751	65.377	81.154
Gini	1,035,486	0.418	0.025	0.403	0.417	0.431
Poverty	1,035,486	0.131	0.049	0.094	0.127	0.161
College educated	1,035,486	0.204	0.063	0.156	0.203	0.247

Panel I.B – Employment Sample

Variable	Obs.	Mean	St. dev.	P25	P50	P75
Predicted immigration	32,164	0.022%	0.053%	0.002%	0.007%	0.021%
Unemployment	32,164	5.553	2.569	3.829	5.025	6.638
Labor force per capita	32,164	46.806	9.764	41.933	47.082	51.927
Structurally tight	32,164	0.280	0.449	0.000	0.000	1.000
Sanctuary	32,164	0.133	0.339	0.000	0.000	0.000

Panel I.C – Local Government Finance Sample (Thousands $)

Variable	Obs.	Mean	St. dev.	P25	P50	P75
Total revenue	25,090	572,656	3,078,627	46,481	109,285	302,534
Total taxes	25,090	231,406	1,365,860	13,968	35,130	103,192
Property tax	25,090	166,943	788,727	10,630	26,042	77,154
Total select sales tax	25,090	11,037	78,120	182	817	3,303
Total other capital outlays	25,090	11,968	53,519	580	2,130	7,091
Total assist subsidies	25,090	3,332	49,930	0	0	0
Total educ total exp	25,090	240,920	997,427	22,007	51,348	144,468
Total educ direct exp	25,090	235,068	981,343	21,405	50,015	141,308
Total educ current exp	25,090	210,902	884,979	19,322	44,959	126,354
Public welf cash asst	25,090	3,237	49,828	0	0	0
Public welf cap outlay	25,090	145	2,268	0	0	0
Welfare categ total exp	25,090	3,599	116,200	0	0	0
Welfare categ cash assist	25,090	1,177	26,226	0	0	0
Welfare categ ig to state	25,090	2,421	100,892	0	0	0
Welfare ins total exp	25,090	1,068	6,009	0	0	0
Welfare ins cap outlay	25,090	10	156	0	0	0
Welfare ins current exp	25,090	1,057	5,975	0	0	0
Welfare ins construction	25,090	6	132	0	0	0
General construction	25,090	47,333	257,619	1,825	6,423	22,593
General capital outlay other	25,090	10,702	41,258	555	1,993	6,524
Police prot cap outlay	25,090	1,192	6,569	13	117	508
Police prot ig to sta	25,090	2	42	0	0	0

Table II – Shift-share Predicted versus Actual Unauthorized Immigration

This table displays results from a regression with actual unauthorized immigration as the dependent variable and unauthorized immigration predicted by a shift-share measure as the independent variable. Each observation represents a U.S. county and year-month. Actual unauthorized immigration is the number of individuals with a Notice to Appear (NTA) in immigration court for unauthorized entry into the United States over the previous 12 months. We compute the shift-share measure as follows:

$$Shiftshare\ prediction_{j,t} = \sum_i Unauthorized\ immigration_{i,t} \times FBShare_{i,j,t-1}$$

where j is U.S. county, t is year-month, and i is source country. $Unauthorized\ immigration_{i,t}$ is the total number of unauthorized immigrants entering the U.S. from country i over the previous twelve months. $FBShare_{i,j,t-1}$ is foreign-born share, the percentage of county j's population that was born in country i, lagged one calendar year. County foreign born population data are from the Census ACS 5-year survey. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. County foreign born population data are from the Census ACS 5-year survey. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. The standard error clustered by county appears below the coefficient estimate. *** indicates statistical significance at the 1% level.

	(1)
Shift-share prediction	0.9143***
	(0.0100)
N	54,128
R^2	0.8699

Table III – Country Push Factors that Explain Unauthorized Immigration to the United States

This table displays regression results with annual unauthorized immigration from a country to the United States as the dependent variable. We include data from the top twenty countries supplying immigrants to the United States, including China, Columbia, Dominican Republic, Ecuador, El Salvador, Guatemala, Guinea, Haiti, Honduras, India, Mauritania, Mexico, Nicaragua, Peru, Russia, Senegal, Turkey, and Venezuela. We take the log of each country's annual immigration count. Data are from the World Bank.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	12.62***	11.17**	14.64**	10.62*	17.95***	14.35**	19.95***	15.62**
	(4.82)	(4.70)	(6.40)	(5.97)	(6.43)	(6.22)	(7.05)	(6.41)
Death rate	0.18	0.12	0.58***	-0.03	0.41**	-0.03	0.60***	-0.24
	(0.14)	(0.20)	(0.20)	(0.24)	(0.19)	(0.26)	(0.23)	(0.27)
GDP growth	0.11***	0.07***	0.07**	0.03	0.19***	0.08*	0.21***	0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.07)	(0.07)
Inflation	0.08***	0.04***	0.09***	0.01	0.10***	0.03**	0.05*	0.01
	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Labor force participation	-0.07	-0.05	-0.16*	-0.03	-0.19*	-0.08	-0.23**	-0.08
	(0.08)	(0.07)	(0.10)	(0.09)	(0.10)	(0.10)	(0.11)	(0.10)
Stability percentile	-0.06**	-0.05***	-0.04	-0.03	-0.08***	-0.06**	-0.08**	-0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R-sq	0.85	0.89	0.73	0.85	0.76	0.86	0.70	0.84

Table IV – Unauthorized Immigration and Municipal Bond Yields

Panel A presents regressions of municipal bond yield spreads on predicted unauthorized push immigration quintiles, bond controls, and county controls as well as issuer and year-month fixed effects. Newly issued bonds from County, City, and other bond issuers within a single county are included. Bonds yields are matched to zero-coupon treasury yields with the same duration as the bond. *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a county and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. Panel A measures predicted immigration with quintiles; Panel B uses a continuous measure. County foreign born population and other data are from the Census ACS 5-year survey, lagged by one year. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Bond data are from the Mergent and IPREO iDeal Databases. Treasury Yield data are from Refinitiv and Bloomberg. Results are presented for All issuers, Cities, and Counties, and by All, General Obligation (GO) and Revenue (REV) bonds. Standard errors clustered by county are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Panel A –Predicted Unauthorized Immigration Quintiles

Issuer:	ALL ISSUERS			CITY ISSUERS			COUNTY ISSUERS		
Bond type:	ALL	GO	REV	ALL	GO	REV	ALL	GO	REV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pred. imm. quint. 2	0.0187	0.0274*	0.0113	0.0213	0.0274	0.0172	0.0113	0.0321	-0.0166
	(0.0119)	(0.0161)	(0.0202)	(0.0142)	(0.0181)	(0.0274)	(0.0219)	(0.0300)	(0.0344)
Pred. imm. quint. 3	0.0172	0.0141	0.0325	0.0191	0.0163	0.0332	0.00974	0.0248	-0.00796
	(0.0134)	(0.0178)	(0.0229)	(0.0161)	(0.0205)	(0.0293)	(0.0249)	(0.0322)	(0.0410)
Pred. imm. quint. 4	0.0111	0.0109	0.0246	0.0209	0.0213	0.0266	0.0103	0.0225	0.00394
	(0.0150)	(0.0201)	(0.0245)	(0.0185)	(0.0242)	(0.0317)	(0.0274)	(0.0351)	(0.0468)
Pred. imm. quint. 5	0.0137	0.0197	0.0183	0.0334*	0.0316	0.0494	0.00284	0.0373	-0.0445
	(0.0165)	(0.0223)	(0.0264)	(0.0202)	(0.0262)	(0.0349)	(0.0320)	(0.0402)	(0.0527)

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Table IV Panel A - continued from previous page									
Competitive	-0.0581***	-0.0870***	-0.00718	-0.0432***	-0.0824***	0.0395	-0.0621***	-0.0803***	-0.0215
	(0.00955)	(0.00801)	(0.0186)	(0.0132)	(0.00899)	(0.0279)	(0.0161)	(0.0148)	(0.0264)
Coupon	-0.0204***	-0.0416***	0.0111	-0.0305***	-0.0522***	0.00835	-0.0278***	-0.0283***	-0.0296***
	(0.00525)	(0.00467)	(0.00796)	(0.00767)	(0.00525)	(0.0130)	(0.00628)	(0.00629)	(0.0103)
Amount	0.00315	-0.00270	0.0145***	0.0142***	0.00555*	0.0351***	0.00379	-0.00309	0.0171***
	(0.00240)	(0.00243)	(0.00433)	(0.00295)	(0.00299)	(0.00571)	(0.00336)	(0.00355)	(0.00464)
Duration	0.0468***	0.0508***	0.0403***	0.0453***	0.0493***	0.0369***	0.0507***	0.0528***	0.0464***
	(0.000977)	(0.000676)	(0.00184)	(0.00145)	(0.000767)	(0.00307)	(0.00121)	(0.00136)	(0.00188)
Callable	0.106***	0.0667***	0.151***	0.104***	0.0675***	0.159***	0.0800***	0.0622***	0.115***
	(0.00683)	(0.00467)	(0.0114)	(0.0104)	(0.00664)	(0.0184)	(0.00645)	(0.00581)	(0.0158)
Insured	-0.0575***	-0.0831***	0.00448	-0.0146	-0.0116	-0.00558	-0.137***	-0.169***	0.0144
	(0.0201)	(0.0263)	(0.0186)	(0.0162)	(0.0197)	(0.0232)	(0.0392)	(0.0417)	(0.0467)
GO	0.00509			0.00944			-0.00252		
	(0.00932)			(0.0126)			(0.0155)		
Refunding	0.0278***	0.0325***	0.0115	0.0348***	0.0326***	0.0280	0.0417***	0.0430***	0.0271*
	(0.00560)	(0.00589)	(0.0109)	(0.00813)	(0.00849)	(0.0190)	(0.00730)	(0.00771)	(0.0164)
Population	-0.00747**	-0.0110**	-0.00492	-0.00559*	-0.00861*	-0.00309	-0.106	-0.560***	0.0192
	(0.00352)	(0.00554)	(0.00457)	(0.00311)	(0.00444)	(0.00470)	(0.0809)	(0.102)	(0.0769)
Household income	-0.00303***	-0.00348***	-0.00191	-0.00259***	-0.00247**	-0.00303**	-0.00571***	-0.00593***	-0.000715
	(0.000816)	(0.000864)	(0.00125)	(0.000948)	(0.000983)	(0.00153)	(0.00154)	(0.00145)	(0.00310)
Gini	-0.0951	-0.122	-0.211	-0.235	-0.385	0.178	-0.231	-0.371	-0.0942
	(0.234)	(0.264)	(0.360)	(0.282)	(0.315)	(0.505)	(0.368)	(0.422)	(0.669)
Poverty	-0.0581	0.128	-0.0334	0.0458	0.278	-0.450	0.486	0.618	0.578
	(0.212)	(0.232)	(0.323)	(0.269)	(0.272)	(0.448)	(0.343)	(0.398)	(0.606)
College educated	0.219	0.139	0.354	0.367*	0.356	0.492*	0.0109	-1.067**	-0.121
	(0.183)	(0.252)	(0.238)	(0.211)	(0.282)	(0.285)	(0.403)	(0.508)	(0.752)
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,034,693	612,428	422,122	560,323	355,401	204,812	250,616	165,508	85,080
Adj. R-sq	0.753	0.763	0.740	0.764	0.756	0.779	0.788	0.786	0.795

Panel B –Predicted Unauthorized Immigration Continuous Measure

Issuer:	ALL			CITY			COUNTY		
Bond type:	ALL	GO	REV	ALL	GO	REV	ALL	GO	REV
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Pred. imm. pct	-4.374	4.883	-8.020	-3.819	-9.617	15.62	20.07**	27.94***	-9.338
	(8.777)	(12.80)	(11.43)	(8.363)	(12.14)	(12.41)	(8.516)	(7.295)	(19.25)
Bond controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Issuer FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,034,693	612,428	422,122	560,323	355,401	204,812	250,616	165,508	85,080
Adj. R-sq	0.753	0.763	0.740	0.764	0.756	0.779	0.788	0.786	0.795

Table V – Unauthorized Immigration and Municipal Bond Yields in Structurally Tight Labor Markets

The table presents regressions of municipal bond yield spreads on predicted unauthorized push immigration quintiles, a tight county indicator, interactions between the quintiles and the tight indicator, bond controls, and county controls as well as issuer and year-month fixed effects. Newly issued bonds from County, City, and other bond issuers within a single county are included. Bonds yields are matched to zero-coupon treasury yields with the same duration as the bond. *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a county and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. The *Tight County* indicator is equal to 1 if (a) the two-year trailing average unemployment rate is below the sample average and (b) the trailing two-year average labor force-to-population ratio is below the sample average. County foreign born population and other data are from the U.S. Census ACS 5-year survey, lagged by one year. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Bond data are from the Mergent and IPREO iDeal Databases. Treasury yield data are from Refinitiv and Bloomberg. Unemployment and labor force data are from the Bureau of Labor Statistics. Results are presented for All issuers, Cities, Counties, and by All, General Obligation (GO) and Revenue (REV) bonds. Standard errors clustered by county are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Panel V.A – Regression Coefficients

Issuer:	ALL ISSUERS			CITY ISSUERS			COUNTY ISSUERS		
Bond type:	ALL	GO	REV	ALL	GO	REV	ALL	GO	REV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Structurally tight	0.0555***	0.0573**	0.0346	0.0751***	0.0654**	0.0870*	0.0603*	0.0341	0.110*
	(0.0206)	(0.0242)	(0.0365)	(0.0261)	(0.0299)	(0.0495)	(0.0365)	(0.0441)	(0.0662)
Pred. imm. quint. 2	0.0287**	0.0361**	0.0128	0.0378**	0.0369*	0.0456	0.0167	0.0329	-0.0196
	(0.0137)	(0.0181)	(0.0244)	(0.0156)	(0.0196)	(0.0303)	(0.0250)	(0.0362)	(0.0386)
Pred. imm. quint. 3	0.0365**	0.0329*	0.0423	0.0426**	0.0323	0.0647*	0.0297	0.0395	0.0199
	(0.0150)	(0.0194)	(0.0267)	(0.0177)	(0.0219)	(0.0336)	(0.0267)	(0.0369)	(0.0460)
Pred. imm. quint. 4	0.0330**	0.0313	0.0427	0.0508**	0.0418	0.0711**	0.0307	0.0303	0.0447
	(0.0165)	(0.0217)	(0.0276)	(0.0200)	(0.0257)	(0.0352)	(0.0295)	(0.0394)	(0.0508)
Pred. imm. quint. 5	0.0394**	0.0418*	0.0419	0.0693***	0.0575**	0.100***	0.0230	0.0465	-0.00874
	(0.0177)	(0.0238)	(0.0287)	(0.0217)	(0.0276)	(0.0381)	(0.0334)	(0.0441)	(0.0559)
Tight × PI quint. 2	-0.0329	-0.0318	-0.000578	-0.0543*	-0.0402	-0.0681	-0.0150	0.00391	-0.0125
	(0.0231)	(0.0286)	(0.0420)	(0.0291)	(0.0360)	(0.0556)	(0.0404)	(0.0500)	(0.0752)
Tight × PI quint. 3	-0.0684***	-0.0714**	-0.0312	-0.0750**	-0.0627*	-0.0698	-0.0637	-0.0453	-0.0996
	(0.0237)	(0.0278)	(0.0421)	(0.0297)	(0.0356)	(0.0556)	(0.0418)	(0.0488)	(0.0742)
Tight × PI quint. 4	-0.0785***	-0.0760***	-0.0659*	-0.102***	-0.0813**	-0.125**	-0.0657	-0.0236	-0.142**
	(0.0224)	(0.0267)	(0.0394)	(0.0282)	(0.0328)	(0.0533)	(0.0400)	(0.0482)	(0.0713)
Tight × PI quint. 5	-0.0961***	-0.0862***	-0.0862**	-0.130***	-0.109***	-0.148**	-0.0663*	-0.0293	-0.125*
	(0.0237)	(0.0271)	(0.0401)	(0.0304)	(0.0319)	(0.0574)	(0.0394)	(0.0467)	(0.0687)
Bond Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,034,693	612,428	422,122	560,323	355,401	204,812	250,616	165,508	85,080
Adj. R-sq	0.753	0.764	0.740	0.765	0.756	0.779	0.788	0.786	0.795

Panel V.B – F-tests of summed regression coefficients from Panel V.A

Issuer:	ALL ISSUERS			CITY ISSUERS			COUNTY ISSUERS		
Bond type:	ALL	GO	REV	ALL	GO	REV	ALL	GO	REV
Sum of coefficients	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI quint. 2 + Tight × PI quint. 2	-0.0042	0.0042	0.0122	-0.0166	-0.0033	-0.0225	0.0017	0.0368	-0.0321
	(0.0201)	(0.0255)	(0.0349)	(0.0266)	(0.0337)	(0.0493)	(0.0356)	(0.0425)	(0.0658)
PI quint. 3 + Tight × PI quint. 3	-0.0319	-0.0385	0.0111	-0.0324	-0.0304	-0.00511	-0.0340	-0.00580	-0.0797
	(0.0217)	(0.0265)	(0.0367)	(0.0275)	(0.0344)	(0.0478)	(0.0399)	(0.0447)	(0.0674)
PI quint. 4 + Tight × PI quint. 4	-0.0455**	-0.0447*	-0.0232	-0.0510**	-0.0396**	-0.0539	-0.0350	0.00674	-0.0971
	(0.0214)	(0.0267)	(0.0364)	(0.0276)	(0.0340)	(0.0483)	(0.0397)	(0.0464)	(0.0697)
PI quint. 5 + Tight × PI quint. 5	-0.0567**	-0.0444	-0.0442	-0.0605**	-0.0516	-0.0477	-0.0433	0.0172	-0.134*
	(0.0238)	(0.0289)	(0.0391)	(0.0307)	(0.0356)	(0.0536)	(0.0431)	(0.0488)	(0.0722)

Table VI – Unauthorized Immigration and Municipal Bond Yields in Sanctuary Counties

The table presents regressions of municipal bond yield spreads on predicted unauthorized push immigration quintiles, a sanctuary county indicator, interactions between the quintiles and the sanctuary county indicator, bond controls, and county controls as well as issuer and year-month fixed effects. Newly issued bonds from County, City, and other bond issuers within a single county are included. Bonds yields are matched to zero-coupon treasury yields with the same duration as the bond. *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a county and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. The sanctuary indicator is equal to 1 if the county is designated as a "sanctuary county" as of the bond issuance date. County foreign born population and other data are from the Census ACS 5-year survey, lagged by one year. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Bond data are from the Mergent and IPREO iDeal Databases. Treasury yield data are from Refinitiv and Bloomberg. Sanctuary county status is from the Center for Immigration Studies. Unemployment and labor force data are from the Bureau of Labor Statistics. Results are presented for All issuers, Cities, Counties, and by All, General Obligation (GO) and Revenue (REV) bonds. Standard errors clustered by county are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level of significance, respectively.

Panel VI.A – Regression Coefficients

Issuer:	ALL ISSUERS			CITY ISSUERS			COUNTY ISSUERS		
Bond type:	ALL	GO	REV	ALL	GO	REV	ALL	GO	REV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sanctuary	-0.0950**	-0.0960	-0.153***	-0.160***	-0.229***	-0.0521	-0.128	-0.130	-0.204**
	(0.0480)	(0.0620)	(0.0489)	(0.0528)	(0.0753)	(0.0633)	(0.0932)	(0.110)	(0.0998)
Pred. imm. quint. 2	0.0171	0.0262	0.00914	0.0204	0.0243	0.0173	0.00798	0.0313	-0.0197
	(0.0122)	(0.0167)	(0.0206)	(0.0145)	(0.0187)	(0.0275)	(0.0223)	(0.0309)	(0.0344)
Pred. imm. quint. 3	0.0116	0.00663	0.0274	0.0151	0.00869	0.0337	0.00317	0.0175	-0.00983
	(0.0136)	(0.0183)	(0.0226)	(0.0164)	(0.0209)	(0.0296)	(0.0256)	(0.0332)	(0.0413)
Pred. imm. quint. 4	0.0118	0.00858	0.0241	0.0145	0.00887	0.0300	0.0129	0.0220	0.0121
	(0.0153)	(0.0206)	(0.0247)	(0.0185)	(0.0241)	(0.0320)	(0.0280)	(0.0359)	(0.0494)
Pred. imm. quint. 5	0.00765	0.0143	0.00870	0.0245	0.0181	0.0515	-0.00480	0.0250	-0.0392
	(0.0173)	(0.0233)	(0.0271)	(0.0210)	(0.0270)	(0.0356)	(0.0329)	(0.0416)	(0.0551)
Sanctuary × PI quint. 2	0.0409	0.0336	0.0774	0.0252	0.0793	-0.0193	0.0651	0.000324	0.359***
	(0.0455)	(0.0583)	(0.0613)	(0.0434)	(0.0650)	(0.164)	(0.0967)	(0.111)	(0.135)
Sanctuary × PI quint. 3	0.0826*	0.0949	0.107*	0.127**	0.204***	-0.00250	0.0931	0.0718	0.200*
	(0.0499)	(0.0621)	(0.0605)	(0.0553)	(0.0762)	(0.0878)	(0.0958)	(0.111)	(0.109)
Sanctuary × PI quint. 4	0.0520	0.0727	0.0852	0.142**	0.231***	-0.0208	0.0479	0.0251	0.159
	(0.0506)	(0.0638)	(0.0549)	(0.0592)	(0.0792)	(0.0736)	(0.0945)	(0.113)	(0.104)
Sanctuary × PI quint. 5	0.0780	0.0857	0.118**	0.154***	0.235***	-0.0130	0.102	0.0975	0.166
	(0.0490)	(0.0624)	(0.0521)	(0.0544)	(0.0763)	(0.0690)	(0.0951)	(0.112)	(0.104)
Bond Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,034,693	612,428	422,122	560,323	355,401	204,812	250,616	165,508	85,080
Adj. R-sq	0.753	0.763	0.740	0.764	0.756	0.779	0.788	0.786	0.795

Panel VI.B – F-tests of summed regression coefficients from Panel VI.A

Issuer:	ALL ISSUERS			CITY ISSUERS			COUNTY ISSUERS		
Bond type:	ALL	GO	REV	ALL	GO	REV	ALL	GO	REV
Sum of coefficients	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PI quint. 2 + Sanctuary × PI quint. 2	0.0581	0.0597	0.0865	0.0456	0.104	-0.00199	0.0731	0.0316	0.339**
	(0.0439)	(0.0562)	(0.0582)	(0.0409)	(0.0621)	(0.164)	(0.0949)	(0.109)	(0.133)
PI quint. 3 + Sanctuary × PI quint. 3	0.0941*	0.102*	0.134**	0.142***	0.213***	0.0312	0.0963	0.0893	0.190*
	(0.0484)	(0.0602)	(0.0576)	(0.0534)	(0.0736)	(0.0825)	(0.0928)	(0.107)	(0.108)
PI quint. 4 + Sanctuary × PI quint. 4	0.0638	0.0812	0.109**	0.157***	0.240***	0.00912	0.0608	0.0471	0.171
	(0.0492)	(0.0622)	(0.0520)	(0.0578)	(0.0774)	(0.0692)	(0.0924)	(0.109)	(0.104)
PI quint. 5 + Sanctuary × PI quint. 5	0.0857*	0.1000	0.127**	0.179***	0.253***	0.0385	0.0970	0.122	0.126
	(0.0483)	(0.0616)	(0.0509)	(0.0540)	(0.0751)	(0.0659)	(0.0942)	(0.110)	(0.107)

Table VII – Unauthorized Immigration and Employment Outcomes

This table displays results from regressions of future employment measures on predicted unauthorized immigration quintiles as well as measures of structurally tight labor markets, sanctuary county status, and interactions of those two with the immigration quintiles. Future employment outcomes are 2-year average unemployment rates, 2-year average labor force rates, and a measure of structurally tight labor markets over the next 2-years. *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a county and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. The *Tight County* indicator is equal to 1 if (a) the two-year trailing average unemployment rate is below the sample average and (b) the trailing two-year average labor force-to-population ratio is below the sample average. The sanctuary indicator is equal to 1 if the county is designated as a "sanctuary county" as of the bond issuance date. County foreign born population and other data are from the Census ACS 5-year survey, lagged by one year. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Bond data are from the Mergent and IPREO iDeal Databases. Treasury Yield data are from Refinitiv and Bloomberg. Unemployment and Labor Force data are from the Bureau of Labor Statistics. Sanctuary county status is from the Center for Immigration Studies. County and year-month fixed effects are included in the regressions. Standard errors clustered by county are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel VII.A – Future Unemployment, Labor Force, and Structural Tightness

	Unemployment rate t+1			Labor force per capita t+1			Tight t+1		
Categorical variable:	---	Tight	Sanctuary	---	Tight	Sanctuary	---	Tight	Sanctuary
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Category (tight/sanctuary)		0.0273	0.160**		-0.751	-0.841		-0.104***	0.0323
		(0.0329)	(0.0766)		(0.491)	(0.705)		(0.0173)	(0.0290)
Pred. imm. quint. 2	0.0186	0.00519	0.0166	-0.594	-0.757	-0.583	-0.00213	0.0112	-0.00549
	(0.0226)	(0.0261)	(0.0232)	(0.473)	(0.558)	(0.495)	(0.0110)	(0.0117)	(0.0114)
Pred. imm. quint. 3	-0.00281	-0.0225	-0.0170	-0.846	-1.014	-0.862	0.00410	0.0223*	0.00515
	(0.0277)	(0.0314)	(0.0286)	(0.701)	(0.798)	(0.727)	(0.0128)	(0.0135)	(0.0132)
Pred. imm. quint. 4	0.0396	-0.00504	0.0166	-1.106	-1.383	-1.144	-0.0242	0.00181	-0.0204
	(0.0325)	(0.0356)	(0.0332)	(1.089)	(1.251)	(1.151)	(0.0148)	(0.0154)	(0.0154)
Pred. imm. quint. 5	0.0853**	0.00623	0.0407	-0.712	-0.907	-0.750	-0.0240	0.0155	-0.0123
	(0.0394)	(0.0430)	(0.0403)	(1.105)	(1.223)	(1.152)	(0.0177)	(0.0182)	(0.0182)
Category × PI quint. 2		0.0557	0.0622		0.654*	-0.144		-0.0549**	0.0440
		(0.0363)	(0.0782)		(0.362)	(0.461)		(0.0218)	(0.0322)
Category × PI quint. 3		0.0843**	0.266***		0.677*	0.106		-0.0782***	-0.00770
		(0.0390)	(0.0834)		(0.410)	(0.525)		(0.0219)	(0.0356)
Category × PI quint. 4		0.167***	0.388***		1.058*	0.255		-0.0963***	-0.0360
		(0.0404)	(0.0952)		(0.636)	(0.776)		(0.0217)	(0.0358)
Category × PI quint. 5		0.285***	0.615***		0.780	0.284		-0.147***	-0.117***
		(0.0491)	(0.108)		(0.491)	(0.672)		(0.0236)	(0.0378)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	25,733	25,733	25,733	25,733	25,733	25,733	25,733	25,733	25,733
Adj. R-sq	0.880	0.880	0.881	0.668	0.668	0.668	0.515	0.529	0.515

Panel VII.B – F-tests of summed regression coefficients from Panel VII.A

	Unemployment rate t+1		Labor force per capita t+1		Structurally tight t+1	
Categorical variable:	Tight	Sanctuary	Tight	Sanctuary	Tight	Sanctuary
Sum of coefficients	(2)	(3)	(5)	(6)	(8)	(9)
PI quint. 2 + Category × PI quint. 2	0.0609*	0.0787	-0.103	-0.728**	-0.0292	0.0359
	(0.0313)	(0.0763)	(0.237)	(0.345)	(0.0184)	(0.0277)
PI quint. 3 + Category × PI quint. 3	0.0618*	0.249***	-0.337	-0.757*	-0.0364*	-0.0054
	(0.0354)	(0.0814)	(0.422)	(0.438)	(0.0188)	(0.0310)
PI quint. 4 + Category × PI quint. 4	0.162***	0.405***	-0.326	-0.889	-0.0581***	-0.0277
	0.0406	0.0942	0.640	0.549	0.0199	0.0318
PI quint. 5 + Category × PI quint. 5	0.291***	0.656***	-0.127	-0.466	-0.0827***	-0.0617*
	(0.0500)	(0.108)	(0.768)	(0.668)	(0.0219)	(0.0365)

Table VIII – Unauthorized Immigration and Municipal Revenues and Taxes

This table displays results from regressions of local government finance on predicted unauthorized immigration quintiles. Measures of local government finance include annual revenues, taxes, and expenditures. Panel A uses logged values as dependent variables. Panel B uses per capita values as dependent variables. *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a county and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. County foreign-born population and other data are from the Census ACS 5-year survey, lagged by one year. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Standard errors clustered by county are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Total revenue		Total taxes		Property tax		Total select sales tax	
Horizon:	1-year	2-year	1-year	2-year	1-year	2-year	1-year	2-year
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pred. imm. quint. 2	0.001	-0.002	0.000	0.002	0.006	0.006	0.004	-0.016
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.033)	(0.031)
Pred. imm. quint. 3	0.001	-0.002	0.008	0.004	0.009	0.004	-0.030	-0.052
	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.039)	(0.037)
Pred. imm. quint. 4	0.004	0.001	0.004	0.003	0.005	0.003	-0.070*	-0.091**
	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.041)	(0.039)
Pred. imm. quint. 5	0.007	0.002	0.000	-0.001	0.003	-0.001	-0.101**	-0.124***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.049)	(0.047)
County FE?	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
N	25,090	25,090	25,090	25,090	25,090	25,090	25,090	25,090
R-squared	0.995	0.996	0.994	0.996	0.994	0.995	0.935	0.953

Table IX – Unauthorized Immigration and Municipal Expenditures

This table displays results from regressions of local government finance on predicted unauthorized immigration quintiles. Measures of local government finance include annual revenues, taxes, and expenditures. Panels A and B use logged values as dependent variables. Panel C uses per capita values as dependent variables. *Predicted immigration* is the predicted number of unauthorized immigrants to a county in the previous 12 months divided by the county population. We predict immigration as the sum of the product of the county share of foreign-born residents from a county and the predicted number of unauthorized immigrants from the same country over the previous year based on "push" factors from the country. The latter come from specification (7) in Table III. County foreign born population and other data are from the Census ACS 5-year survey, lagged by one year. Unauthorized immigration data are from the Syracuse Transactional Records Access Clearinghouse (TRAC) Notice to Appear (NTA) data. Standard errors clustered by county are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel IX.A – Welfare Expenditures (Excluding Capital Outlays and Construction)

	Public welf cash asst		Welf categ total exp		Welf categ cash assist		Welf categ ig to state	
Horizon:	1-year	2-year	1-year	2-year	1-year	2-year	1-year	2-year
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pred. imm. quint. 2	-0.002	-0.007	-0.029	-0.026	-0.027	-0.026	-0.009	0.000
	(0.030)	(0.026)	(0.028)	(0.024)	(0.028)	(0.024)	(0.007)	(0.003)
Pred. imm. quint. 3	-0.014	0.011	-0.022	-0.013	-0.022	-0.014	-0.007	0.001
	(0.037)	(0.028)	(0.036)	(0.030)	(0.035)	(0.030)	(0.013)	(0.004)
Pred. imm. quint. 4	-0.000	0.009	0.045	0.023	0.044	0.024	0.024*	0.007*
	(0.044)	(0.034)	(0.040)	(0.032)	(0.039)	(0.032)	(0.014)	(0.004)
Pred. imm. quint. 5	0.103*	0.037	0.103**	0.042	0.095*	0.042	0.038***	0.008**
	(0.056)	(0.046)	(0.049)	(0.045)	(0.048)	(0.045)	(0.015)	(0.004)
County FE?	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
N	25,090	25,090	25,090	25,090	25,090	25,090	25,090	25,090
R-squared	0.803	0.945	0.724	0.859	0.711	0.842	0.830	0.975

Panel IX.B – Welfare Institutions Expenditures and Federal Cash Assistance

	Public welf cash asst		Welf categ total exp		Welf categ cash assist	
Horizon:	1-year	2-year	1-year	2-year	1-year	2-year
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Pred. imm. quint. 2	0.056	0.045	0.052	0.043	0.015	-0.005
	(0.038)	(0.037)	(0.038)	(0.036)	(0.034)	(0.030)
Pred. imm. quint. 3	0.036	0.047	0.029	0.042	0.018	0.000
	(0.041)	(0.039)	(0.041)	(0.038)	(0.039)	(0.033)
Pred. imm. quint. 4	0.118**	0.115**	0.106**	0.109**	0.043	0.037
	(0.047)	(0.045)	(0.047)	(0.044)	(0.047)	(0.041)
Pred. imm. quint. 5	0.131**	0.134**	0.112**	0.119**	0.135**	0.058
	(0.056)	(0.054)	(0.056)	(0.053)	(0.061)	(0.056)
County FE?	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y
N	25,090	25,090	25,090	25,090	25,090	25,090
R-squared	0.852	0.881	0.852	0.880	0.798	0.886

Panel IX.C: Construction and Capital Outlays (Excluding Police)

	General construction		Gen capital outlay other		Welf ins construction		Welf ins cap outlay		Public welf cap outlay	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1-year	2-year	1-year	2-year	1-year	2-year	1-year	2-year	1-year	2-year
Pred. imm. quint. 2	0.021	0.012	0.049*	0.014	0.028	0.021	0.042**	0.023	0.049	0.040
	(0.036)	(0.033)	(0.027)	(0.019)	(0.017)	(0.017)	(0.017)	(0.018)	(0.031)	(0.031)
Pred. imm. quint. 3	0.007	0.006	0.058*	-0.003	0.032	0.031*	0.020	0.014	0.049	0.051
	(0.042)	(0.038)	(0.032)	(0.023)	(0.019)	(0.018)	(0.019)	(0.020)	(0.036)	(0.036)
Pred. imm. quint. 4	0.022	0.027	0.059*	-0.010	0.026	0.027	0.023	0.020	0.078*	0.086*
	(0.048)	(0.044)	(0.035)	(0.027)	(0.021)	(0.021)	(0.023)	(0.024)	(0.043)	(0.044)
Pred. imm. quint. 5	0.127**	0.090*	0.088**	-0.026	0.041	0.048*	0.060**	0.059*	0.074	0.099*
	(0.057)	(0.051)	(0.043)	(0.034)	(0.026)	(0.027)	(0.029)	(0.031)	(0.057)	(0.055)
County FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	25,090	25,090	25,090	25,090	25,090	25,090	25,090	25,090	25,090	25,090
R-squared	0.845	0.887	0.929	0.932	0.489	0.587	0.654	0.732	0.709	0.791

Panel IX.D: Education Expenditures

	Total educ total exp		Total educ direct exp		Total educ current exp	
	(1)	(2)	(3)	(4)	(5)	(6)
	1-year	2-year	1-year	2-year	1-year	2-year
Pred. imm. quint. 2	0.010	0.005	0.012	0.005	0.010	0.006
	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)
Pred. imm. quint. 3	0.005	0.005	0.009	0.006	0.011	0.006
	(0.012)	(0.010)	(0.012)	(0.010)	(0.011)	(0.009)
Pred. imm. quint. 4	0.013	0.015	0.008	0.016	0.009	0.015*
	(0.015)	(0.010)	(0.015)	(0.010)	(0.014)	(0.009)
Pred. imm. quint. 5	0.020	0.020**	0.016	0.023**	0.012	0.020**
	(0.016)	(0.010)	(0.014)	(0.010)	(0.012)	(0.008)
County FE?	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y
N	25,090	25,090	25,090	25,090	25,090	25,090
R-squared	0.985	0.992	0.986	0.992	0.990	0.995

Panel IX.E – Law Enforcement Expenditures

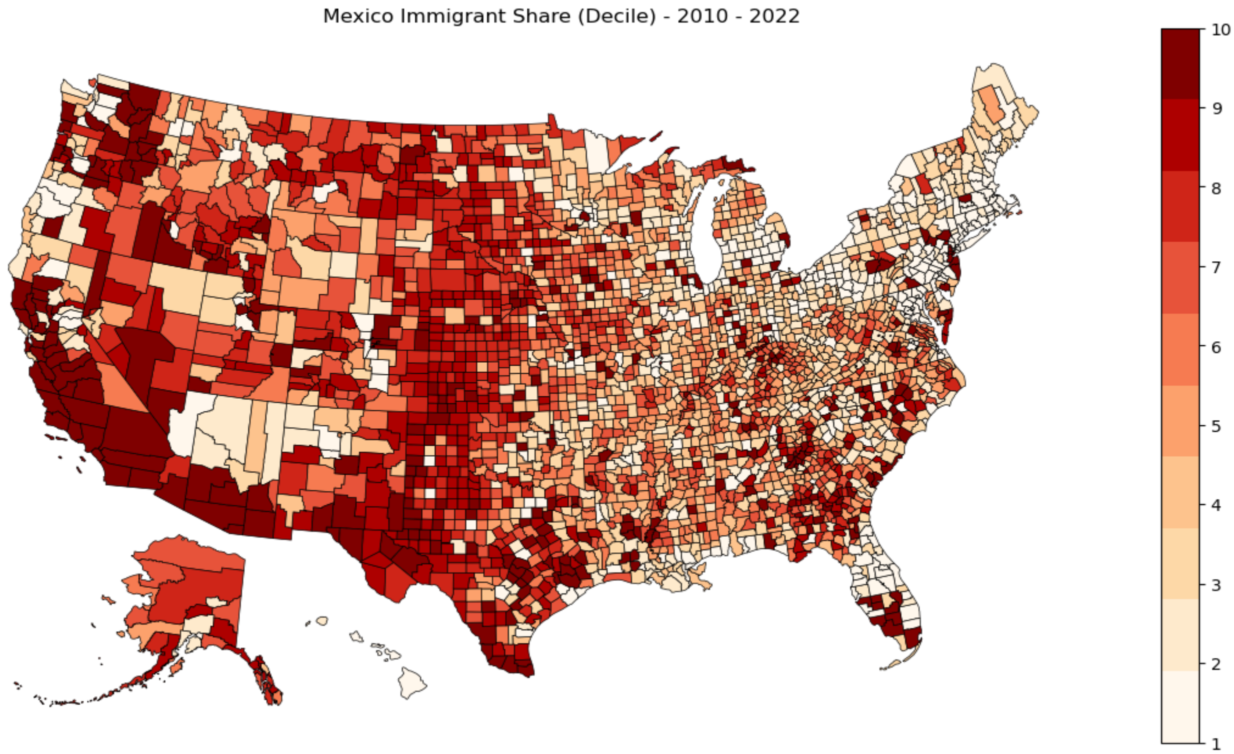
	Police prot ig to state		Police prot cap outlay	
	(1)	(2)	(3)	(4)
	1-year	2-year	1-year	2-year
Pred. imm. quint. 2	0.003	-0.000	0.062	0.060
	(0.007)	(0.006)	(0.043)	(0.041)
Pred. imm. quint. 3	0.010	0.016*	0.071	0.050
	(0.009)	(0.008)	(0.052)	(0.049)
Pred. imm. quint. 4	-0.002	0.003	0.118*	0.087
	(0.011)	(0.010)	(0.062)	(0.058)
Pred. imm. quint. 5	0.023*	0.015	0.146*	0.109
	(0.014)	(0.011)	(0.075)	(0.069)
County FE?	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y
N	25,090	25,090	25,090	25,090
R-squared	0.681	0.800	0.826	0.876

UNAUTHORIZED IMMIGRATION AND LOCAL GOVERNMENT FINANCES

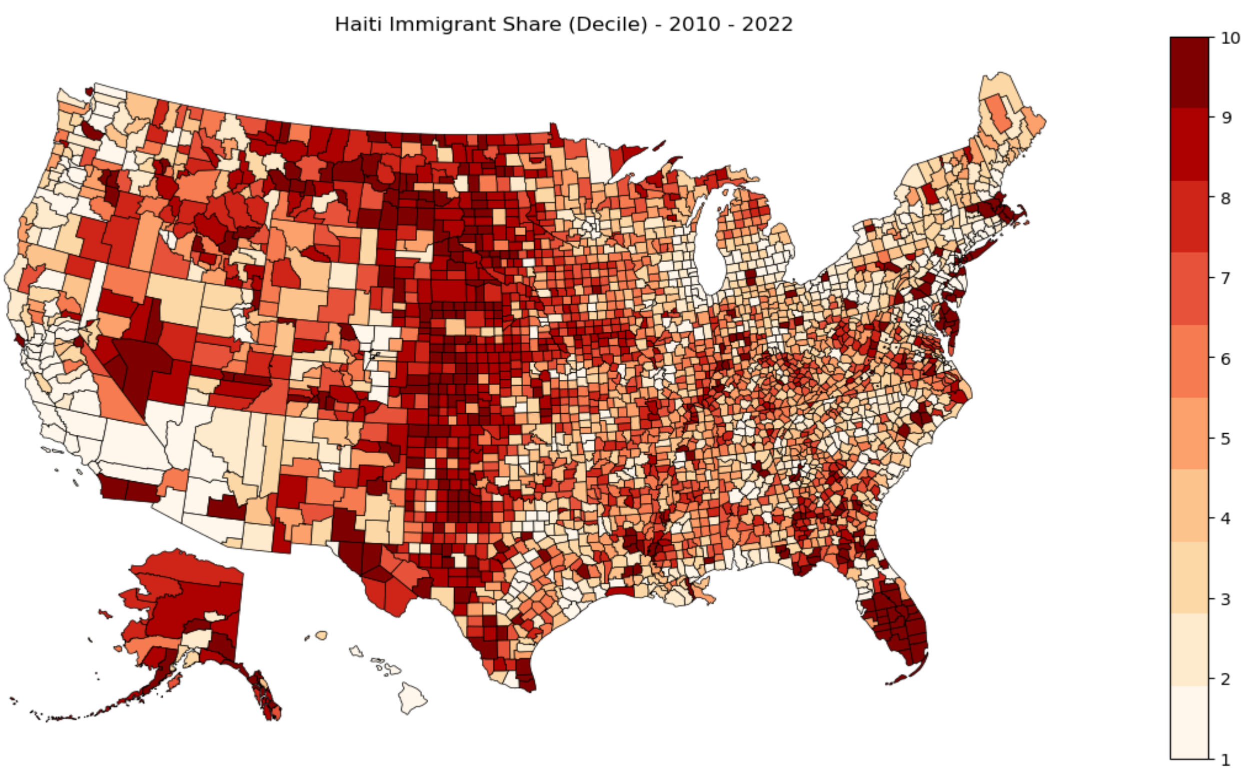
Internet Appendix

Figure A1. Unauthorized Immigration Data Example

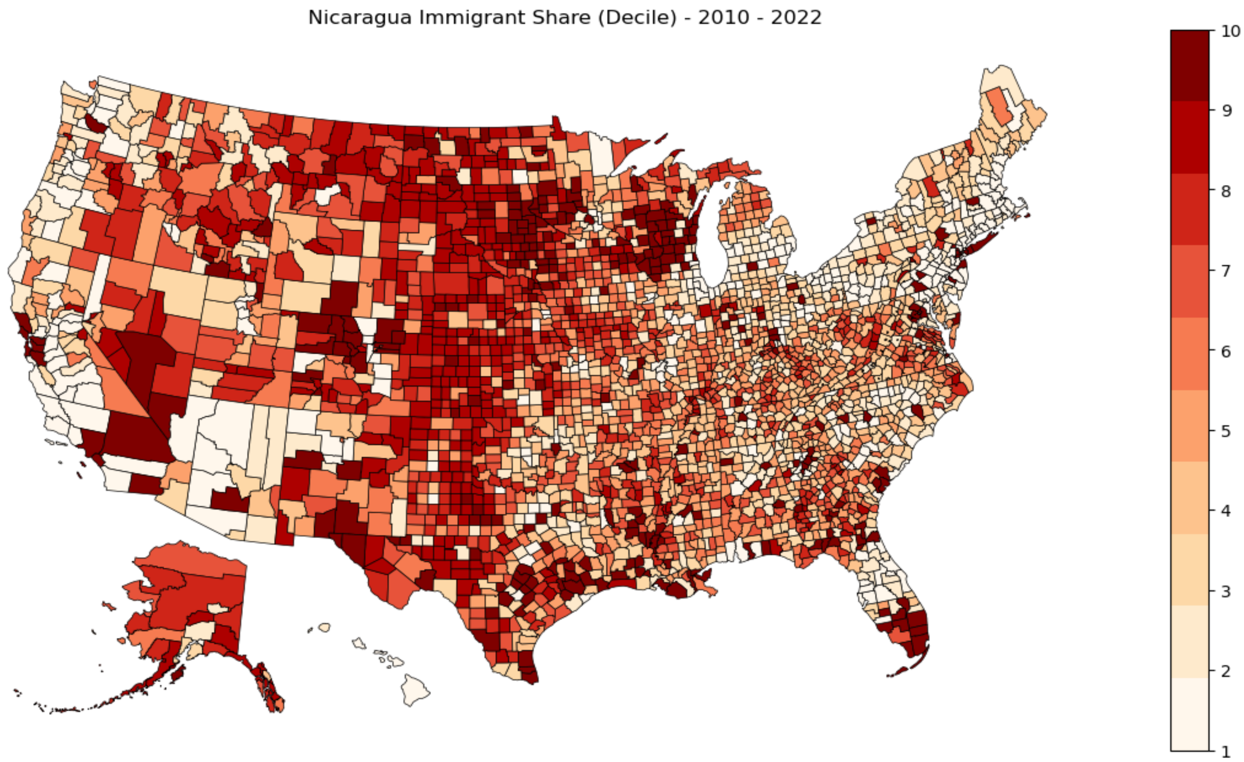
This figure displays a screenshot of unauthorized immigration data. The Syracuse Transactional Records Access Clearinghouse (TRAC) Immigration database provides Notice to Appear (NTA) data by year, month, country of origin, county, state, and time since arrival to the US.



Panel A – Mexico



Panel B – Haiti



Panel C – Nicaragua

Figure A2. Examples of Foreign-Born Population Distributions

This figure displays distributions of populations of foreign-born residents for Mexico, Haiti, and Nicaragua (Panels A, B, and C, respectively). We rank counties by the fraction of the population that was born in a given non-US country. Data are from the Census American Community Survey 5-Year Database (ACS5).