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# Does unauthorized immigration drive community crime rates? Evidence from 11,500 U.S. neighborhoods

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## ABSTRACT

Research on the immigration-crime nexus has grown substantially, yet few studies differentiate among immigrants of different legal statuses, including undocumented immigrants. Of those that do, analyses are conducted at state and metropolitan area levels, leaving unanswered the question of how the presence of undocumented immigrants is associated with neighborhood crime rates—our focus. To construct neighborhood-level estimates of the undocumented population, we access restricted-use individual-level Census data, where tract of residence can be identified, and apply an imputation procedure. We combine these estimates with a dataset containing crime information for roughly 11,500 neighborhoods across U.S. cities over a decade. Controlling for change in foreign-born citizens and lawful permanent residents as well as other correlates of community crime rates, we estimate neighborhood-level fixed effects models to determine how change in undocumented residents is associated with change in violent and property crime levels between 2010 and 2018. We find that neighborhoods that experienced greater increases in the share of undocumented residents saw greater reductions in property crime and no detectable change in violent crime. We also document distinct patterns in which increasing undocumented residents is associated with decreasing aggravated assaults but increasing robberies, consistent with a possible victimization explanation.

## KEYWORDS

Immigration;  
undocumented;  
crime; neighborhoods

Immigration is dynamic. In January 2025, 53.3 million immigrants resided in the United States, the largest number ever recorded. Over the next few months, however, as more immigrants were leaving than arriving, the foreign-born population began shrinking. By June 2025, the number of immigrants in the U.S. had shrunk by more than a million people, marking its first decline since the 1960s (Kramer & Passel, 2025).

At the same time, the term “immigrant” is ambiguous because it encompasses many distinct statuses (Caraballo, 2024). Naturalized citizens, for example, are individuals who have immigrated to the U.S., taken the required steps to become citizens, and have been approved by the United States Citizenship and Immigration Services (USCIS). On the other hand, visa holders—otherwise known as documented immigrants—are individuals who have entered the country legally but are not considered U.S. citizens; they include Lawful Permanent Residents (LPRs), also known as green card recipients, and conditional permanent residents, or green card holders who reside in the U.S. on a temporary basis. Finally, individuals who reside illegally in the U.S., either because they entered illegally or because they reside on an expired visa, are considered undocumented immigrants. Additional statuses

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exist, including refugees and asylum seekers, further underscoring the diverse nature of the immigrant population.

Why do these statuses matter? The U.S. foreign-born population is unevenly distributed across these groupings. As of 2023, 46% of immigrants were naturalized U.S. citizens, nearly 23% were lawful permanent residents, and another 4% were lawful temporary residents. The remaining individuals, comprising 27% of all immigrants, fell into the undocumented category (Kramer & Passel, 2025).

Beyond this, differentiation in status creates diverse life experiences for immigrants, with potential consequences for crime (Kubrin & Ousey, 2025). Nowhere is this distinction more evident than with respect to legal status. Undocumented and documented immigrants are differentiated by their formal legal classification, and this distinction has real-world consequences. Legal status determines access to pathways of legitimate opportunities, including but not limited to formal employment and social support programs. Legal status is also likely to generate between-immigrant inequities on pathways to social integration by shaping the ability of immigrants to participate in formal institutions, such as accessing education, obtaining health care benefits, or engaging in civic activities. In short, legal status is a dimension that meaningfully differentiates among immigrants, hinting at ways that inequalities in economic opportunities, social resources, and crime are created (Kubrin & Ousey, 2025).

Differentiation can also lead to disparate treatment by members of the host country (Kubrin & Ousey, 2025). This is certainly the case in the U.S., where “policies and public sentiments toward unauthorized migrants have grown increasingly hostile as they become demonized and viewed as threats and dangers to American society” (Adelman et al., 2021, p. 378). Nearly a decade ago, Light and Miller (2018) suggested “concerns over illegal immigration have arguably been the federal government’s highest criminal law enforcement priority in recent decades” (p. 372). Few would suggest this is no longer the case today.

Whether because of their perceived personal characteristics or because legal status is linked to social, economic, and legal disadvantages, undocumented immigrants are commonly perceived as more likely to criminally offend compared to their documented counterparts or native-born citizens. Likewise, places with high or growing concentrations of undocumented immigrants are also perceived to have higher crime rates, in part because these communities are thought to experience greater difficulty creating social ties and networks and developing collective efficacy, which constrain crime rates (Kubrin & Ousey, 2025). Combining these insights, it becomes clear that “1) the unauthorized population is by far the most divisive feature of contemporary immigration; 2) the U.S. government has devoted billions of criminal justice resources aimed at increasing public safety by reducing undocumented immigration; and 3) there are salient theoretical reasons to think lawful and unauthorized immigration may have independent influences on crime” (Light & Miller, 2018, pp. 17–18).

It is in this context that we analyze how unauthorized immigration and crime are related. Building on a small but important research base (Adelman et al., 2021; Green, 2016; Light & Miller, 2017, 2018), we examine how the presence of undocumented immigrants is associated with neighborhood crime rates in U.S. cities. Accessing restricted-use individual-level Census data where tract of residence can be identified and applying an imputation procedure similar to those used by the Department of Homeland Security and other organizations, we construct neighborhood-level estimates of the undocumented population. We combine these estimates with a novel dataset containing crime information for roughly 11,500 neighborhoods across a diverse range of U.S. cities between 2010 and 2018. Capturing the dynamic nature of immigration, we estimate neighborhood-level fixed effects models to assess how change in the percent undocumented residents in neighborhoods is associated with change in violent and property crime levels over a decade, controlling for correlates of neighborhood crime rates, including the change in foreign-born citizens and lawful permanent residents. Before detailing our methods and findings, we present theoretical perspectives on undocumented immigration and crime as well as review the handful of empirical studies on this topic.

## Theoretical perspectives on undocumented immigration and crime

Several theoretical frameworks posit a relationship between immigration and crime (for a review, see Kubrin & Ousey, 2023:Chapter 2). Given our aim and consistent with related work (e.g., Adelman et al., 2021, p. 379; Light & Miller, 2018, p. 372), we focus our discussion on the applications of theory to unauthorized immigration specifically. Notably, there is inconsistency in the predictions of these theoretical frameworks, with some positing a positive relationship between an influx of undocumented residents and crime levels and others anticipating a negative relationship.

Regarding those theorizing a positive relationship, one argument focusing on selection effects is that undocumented immigrants have a greater criminal propensity because they are disproportionately likely to be poor young males who migrate from relatively impoverished Latin American countries to work in low-wage jobs requiring little formal education (Rumbaut & Ewing, 2007, p. 4). These background characteristics related to age, sex, socioeconomic status and education level suggest undocumented immigrants will offend at higher rates compared to their documented counterparts and the native-born, generating a positive association between unauthorized immigration and crime rates in communities.

Another theoretical framework emphasizes the economic challenges undocumented immigrants uniquely face. Due to limited financial means, undocumented immigrants settle in structurally disadvantaged communities where criminogenic conditions prevail, providing increased opportunities for drug dealing and joining gangs (Ousey & Kubrin, 2009). At the same time, immigrants who are in the U.S. illegally are excluded from the formal labor market, limiting their means of earning a living. As Light and Miller (2018, p. 373) point out, “undocumented immigrants face a ‘double disadvantage’ in the U.S. labor force: first by being disproportionately driven into the secondary labor market and second by paying a wage penalty within these occupations.” In short, available jobs for this population are likely to be low-skilled and low-pay, conditions which can lead to economic hardship and create pressure, or strain, to capitalize on unlawful means of financial acquisition.

Legal status also shapes immigrants’ interactions with law enforcement specifically, and the criminal justice system generally, with consequences for crime (Kubrin & Ousey, 2025). Lacking legal status often means having to “live in the shadows” (Aranda, 2016), which can hinder undocumented individuals from seeking assistance from law enforcement when conflicts arise or following victimization (Light & Miller, 2018). Beyond this, immigrants from certain cultures tend not to rely on legal authorities for personal dispute resolution, preferring instead to take matters into their own hands or keep problems private (Adelman et al., 2021; Trager & Kubrin, 2014), while others carry a sense of distrust for legal systems and the police from their country of origin, believing that legal involvement is ineffective (Khashu et al., 2005).

Not all theoretical perspectives emphasize the criminological consequences of unauthorized immigration. Some hypothesize a negative relationship between unauthorized immigration and crime rates across communities. On the selective nature of immigration, for example, one argument is that undocumented immigrants possess characteristics that dampen their likelihood of offending (Kubrin & Ousey, 2025). Undocumented individuals, especially those who cross the border illegally, resort to physically demanding routes of migration that require walking for days with no place to rest or shelter with minimal food intake. These immigrants leave their home countries and families behind, willing to endure the journey and start from scratch to better the standard of living for themselves and their families. This desire to migrate manifests characteristics like ambition, hard work, resilience, and a willingness to delay gratification—traits not typically associated with criminality (Butcher Kristin & Piehl, 2005; see also Light & Miller, 2018, p. 374). Consistent with deterrence theory, undocumented immigrants have more to lose if they violate the law.

## Unauthorized immigration and crime: Limited research

These perspectives provide compelling arguments for why legal status may matter. What does empirical evidence say? Two questions, at different levels of analysis, motivate researchers

(Adelman et al., 2021, p. 377): At the micro level, are undocumented immigrants more likely to criminally offend than their documented counterparts or native-born individuals? At the macro level, how are unauthorized immigration and crime related across places, if at all? This latter question is the focus of the current study.

While there are hundreds of macro-level studies on the immigration-crime nexus across places, including neighborhoods, only a handful consider specifically how unauthorized immigration is associated with crime (Adelman et al., 2021, p. 378). As such, legal status is largely ignored in the research. This is due to data challenges. Official crime data, for instance, do not capture an individual's immigrant status (e.g., native born vs. foreign born), limiting researchers' ability to ascertain the true distribution of criminals who are immigrants, let alone distinguish between immigrants of different legal statuses (Kubrin & Ousey, 2023). This limitation is not unique to crime data; it is a broader issue that affects all national data sets employed by researchers. While undocumented residents routinely respond to government surveys such as the Decennial Census and the Current Population Survey (CPS), these surveys do not ask the foreign-born about their legal status. Thus, "we lack reliable and accurate data about inflows and outflows of immigrants as a whole, much less along 'legal' and 'illegal' dimensions" (Mears, 2002, p. 285). At the same time, "researchers have not had access to trustworthy estimates of the undocumented population" (Light & Miller, 2018, p. 379). Fortunately, updated methods for estimating the undocumented population are increasingly available. Below we review the few macro-level studies that capitalize on these improved estimation procedures.

Michael Light and his colleagues (Light & Miller, 2018; Light et al., 2017) created a dataset that combines estimates of the undocumented population from two sources, the Center for Migration Studies and the Pew Research Center,<sup>1</sup> with socioeconomic, demographic, and crime data from other sources. They use these data to analyze the longitudinal unauthorized immigration-crime association across 50 states and Washington, DC, from 1990 to 2014. Light and Miller (2018) report four key findings (pp. 384–388): First, increased concentrations of undocumented immigrants are associated with statistically significant decreases in violent crime, net of socioeconomic disadvantage, labor market conditions, population age structure, urbanization, incarceration and police officer rates, the prevalence of guns and drugs, and state and year fixed effects. Specifically, a one-unit increase in the proportion of the population that is undocumented corresponds with a 12% decrease in violent crime. Second, the reductions in violent crime associated with unauthorized immigration occur above and beyond the significant reductions stemming from lawful immigration. Stated alternatively, authorized and unauthorized immigration have independent negative relationships with violence. Third, comparing the estimates across various models reveals that the covariates do little to explain the unauthorized immigration–violence relationship. And finally, these findings hold under different weighting scenarios for the estimates. In additional analyses, Light and Miller (2018) ascertain whether the findings are biased due to selective migration (that is, if undocumented immigrants relocate to areas to avoid violence) or under-reporting (that is, if those who lack legal status are hesitant to report violent victimization out of fear of detection). In the end, they find little evidence that their results are due to selective migration or decreased reporting (pp. 393–394).

Using these same data, Light et al. (2017) analyze the influence of unauthorized immigration on drug arrests, drug overdose fatalities, driving under the influence (DUI) arrests, and DUI deaths at the state level. They find that increased unauthorized immigration is significantly associated with reductions in drug arrests, drug overdose deaths, and DUI arrests, net of other factors. They find no significant relationship between increased unauthorized immigration and DUI deaths. They conclude: "Our study does not contradict assertions that drugs are smuggled across the U.S. border (they are) or that individual undocumented immigrants have been arrested for drunk driving (they have). Our findings do, however, significantly undermine arguments that the public is at greater risk for DUI or drug problems as a result of undocumented immigration. If anything, we suggest the opposite" (p. 1453).

Related research on drug-related crime by Green (2016) yields more inconsistent results. Using 2012–2014 state-level estimates of the undocumented population from the Migration Policy Institute,

Green (2016) finds no association between the overall immigrant population and drug-related crime but a small significant positive association between the undocumented immigrant population and drug-related arrests. In other analyses that examine violent crime, Green (2016) documents that the undocumented population is significantly negatively associated with violent crime at the state level, consistent with Light and Miller (2018). He concludes, “The findings in this case are consequently largely in line with the extant research on the immigrant-crime nexus. That is, there is no significant association between immigration and violent crime, while perhaps a weak association between undocumented immigration and drug-related crime at best” (p. 519).

Finally, arguing that state-level analyses mask important variation at lower levels of aggregation, in part because most undocumented immigrants live in urbanized areas, Adelman et al. (2021, p. 380) analyze the association between unauthorized immigration and violent and property crime rates across U.S. metropolitan areas. In cross-sectional analyses, they employ two sets of estimates for the undocumented population in metropolitan areas, acquired from the Pew Research Center and the Migration Population Institute, along with Uniform Crime Report data and American Community Survey data from the U.S. Census Bureau. Consistent with Light and Miller (2017, 2018) and Green (2016), they find no statistically significant relationship between unauthorized immigration and violent crime after controlling for socio-demographic structural factors related to metropolitan-level crime rates. For property crime, specifically overall property crime, larceny, and burglary, they find that “as immigration—in this case, unauthorized immigration specifically—increases in metropolitan areas, crime decreases” (p. 392). These findings are consistent across both estimates of undocumented populations.

## Our contribution

This review shows a small but growing body of research is tackling an important and challenging question about the criminological consequences of unauthorized immigration. Yet, there is much left to learn. In the conclusion of their study, Light and Miller (2018) identify directions for future research, which provide motivation for the current study.

A logical extension of their study, they note, is “to explore the undocumented—violence nexus across different contexts” (p. 18). Light and Miller (2018) suggest researching more proximal units of analysis: “Though the use of state-level data helps ameliorate concerns regarding sampling variability, states likely miss important community level processes. Thus, as methods for enumerating the unauthorized population improve, researchers would do well in the future to consider the macro-level influence of undocumented immigration on crime at more proximal units of analysis, such as cities or neighborhoods” (p. 394; see also Adelman et al., 2021, p. 380). We respond to this charge. Our study introduces a new context, a more proximal unit of analysis, not yet examined in research on the unauthorized immigration–crime relationship: neighborhoods. In their state-level analysis, Light and Miller (2018) emphasize one benefit is their ability “to examine the undocumented immigration–violence link across the entire United States and to make generalizable conclusions that are not limited to select jurisdictions (e.g., Chicago)” (p. 376). Given our data span nearly 11,500 neighborhoods in cities across the U.S., representing approximately 46 million residents, we too can make generalizable conclusions beyond specific jurisdictions.

Continuing their discussion, Light and Miller (2018) emphasize analytical approaches that capture dynamic elements of immigration by modeling change over time. Analyses of this type, they note, “await future data collection efforts as longitudinal information on the unauthorized population at lower levels of aggregation is currently unavailable” (p. 18). We agree with Light and Miller’s (2018) modeling preference as longitudinal research offers greater analytical rigor, especially increased ability to control for confounding influences, but also because immigration is not static. While cross-sectional analyses are best suited for analyzing stock effects, or whether stable features of aggregate social units are correlated with one another, longitudinal and change analyses are best for capturing flow effects, or how temporal change in one social process relates



to change in another (Ousey & Kubrin, 2009, p. 448). Moreover, research documents differences in cross-sectional and longitudinal estimates of key macro-social predictors, including immigration (Ousey & Kubrin, 2018; Wadsworth, 2010). This underscores the problematic nature of generalizing about the longitudinal immigration–crime relationship from cross-sectional studies. Responding to their charge, our study treats immigration as a dynamic process by examining associated changes in the undocumented population and crime rates across neighborhoods.

Yet another future direction Light and Miller (2018) identify involves different crime types to investigate (see also Kubrin & Ousey, 2009). They recommend that “Extending this line of inquiry beyond violent crime is an important consideration for further research. Property offenses may be particularly interesting as there are theoretical reasons to suspect undocumented immigration may have divergent effects on violent and property crime” (p. 19), an argument espoused by Adelman et al. (2021). Once again, we heed their call and analyze both violent and property crime rates in our study.

A final recommendation emphasizes the need to research potential mechanisms, or “the social processes through which undocumented immigration influences violent crime” (Light & Miller, 2018, p. 19). Given findings demonstrating the stability of the undocumented—violence association with and without covariates, they call for “more explicit focus on difficult-to-measure processes such as informal social control, cultural penetration, and selection may be useful for understanding how undocumented immigration affects criminal violence” (p. 19). A challenging request, we agree this constitutes an important next step. In that spirit, although we do not measure specific mechanisms, we draw on theories of victimization that imply opposite relationships with two types of violent crime: aggravated assaults and robbery. As we discuss below, prior scholarship argues that the undocumented population is uniquely at risk of victimization for robbery, but not aggravated assault (Barranco & Shihadeh, 2015; Hipp et al., 2009; Kubrin et al., 2025). We therefore disaggregate violent crime to examine robbery and aggravated assault separately to assess whether potential victimization might help make sense of the findings.<sup>2</sup> Acknowledging this approach falls significantly short of measuring theoretical processes at play, we suggest the findings still offer insight to guide future research on theoretical mechanisms, a point we return to in the study’s conclusion.

In sum, the current study responds to Light and Miller’s (2018) recommendations for future research by analyzing how change in the size of the undocumented immigrant population is associated with change in violent and property crime levels using a novel dataset with information on crime in a large and diverse sample of U.S. neighborhoods.

## Data and methods

To determine whether unauthorized immigration drives neighborhood crime rates in the U.S., we combined estimates of the undocumented population with a novel dataset containing crime information for roughly 11,500 census tracts in a diverse range of cities from 2010 to 2018, a period when crime was declining in the U.S. The study time frame is important because in a time period where, nationally (and in our sample of neighborhoods), crime is falling and the percentage of undocumented immigrants is also decreasing (see below), a simple national-level correlation may generate an incorrect conclusion: that falling levels of undocumented immigration are responsible for falling violent crime rates. For the analysis, we estimated neighborhood-level fixed effects models to determine how change in the percent of undocumented residents in neighborhoods is associated with change in violent and property crime levels over that time period, controlling for change in the percent of foreign-born citizens and lawful residents as well as other correlates of community crime rates.

## Data

Data for this study are drawn from two sources. Crime data come from the National Incident Crime Study (NICS), which collected information on crime for cities across the U.S. directly from law enforcement agencies or from publicly available websites (Hipp et al., 2023; Kubrin & Hipp, 2025;



Kubrin et al., 2025). Demographic data come from a Census Research Data Center (CRDC), which allows us to aggregate data to our unit of analysis, census tracts, based on individual responses to the Census American Community Survey (ACS).<sup>3</sup>

Accessing individual-level CRDC data is crucial for the study, as these data enabled us to create an estimate of the number of undocumented immigrants for neighborhoods in our sample. Such an estimate is not possible with public-use Census data aggregated to small units such as census tracts. CRDC data include a variable that indicates which persons are foreign born, and then another that notes which foreign-born persons in each census tract are citizens. Of those who are *not* citizens, we used an algorithm to distinguish between lawful permanent residents (LPRs) and undocumented residents (see below). Given that the size of the annual samples is too small to obtain stable estimates, we mimic the strategy utilized in public use ACS data and constructed 5-year estimates based on the 5 years surrounding the year of interest in the study (2008–2012 and 2016–2020). For all constructs, we created measures in 2010 and 2018 and computed the difference in these measures over this decade. These difference measures were used in the models.

### Dependent variables

We use NICS data to compute crime levels in census tracts (Kubrin & Hipp, 2025; Kubrin et al., 2025). For time points 2010 and 2018, we use 3-year averages to account for annual fluctuations. Accordingly, crime data from 2009 to 2011 and 2017 to 2019 were cleaned and geocoded to latitude–longitude point locations using ArcGIS 10.6 and assigned the appropriate census tract. The geocoding match rate was over 90% in each city. We compared city-total estimates to police agency totals reported to the Uniform Crime Reports (UCR) and used only those that differed by 30% or less (most crime totals closely matched those of the UCR). Our analytic sample includes roughly 11,500 tracts (with a population of at least 500) in cities across the U.S. that have a population of at least 10,000.<sup>4</sup>

Although not a random sample, checks show that NICS neighborhoods are generally representative of U.S. neighborhoods in 2010 and 2018. Comparing NICS tracts in cities with at least 10,000 population to all tracts in cities with at least 10,000 population revealed considerable similarity for nearly all standard socio-demographic measures (Kubrin & Hipp, 2025; see also Kubrin et al. [2025] for detailed information about how NICS data were collected).

The dependent variables are change in census-tract log transformed counts of crime incidents, specifically violent crime, property crime, robbery, and aggravated assault. To create the measure of change in violent crimes between 2010 and 2018, at each time point we computed the average number of violent crimes occurring in the 3 years surrounding the time point. Thus, we computed the average number of violent crimes (homicides, robberies, and aggravated assaults) in 2017–2019 and in 2009–2011 and log transformed these values. We then subtracted the earlier average from the later average to create our outcome variable *change in logged violent crimes* over the decade. We similarly constructed a measure of *change in logged property crimes* (burglaries, motor vehicle thefts, and larcenies). For additional analyses (see below), we disaggregated the violent crime measure into *change in logged robberies* and *change in logged aggravated assaults*.

### Independent variables

Our key independent variables capture the percentage of residents in each census tract who are foreign born. To replicate existing literature, we constructed a measure of the *change in immigrants* over the decade, which subtracts the percentage foreign-born in 2010 from the percentage in 2018. To capture legal status, we disaggregated this measure into three subcomponents. The first is the *change in foreign-born citizens*, which is denoted in the Census from a survey question. For non-citizens, we disaggregated this population into those who are legal residents and those who lack legal status using an algorithm pioneered by Warren and Passel (1987).

More specifically, we employed an imputation procedure based on the same methods that institutions such as the Department of Homeland Security use to estimate the size and characteristics of the undocumented population in the U.S. In the last decade, researchers have begun to apply this procedure to microdata. For instance, Borjas and Cassidy (2019) apply the imputation to public-use CPS data, and Christopher (2023) applies it to public-use ACS data. To our knowledge, this is the first study to apply the imputation to restricted-use microdata in the CRDC. As a result, we can produce estimates of the undocumented population at a more geographically granular level than would otherwise be possible with publicly available data. Our approach, outlined below, is identical to that which Christopher (2023) applied to the public-use version of the ACS where estimates by state of residence (and by country of birth) were shown to closely resemble the corresponding estimates produced by others, including Pew Research, the Center for Migration Studies, and the Department of Homeland Security.

First, any individual who is recorded to be a citizen or reports being born in the U.S. is flagged as a citizen. Then, among non-citizens, while it is challenging to identify who is undocumented, it is easier to identify who is not undocumented. If any non-citizen satisfies at least one of the following conditions, they are flagged as an LPR:

- Arrived in the United States before 1980 (these individuals are assumed to have achieved legal status through IRCA 1982);
- Is a veteran or currently serving in the U.S. military;
- Received public health insurance, Medicaid, Medicare, or VA insurance<sup>5</sup>;
- Received any welfare payment, SSI, or Social Security benefits;
- Is employed by the government or in an occupation that requires licensing;
- Born in Cuba (immigrants born in Cuba are overwhelmingly likely to be refugees during our sample period);
- Received SNAP/food stamps (only applied when it can be determined that receipt was not on behalf of a U.S. citizen child);
- Arrived in the U.S. as an adult and is currently enrolled in undergraduate, graduate, or professional school (to account for student visas);
- Works in a computer-related occupation, holds at least a bachelor's degree, and has been in the U.S. no more than 6 years (to account for H-1B visas);
- Has a spouse who has been identified as a citizen or LPR.

After LPRs are identified, the balance of non-citizen immigrants is then flagged as undocumented, representing a small overestimate of the true undocumented population, as there will be some non-citizen legal residents who do not satisfy any of the above criteria. We aggregated these individuals to the tract level to compute the percentage of the tract population that is *LPR immigrants* and the percent *undocumented immigrants*.

To minimize the possibility of obtaining spurious effects, the analysis includes control variables often reported in the ecology of crime literature. We included the *change in concentrated disadvantage*, constructed as a factor score from a principal components analysis of the following variables: average household income; percent with at least a bachelor's degree; percent in poverty; percent single parent households. We created a *change in residential stability* measure as a mean of z-scores of the average length of residence and percent owners. We accounted for neighborhood racial/ethnic composition with measures of *change in Latino/as*, *Asians*, *Blacks*, and *other race* (with White as the reference category). For each time point we also computed levels of *racial/ethnic heterogeneity* as a Herfindahl Index of one minus a sum of squares of these five racial/ethnic groups and computed the difference. As vacant units provide crime opportunities, we computed the *change in vacancies*. Likewise, high population density often creates crime opportunities, so we computed a *change in population density* measure. The age crime curve suggests that adolescents and young adults are the most crime prone age groups, so we computed *change in*

population aged 16 to 29. Finally, we include a *change in population (logged)* measure to account for the fact that larger populations generate more crime opportunities.

## Methods

The change variables allow us to treat immigration as a dynamic process. For the analyses, we estimate fixed effects models, which have the advantage of comparing *within* neighborhoods rather than only *across* them, accounting for all unchanging variables not included in the models. We estimated models in which the outcome variable was the change in crime (violent, property, robbery, aggravated assault):

$$\Delta y = \beta_0 + \beta_1 \Delta Imm + \Delta XB + \varepsilon$$

where  $\Delta y$  is the change in logged crime over the decade,  $\beta_0$  is an intercept,  $\Delta Imm$  is the change in the immigrant measure over the decade with a  $\beta_1$  relationship with the change in crime,  $\Delta X$  is the matrix of other variables whose relationships with the change in crime are captured in the B matrix of parameters, and  $\varepsilon$  is an error term with an assumed normal distribution with a mean of zero.

For each crime type, we estimated four models, all of which included all control variables. The first included only the change in immigrants, to replicate a standard approach in the literature. The second replaced this measure with a measure of change in the undocumented population. The third included both change measures to isolate the role of the undocumented variable when accounting for the change in all immigrants. Disaggregating the percent immigrant variable into its three subcomponents, the final model included measures for change in foreign born citizens, LPRs, and undocumented immigrants.

## Results

### Descriptive results

We begin with descriptive results for our immigrant variables. The bottom two rows of [Table 1](#) provide means (and standard deviations) for the share (between 0 and 1) of the tract population that is undocumented in each time period. For the average tract in our sample, 5.6% of residents were undocumented in 2010, a figure which fell to 4.8% in 2018 (or 0.056 and 0.048, respectively).<sup>6</sup> Whereas the average tract showed a small increase in percent immigrants over this time period (0.4 percentage points), there was significant variability across neighborhoods with a standard deviation of 5.7 percentage points. Furthermore, whereas the average neighborhood experienced an increase of 1.4 percentage points in foreign born citizens, it experienced decreases of 0.2 percentage points in LPRs and 0.8 percentage points in undocumented immigrants. There was also variability in change for these subgroups, with standard deviations ranging from 2.9 to 4.1 percentage points. Finally, although the average tract experienced an increase in aggravated assaults over the decade, the average tract experienced decreasing counts of robberies, violent and property crime.

The final column in [Table 1](#) displays the correlations of these variables with our variable of interest, change in percent undocumented immigrants. For the crime measures, although change in percent undocumented immigrants has a modest positive correlation with robberies, it has a negative correlation with violent crime and more substantial negative correlations with property crime and aggravated assault. Not surprisingly, there is a positive correlation between change in percent undocumented and change in percent immigration overall, although this value ( $r = .53$ ) indicates that these are distinct measures. There is a negative correlation between change in the percent undocumented population and change in percent citizen immigrants, and modest positive correlations between change in percent undocumented immigrants and change in concentrated disadvantage, percent Latino/a, and levels of racial/ethnic heterogeneity.

We are limited in our ability to exhaustively describe the neighborhoods with higher concentrations of undocumented populations due to rules regarding the restricted nature of CRDC data.

**Table 1.** Summary statistics of variables used in analyses.

|                                                          | Mean   | Standard<br>Deviation | Corr with % change undocumented<br>immigrants |
|----------------------------------------------------------|--------|-----------------------|-----------------------------------------------|
| <b>Dependent variables</b>                               |        |                       |                                               |
| Change in Logged Violent Crime Count                     | −0.082 | 0.478                 | −0.009                                        |
| Change in Logged Property Crime Count                    | −0.191 | 0.382                 | −0.041                                        |
| Change in Logged Robbery Count                           | −0.256 | 0.508                 | 0.081                                         |
| Change in Logged Assault Count                           | 0.060  | 0.554                 | −0.053                                        |
| <b>Independent variables</b>                             |        |                       |                                               |
| Change in % Immigrants                                   | 0.004  | 0.057                 | 0.533                                         |
| Change in % Undocumented Immigrants                      | −0.008 | 0.037                 |                                               |
| Change in % Citizen Immigrants                           | 0.014  | 0.041                 | −0.158                                        |
| Change in % Legal permanent resident (LPR)<br>Immigrants | −0.002 | 0.029                 | −0.020                                        |
| Change in Concentrated disadvantage                      | 0.006  | 0.336                 | 0.111                                         |
| Change in Residential stability                          | 0.000  | 0.378                 | −0.107                                        |
| Change in % Asian                                        | 0.000  | 0.046                 | 0.119                                         |
| Change in % Black                                        | −0.044 | 0.085                 | −0.129                                        |
| Change in % Latino                                       | 0.099  | 0.086                 | 0.329                                         |
| Change in % Other Race                                   | 0.001  | 0.023                 | −0.013                                        |
| Change in Ethnic Heterogeneity                           | 0.085  | 0.118                 | 0.213                                         |
| Change in % Vacant Units                                 | −0.002 | 0.043                 | 0.023                                         |
| Change in % Aged 16–29                                   | −0.004 | 0.051                 | 0.027                                         |
| Change in Population Density                             | 0.508  | 6.190                 | −0.005                                        |
| Change in Logged Population                              | 0.138  | 0.328                 | 0.069                                         |
| % Undocumented Immigrants 2010                           | 0.056  | 0.063                 |                                               |
| % Undocumented Immigrants 2018                           | 0.048  | 0.049                 |                                               |

Note:  $N$  = approximately 11,500 census tracts. FSRDC Project 2534 (CBDRB-FY26-P2534-R12822).

All results presented in this study have undergone extensive review to ensure they do not violate Census confidentiality standards of the underlying microdata, and we therefore cannot describe our sample of Census tracts in detail, provide information on any subset of these tracts, or show the locations of these neighborhoods. In [Appendix Table A1](#) we instead show the correlation of this measure with other key measures at both time points (2010 and 2018) to gain a better understanding these neighborhoods. These neighborhoods tend to be more disadvantaged (correlations of .22 and .14), have high population density (.23 and .21) and residential instability (.28 and .23), and have somewhat more residents aged 16 to 29 (.13 and .10). Neighborhoods with more undocumented individuals also have fewer Black residents (correlation of −.25) and had higher levels of racial/ethnic heterogeneity in 2010 (but not in 2018). The correlations with the crime measures are quite modest, with positive correlations with robbery and negative correlations with aggravated assault and property crime. We turn to fixed-effects models assessing the change in neighborhood crime rates.

### Multivariate results

We first present models analyzing the change in violent crime. In model 1 of [Table 2](#) we see no significant relationship between the change in percent immigrants and the change in violent crime. In model 2, we similarly see no significant relationship between the change in the percent undocumented immigrants and the change in violent crime in tracts. Model 3, which includes both measures, shows neither is significantly associated with violent crime. In model 4, which disaggregates immigrants into the change in citizens, LPRs, and undocumented immigrants, we see that none of these measures are significantly associated with violent crime levels. In short, we find no significant relationship between the increase in percent immigrants—for any status—and the change in violent crime levels across our diverse sample of more than 11,000 neighborhoods nationwide.

While point estimates capturing the relationship between share of residents undocumented and violent crime are negative across models, they are small in magnitude and not statistically

**Table 2.** Change models predicting change in crime from 2010 to 2018 in neighborhoods based on measures of immigrant status.

|                                     | Model 1                         | Model 2              | Model 3                         | Model 4              |
|-------------------------------------|---------------------------------|----------------------|---------------------------------|----------------------|
| <b>Violent crime models</b>         |                                 |                      |                                 |                      |
| Change in % Immigrants              | −0.0104<br>(−0.12)              |                      | 0.0022<br>(0.02)                |                      |
| Change in % Undocumented Immigrants |                                 | −0.0377<br>(−0.30)   | −0.0391<br>(−0.27)              | −0.037<br>(−0.28)    |
| Change in % Citizen Immigrants      |                                 |                      |                                 | 0.0019<br>(0.02)     |
| Change in % LPR Immigrants          |                                 |                      |                                 | 0.0027<br>(0.02)     |
| BIC                                 | 15,620                          | 15,620               | 15,630                          | 15,640               |
| R squared                           | 0.035                           | 0.035                | 0.035                           | 0.035                |
| <b>Property crime models</b>        |                                 |                      |                                 |                      |
| Change in % Immigrants              | −0.1321 <sup>†</sup><br>(−1.87) |                      | −0.0604<br>(−0.76)              |                      |
| Change in % Undocumented Immigrants |                                 | −0.2644**<br>(−2.59) | −0.2241 <sup>†</sup><br>(−1.94) | −0.2747**<br>(−2.60) |
| Change in % Citizen Immigrants      |                                 |                      |                                 | 0.0583<br>(0.62)     |
| Change in % LPR Immigrants          |                                 |                      |                                 | −0.303*<br>(−2.38)   |
| BIC                                 | 10,640                          | 10,640               | 10,650                          | 10,650               |
| R squared                           | 0.016                           | 0.016                | 0.016                           | 0.017                |
| <b>Robbery models</b>               |                                 |                      |                                 |                      |
| Change in % Immigrants              | 0.3198**<br>(3.45)              |                      | −0.0453<br>(−0.43)              |                      |
| Change in % Undocumented Immigrants |                                 | 1.11**<br>(8.31)     | 1.14**<br>(7.57)                | 1.11**<br>(8.05)     |
| Change in % Citizen Immigrants      |                                 |                      |                                 | 0.1472<br>(1.21)     |
| Change in % LPR Immigrants          |                                 |                      |                                 | −0.4387**<br>(−2.63) |
| BIC                                 | 16,950                          | 16,890               | 16,900                          | 16,900               |
| R squared                           | 0.043                           | 0.048                | 0.048                           | 0.049                |
| <b>Aggravated assault models</b>    |                                 |                      |                                 |                      |
| Change in % Immigrants              | −0.3315**<br>(−3.24)            |                      | −0.1438<br>(−1.25)              |                      |
| Change in % Undocumented Immigrants |                                 | −0.6821**<br>(−4.62) | −0.5859**<br>(−3.52)            | −0.7355**<br>(−4.82) |
| Change in % Citizen Immigrants      |                                 |                      |                                 | −0.2149<br>(−1.59)   |
| Change in % LPR Immigrants          |                                 |                      |                                 | 0.0015<br>(0.01)     |
| BIC                                 | 19,250                          | 19,240               | 19,250                          | 19,260               |
| R squared                           | 0.023                           | 0.024                | 0.024                           | 0.024                |

Note: all models include all control variables listed in Table 1.

Note: <sup>†</sup> $p < .1$ ; \* $p < .05$ ; \*\* $p < .01$ . T-values in parentheses. N = approximately 11,500 census tracts. FSRDC Project 2534 (CBDRB-FY26-P2534-R12822).

distinguishable from zero. Point estimates would imply that a tract with a change in the undocumented population one standard deviation above the average (3.74 percentage points higher or about 19 people out of a tract of 500 people) should expect to see about 0.15% fewer violent crimes, with confidence intervals implying a range from a 1.1% decrease to a 0.9% increase. In other words, while we cannot conclude that the relationship is exactly zero, we can rule out changes of more than 1% in either direction.

In the second panel of Table 2, we present results for property crime. In model 1, we find that neighborhoods experiencing an increase in percent immigrants over the decade witness a modest decrease in property crimes ( $p < .10$ ). When we replace this measure with a measure for the change in undocumented immigrants (model 2), we find that neighborhoods experiencing an increase in percent undocumented immigrants tend to experience a decrease in property

crime. A one standard deviation increase in this measure is associated with about a 1% decrease in property crime ( $=\exp(-.2644 \cdot .0374) - 1 = -.0098$ ). When we include both measures (model 3), we see that a change in undocumented immigration has a much stronger relationship with property crime than does a similar size change in total immigrants. This finding is reinforced in model 4 when we disaggregate immigrants into the three subgroups; whereas an increase in percent citizen immigrants has no detectable relationship with the change in property crime, increases in non-citizen immigrants (legal or not) are associated with falling property crime levels.

In a final set of analyses, we disaggregate violent crime into acquisitive (robbery) and instrumental (aggravated assault) crime and estimate models to determine whether the overall null results for violent crime are masking key differences between these two crime types. What motivates these analyses? Scholars argue that Latino/a immigrants are more likely to participate in the cash economy (Barranco & Shihadeh, 2015; Hipp et al., 2009), with consequences for neighborhood crime rates (Kubrin et al., 2025). This is because these individuals are attractive targets for robberies, as they are more likely to carry cash and patronize fringe lenders such as check cashing establishments and pawnshops. Indeed, the third and fourth panels of Table 2 show results strongly supportive of this hypothesis.

In the third panel of Table 2, we present results for robbery. Model 1 shows that an increase in the percent immigrants in a neighborhood is associated with increases in robberies. Model 2 shows that this positive relationship is even stronger for the change in percent undocumented immigrants, as a one standard deviation increase in this variable is associated with about a 4% increase in robberies, on average. In model 3 when we include both measures, we find that it is indeed the undocumented immigrants measure that is driving this result: whereas an increase in the percent undocumented population is associated with an increase in robberies, there is virtually no relationship between the change in total immigrants and the change in robberies. Model 4 disaggregates immigrants into the three subgroups, revealing that whereas an increase in the undocumented population is associated with increasing robberies, increasing citizen immigrants has no relationship with robberies, and increasing LPRs is associated with declining levels of robbery. Thus, it is change in the percent undocumented that is strongly associated with increasing robberies, a finding consistent with the hypothesis that this group may serve as attractive targets for instrumental crimes.

The fourth panel of Table 2 presents results for aggravated assault. These results are opposite of those for robbery. In model 1, an increase in percent total immigrants in a neighborhood is associated with a strong decrease in aggravated assaults. Model 2 shows that a one standard deviation increase in the percent undocumented is associated with a 2.5% decrease in aggravated assaults, on average. In model 3 when we include both measures, we observe that it is change in the undocumented population driving the result. Model 4 reinforces this observation, as the change in the percent undocumented population is associated with decreasing aggravated assaults, but changes in the other two groups (LPRs or citizen immigrants) have no detectable relationship with aggravated assaults over time.

Finally, Table 3 presents results for the complete set of control variables for model 3 results for violent and property crime from Table 2. The control variables generally show relationships consistent with expectations. Increases in concentrated disadvantage are associated with increasing violent crime, but slightly decreasing property crime levels. A one standard deviation increase in concentrated disadvantage is associated with a 3% increase in violent crime. Consistent with prior literature that Black Americans remain exposed to higher levels of neighborhood violence, a similar increase in percent Black is associated with a 6% increase in violent crime and a 2.7% increase in property crime. Although increases in residential stability are not associated with change in violent or property crime, a one standard deviation increase in the percent aged 16–29 is associated with 1.1% more property crime. These relationships are similar in magnitude to those we observe for the change in undocumented population, which were between 1% and 4%.



**Table 3.** Full change models including control variables.

|                                     | Violent crime                 | Property crime                  |
|-------------------------------------|-------------------------------|---------------------------------|
| Change in % Immigrants              | 0.0022<br>(0.02)              | −0.0604<br>(−0.76)              |
| Change in % Undocumented Immigrants | −0.0391<br>(−0.27)            | −0.2241 <sup>†</sup><br>(−1.94) |
| Change in Concentrated disadvantage | 0.0892**<br>(6.43)            | −0.0203 <sup>†</sup><br>(−1.81) |
| Change in Residential stability     | 0.0188<br>(1.59)              | 0.0047<br>(0.49)                |
| Change in % Asian                   | −0.1907<br>(−1.64)            | −0.0596<br>(−0.64)              |
| Change in % Black                   | 0.6903**<br>(11.74)           | 0.3089**<br>(6.50)              |
| Change in % Latino                  | 0.0081<br>(0.11)              | −0.0384<br>(−0.67)              |
| Change in % Other Race              | 0.4864*<br>(2.44)             | 0.2935 <sup>†</sup><br>(1.82)   |
| Change in Ethnic Heterogeneity      | −0.0344<br>(−0.76)            | −0.085*<br>(−2.34)              |
| Change in % Vacant Units            | 0.1799 <sup>†</sup><br>(1.71) | −0.0484<br>(−0.57)              |
| Change in % Aged 16–29              | −0.0197<br>(−0.23)            | 0.2186**<br>(3.11)              |
| Change in Population Density        | −0.003**<br>(−3.95)           | −0.0025**<br>(−4.05)            |
| Change in Logged Population         | 0.1587**<br>(10.68)           | 0.1034**<br>(8.61)              |
| BIC                                 | 15,630                        | 10,650                          |
| R squared                           | 0.035                         | 0.016                           |

Note: <sup>†</sup> $p < .1$ ; \* $p < .05$ ; \*\* $p < .01$ . *T*-values in parentheses. *N* = approximately 11,500 census tracts. FSRDC Project 2534 (CBDRBFY26-P2534-R12822).

## Discussion

The study yields two broad results. First, neighborhoods that experienced greater increases in the share of residents who are undocumented saw greater reductions in property crime and no detectable change in violent crime (point estimates are negative, but confidence intervals do not rule out that the relationship is null). This is consistent with Adelman et al. (2021, p. 380), who find precisely the same relationships between undocumented immigrants and crime across metropolitan areas. Our results imply that, even within metropolitan areas, across neighborhoods, a growing undocumented population is associated with falling property crime (and no significant change in violent crime).

Second, the nonsignificant relationship between changes in the undocumented population and changes in violent crime may obfuscate important heterogeneity. At the neighborhood level, we find that a growing undocumented population is associated with a significant reduction in assaults but a significant increase in robberies. Similar offense-specific divergence is documented in victimization research. Lauritsen and Heimer (2010), for example, show that robbery victimization and aggravated assault victimization do not necessarily follow the same pattern, with robbery appearing more responsive to economic and exposure-related conditions than is aggravated assault.

The mechanism behind this result remains uncertain. On the one hand, one might argue that robbery, as an income-generating crime, is an alternative to employment when labor market opportunities are restricted or unavailable and, therefore, should be expected to increase in the face of an increase in a population that disproportionately lacks formal employment options. However, this theory would also predict increases in many types of property crime (e.g., burglary, theft), which is inconsistent with our findings. On the other hand, an increase in robberies (despite decreases in all other crime categories) would be consistent with the idea that undocumented immigrants are



disproportionately likely to be targets of robbery given greater involvement in the cash economy, as discussed earlier. Research is typically unable to assess whether undocumented individuals specifically are targeted given the difficulty of determining undocumented status of potential victims. But studies find that Latino immigrants are targeted, highlighting this possibility (Barranco & Shihadeh, 2015). The finding that immigrants face a disproportionately high risk of being robbed due to a reliance on cash, fear of deportation, and reluctance to report victimization is referred to as the “Walking ATM” phenomenon (Barranco & Shihadeh, 2015; Shihadeh et al., 2025). Other neighborhood-level research finds evidence consistent with this victimization argument (Hipp et al., 2009; Kubrin et al., 2025).

Regarding study findings, one question relates to the concern that longitudinal studies of immigration and crime may be underpowered (Riaz, 2026). Riaz (2026) argues that when using aggregated data, especially for large geographic units such as cities or counties, the proportional change in immigrant concentration in units will be relatively small. This, combined with the typically smaller sample sizes of such large macro units, can result in limited statistical power to detect a relationship—what Riaz refers to as “null by design.” A key advantage of our neighborhood-level analytic strategy is the increased statistical power. Specifically, our study is less encumbered by this problem for two reasons: first, the smaller size of the units allows a change in undocumented immigrants to be a much larger proportion of the unit compared to larger macro units, and second, our sample of 11,500 tracts is far larger than the sample sizes Riaz described.<sup>7</sup> That we detected significant relationships is one notable piece of evidence that our study is not underpowered. That the instance in which we did not detect a significant relationship was the result of offsetting relationships in opposite directions is motivation for future studies to further investigate null estimates when powered to do so.

## Conclusion

A growing body of research examines the relationship between unauthorized immigration and crime. Due to data limitations, conclusions about the relationship have been limited to comparisons across states or large metropolitan areas. Leveraging restricted data and state of the art imputation methods, we assess the relationship with greater geographic precision. Our findings buttress those of existing analyses conducted across metropolitan areas. Accounting for all time-invariant neighborhood characteristics, as well as demographic and economic changes, an increase in a neighborhood’s undocumented population is associated with reduced property crime and no significant change in violent crime. While violent assaults decrease significantly more in neighborhoods where increases in the undocumented population are larger, robberies increase significantly more.

While our findings can address many of the lingering concerns about whether the relationship between immigrant status and crime is robust across geographic levels (i.e., if metropolitan areas with more undocumented immigrants experience less crime, does that mean that neighborhoods with more undocumented immigrants would also experience less crime?), we are limited in our ability to investigate the specific mechanisms behind our findings and urge future work to devote greater attention to these. In particular, because we lack data on the identity of perpetrators and victims, the theory that increases in robberies are driven by increased victimization of undocumented residents, while consistent with the results across our analyses, cannot be determined with the data available to us. Furthermore, whereas prior work has noted the potential disproportionate under-reporting of crime experienced by undocumented victims to be inconsequential (Chalfin, 2015; Light & Miller, 2018), our data and methods cannot rule out the possibility that reduced reporting by undocumented victims is responsible for some of the observed change in crime. In other words, although the total crime in a neighborhood is reduced, it is possible there are actually more incidents of undocumented victims than we are detecting.

With these findings, law enforcement may be better equipped to target their efforts toward neighborhoods at the greatest risk of crime. All else equal, our findings suggest that law enforcement activity to prevent property crime and violent assaults would be optimally concentrated in neighborhoods where residents are disproportionately U.S. citizens.

Additionally, consistent with a small literature on the role of financing in immigrant populations, our findings suggest that reductions in robbery, specifically, may best be achieved by expanding financial opportunities to undocumented immigrants to reduce the incentives offenders have to target them. Finally, while we cannot rule out the possibility that some factor correlated with both the change in the share undocumented and the change in crime prevents a traditional causal interpretation of our estimates, if there is no such factor, our estimates suggest that reducing a neighborhood's undocumented population will increase rates of property crime and assault and, in general, would optimally be avoided by agencies charged with reducing such crime.

## Notes

1. To learn more about how these estimates were created, see Light and Miller (2018, pp. 379–380).
2. In our study, the absence of a statistically detectable relationship between unauthorized immigration and violent crime can be explained by offsetting relationships with different types of violent crime that are bundled together under the same “violent” umbrella. It would be important to understand whether this aggregation problem may explain other null relationships between immigration and violent crime.
3. Throughout we refer to “tract” and “neighborhood” interchangeably.
4. To comply with Census disclosure rules related to accessing CRDC data, we are unable to provide more specific counts of the number of tracts and cities that comprise our sample.
5. Technically, our estimates of the 2018 undocumented population are derived from pooled 5-year ACS data, which includes the year 2020. In 2020, California became the first state where an undocumented person over the age of 18 could be eligible for Medicaid when the state expanded eligibility to undocumented immigrants aged 26 or younger. Our estimates of the 2018 undocumented population do not account for the possibility that, in the last year of the 5-year sample data, there could have been undocumented immigrants in California who were 26 or younger who were enrolled in Medicaid.
6. Although these values are somewhat inflated compared to national-level estimates, this can be explained by the nature of our sample, which disproportionately includes urban areas. Nearly all undocumented immigrants live in metropolitan areas (Passel & Cohn, 2009, p. 1) (as cited in Adelman et al., 2021, p. 378). Furthermore, the decrease in undocumented at the tract level is consistent with national-level decreases over this time period estimated by DHS and Pew.
7. Riaz described computing the minimum detectable gap as the size of the effect that a study is powered to detect. In our case, we computed a value of .35 for our undocumented population variable in a model for violent crime. This is only a little bit larger than our coefficient for property crime (which was significant) and was much smaller than the absolute value of the coefficients for aggravated assault and robbery. If the relationship with violent crime were of the same magnitude (in either direction) as the relationship detected with aggravated assault or with robbery, we would have had the power to detect the effect as statistically distinguishable from zero.

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## Appendix

**Table A1.** Correlations between percent undocumented immigrants and key independent variables at two time points.

|                                 | 2010   | 2018   |
|---------------------------------|--------|--------|
| <b>Dependent variables</b>      |        |        |
| Logged Violent Crime Count      | 0.008  | −0.019 |
| Logged Property Crime Count     | −0.045 | −0.034 |
| Logged Robbery Count            | 0.047  | 0.028  |
| Logged Aggravated Assault Count | −0.022 | −0.040 |
| <b>Independent variables</b>    |        |        |
| Concentrated disadvantage       | 0.220  | 0.138  |
| Residential stability           | −0.282 | −0.231 |
| % Asian                         | 0.252  | 0.302  |
| % Black                         | −0.255 | −0.254 |
| % Latino                        | 0.680  | 0.557  |
| % Other Race                    | −0.090 | −0.101 |
| Racial/ethnic Heterogeneity     | 0.229  | 0.009  |
| % Vacant Units                  | −0.045 | −0.081 |
| % Aged 16–29                    | 0.125  | 0.098  |
| Population Density              | 0.232  | 0.210  |
| Logged Population               | 0.141  | 0.185  |

*Note:* FSRDC Project 2534 (CBDRB-FY26-P2534-R12822).