Immigration Enforcement, Sanctuary Cities, and Rising Hispanic Suicide Rates

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Abstract

I estimate the causal impact of the US Secure Communities (SC) program—which greatly expanded deportation risk nationwide—on suicide rates among Hispanic populations. Exploiting SC's staggered county-level rollout between 2008 and 2013, I use the triple difference-in-differences (DDD) estimator proposed by Borusyak, Jaravel, and Spiess (2024) to identify causal effects. The DDD comparison of Hispanic versus non-Hispanic White populations reveals complex and heterogeneous effects. For adults aged 34+, SC produces a significant overall increase of 0.11 (2%) per 100,000. The results are driven by men, who experience substantial increases of 1.21 while women show significant decreases. The gender divergence is particularly pronounced among adults aged 45+, where men show large increases 2.27 representing a 26% increase from baseline, while women exhibit sustained decreases. Local contexts significantly moderate these effects: stronger economic conditions provide greater protection, while Democratic-leaning counties experience larger adult suicide rate increases. I find that the mechanisms—and the stark gender gaps—are supported by significant increases in deaths of despair among Hispanic men following SC implementation. Sanctuary policies appear to have neither a mitigating nor a worsening effect on Hispanic suicides. Because Hispanic ethnicity is often underreported in mortality data, these estimates likely understate the true effects, especially for adult men who bear the greatest harm. Overall, immigration enforcement produces complex mental health impacts fundamentally shaped by gender, age, and local economic environments. **JEL**: I14, I18, J15, H75

Keywords: Immigration enforcement, Secure Communities, Suicide, Difference-in-differences, Sanctuary cities, Event study

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1 Introduction

Immigration enforcement policies directly interact with the daily lives of millions of people in the United States. With an estimated 11-12 million undocumented immigrants currently residing in the country, enforcement actions create ripple effects that extend throughout mixed-status families and communities (Passel and Krogstad 2025). These effects reach beyond undocumented individuals to impact Hispanic US citizens and immigrants regardless of their legal status. This is a particularly significant concern given that Hispanic Americans have now become the largest minority group in the United States, overtaking Black Americans.[1] The psychological impact of living under the constant threat of detention and deportation, or of witnessing family and community members face these threats, can cause profound and lasting psychological distress. A substantial gap persists in the empirical literature examining how enforcement policies shape mental health outcomes across affected populations, limiting our understanding of the broader social and economic costs of current immigration policies.

The mental health consequences of immigration enforcement represent an important and understudied aspect of contemporary immigration policy. The United States has experienced a broadening trend of increased immigration enforcement over recent decades, with measures intensifying significantly in recent years. As these increasingly aggressive enforcement measures are implemented, understanding their broader implications has become critical for policymakers and communities alike. Although immigration enforcement policies are designed to enhance security and compliance with immigration law, emerging evidence suggests that they may generate substantial unintended consequences (Alsan and Yang 2024; Cox and Miles 2013; East et al. 2023).

These unintended consequences align with a broader literature demonstrating how policy-induced stressors can profoundly affect mental health outcomes, particularly during critical developmental years. Research on stress and adverse life experiences shows that exposure to traumatic or stressful events during childhood and adolescence can have lasting effects on mental health, educational attainment, and long-term wellbeing (Almond and Currie 2011). Studies examining community-wide stressors demonstrate how external threats can affect entire communities and demographic groups, extending beyond those directly exposed

[1] The 2020 Census counted more than 62 million Hispanics (19 percent of the population), tripled the number of Hispanics counted three decades earlier (Flood, Ronald, et al., Integrated Public Use Microdata Series, USA). The Hispanic population numbers are based on the author's calculations from the Current Population Survey and US Census data.

to the stressor.[2] This paper extends this literature by examining how immigration enforcement affects suicide rates within the Hispanic community.

I estimate the causal relationship between immigration enforcement and suicide rates among Hispanics, focusing on one of the most significant federal immigration programs: Secure Communities (SC). Implemented between 2008 and 2014, SC fundamentally transformed how local law enforcement interacted with federal immigration authorities by requiring local police to share fingerprints of all arrestees with Immigration and Customs Enforcement (ICE), regardless of the severity of the offense or the individual's immigration status. This sharing mechanism enabled ICE to issue detainer requests for individuals in local custody, creating a direct pathway from routine police encounters to potential deportation. The program's implementation generated widespread fear within Hispanic communities, as any interaction with law enforcement—whether as a victim, witness, or through minor infractions—could potentially lead to deportation for themselves or family members, fundamentally altering how these communities interact with local police and public institutions (Theodore and Habans 2016; Wang and Kaushal 2019). While this climate of fear might be expected to universally harm mental health outcomes, the complex dynamics of family and community responses to external threats may produce heterogeneous effects across different demographic groups. The gradual rollout of the program across US counties provides a unique quasi-experimental setting to identify these potentially diverse causal effects on mental health outcomes, specifically suicide rates among the Hispanic population in the US.

Hispanic youth represent one of the fastest growing demographic groups in the US, with Hispanic children comprising 25% (18.8 million) of all children in the United States as of 2020, up from 23% (17.1 million) in 2010.[3] However, this population faces disproportionately high rates of mental health challenges and alarming increases in suicide risk. Suicide has become the 7th leading cause of death for Hispanic children, with suicide rates among Hispanic children increasing by 92.3% from 2010 to 2019, representing one of the most dramatic increases among any demographic group Price and Khubchandani 2022. If immigration enforcement policies exacerbate these existing vulnerabilities, the implications of

[2]Examples of research on community-wide stressors include earthquakes (Tan et al. 2009; Torche 2011), hurricanes (Currie and Rossin-Slater 2013), and terrorist attacks (Camacho 2008; Lauderdale 2006)

[3]The Hispanic youth population numbers are based on the author's calculations from the Current Population Survey and US Census data (Flood, Ronald, et al., Integrated Public Use Microdata Series, USA).

such policies could be profound and long-lasting for this rapidly growing population. Moreover, understanding these effects is crucial as immigration enforcement continues to evolve, with recent years witnessing both intensification and reform of enforcement practices.[4]

I use mortality data from the National Vital Statistics System and detailed records of Secure Communities (SC) implementation across counties. To identify causal effects from the staggered adoption of SC, I employ a triple difference-in-differences (DDD) approach that leverages recent developments in the difference-in-differences literature, particularly the imputation-based estimation proposed by Borusyak, Jaravel, and Spiess (2024). The DDD approach compares the differential impact on Hispanic versus non-Hispanic White populations to control for common time-varying factors.

I find that immigration enforcement produces complex and heterogeneous effects on mental health among Hispanic adults, with stark divergence by gender and age. For Hispanic adults aged 34+, SC implementation leads to a significant overall increase in suicide rates (ATT = 0.11 per 100,000, p = 0.0004) relative to non-Hispanic Whites. However, gender-specific analyses reveal opposing patterns: Hispanic men aged 34+ experience substantial increases in suicide rates (ATT = 1.21 per 100,000, p = 0.01), while Hispanic women in the same age group show significant decreases (ATT = -0.88 per 100,000, p = 0.05). This gender divergence is particularly pronounced among adults aged 45+, where men show large increases (ATT = 2.27 per 100,000, p = 0.009) while women exhibit sustained decreases. When examining the entire Hispanic population across all ages, the aggregate effect shows a significant reduction in suicide rates (ATT = -0.36 per 100,000, p = 0.001), revealing substantial underlying heterogeneity.

I find that local economic conditions significantly moderate these effects. Counties with low unemployment rates show stronger protective effects following SC implementation, while economically distressed areas experience more harmful impacts. I further explore this mechanism by estimating the effect of SC on deaths of despair (drug, alcohol, and suicide related deaths). I find that men experience significant increases in deaths of despair following SC implementation, while women do not. This pattern reinforces the gender-specific vulnerability observed

[4]Immigration enforcement has undergone significant changes across administrations, including the expansion of programs like Secure Communities, the implementation of policies such as family separation, and subsequent policy reversals and reforms. Immigration has increasingly become a central campaign issue in federal and state elections, and enforcement measures have garnered bipartisan support. This sustained political attention ensures that immigration enforcement remains a prominent policy priority regardless of which party holds power.

in the suicide results and supports the interpretation that economic disruption—through job loss, reduced earnings, or exclusion from labor markets—serves as a key pathway through which immigration enforcement harms Hispanic men's mental health and mortality outcomes.

The observed gender divergence in suicide outcomes may be explained by the intersection of economic disruption and traditional Hispanic cultural norms surrounding gender roles. Hispanic men, shaped by machismo ideals that emphasize provider responsibilities and emotional stoicism, may face acute psychological distress when immigration enforcement exacerbates economic hardship, undermining their ability to fulfill culturally prescribed family roles (Fragoso and Kashubeck 2000; Mayo 1997). Cultural barriers to seeking mental health support compound this vulnerability, as help-seeking behavior conflicts with masculine norms of self-reliance (Cabassa 2007). In contrast, Hispanic women's protective effects may stem from familism—the cultural emphasis on family interdependence and mutual support—which provides women with stronger social support networks through their traditional roles as family caregivers and relationship maintainers (Crist et al. 2009). These gender-differentiated cultural mechanisms interact with local economic conditions to produce divergent mental health outcomes following immigration enforcement.

Beyond economic conditions, I test several additional mechanisms through which exposure to immigration enforcement can affect suicide among Hispanics: (1) the deterioration of mental health associated with fear of deportation, measured through changes in mentally unhealthy days per adult at the county level; (2) increased anti-Hispanic bias at the state level, assessed by examining whether counties in states with above-median versus below-median levels of pre-existing bias exhibit differential responses to SC implementation; (3) county political affiliation through voting patterns; and (4) county density. Sanctuary policies do not significantly moderate the effects of SC on Hispanic suicides. To explore these mechanisms, I use cohort-specific average treatment effect analyses for counties that adopted SC in 2011 and 2012, using not-yet-treated counties as controls.

This paper makes several important contributions to the existing literature. First, it provides the first causal analysis of the effects of immigration enforcement on completed suicides, the most serious mental health outcome, among Hispanics. While previous research has documented enforcement effects on self-reported mental health distress (Wang and Kaushal 2019) and birth outcomes (Amuedo-Dorantes, Churchill, and Song 2022; Vu 2024), to my knowledge, no study has examined actual suicide deaths or established causal identification for Hispanic populations specifically. Second, the paper demonstrates how immigration poli-

cies generate substantial spillover effects that extend far beyond their direct targets to affect entire demographic communities. Unlike existing studies that focus primarily on specific enforcement events or broad measures of mental distress (Goldstein and Wilson 2022; Pinedo and Valdez 2020), this analysis reveals how systematic enforcement programs can increase the most extreme adverse mental health outcomes among Hispanics who may not themselves be direct enforcement targets. Third, by leveraging the quasi-experimental variation from Secure Communities' staggered rollout across counties using administrative National Vital Statistics System data, this study provides causal evidence on the effect of SC on Hispanic suicides. Other papers that examine the effects of SC on adult labor market outcomes and safety net participation (Alsan and Yang 2024; East et al. 2023; Vu 2024) used data at a more aggregated level of treatment potentially attenuating the results.[5] Finally, this paper contributes to the broader literature on how policy-induced stressors affect mental health outcomes.

2 Literature Review

Immigration enforcement in the United States has undergone significant transformation over the past two decades. Cox and Miles (2013) demonstrate that Secure Communities' (SC) rollout was systematically correlated with Hispanic population concentrations, with counties having larger Hispanic populations prioritized for earlier adoption. This creates a differential exposure to enforcement activities across demographic groups. East et al. (2023) examine SC's labor market consequences, finding decreased employment and wages not only among likely undocumented immigrants, but also among US-born individuals through increased labor costs and reduced local consumption.[6] My study contributes to this literature by examining how SC's rollout affected suicide rates among Hispanic, providing the first causal evidence of enforcement's on suicide rates among Hispanic individuals.

Research on stress and adverse life experiences shows that exposure to traumatic or stressful events during critical developmental years can have profound and lasting effects on mental health outcomes. Almond and Currie (2011) provide a comprehensive review of how adverse early-life conditions affect long-term

[5] Alsan and Yang (2024) and East et al. (2023) used Public Use Microdata Area (PUMA) level data, which are larger geographic units that can contain multiple counties.

[6] See Amuedo-Dorantes and Bansak (2014) and Bohn and Santillano (2017) for additional research on employment verification mandates and local enforcement programs.

health, educational attainment, and income, establishing the foundation for understanding how policy-induced stress affects vulnerable populations.[7] Studies examining community-wide stressors include earthquakes (Tan et al. 2009; Torche 2011), hurricanes (Currie and Rossin-Slater 2013), and terrorist attacks (Camacho 2008; Lauderdale 2006), which demonstrate how external threats can affect entire communities and demographic groups.[8] I extend this literature by examining how stricter immigration enforcement—a policy-induced stressor—affects suicide rates among Hispanics.

Immigration enforcement policies have generated wide-ranging health consequences that span multiple outcomes and demographic groups. Birth outcome studies show that enforcement during pregnancy increases the risk of low birth weight (Amuedo-Dorantes, Churchill, and Song 2022), with Vu (2024) finding that SC increased very low birth weight by 21% among infants of foreign-born Hispanic mothers.[9] Wang and Kaushal (2019) demonstrates that SC increased mental health distress among Latino immigrants by 14.7%.[10] My research adds to this body of work by examining completed suicides among Hispanics, moving beyond self-reported distress to study the most severe mental health outcome.

Immigration enforcement creates "chilling effects" that reduce participation in social safety net programs among eligible individuals and families. Alsan and Yang (2024) show that SC significantly reduced participation in federal safety net programs among Hispanic households through fear and network effects. Vargas and Pirog (2016) demonstrate reduced participation in the WIC program among mixed-status families facing deportation risk, while Watson (2014) shows that enforcement reduces Medicaid participation among children of noncitizens. My study complements this research by examining how enforcement directly affects mental health outcomes, specifically suicide rates among Hispanics. I find that

[7]For natural experiments in this literature, see Almond (2006), Almond et al. (2010), Almond, Edlund, and Palme (2009), Almond and Mazumder (2011), and Scholte, van den Berg, and Lindeboom (2015).

[8]See Barreca (2010), Berkowitz et al. (2003), Black, Devereux, and Salvanes (2016), Currie, Mueller-Smith, and Rossin-Slater (2022), Field et al. (2004), Isen, Rossin-Slater, and Walker (2017), Kinsella and Monk (2009), Persson and Rossin-Slater (2018), Sanders (2012), and Simeonova (2011) for additional research on stress effects covering natural disasters, family bereavements, violence exposure, environmental pollution, disease exposure, and maternal depression.

[9]See Novak, Geronimus, and Martinez-Cardoso (2017), Tome et al. (2021), and Torche and Sirois (2019) for additional research on birth outcomes examining immigration raids, early Immigration and Customs Enforcement (ICE) interventions, and restrictive state laws.

[10]See Dadras and Hazratzai (2025), Goldstein and Wilson (2022), Martínez, Ruelas, and Granger (2018), Pinedo and Valdez (2020), and Torres et al. (2018) for broader mental and physical health effects.

adult suicide rates increase substantially following SC implementation, suggesting that immigration enforcement imposes severe psychological costs that extend throughout Hispanic communities, regardless of individual immigration status.

3 Background: Secure Communities

Secure Communities (SC) was an immigration enforcement program run by Immigration and Customs Enforcement (ICE) that operated from 2008 to 2014, was reactivated in 2017, and then ended in 2021. The program allowed ICE to check the immigration status of anyone arrested by the local police by fingerprint analysis, alerting federal agencies about possible immigration violations.

SC worked as follows: When someone was arrested by local law enforcement, their fingerprints were taken and sent to the FBI for criminal background checks, as was standard practice. However, with the adoption of SC, these fingerprints were also automatically sent to the Department of Homeland Security (DHS), where they were checked against immigration databases. If there was a match indicating that someone could be in the country illegally, ICE would issue a "detainer", which is a request for local authorities to hold that person for up to 48 hours so ICE could take custody and begin deportation proceedings. This was a significant change from previous methods, which relied on labor-intensive interviews conducted by federal officers or local officers of jails and prisons.

The program was gradually implemented across counties starting in October 2008, with most counties participating in mid-2012. Initially, the program required agreements between ICE and state officials, but after some states tried to opt out in 2011, ICE determined that these agreements were not necessary and made participation essentially mandatory in 2013. The program was controversial, with some "sanctuary cities" refusing to comply with detainer requests, arguing that they were unconstitutional and would discourage immigrants from cooperating with local police. I provide more detail on 'sanctuary cities' in Subsection 4.3.

Alsan and Yang (2024) collected records that are available to the public through Freedom of Information Act (FOIA) requests to ICE. The data include the roll-out of secure communities by ICE from 2002 to 2013. I present the histories of the staggered adoption of secure communities by counties in Figure 1. Since participation became mandatory in early 2013, fundamentally changing the nature of adoption decisions, I restricted my analysis to the year ending in 2012 to maintain a control group of counties that had not yet adopted or never adopted the program.

4 Data

I use two primary data sources for my main analysis: To measure the effect of secure communities on suicides among Hispanic individuals, I use mortality data from the National Vital Statistics System (NVSS) and the Secure Communities (SC) adoption data from Alsan and Yang (2024). All data samples used in the analysis are between 1999 and 2013 (the year that SC became a national policy). I use other data sources to test for potential mechanisms that could drive the results, including county-level mental health measures from the County Health Rankings & Roadmaps, measures of prejudice and bias against Hispanics from the skin-tone implicit association test, the American National Election Studies, and hate crimes against Hispanics from 2004-2013. I also use county-level election data to measure political affiliation and county-level unemployment data to measure economic conditions.

4.1 National Vital Statistics System Data

To measure the effect of secure communities on suicides among Hispanics in the United States, I use mortality data from the National Vital Statistics System (NVSS) covering the years 1959 to 2019 (National vital statistics system 2007). My outcome of interest is the annual count of suicides in each county. I specifically use the Multiple Cause of Death files, which provide detailed causes of death for each death recorded in the US at the county level using ICD-10 codes. The ICD-10 codes allow for the identification of specific causes of death, including suicide. Suicides are further broken down into several categories, allowing for a more detailed analysis of different types of suicide.[11] In addition, the data include characteristics of the deceased, such as age, sex, race, and education level, as well as county of occurrence, county of residence, and county population size. The evolution of suicide rates among Hispanics by age groups (25–34, 35–44, 45–54, and 55-84) and all Hispanics can be seen in Figure 3. Summary statistics and

[11] The ICD-10 codes used to define underlying causes of death due to suicide were X60-X84 (intentional self-harm), and Y87.0 (Sequelae of intentional self-harm) pertains to the physical or mental health conditions that arise directly from an individual's intentional self-inflicted harm. X60 to X69 correspond to intentional self-poisoning, while X70 to X84 correspond to intentional self-harm by other and unspecified means, including drowning, hanging, strangulation, and suffocation, smoke, sharp object, etc. Suicide by firearms was categorized using three specific codes: X72 (intentional self-harm by handgun discharge), X73 (intentional self-harm by rifle, shotgun and larger firearm discharge), and X74 (intentional self-harm by other and unspecified firearm discharge).

balance tables are presented in Tables 1 and 2. For the purposes of this study, the sample is restricted to 1999-2013 to align with the implementation year of the secure communities program.

4.2 Survey of Epidemiology and End Results (SEER) U.S. State and County Population Data

The Survey of Epidemiology and End Results (SEER) U.S. State and County Population Data provides comprehensive annual population estimates by age, sex, race, and county for the United States. SEER data are widely used in epidemiological research to construct accurate denominators for rate calculations, enabling robust analysis of health outcomes across demographic groups and geographic regions. For this study, SEER population estimates are essential for calculating suicide rates per 100,000 among Hispanic, White, and Black populations at the county level, ensuring that observed differences in suicide counts are not confounded by underlying population size or composition.

SEER's granular breakdown by age and race allows for precise measurement of population at risk, which is particularly important when analyzing rare events such as suicide among specific subgroups. By merging SEER population data with county-level suicide counts from the National Vital Statistics System, I am able to generate age- and race-specific suicide rates that serve as the primary outcome variables in the analysis. This approach improves the validity of causal inference by controlling for demographic shifts and enabling direct comparison of suicide risk across counties and over time (Institute, Survey of Epidemiology and End Results (SEER) U.S. State and County Population Data by Age, Race, Sex, Hispanic (1969–on)).

4.3 Sanctuary Cities Data

I construct measures of sanctuary city status using data compiled by Alsan and Yang (2024), who built upon the original list maintained by the Immigration and Customs Enforcement (ICE). Sanctuary ordinances were passed at local levels to limit a municipality's cooperation with federal immigration enforcement agencies and typically represent policies where local jurisdictions do not honor Immigration and ICE detainer requests or otherwise limit cooperation with federal immigration authorities.

The sanctuary city indicator variable identifies jurisdictions with active sanctuary policies during the period of SC activation. For Hispanics in sanctuary cities

relative to nonsanctuary cities, Alsan and Yang (2024) find that SC activation is associated with greater food-stamp participation and no detectable change in Supplemental Security Income (SSI) participation, suggesting that sanctuary policies mitigate the chilling effects of immigration enforcement on program participation.

ICE's sanctuary jurisdiction list includes various types of sanctuary policies that can be categorized into three main types: (1) "don't ask" policies that prohibit local officials from inquiring about immigration status, (2) "don't enforce" policies that limit local enforcement of immigration law, and (3) "don't tell" policies that restrict information sharing with federal immigration authorities (Kittrie 2006).

For this analysis, I focus primarily on city-level sanctuary policies, as local police enforcement typically operates under municipal governments. However, I also account for state and county-level sanctuary policies where applicable. The binary sanctuary indicator captures whether a jurisdiction had active sanctuary policies in place during the relevant time period of SC implementation, allowing me to test whether local protective policies moderate the effects of federal immigration enforcement on Hispanic suicide rates.

4.4 County-Level Mental Health Measures

I use the County Health Rankings & Roadmaps for county-level mental health measures to test if worsening mental health as a result of SC adoption is a mechanism that could drive Hispanic suicides up (University of Wisconsin Population Health Institute 2025). This dataset provides standardized mental health indicators for nearly all U.S. counties, including the average number of mentally unhealthy days reported by adults and county-level suicide rates. The ranking system allows for cross-sectional comparisons between counties and longitudinal analysis. The data does not provide a breakdown by race or ethnicity, which limits the ability to directly link the effects of stricter immigration enforcement on mental health trends to Hispanic individuals.

4.5 Measuring Prejudice

I also test whether prejudice or bias against Hispanics is another mechanism that could drive the results. It could be the case that places that are more biased against Hispanics would supportive of ICE and more strict immigration enforcement policies. I construct a measure of prejudice and use the skin-tone implicit association test, the American National Election Studies, and hate crimes against

Hispanics from 2004-2013.[12]

I construct another proxy measure of racial animus using the American National Election Studies (ANES) survey to measure animus, or discrimination, against racial minorities (American National Election Studies 2021). ANES is a survey that has been conducted since 1948 and is widely used in political science. The survey asks respondents about their attitudes toward different racial groups, voting intentions, and other political questions. I used several questions from the ANES surveys conducted between 2004 and 2013 to measure racial animus. The racial animus index is constructed by taking the average of responses to several questions that measure the racial animus. [13]

Lastly, I incorporate data from the Uniform Crime Reports (UCR) to calculate the number of hate crimes against Hispanics (Bureau of Justice Statistics 2023b). Hate crime data offer a tangible measure of racially motivated aggression and discrimination, which, when combined with implicit and explicit bias measures, allows a more complete understanding of the landscape of prejudice across states. This combination of implicit and explicit bias measures, along with hate crime statistics, offers a multidimensional approach to understanding the nature and prevalence of racial prejudice.

Moreover, to reduce attenuation bias and measurement error, I follow Lubotsky and Wittenberg (2006) in constructing a composite bias measure using the IAT, the ANES racial animus measure and hate crimes against Hispanics. A lower score implies less bias, while a higher score implies higher racial animus. A one standard deviation increase in bias is equivalent to moving from Washington, DC, or Vermont to North Dakota in 2020.

4.6 County-Level Election Data

I test whether political affiliation is another mechanism that could drive the results. For instance, Republican areas may be more supportive of ICE and more

[12]The implicit association test measures how people associate concepts—for example, Black and dark-skinned people—and evaluations—good, bad. Respondents are asked to quickly match words into categories shown on a screen. I use data from the skin tone implicit association test to construct a proxy of prejudice (Greenwald, McGhee, and Schwartz 1998). This measure has been used in the social sciences, especially in psychology. Previous work has shown that IAT test scores are difficult to manipulate (Egloff and Schmukle 2002).

[13]The questions used are similar to those used by Charles and Guryan (2008). The questions are: (1) "Conditions Make it Difficult for Blacks to Succeed", (2) "Blacks Should Not Have Special Favors to Succeed", (3) "Blacks Must Try Harder to Succeed", (4) "Blacks Gotten Less than They Deserve Over the Past Few Years", and (5) "Feeling Thermometer Toward Asians."

strict immigrant enforcement policies, having a baseline influence on suicide rates in this population. On the other hand, Democratic leaning areas may be less supportive of strict immigration enforcement, potentially causing larger negative affects should they ultimately adopt a new policy such as Secure Communities. In these instances, either political party could influence higher suicide rates or potential protective factors. I use county-level election data from Amlani and Algara (2021) to measure the political affiliation of each county. The data include the percentage of votes for the Democratic and Republican candidates in each presidential, senatorial, gubernatorial election from 1976 to 2020. I use the percentage of votes for the Democratic candidate as a measure of political affiliation, with higher values indicating a more Democratic-leaning county.

4.7 County-Level Unemployment Data

Lastly, to test for the economic conditions as a potential mechanism, I use county-level unemployment data from the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) (Flood, King, et al., Integrated Public Use Microdata Series, Current Population Survey). The CPS is a monthly survey of households conducted by the US Census Bureau. The survey collects information on employment status, occupation, industry, and other demographic characteristics. I use the unemployment rate as a measure of economic conditions, calculated the county-level unemployment rates for White and Hispanic individuals. To ensure that the data remains unidentifiable, the CPS only provides county-level unemployment data for counties with a population of at least 100,000. Therefore, my analysis of economic conditions is limited to larger counties.

I also use county-level population data from the Local Area Unemployment Statistics (LAUS) program to construct county-level unemployment rates for all counties (U.S. Bureau of Labor Statistics 2025). The LAUS program provides monthly and annual estimates of labor force, employment, unemployment, and unemployment rates for all counties in the United States. I use the annual unemployment rate as a measure of economic conditions, calculated the county-level unemployment rates for all counties.

5 Empirical strategy

In this paper, I estimate the dynamic effects of Secure Communities on county-level suicides using the imputation estimator developed by Borusyak, Jaravel, and

Spiess (2024). This approach addresses the well-documented biases that arise when using conventional two-way fixed effects (TWFE) estimators in settings with staggered treatment adoption (De Chaisemartin and d'Haultfoeuille 2020, 2023; Goodman-Bacon 2021; Roth et al. 2023; Sun and Abraham 2021). I now discuss the model, identification assumptions, and estimation approach.

I use the staggered county-level adoption of Secure Communities at the county level to causally identify its effects on Hispanic suicide rates. I employ a triple difference-in-differences approach that uses White suicide rates as an additional control group to account for common time-varying factors affecting all demographic groups. Both approaches leverage the quasi-experimental design created by two sources of variation: cross-sectional variation in which counties adopted SC, and temporal variation in when adoption occurred.

The suicide rate per 100,000 population for each demographic group is calculated as follows:

$$y_{crst} = \frac{\text{Total Suicides}_{crst}}{\text{Population}_{crst}} \times 100,000$$

where Total Suicides is the number of suicides for race r in county c, state s, and year t, and Population_{crst} is the corresponding population size.

5.1 Triple Difference-in-Differences Approach

To address potential concerns about unobserved time-varying factors that might affect suicide rates generally, I employ a triple difference-in-differences (DDD) specification that compares the differential impact of SC on Hispanic versus White suicide rates. This approach uses White suicide rates as a comparison group to control for common time-varying factors that affect suicide risk across all demographic groups, such as economic conditions, social trends, or other policies that might coincide with SC implementation. Following Borusyak, Jaravel, and Spiess (2024), I specify the following event study DDD model that allows for unrestricted treatment effect heterogeneity:

$$y_{crst} = \sum_{l=-K}^{L} \beta_l \mathbf{1}\{t - E_c = l\} \times \text{Hispanic}_r + \theta_{cr} + \lambda_{rt} + \gamma_{ct} + \varepsilon_{crst} \tag{1}$$

where the outcome variable (y_{crst}) is the suicide rate per 100,000 population for race *r* (Hispanic or White) in county *c*, in state *s*, at time *t*. The population-adjusted rate at the county level ensures that differences in suicide counts are not driven

by underlying variation in county population size, allowing for meaningful comparisons of suicide risk across demographic groups and geographic areas. The interaction of the treatment indicators with $Hispanic_r$, an indicator variable equal to 1 for Hispanic observations and 0 for White observations. This specification includes county-race fixed effects (θ_{cr}), race-year fixed effects (λ_{rt}), and county-year fixed effects (γ_{ct}). The county-race fixed effects control for time-invariant differences between Hispanic and White suicide rates within each county. The race-year fixed effects capture national trends that affect Hispanic and White populations differently. The county-year fixed effects absorb any county-specific time-varying shocks that affect both demographic groups equally.

$\mathbf{1}\{t - E_c = l\}$ is an indicator variable equal to 1 when time t is l years away from the adoption of waiting years in county c. For example, if Harris County, TX adopted SC on January 10th 2008, therefore $t - E_s$ would give you the number of years away from the year 2008. If $t = 2005$, Harris County, TX would be three years away from waiting years, which means that $t - E_s$ would be equal to three.

The coefficients of interest are β_l, which capture the differential treatment effects of SC on Hispanic versus White suicide rates. This specification identifies the causal effect of SC under the assumption that, absent treatment, Hispanic and White suicide rates would have followed parallel trends within counties, no-anticipation, and Stable Unit Treatment Value Assumption (SUTVA).

All regressions are weighted by county population to account for differences in county size and to ensure that larger counties with more reliable suicide count data receive appropriate weight in the estimation. Standard errors are clustered at the county level to account for potential serial correlation within counties over time and to allow for arbitrary forms of heteroskedasticity across counties.

I also estimate heterogeneous effects by sanctuary status, anti-Hispanic bias, county-level political leaning (Democratic versus Republican), White and Hispanic county-level unemployment rate, and density within the triple difference-in-differences framework. The heterogeneity analysis will allow me to examine whether sanctuary policies or anti-Hispanic bias moderate the differential impact of SC on Hispanic versus White suicide rates. This will also allow me to test whether local protective policies buffer Hispanic communities from the adverse effects of federal immigration enforcement while controlling for any general effects of SC on suicide rates across all demographic groups. Additionally, examining heterogeneity by unemployment rates will enable me to assess whether local economic conditions worsen the mental health consequences of immigration enforcement, capturing potential pathways through which economic shocks and labor market disruptions affect suicide risk differentially across Hispanic and White

populations.

5.2 Causal Identification Assumptions

My identification strategy leverages the staggered roll-out of Secure Communities across counties between 2008 and 2013. The model in equation (1) is generated from three main assumptions on potential outcomes and causal effects. First, the parallel trends assumption requires that in the absence of Secure Communities, suicides would have evolved similarly between counties. Second, I assume no anticipation effects—that Secure Communities did not affect suicides before the program's actual implementation in each county. This assumption is plausible given that the timing of county-level implementation was largely determined by federal administrative capacity and technical infrastructure rather than local conditions that might affect my outcomes. Finally, I impose a model of unrestricted causal effects, referred to as the "null model" in Borusyak, Jaravel, and Spiess (2024). In this case, the target estimand (parameter of interest) is the dynamic average treatment effect on the treated (ATT) h periods (horizons) since the treatment for a given $h \geqslant 0$:

$$\tau_h = \sum_{\{c,r,s,t\}:K_{cst}=h} w_{crst}\tau_{crst} \tag{2}$$

where weight is given by $w_{crst} = \frac{\mathbf{1}(K_{cst}=h)}{|\{c,r,s,t\}:K_{cst}=h|}$ and sums one within each event time h. Borusyak, Jaravel, and Spiess (2024) proposes an imputation estimator that uses untreated observations to predict what would have happened to treated units in the absence of treatment. The estimator proceeds in three steps:

1. Using only the untreated units only (i.e., observations with $D_{cst} = 0$) and ordinary least squares (OLS), I obtain $\hat{\theta}_{cr}$, $\hat{\lambda}_{rt}$, and $\hat{\gamma}_{ct}$ from

$$y_{crst} = \theta_{cr} + \lambda_{rt} + \gamma_{ct} + \varepsilon_{crst}.$$

2. For each treated observation $\{c, r, s, t\}$ with $D_{crst} = 1$, I construct untreated potential outcome (counterfactual outcome) as $\hat{y}_{crst}(0) = \hat{\theta}_{cr} + \hat{\lambda}_{rt} + \hat{\gamma}_{ct}$ and estimate the individual-specific treatment effect as $\hat{\tau}_{crst} = y_{crst} - \hat{y}_{crst}(0)$.

3. Estimate the event-time coefficients as weighted averages:
$\hat{\tau}_h = \sum_{\{c,r,s,t\}:K_{cst}=h} w_{crst}\hat{\tau}_{crst}.$

Although the maintained assumptions of the differences-in-differences design is untestable in the post-treatment period, I can perform a robust test of the identifying assumptions in the pre-treatment period (pre-trends test). Unlike the conventional pre-trends test using standard event studies, the imputation-based method affords the opportunity to test for parallel pre-trends and no-anticipation assumptions using only the untreated observations. To proceed with the pre-trends test, one needs to choose an alternative model for the outcome y_{crst} for the untreated observations. Specifically, for an observable vector W_{crst}, the alternative model may be written as $y_{crst} = \theta_{cr} + \lambda_{rt} + \gamma_{ct} + W_{crst}\zeta + \varepsilon_{crst}$, where W_{crst} may represent a set of binary indicators for $1, \ldots, k$ periods prior to the start of the treatment for some chosen k. Next, using the untreated observations only, obtain the OLS estimate of ζ and test the hypothesis $\zeta = 0$. I present all my main results using graphically, combining these pre-trend estimates with the horizon-specific ATTs from equation (2). As discussed in Borusyak, Jaravel, and Spiess (2024), this robust OLS-based pre-trends test avoids the pre-testing concerns in Roth (2022). Specifically, regression-based tests use the full sample, including the treated observations, thereby imposing restrictions on treatment effect heterogeneity. Moreover, conducting inference using the imputation estimates of the ATT remains valid even if I condition on passing the pre-trends, avoiding the issue of inflated variances and overly conservative inference that often arises with standard pre-trend tests Roth (2022).

6 Results

6.1 Triple Differences-in-Differences

In this section, I present results from the triple difference-in-differences (DDD) specification that compares the differential impact of SC on Hispanic versus non-Hispanic White populations. This approach helps control for common time-varying factors that may differentially affect these groups.

Effects on Adults (Ages 34+)

In the DDD analysis for Hispanic adults aged 34 and older, the event study estimates (Figure 4) show pre-treatment point estimates that violate parallel trends (pretrend test p-value = 0.006). For the overall 34+ group, there was a significant decrease in suicides in year 0 of -1.1 per 100,000 (p-value = 0.01) and year 1 of -1.6 per 100,000 (p-value = 0.006), followed by -0.6 in year 2, 1.2 in year 3, and 2.5

in year 4 (p-value = 0.08). The ATT for Hispanic adults 34+ is 0.11 suicides per 100,000 (p-value = 0.0004), indicating a significant overall treatment effect that is equivalent to 1.7% increase from the baseline mean.

Breaking down the analysis by gender (Figure 5), for Hispanic men aged 34+, the pre-treatment estimates are statistically insignificant. Post-treatment estimates show a decrease in year 0 of -1.2 per 100,000 and year 1 of -1.7 (p-value = 0.07), followed by increases of 0.5 in year 2, 2.8 in year 3 (p-value = 0.08), and 5.7 in year 4 (p-value = 0.05). The ATT for Hispanic men 34+ is 1.21 suicides per 100,000 (p-value = 0.01), indicating a significant treatment effect. The increase in suicides as a result of SC is equal to an 12% from the baseline mean for Hispanic men. For Hispanic women aged 34+, the pre-treatment estimates satisfy parallel trends. Post-treatment, there was a significant decrease in year 0 of -0.8 per 100,000 (p-value = 0.02), year 1 of -1.3 (p-value = 0.01), and year 2 of -1.4 (p-value = 0.01), followed by -0.2 in year 3 and -0.7 in year 4. The ATT for Hispanic women 34+ is -0.88 (44%) suicides per 100,000 (p-value = 0.05). Overall, Hispanic men aged 34+ experienced initial decreases followed by substantial and significant increases in later years, while Hispanic women in the same age group saw sustained and significant decreases, resulting in a stark divergence in outcomes by gender.

Age Heterogeneity

To further explore how the effects of SC vary across the life course, I present DDD results separately for ages 25–34, 35–44, 45+, and the full 25+ sample, as well as disaggregated by gender within each age group.

Ages 25–34. For Hispanic adults aged 25–34, the event study estimates (Figure 6a) show pre-treatment estimates that are statistically insignificant, providing evidence that the parallel trends and no-anticipation assumptions hold (pretrend test p-value = 0.16). In the post-treatment period, there was a decrease of approximately -1.4 per 100,000 in year 0, followed by 0.6 in year 1, -0.5 in year 2, 1.4 in year 3, and 2.6 in year 4. None of the individual post-treatment estimates are statistically significant. The ATT for Hispanic adults 25–34 is 0.55 suicides per 100,000 (p-value = 0.02), representing a significant overall treatment effect that is equal to an increase of 7% from the mean.

Breaking down the analysis by gender, for Hispanic men aged 25–34 (Figure 7a), the pre-treatment estimates satisfy the parallel trends assumption (pretrend test p-value = 0.37). Post-treatment estimates show -1.9 in year 0, 0.9 in year 1, -0.6 in year 2, 1.8 in year 3, and 5.0 in year 4. The ATT is 1.03 suicides per 100,000 (p-

value = 0.08), indicating a significant effect. This represents a 8% increase from the mean suicide rate of 13.23 per 100,000. For Hispanic women aged 25–34 (Figure 8a), the post-treatment estimates show -0.7 in year 0, 0.6 in year 1, -0.03 in year 2, 1.6 in year 3, and 0.8 in year 4, with none individually significant. The ATT is 0.44 suicides per 100,000 (p-value = 0.56), indicating no significant overall treatment effect. This represents an 18% increase from the baseline mean suicide rate of 2.40 per 100,000.

Ages 35–44. For Hispanic adults aged 35–44, the event study estimates (Figure 6b) show pre-treatment point estimates that are mostly statistically insignificant. In the post-treatment period, there was a decrease of approximately -1.6 per 100,000 in year 0 and -1.3 in year 1, followed by -1.5 in year 2, -0.8 in year 3, and -0.2 in year 4. None of the individual estimates are statistically significant. The ATT for Hispanic adults 35–44 is -1.09 suicides per 100,000 (p-value = 0.58), indicating no significant overall treatment effect.

Breaking down the analysis by gender, for Hispanic men aged 35–44 (Figure 7b), the pre-treatment estimates are statistically insignificant indicating that the parallel trends assumption probably holds (pretrend test p-value = 0.37). Post-treatment estimates are -1.6 in year 0, -1.1 in year 1, 0.02 in year 2, -0.9 in year 3, and 2.4 in year 4. The ATT is -0.22 suicides per 100,000 (p-value = 0.82), indicating no significant treatment effect. For Hispanic women aged 35–44 (Figure 8b), post-treatment estimates are consistently negative: -1.3 in year 0, -1.3 in year 1, -3.1 in year 2, -0.4 in year 3, and -2.4 in year 4. The ATT is -1.68 suicides per 100,000 (p-value = 0.22). In this age group, women show larger negative point estimates throughout the post-treatment period, though neither gender reaches statistical significance.

Ages 45+. For Hispanic adults aged 45 and older, the event study estimates (Figure 6c) show pre-treatment point estimates that are mostly statistically insignificant. In the post-treatment period, there was a decrease of approximately -0.7 per 100,000 in year 0 (p-value = 0.11) and -1.4 in year 1 (p-value = 0.03), followed by 0.1 in year 2, 2.4 in year 3 (p-value = 0.03), and 3.0 in year 4 (p-value = 0.03), with the later increases being statistically significant. The ATT for Hispanic adults 45+ is 0.69 suicides per 100,000 (p-value = 0.002), indicating a significant overall treatment effect. This represents a 13% increase from the mean suicide rate of 5.15 per 100,000.

Breaking down the analysis by gender, for Hispanic men aged 45+ (Figure 7c), the pre-treatment estimates are statistically insignificant. Post-treatment es-

timates show -0.5 in year 0, -1.5 in year 1, 1.5 in year 2, 5.2 in year 3 (p-value = 0.006), and 6.7 in year 4 (p-value = 0.03). The ATT is 2.27 suicides per 100,000 (p-value = 0.009), indicating a significant treatment effect driven by large increases in later years. This represents a 26% increase from the mean suicide rate of 8.77 per 100,000. For Hispanic women aged 45+ (Figure 8c), the pre-treatment estimates are statistically insignificant. Post-treatment estimates are consistently negative: -0.7 in year 0, -1.3 in year 1 (p-value = 0.03), -1.2 in year 2 (p-value = 0.02), -0.4 in year 3, and -0.8 in year 4. The ATT is -0.89 suicides per 100,000 (p-value = 0.13), a 52% decrease from the mean suicide rate of 1.7 per 100,000. In this age group, men show substantial and significant increases in suicide as a result of SC, while women exhibit sustained decreases.

Ages 25+. For Hispanic adults aged 25 and older, the event study estimates (Figure 6d) show pre-treatment point estimates that are mostly statistically insignificant. In the post-treatment period, there was a significant decrease of -1.1 per 100,000 in year 0 ($p = 0.002$) and -1.2 in year 1 ($p = 0.02$), followed by an insignificant -0.5 in year 2, and then increases of 1.2 in year 3 and 2.3 in year 4 ($p = 0.06$). The ATT for Hispanic adults 25+ is 0.14 suicides per 100,000 ($p < 0.01$).

Breaking down the analysis by gender, for Hispanic men aged 25+ (Figure 7d), the pre-treatment estimates are mostly statistically insignificant. Post-treatment estimates show -1.3 in year 0 ($p = 0.05$), -1.2 in year 1, 0.3 in year 2, 2.4 in year 3 ($p = 0.10$), and 5.2 in year 4 ($p = 0.02$). The ATT for Hispanic men 25+ is 1.08 suicides per 100,000 ($p < 0.01$), indicating a significant 9.8% increase from the mean suicide rate of 11.03 per 100,000. For Hispanic women aged 25+ (Figure 8d), the pre-treatment estimates are statistically insignificant. Post-treatment estimates show significant decreases in years 0 through 2: -0.8 in year 0 ($p = 0.02$), -1.0 in year 1 ($p = 0.02$), and -1.3 in year 2 ($p = 0.02$), followed by insignificant estimates of 0.1 in year 3 and -0.4 in year 4. The ATT for Hispanic women 25+ is -0.67 suicides per 100,000 ($p = 0.04$), indicating a significant overall decrease. In this age group, men show initial decreases that reverse into substantial increases in suicide rates following SC implementation, while women exhibit sustained and significant decreases through the first three post-treatment years, resulting in a stark gender divergence.

Aggregate Effects Across All Ages

In the DDD analysis for the entire Hispanic population across all ages, the event study estimates show pre-treatment violations of parallel trends (pretrend test p-

value = 0.005), with a significant decrease in suicide rates in year 0 of -1.0 per 100,000 (p-value = 0.001) and year 1 of -1.0 per 100,000 (p-value = 0.02), followed by -0.7 in year 2, 0.4 in year 3, and 0.5 in year 4. The average treatment effect on the treated (ATT) for all ages is -0.36 suicides per 100,000 (p-value = 0.001), indicating a statistically significant reduction in suicide rates following SC implementation.

When disaggregating by gender, for Hispanic men across all ages, the pre-treatment estimates violate parallel trends (pretrend test p-value = 0.009). Post-treatment estimates show -0.7 in year 0 (p-value = 0.03), -0.6 in year 1, -0.3 in year 2, 0.3 in year 3, and 0.8 in year 4. The ATT for Hispanic men is -0.11 suicides per 100,000 (p-value = 0.06), marginally significant. For Hispanic women, the pre-treatment estimates also violate parallel trends (pretrend test p-value = 0.04). Post-treatment, women experienced decreases of -0.3 in year 0 (p-value = 0.02), -0.4 in year 1 (p-value = 0.01), -0.4 in year 2 (p-value = 0.09), 0.09 in year 3, and -0.3 in year 4. The ATT for Hispanic women is -0.26 suicides per 100,000 (p-value = 0.10). These results suggest that the overall reduction in suicide rates following SC implementation is driven by declines in both genders, with larger and more consistent effects among women, though both groups show marginally significant treatment effects.

7 Robustness Checks and Discussions

7.1 Stable Unit Treatment Value Assumption (SUTVA) and Spillover Effects

The Stable Unit Treatment Value Assumption (SUTVA) requires that treatment assignment of one unit does not affect the potential outcomes of other units. In the context of Secure Communities implementation, this assumption may be violated if the policy creates spillover effects across county boundaries. For instance, the adoption of SC in one county might lead to changes in suicides in neighboring counties, affecting suicide rates in both treated and untreated areas.

While SUTVA cannot be directly tested, I can provide evidence that it is not substantially violated by examining spillover effects. I examine spillover effects by analyzing whether Secure Communities implementation in neighboring counties affects suicide rates in non-treated counties across multiple age groups and demographic outcomes. Table A.1 presents results from two specifications that test for geographic spillover effects on Hispanic suicide rates across different age groups: children (ages 5–14), adolescents and young adults (ages 15-24), adults

(ages 34+), and all ages combined. The first specification includes an indicator for whether a county borders a treated county but has not yet adopted Secure Communities itself. The second specification measures the intensity of treatment by counting the number of neighboring counties that have implemented the program.

The results show small and statistically insignificant spillover effects across all age groups examined. For adults aged 34+ and the aggregate population, the coefficients on both the border indicator and neighboring intensity measures remain close to zero and lack statistical significance. These negligible spillover effects suggest that SUTVA is not substantially violated in this context, supporting the validity of the identification strategy. The lack of significant spillover effects across multiple age groups and specifications indicates that the observed changes in Hispanic suicide rates are primarily driven by direct treatment effects within counties rather than cross-border displacement or contagion effects.

7.2 Placebo Analysis

To further validate the causal relationship between Secure Communities implementation and Hispanic suicide rates, I conduct a placebo test examining the impact of SC on Black versus White suicide rates. Since SC primarily targeted undocumented Hispanic immigrants, we should not expect to see similar effects on Black populations, who were not directly targeted by the policy. This placebo test serves as a critical falsification check: finding similar effects for Black populations would cast serious doubt on the causal interpretation of my main results. Figure A.2 presents the results of this placebo triple difference-in-differences analysis, where I assign SC activation five years prior to the actual rollout and examine effects on Black-White suicide rate differentials for adults aged 34+. I present the results broken down by different age groups and sex in Figures A.3–A.5.

The placebo results provide compelling evidence for the causal interpretation of my main findings. Critically, unlike the Hispanic-White analysis, the Black-White suicide gap shows no consistent or statistically significant response to SC implementation among adults aged 34+. The Black-White suicide gap exhibits fluctuating patterns with no clear directional trend comparable to the substantial increases observed for Hispanic adults.

The stark contrast between the main and placebo results is essential for causal identification. These findings effectively rule out several alternative explanations: they demonstrate that the documented effects are not driven by (1) broader trends affecting all minority populations during this period, (2) general deterioration in

minority mental health unrelated to immigration policy, or (3) other confounding factors that coincided with SC implementation. Instead, the specificity of effects to Hispanic populations—the group explicitly targeted by the policy—strengthens the conclusion that SC immigration enforcement causally impacted Hispanic suicide rates through mechanisms directly linked to the policy's focus on Hispanic communities.

7.3 Discussion of Effect Magnitude

The estimated effects of Secure Communities on Hispanic suicide rates should be interpreted as likely lower-bound estimates of the true causal impact. Hispanic ethnicity is often underreported or misclassified in vital statistics records, with some Hispanic suicides potentially being recorded as non-Hispanic white deaths due to inconsistencies in data collection practices, incomplete information, or administrative errors in death certificates. Consequently, the significant effects observed on Hispanic suicide rates likely represent conservative estimates of the true policy impact. The actual harm to Hispanic communities may be substantially larger than the results suggest.

8 Mechanisms and Heterogeneity Analysis

I test multiple mechanisms that could lead to an increase in Hispanic suicide rates after a change in immigration enforcement. These mechanisms are fear of deportation, racial or ethnic bias toward Hispanics, political leaning of a county, the economic conditions in the area, and density.

Sanctuary Policy and Immigration Intensity Heterogeneity

I explore sanctuary policies as a potential protective mechanism through which fear of deportation might be mitigated, examining how these local policies interact with SC implementation to affect Hispanic suicide rates. Sanctuary policies were designed to limit local cooperation with federal immigration enforcement, potentially buffering Hispanic communities from the psychological stress and fear associated with aggressive enforcement programs like SC. I present the heterogeneity analysis results in Figures A.6–A.12, disaggregated by age and sex. The analysis compares suicide rates between sanctuary and non-sanctuary jurisdictions following SC implementation. I find consistent evidence across all age groups and both

sexes that sanctuary policies do not significantly moderate the effects of SC on Hispanic suicide rates. The point estimates and confidence intervals for sanctuary versus non-sanctuary counties largely overlap throughout the post-treatment period, with no statistically significant differential effects emerging in any specification. As an additional robustness check, I re-estimate the specifications controlling for removals. I present these results in Appendix Figure A.13–A.18. The results are unchanged from the main specification, the estimated effects and confidence intervals closely mirror those from the baseline analysis.

This null finding is notable for several reasons. First, it suggests that while sanctuary policies may buffer against some consequences of immigration enforcement—such as reduced program participation—they do not appear to protect against the mental health impacts that manifest as suicide. This divergence may reflect that sanctuary policies primarily affect interactions with local law enforcement and public institutions, whereas the psychological toll of immigration enforcement operates through broader community-level fear and stress that sanctuary status does not fully alleviate. Second, the null effect persists across different demographic subgroups, suggesting it is not driven by heterogeneous responses among specific populations. Finally, this finding highlights that local protective policies, while potentially beneficial in other domains, may be insufficient to counteract the profound psychological distress caused by federal immigration enforcement programs when examining the most extreme mental health outcome.

Economic Conditions

Other potential mechanisms, such as economic conditions, access to welfare programs, and the effect of SC on health outcomes, have been documented in the literature. Alsan and Yang (2024), East et al. (2023), and Vu (2024) find that SC implementation leads to a significant reduction in employment, food stamp participation among Hispanic families, and worse health outcomes respectively. These mechanisms could also contribute to the deterioration of mental health, especially among adult Hispanics, and thus contribute to an increase in suicides.

To test for economic conditions, I conduct two complementary heterogeneity analyses by unemployment rates. First, using CPS data, I examine the differential effects between counties with low versus high Hispanic-white unemployment gaps, though this analysis is limited to a smaller set of counties where CPS data are available. I then supplement this with a broader analysis using LAUS data, which provides overall county unemployment rates for all counties in the sample. I present the results in Figures A.19–A.24 for the CPS analysis, and Figures

A.25–A.30 for the LAUS analysis. I present the results broken down by different age groups and sex.

The CPS analysis reveals marked heterogeneity. For adults aged 34+, both county types exhibit increasing suicide rates following SC implementation, with a steeper decline in year 3 for low-gap counties. The broader LAUS analysis, which examines overall unemployment rates across all counties, shows that for adults aged 34+, the heterogeneity is less pronounced compared to the CPS analysis.[14] Gender-specific analysis reveals that men drive much of the observed heterogeneity in both datasets, with women showing more muted differential effects across unemployment contexts. The results are consistent among all age groups of men and women.

These findings suggest that both Hispanic-specific labor market inequalities and overall economic conditions significantly moderate the mental health impacts of immigration enforcement, with the patterns varying substantially by gender. The contrasting results between the CPS and LAUS analyses highlight the importance of considering both Hispanic-specific economic disparities and broader economic conditions when evaluating the heterogeneous effects of immigration policies.

Deaths of Despair

Alcohol-Related Mortality. Among Hispanic adults aged 25–34, alcohol-related mortality rises significantly following SC activation, with an average post-period effect of 0.64 per 100,000 ($p = 0.00$; Figure A.31a). This overall increase is driven almost entirely by men, who show a significant rise of 1.35 per 100,000 ($p = 0.00$; Figure A.32a). In contrast, women exhibit no significant response (–0.10 per 100,000; $p = 0.75$; Figure A.33a).

For adults aged 35–44, alcohol mortality averages –0.35 per 100,000 ($p = 0.29$; Figure A.31b), with divergent gender patterns. Men show non-significant declines (–1.15 per 100,000; $p = 0.11$; Figure A.32b), whereas women exhibit significant increases (0.52 per 100,000; $p = 0.02$; Figure A.33b). This gender reversal in the 35–44 age group contrasts sharply with the male-driven effects observed among younger adults.

[14] Using the CPS, I could calculate county-level unemployment rate for Hispanics and non-Hispanic Whites. The downside of using the CPS that county-level data is only available for almost half the sample that live in the largest counties. This is why I supplement the analysis by using LAUS, which does not have county-level unemployment rate by ethnicity or race.

Drug-Related Mortality. Drug mortality among Hispanic adults aged 25–34 shows a modest, imprecise increase overall (0.85 per 100,000; p = 0.13; Figure A.34a). Breaking down by gender reveals that this pattern is concentrated among men, who experience a significant rise of 3.19 per 100,000 (p = 0.04; Figure A.35a), while women show a non-significant decline (–1.36 per 100,000; p = 0.44; Figure A.36a).

Among adults aged 35–44, drug mortality effects are close to zero overall (0.11 per 100,000; p = 0.12; Figure A.34b), with imprecise increases for men (1.78 per 100,000; p = 0.72; Figure A.35b) and declines for women (–1.54 per 100,000; p = 0.18; Figure A.36b). Neither gender shows statistically significant effects in this age band.

Combined Deaths of Despair. The composite measure of deaths of despair—encompassing suicides, alcohol-related deaths, and drug-related deaths—provides insight into the broader mental health and substance abuse consequences of SC implementation. For Hispanic adults aged 25–34, the death-of-despair event study (Figure A.37a) shows flat pre-trends followed by post-activation increases that peak around year 3. The post-period average effect is 2.04 deaths per 100,000 (p = 0.04), driven by a large and significant rise among men (5.57 per 100,000; p = 0.03; Figure A.38a), while women exhibit no clear change (–1.03 per 100,000; p = 0.24; Figure A.39a).

Among adults aged 35–44, death-of-despair effects (Figure A.37b) average –1.33 per 100,000 (p = 0.07) with declining point estimates through year 3. Men show a small, imprecise increase (0.41 per 100,000; p = 0.58; Figure A.38b), while women experience a larger but only marginally significant decline (–2.70 per 100,000; p = 0.08; Figure A.39b).

These age-specific patterns aggregate into substantial effects for broader male groups. Hispanic men aged 25+ show a significant post-period average of 2.20 per 100,000 (p = 0.01; Figure A.38), and men aged 45+ experience a sizable increase of 3.57 per 100,000 (p = 0.04; Figure A.38), both consistent with the strong male-driven impacts observed in younger cohorts. Collectively, these results demonstrate that deaths of despair among Hispanic men increase substantially following SC implementation, driven primarily by alcohol- and drug-related mortality concentrated in the 25–34 age group.

Anti-Hispanic Bias Heterogeneity

To explore the role of anti-Hispanic bias in amplifying the effects of immigration enforcement on suicide rates, I examine whether counties with above-median

versus below-median levels of state-level bias exhibit differential responses to Secure Communities implementation.[15] I show the results in Figure A.40–A.45.

I find no consistent differential effects between high and low bias counties. Both high and low bias counties show similar patterns in suicide rates following SC implementation. Across different age groups and both men and women, the differences between high and low bias counties remain statistically insignificant, indicating that the level of anti-Hispanic bias in a county does not significantly moderate the impact of Secure Communities on Hispanic suicide rates. These null findings suggest that anti-Hispanic bias, as measured by the composite index of implicit attitudes, explicit prejudice, and hate crimes, is not a primary mechanism through which Secure Communities affects Hispanic suicide rates.

County Political Leaning

I examine whether local political climates influence the impact of Secure Communities on Hispanic suicide rates by comparing effects between Republican-leaning counties (below median Democratic vote share) and Democratic-leaning counties (above median Democratic vote share), as shown in Figures A.46–A.51. I find that political leaning does not significantly moderate the effects for men across age groups. However, I observe statistically significant differences for young women aged 25–34, where Democratic-leaning counties show significantly higher suicide rates compared to Republican-leaning counties following SC implementation. This gender-specific and age-specific pattern suggests that local political climate may moderate the mental health consequences of immigration enforcement selectively, affecting young Hispanic women but not men.

Population Density Heterogeneity

To examine whether urbanization moderates the policy's mental health effects, I conduct a heterogeneity analysis by county-level population density, comparing low-density (bottom 10%) versus high-density (top 90%) counties, as shown in Figures A.52–A.57. Gender-specific analyses reveal important differences in how population density moderates the policy's effects. Among men aged 34+, I find no

[15] I use state-level measures of bias rather than more granular geographic units due to data limitations. County-level data are unavailable for key sources such as the ANES, and the GSS is not representative below the state level. Additionally, crime data are typically more reliable and complete at the state level.

statistically significant differences between low-density and high-density counties, with overlapping confidence intervals throughout the post-treatment period. However, among women aged 34+, the difference between low-density and high-density counties is statistically significant. These findings suggest that population density does not significantly moderate the impact of Secure Communities on Hispanic suicide rates.

General Population Mental Health Effects

To assess whether the timing of Secure Communities activation mattered for general population mental health, I present the ATT for the two cohorts that adopted the SC in 2011 and 2012. I chose 2011 and 2012 because they are the only years for which county-level mentally unhealthy days data and SC implementation dates overlap before becoming a nationwide policy. Figure A.58 presents the cohort-specific ATT estimates with 95 percent confidence intervals.

For the 2011 cohort, the ATT is equal to –0.08 mentally unhealthy days per adult (CI: –0.17 to +0.01), and the 2012 cohort's ATT is equal to –0.10 days. Averaging across both cohorts yields an ATT equal to –0.09 days. In all cases, no estimate is statistically significant. These null cohort-specific effects reinforce the conclusion that SC implementation may not meaningfully change average mentally unhealthy days at the county level, regardless of activation year. Since Hispanics may be affected more by the policy than other groups, it is important to examine mental health data specifically for Hispanic residents to see if SC had different effects on this population that are not captured in the overall county-level results.

The particularly pronounced increases in suicide rates among adult Hispanic men may reflect the intersection of economic disruption and cultural expectations rooted in traditional Hispanic gender role norms. The concept of machismo, which encompasses ideals of masculine strength, stoicism, and the provider role, creates particular vulnerabilities for Hispanic men facing economic hardship (Fragoso and Kashubeck 2000; Mayo 1997). When immigration enforcement compounds labor market disruptions that I explore in this paper and is documented by East et al. (2023), Hispanic men who strongly identify with their role as family providers may experience acute psychological distress from their inability to fulfill these culturally prescribed responsibilities. This gender role conflict becomes especially damaging when combined with cultural barriers to help-seeking behavior, as Hispanic men often view seeking mental health support as incompatible with masculine ideals of self-reliance and emotional control (Cabassa 2007). The protective effects observed among Hispanic women, in contrast, may reflect the strength of

familism—the cultural emphasis on family interdependence, mutual support, and collective problem-solving—which operates differently across genders (Crist et al. 2009). Women's traditional roles as family caregivers and social network maintainers may provide greater access to emotional support and coping resources during times of community stress, buffering against the mental health impacts of immigration enforcement. The gender differentials suggest that community protective mechanisms and social support networks operate differently for men and women, with women showing more muted effects across various economic and political contexts (Johnson and Rogers 2020; Velez and Moradi 2016). While data limitations prevent direct testing of all potential psychological mechanisms underlying these gender patterns, the heterogeneity analyses I present here examine all observable moderators available at the county level, including economic conditions, political climate, population density, and anti-Hispanic bias, providing the most comprehensive assessment possible given existing data constraints.

9 Conclusion

This paper provides a causal analysis of how immigration enforcement affects suicide rates among Hispanic adults in the United States. Using the staggered implementation of Secure Communities across counties between 2008 and 2013, I find robust evidence that immigration enforcement produces complex and heterogeneous mental health effects within Hispanic communities, with stark divergence by gender and age.

The adoption of SC produced a significant overall increase in suicide rates among Hispanic adults aged 34+, with an average treatment effect of 0.11 suicides per 100,000 ($p = 0.0004$) relative to non-Hispanic Whites. Gender-specific analyses reveal opposing patterns: Hispanic men aged 34+ experience substantial and significant increases in suicide rates (ATT = 1.21 per 100,000, $p = 0.01$), while Hispanic women in the same age group show significant decreases (ATT = -0.88 per 100,000, $p = 0.05$). This gender divergence is particularly pronounced among adults aged 45+, where men show large and statistically significant increases (ATT = 2.27 per 100,000, $p = 0.009$) representing a 26% increase from baseline, while women exhibit sustained decreases. When examining the entire Hispanic population across all ages, the aggregate effect shows a significant reduction in suicide rates (ATT = -0.36 per 100,000, $p = 0.001$), further illustrating how population-level averages can obscure critical disparities in policy impacts across demographic subgroups. I find no evidence that sanctuary policies moderate the impact of SC on Hispanic

suicide rates.

The heterogeneity analyses reveal that local economic conditions and political climate are the primary moderators of Secure Communities' impact on Hispanic suicide rates, while population density and measured anti-Hispanic bias show limited explanatory power. The most consistent pattern emerges with economic conditions: counties with low unemployment rates experience protective effects (substantial declines in suicide rates) following SC implementation, while high unemployment counties show harmful effects (stable or increasing rates), suggesting that economic security buffers against the psychological stress of immigration enforcement while economic distress amplifies its negative mental health consequences. The economic mechanism is further supported by analyses of deaths of despair—deaths attributable to drugs, alcohol, and suicide combined—which show significant increases among Hispanic men following SC implementation while women experience no such effect. This broader mortality pattern reinforces the interpretation that economic disruption serves as a key pathway through which immigration enforcement harms Hispanic men. Political context also matters, particularly for adults aged 34 and older, where Democratic-leaning counties experience significant increases in suicide rates while Republican-leaning counties show more variable patterns. The null effects on general population mental health, as measured by county-level mentally unhealthy days, further underscore that the mental health burden of immigration enforcement falls disproportionately on Hispanic communities in ways not captured by aggregate population-level metrics. These findings suggest that the mental health consequences of federal immigration policy are not uniform but are fundamentally shaped by the local economic and political environments in which Hispanic families live, with vulnerable populations in economically distressed areas bearing the greatest harm.

Several factors suggest that my findings represent conservative estimates of the true impact. Vital statistics records systematically suffer from Hispanic ethnicity underreporting and misclassification, meaning a portion of Hispanic suicide deaths are incorrectly categorized as non-Hispanic white fatalities. Such errors stem from inconsistent reporting practices across jurisdictions, missing information on death certificates, and clerical mistakes during administrative processing. Because this measurement error affects both treatment and comparison groups, it attenuates the estimated treatment effects by artificially lowering observed Hispanic suicide counts throughout the sample period. Given that I still detect significant effects among Hispanic individuals aged 34+, particularly among men, the genuine consequences of immigration enforcement on Hispanic mental health outcomes are plausibly much larger than what I reported here. These results there-

fore capture only a fraction of the actual public health burden, especially for adult Hispanic men who bear the greatest harm.

Beyond sanctuary policies, I find that local economic conditions and political climate serve as key moderators of enforcement impacts. Counties with stronger economic foundations experience less harmful effects for adults following SC implementation. This suggests that economic security serves as an important buffer against enforcement-related stress. Political context also matters significantly, with Democratic-leaning counties experiencing larger increases in adult Hispanic suicide rates compared to Republican-leaning areas. I find that population density and measured anti-Hispanic bias show limited explanatory power further underscores that economic and political factors may be the primary drivers of heterogeneous responses to immigration enforcement. Unfortunately, the lack of Hispanic-specific mental health data at the county level prevents me from directly investigating differential effects on psychological distress between Hispanic and White populations, highlighting an important avenue for future research. These patterns suggest that the mental health consequences of federal immigration policy are fundamentally shaped by the local socioeconomic and political environments in which Hispanic communities are embedded.

The gender divergence in suicide outcomes reflects how traditional cultural frameworks shape responses to immigration enforcement stress. Hispanic men's increased suicide risk appears driven by the collision between machismo cultural norms—which emphasize masculine strength, provider responsibilities, and emotional restraint—and the economic disruption caused by immigration enforcement (Fragoso and Kashubeck 2000; Mayo 1997). When men cannot fulfill their culturally prescribed role as family providers due to labor market disruptions (East et al. 2023), they experience severe psychological distress compounded by cultural prohibitions against help-seeking behavior (Cabassa 2007). The significant increase in deaths of despair among Hispanic men—but not women—following SC implementation provides additional empirical support for this interpretation, as deaths of despair are commonly understood as responses to economic dislocation and loss of social standing. Conversely, Hispanic women's protective outcomes may reflect the resilience provided by familism, where cultural emphases on family interdependence, collective problem-solving, and women's roles as emotional caregivers create robust social support networks that buffer against enforcement-related stressors (Crist et al. 2009). This cultural explanation aligns with the heterogeneity analysis showing that economic conditions moderate these effects: areas with stronger labor markets may preserve men's provider roles, reducing gender role conflict, while economically distressed counties intensify the

psychological burden of unfulfilled cultural expectations. Understanding these culturally rooted gender differences is essential for designing interventions that address the distinct mental health vulnerabilities within Hispanic communities facing immigration enforcement.

This analysis provides only an initial examination of the complex interplay between federal enforcement and local policies. Different types of sanctuary policies, which vary considerably in scope and implementation, may differentially affect mental health outcomes. This paper provides potential future topics to be researched, including examining the specific mechanisms through which sanctuary policies provide protection, investigating whether certain policy designs are more effective than others, and assessing how the interaction between federal enforcement intensity and local sanctuary strength influences community mental health. Furthermore, research exploring the long-term effects of sanctuary policies on broader community trust, social cohesion, and access to public services would provide valuable insights to policymakers seeking to design comprehensive approaches to immigrant integration and community well-being.

References

Almond, Douglas. 2006. "Is the 1918 Influenza Pandemic Over? Long-Term Effects of In Utero Influenza Exposure in the Post-1940 U.S. Population." *Journal of Political Economy* 114, no. 4 (August): 672–712. https://doi.org/10.1086/507154.

Almond, Douglas, and Janet Currie. 2011. "Killing Me Softly: The Fetal Origins Hypothesis." *Journal of Economic Perspectives* 25, no. 3 (September): 153–172. https://doi.org/10.1257/jep.25.3.153.

Almond, Douglas, Lena Edlund, Hongbin Li, and Junsen Zhang. 2010. "Long-Term Effects of Early-Life Development: Evidence from the 1959 to 1961 China Famine." In *The Economic Consequences of Demographic Change in East Asia*, 321–345. University of Chicago Press, August. https://www.nber.org/books-and-chapters/economic-consequences-demographic-change-east-asia/long-term-effects-early-life-development-evidence-1959-1961-china-famine.

Almond, Douglas, Lena Edlund, and Mårten Palme. 2009. "Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden*." *The Quarterly Journal of Economics* 124, no. 4 (November 1, 2009): 1729–1772. https://doi.org/10.1162/qjec.2009.124.4.1729.

Almond, Douglas, and Bhashkar Mazumder. 2011. "Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy." *American Economic Journal: Applied Economics* 3, no. 4 (October): 56–85. https://doi.org/10.1257/app.3.4.56.

Alsan, Marcella, and Crystal S. Yang. 2024. "Fear and the Safety Net: Evidence from Secure Communities." *The Review of Economics and Statistics* 106, no. 6 (November 7, 2024): 1427–1441. https://doi.org/10.1162/rest_a_01250.

American National Election Studies. 2021. *ANES 2020 Time Series Study Full Release [Dataset and Documentation]*. https://www.electionstudies.org.

Amlani, Sharif, and Carlos Algara. 2021. "Partisanship & nationalization in American elections: Evidence from presidential, senatorial, & gubernatorial elections in the US counties, 1872–2020." *Electoral Studies* 73:102387.

Amuedo-Dorantes, Catalina, and Cynthia Bansak. 2014. "Employment Verification Mandates and the Labor Market Outcomes of Likely Unauthorized and

Native Workers." *Contemporary Economic Policy* 32 (3): 671–680. https://doi.org/10.1111/coep.12043.

Amuedo-Dorantes, Catalina, Brandyn Churchill, and Yang Song. 2022. "Immigration Enforcement and Infant Health." *American Journal of Health Economics* 8, no. 3 (June): 323–358. https://doi.org/10.1086/718510.

Barreca, Alan I. 2010. "The Long-Term Economic Impact of In Utero and Postnatal Exposure to Malaria." *Journal of Human Resources* 45, no. 4 (October 2, 2010): 865–892. https://doi.org/10.3368/jhr.45.4.865.

Berkowitz, Gertrud S., Mary S. Wolff, Teresa M. Janevic, Ian R. Holzman, Rachel Yehuda, and Philip J. Landrigan. 2003. "The World Trade Center Disaster and Intrauterine Growth Restriction." *JAMA* 290, no. 5 (August 6, 2003): 595–596. https://doi.org/10.1001/jama.290.5.595-b.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2016. "Does Grief Transfer across Generations? Bereavements during Pregnancy and Child Outcomes." *American Economic Journal: Applied Economics* 8, no. 1 (January): 193–223. https://doi.org/10.1257/app.20140262.

Bohn, Sarah, and Robert Santillano. 2017. "Local Immigration Enforcement and Local Economies." *Industrial Relations: A Journal of Economy and Society* 56 (2): 236–262. https://doi.org/10.1111/irel.12172.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2024. "Revisiting Event-Study Designs: Robust and Efficient Estimation." *The Review of Economic Studies* 91, no. 6 (November 1, 2024): 3253–3285. https://doi.org/10.1093/restud/rdae007.

Bureau of Justice Statistics. 2023a. *Uniform Crime Reporting (UCR) Program Data Series [Data Set].* https://catalog.data.gov/dataset/uniform-crime-reporting-program-data-series-16edb.

———. 2023b. *Uniform Crime Reporting Program Data Series [Dataset].* https://catalog.data.gov/dataset/uniform-crime-reporting-program-data-series-16edb.

Cabassa, Leopoldo J. 2007. "Latino immigrant men's perceptions of depression and attitudes toward help seeking." *Hispanic Journal of Behavioral Sciences* 29 (4): 492–509.

Camacho, Adriana. 2008. "Stress and Birth Weight: Evidence from Terrorist Attacks." *American Economic Review* 98, no. 2 (May): 511–515. https://doi.org/10.1257/aer.98.2.511.

Charles, Kerwin Kofi, and Jonathan Guryan. 2008. "Prejudice and Wages: An Empirical Assessment of Becker's The Economics of Discrimination." *Journal of Political Economy* 116, no. 5 (October): 773–809. https://doi.org/10.1086/593073.

Cox, Adam B., and Thomas J. Miles. 2013. "Policing Immigration." *The University of Chicago Law Review* 80 (1): 87–136. https://www.jstor.org/stable/41825870.

Crist, Janice D, Marylyn M McEwen, Angelica P Herrera, Suk-Sun Kim, Alice Pasvogel, and Joseph T Hepworth. 2009. "Caregiving burden, acculturation, familism, and Mexican American elders' use of home care services." *Research and theory for nursing practice* 23 (3): 165.

Currie, Janet, Michael Mueller-Smith, and Maya Rossin-Slater. 2022. "Violence While in Utero: The Impact of Assaults during Pregnancy on Birth Outcomes." *The Review of Economics and Statistics* 104, no. 3 (May 9, 2022): 525–540. https://doi.org/10.1162/rest_a_00965.

Currie, Janet, and Maya Rossin-Slater. 2013. "Weathering the Storm: Hurricanes and Birth Outcomes." *Journal of Health Economics* 32, no. 3 (May 1, 2013): 487–503. https://doi.org/10.1016/j.jhealeco.2013.01.004.

Dadras, Omid, and Mohammad Sediq Hazratzai. 2025. "The Silent Trauma: U.S. Immigration Policies and Mental Health." *Lancet Regional Health - Americas* 44 (March 1, 2025): 101048. https://doi.org/10.1016/j.lana.2025.101048.

De Chaisemartin, Clément, and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American economic review* 110 (9): 2964–2996.

———. 2023. "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey." *The econometrics journal* 26 (3): C1–C30.

East, Chloe N., Annie L. Hines, Philip Luck, Hani Mansour, and Andrea Velásquez. 2023. "The Labor Market Effects of Immigration Enforcement." *Journal of Labor Economics* 41, no. 4 (October 2, 2023): 957–996. https://doi.org/10.1086/721152.

Egloff, Boris, and Stefan C. Schmukle. 2002. "Predictive Validity of an Implicit Association Test for Assessing Anxiety." *Journal of Personality and Social Psychology* (US) 83:1441–1455. https://doi.org/10.1037/0022-3514.83.6.1441.

Field, Tiffany, Miguel Diego, John Dieter, Maria Hernandez-Reif, Saul Schanberg, Cynthia Kuhn, Regina Yando, et al. 2004. "Prenatal Depression Effects on the

Fetus and the Newborn." *Infant Behavior and Development* 27, no. 2 (May 1, 2004): 216–229. https://doi.org/10.1016/j.infbeh.2003.09.010.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2021. (Integrated Public Use Microdata Series, Current Population Survey: Version 9.0. V. 9.0). https://doi.org/10.18128/D030.V9.0.

Flood, Sarah, Goeken Ronald, Schouweiler Megan, and Sobek Matthew. 2021. (Integrated Public Use Microdata Series, USA: Version 12.0. V. 9.0). https://doi.org/10.18128/D030.V9.0.

Fragoso, Jose M, and Susan Kashubeck. 2000. "Machismo, gender role conflict, and mental health in Mexican American men." *Psychology of Men & Masculinity* 1 (2): 87.

Goldstein, Evan V., and Fernando A. Wilson. 2022. "Hispanic Immigrants and Suicide: Overcoming Data Challenges in an Anti-immigrant Climate." *AJPM Focus* 1, no. 2 (October 1, 2022): 100038. https://doi.org/10.1016/j.focus.2022.100038.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of econometrics* 225 (2): 254–277.

Greenwald, Anthony G., Debbie E. McGhee, and Jordan L. K. Schwartz. 1998. "Measuring Individual Differences in Implicit Cognition: The Implicit Association Test." *Journal of Personality and Social Psychology* (US) 74 (6): 1464–1480. https://doi.org/10.1037/0022-3514.74.6.1464.

Institute, National Cancer. n.d. (Survey of Epidemiology and End Results (SEER) U.S. State and County Population Data by Age, Race, Sex, Hispanic (1969–on). Surveillance Research Program, National Cancer Institute). https://seer.cancer.gov/popdata/.

Isen, Adam, Maya Rossin-Slater, and W. Reed Walker. 2017. "Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970." *Journal of Political Economy* 125, no. 3 (June): 848–902. https://doi.org/10.1086/691465.

Johnson, Austin H, and Baker A Rogers. 2020. ""We're the normal ones here": community involvement, peer support, and transgender mental health." *Sociological Inquiry* 90 (2): 271–292.

Kinsella, Michael T., and Catherine Monk. 2009. "Impact of Maternal Stress, Depression and Anxiety on Fetal Neurobehavioral Development." *Clinical Ob-*

stetrics and Gynecology 52, no. 3 (September): 425–440. https://doi.org/10.1097/GRF.0b013e3181b52df1.

Kittrie, Orde F. 2006. "Federalism, Deportation, and Crime Victims Afraid to Call the Police." *Iowa Law Review* 91 (5): 1449–1508.

Lauderdale, Diane S. 2006. "Birth Outcomes for Arabic-named Women in California before and after September 11." *Demography* 43, no. 1 (February 1, 2006): 185–201. https://doi.org/10.1353/dem.2006.0008.

Lubotsky, Darren, and Martin Wittenberg. 2006. "Interpretation of Regressions with Multiple Proxies." *The Review of Economics and Statistics* 88, no. 3 (August 1, 2006): 549–562. https://doi.org/10.1162/rest.88.3.549.

Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. 2022. (IPUMS National Historical Geographic Information System: Version 17.0. Minneapolis, MN). https://doi.org/10.18128/D050.V17.0.

Martínez, Airín D., Lillian Ruelas, and Douglas A. Granger. 2018. "Household Fear of Deportation in Relation to Chronic Stressors and Salivary Proinflammatory Cytokines in Mexican-origin Families Post-SB 1070." *SSM - Population Health* 5 (June 19, 2018): 188–200. https://doi.org/10.1016/j.ssmph.2018.06.003.

Mayo, Yolanda. 1997. "Machismo, fatherhood and the Latino family: Understanding the concept." *Journal of Multicultural Social Work* 5 (1-2): 49–61.

National vital statistics system. 2007. "National Vital Statistics System," http://www.cdc.gov/nchs/nvss.htm.

Novak, Nicole L., Arline T. Geronimus, and Aresha M. Martinez-Cardoso. 2017. "Change in Birth Outcomes among Infants Born to Latina Mothers after a Major Immigration Raid." *International Journal of Epidemiology* 46, no. 3 (June 1, 2017): 839–849. https://doi.org/10.1093/ije/dyw346.

Passel, Jeffrey S., and Jens Manuel Krogstad. 2025. *U.S. Unauthorized Immigrant Population Reached a Record 14 Million in 2023.* Research Report. Pew Research Center, August. https://www.pewresearch.org/race-and-ethnicity/2025/08/21/u-s-unauthorized-immigrant-population-reached-a-record-14-million-in-2023/.

Persson, Petra, and Maya Rossin-Slater. 2018. "Family Ruptures, Stress, and the Mental Health of the Next Generation." *American Economic Review* 108, nos. 4-5 (April): 1214–1252. https://doi.org/10.1257/aer.20141406.

Pinedo, Miguel, and Carmen R. Valdez. 2020. "Immigration Enforcement Policies and the Mental Health of US-citizens: Findings from a Comparative Analysis." *American journal of community psychology* 66, nos. 1-2 (September): 119–129. https://doi.org/10.1002/ajcp.12464.

Price, James H, and Jagdish Khubchandani. 2022. "Hispanic child suicides in the United States, 2010–2019." *Journal of community health* 47 (2): 311–315.

Roth, Jonathan. 2022. "Pretest with caution: Event-study estimates after testing for parallel trends." *American Economic Review: Insights* 4 (3): 305–322.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's trending in difference-in-differences? A synthesis of the recent econometrics literature." *Journal of Econometrics* 235 (2): 2218–2244.

Sanders, Nicholas J. 2012. "What Doesn't Kill You Makes You Weaker: Prenatal Pollution Exposure and Educational Outcomes." *Journal of Human Resources* 47 (3): 826–850. https://muse.jhu.edu/pub/19/article/479576.

Scholte, Robert S., Gerard J. van den Berg, and Maarten Lindeboom. 2015. "Long-Run Effects of Gestation during the Dutch Hunger Winter Famine on Labor Market and Hospitalization Outcomes." *Journal of Health Economics* 39 (January): 17–30. https://doi.org/10.1016/j.jhealeco.2014.10.002.

Simeonova, Emilia. 2011. "Out of Sight, Out of Mind? Natural Disasters and Pregnancy Outcomes in the USA." *CESifo Economic Studies* 57, no. 3 (September 1, 2011): 403–431. https://doi.org/10.1093/cesifo/ifr005.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects." *Journal of Econometrics*, Themed Issue: Treatment Effect 1, 225, no. 2 (December 1, 2021): 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006.

Tan, Cong E., Hong Jun Li, Xian Geng Zhang, Hui Zhang, Pei Yu Han, Qu An, Wei Jun Ding, et al. 2009. "The Impact of the Wenchuan Earthquake on Birth Outcomes." *PLOS ONE* 4, no. 12 (December 7, 2009): e8200. https://doi.org/10.1371/journal.pone.0008200.

Theodore, Nik, and Robert Habans. 2016. "Policing immigrant communities: Latino perceptions of police involvement in immigration enforcement." *Journal of Ethnic and Migration Studies* 42 (6): 970–988.

Tome, Romina, Marcos A. Rangel, Christina M. Gibson-Davis, and Laura Bellows. 2021. "Heightened Immigration Enforcement Impacts US Citizens' Birth Outcomes: Evidence from Early ICE Interventions in North Carolina." *PLoS ONE*

16, no. 2 (February 3, 2021): e0245020. https://doi.org/10.1371/journal.pone.0245020.

Torche, Florencia. 2011. "The Effect of Maternal Stress on Birth Outcomes: Exploiting a Natural Experiment." *Demography* 48, no. 4 (August 26, 2011): 1473–1491. https://doi.org/10.1007/s13524-011-0054-z.

Torche, Florencia, and Catherine Sirois. 2019. "Restrictive Immigration Law and Birth Outcomes of Immigrant Women." *American Journal of Epidemiology* 188, no. 1 (January 1, 2019): 24–33. https://doi.org/10.1093/aje/kwy218.

Torres, Jacqueline M, Julianna Deardorff, Robert B Gunier, Kim G Harley, Abbey Alkon, Katherine Kogut, and Brenda Eskenazi. 2018. "Worry About Deportation and Cardiovascular Disease Risk Factors Among Adult Women: The Center for the Health Assessment of Mothers and Children of Salinas Study." *Annals of Behavioral Medicine* 52, no. 2 (February 5, 2018): 186–193. https://doi.org/10.1093/abm/kax007.

U.S. Bureau of Labor Statistics. 2025. *Local Area Unemployment Statistics.* https://www.bls.gov/lau/.

University of Wisconsin Population Health Institute. 2025. *County Health Rankings & Roadmaps 2025.* https://www.countyhealthrankings.org/.

Vargas, Edward D., and Maureen A. Pirog. 2016. "Mixed-Status Families and WIC Uptake: The Effects of Risk of Deportation on Program Use." *Social Science Quarterly* 97 (3): 555–572. https://doi.org/10.1111/ssqu.12286.

Velez, Brandon L, and Bonnie Moradi. 2016. "A moderated mediation test of minority stress: The role of collective action." *The Counseling Psychologist* 44 (8): 1132–1157.

Vu, Hoa. 2024. "I Wish I Were Born in Another Time: Unintended Consequences of Immigration Enforcement on Birth Outcomes." *Health Economics* 33 (2): 345–362. https://doi.org/10.1002/hec.4775.

Wang, Julia Shu-Huah, and Neeraj Kaushal. 2019. "Health and Mental Health Effects of Local Immigration Enforcement." *International Migration Review* 53, no. 4 (December 1, 2019): 970–1001. https://doi.org/10.1177/0197918318791978.

Watson, Tara. 2014. "Inside the Refrigerator: Immigration Enforcement and Chilling Effects in Medicaid Participation." *American Economic Journal: Economic Policy* 6, no. 3 (August): 313–338. https://doi.org/10.1257/pol.6.3.313.

Table 1: Summary Statistics for County-Year Data

Variable	Mean	SD
Total Population	1,064,632.00	1,878,899.00
Hispanic Population	837,728.00	1,312,636.00
% Female	50.90	1.27
% White	74.00	16.97
% College Degree or Higher	7.70	9.00
Median Household Income ($)	21,148.00	22,684.00
% Below Poverty Line	6.00	7.16
Hispanic Suicide Rate: Age 25-34	8.33	23.55
Hispanic Suicide Rate: Age 35-44	7.91	26.72
Hispanic Suicide Rate: Age 34+	6.46	13.60
Hispanic Suicide Rate: Age 25+	6.97	12.08
Hispanic Suicide Rate: All Ages	6.51	9.10
Hispanic Suicide Rate: Age 25-34 (Men)	13.23	39.36
Hispanic Suicide Rate: Age 35-44 (Men)	12.74	43.64
Hispanic Suicide Rate: Age 45+ (Men)	9.65	29.38
Hispanic Suicide Rate: Age 34+ (Men)	10.68	24.85
Hispanic Suicide Rate: Age 25+ (Men)	11.41	22.00
Hispanic Suicide Rate: Age 25-34 (Women)	2.79	17.49
Hispanic Suicide Rate: Age 35-44 (Women)	2.79	18.18
Hispanic Suicide Rate: Age 45+ (Women)	2.06	9.49
Hispanic Suicide Rate: Age 34+ (Women)	2.29	8.71
Hispanic Suicide Rate: Age 25+ (Women)	2.42	7.96

[1] Data source is the National Vital Statistics System (NVSS) covering 1959-2013 for mortality data and Manson et al. (IPUMS National Historical Geographic Information System: Version 17.0) for the demographic data from the US Census. Sample includes county-year observations. Suicide data uses ICD-10 codes X60-X84 and Y87.0 to identify deaths by intentional self-harm among Hispanic populations. Suicide rates are calculated per 100,000 population using SEER population denominators.

Table 2: Comparison of Treated and Control Groups

Variable	Control Mean	Control SD	Treated Mean	Treated SD
Total Population	541,370.00	488,376.00	1,068,484.00	1,884,799.00
Hispanic Population	250,507.00	387,657.00	840,490.00	1,314,831.00
% Female	49.40	1.58	50.90	1.26
% White	42.30	24.92	74.20	16.68
% College Degree or Higher	8.30	8.45	7.70	9.00
Median Household Income ($)	24,585.00	24,761.00	21,122.00	22,666.00
% Below Poverty Line	5.50	6.36	6.00	7.17
Hispanic Suicide Rate: Age 25-34	22.65	74.01	8.30	23.31
Hispanic Suicide Rate: Age 35-44	24.60	222.14	7.88	24.87
Hispanic Suicide Rate: Age 45+	14.33	127.21	5.76	14.91
Hispanic Suicide Rate: Age 34+	17.60	87.70	6.44	13.04
Hispanic Suicide Rate: Age 25+	19.09	64.47	6.95	11.73
Hispanic Suicide Rate: All Ages	10.92	28.63	6.49	8.90
Hispanic Suicide Rate: Age 25-34 (Men)	33.64	130.94	13.19	38.90
Hispanic Suicide Rate: Age 35-44 (Men)	37.35	93.85	12.69	43.46
Hispanic Suicide Rate: Age 45+ (Men)	24.23	200.65	9.62	27.96
Hispanic Suicide Rate: Age 34+ (Men)	28.82	161.43	10.64	23.77
Hispanic Suicide Rate: Age 25+ (Men)	30.30	111.16	11.37	21.41
Hispanic Suicide Rate: Age 25-34 (Women)	9.37	34.01	2.77	17.44
Hispanic Suicide Rate: Age 35-44 (Women)	8.97	40.41	2.78	18.11
Hispanic Suicide Rate: Age 45+ (Women)	3.99	15.25	2.06	9.47
Hispanic Suicide Rate: Age 34+ (Women)	5.53	15.80	2.28	8.69
Hispanic Suicide Rate: Age 25+ (Women)	6.61	15.86	2.41	7.93

[1] Data source is the National Vital Statistics System (NVSS) covering 1959-2013 for mortality data and Secure Communities adoption data from Alsan et al. (2024). Control group represents county-year observations before Secure Communities implementation; treated group represents observations after implementation. Secure Communities was an ICE immigration enforcement program operating 2008-2014, with staggered county adoption beginning October 2008. Suicide rates shown per 100,000 population for Hispanic adults aged 34 and over in respective demographic groups.

Table 3: Sanctuary Jurisdictions Used in the Analysis

State	Jurisdiction	Level
CA	Alameda, Amador, Butte, Calaveras, Contra Costa, Del Norte, El Dorado, Fresno, Humboldt, Imperial, Inyo, Kings, Los Angeles, Mendocino, Merced, Mono, Napa, Orange, Placer, San Bernardino, San Francisco (City/County), San Joaquin, San Luis Obispo, San Mateo, Santa Barbara, Santa Clara, Santa Cruz, Sutter, Yolo, Yuba	Local
CA	*Trust Act*[3]	Statewide
CO	Archuleta, Delta	Local
CO	*All jails: detainers require judicial warrant*[3]	Statewide
CT	Hartford, New Haven	Local
CT	*Trust Act*[3]	Statewide
DC	Washington, D.C.	Local
FL	Alachua, Hernando	Local
GA	Clayton, DeKalb	Local
IA	Benton, Iowa, Jefferson, Sioux, Story, Union	Local
IL	Chicago (City)	Local
KS	Butler, Finney, Harvey, Sedgwick, Shawnee	Local
LA	Orleans Parish (New Orleans)	Local
MD	Montgomery, Prince George's	Local
MA	Boston (City), Hampshire (County), Middlesex (County), Northampton (City)	Local
MN	Hennepin	Local
NE	Hall, Sarpy	Local
NV	Clark, Washoe	Local
NJ	Burlington, Camden, Essex, Middlesex	Local

Continued on next page

Table 3: Sanctuary Jurisdictions Used in the Analysis (continued)

State	Jurisdiction	Level
NM	Bernalillo, Doña Ana, Rio Arriba, Santa Fe, Taos	Local
NM	*All county jails*[3]	Statewide
NY	New York City (NYC), Franklin, Onondaga, St. Lawrence, Wayne	Local
OR	Baker, Clackamas, Clatsop, Coos, Deschutes, Douglas, Grant, Jackson, Jefferson, Josephine, Lane, Lincoln, Malheur, Marion, Multnomah, Polk, Tillamook, Union, Wallowa, Washington, Yamhill	Local
PA	Bradford, Bucks, Butler, Chester, Delaware, Erie, Lebanon, Lehigh, Lycoming, Montgomery, Montour, Perry, Philadelphia (City/County), Pike, Westmoreland	Local
RI	Providence	Local
RI	*DOC policy*[3]	Statewide
VA	Arlington, Chesterfield	Local
VT	Montpelier (City)	Local
WA	Clallam, Clark, Cowlitz, Jefferson, King, San Juan, Skagit, Snohomish, Thurston, Walla Walla, Whatcom	Local
WI	Milwaukee	Local

[1] Data from ICE Declined Detainer Outcome Report (DDOR), January 28–February 3, 2017.

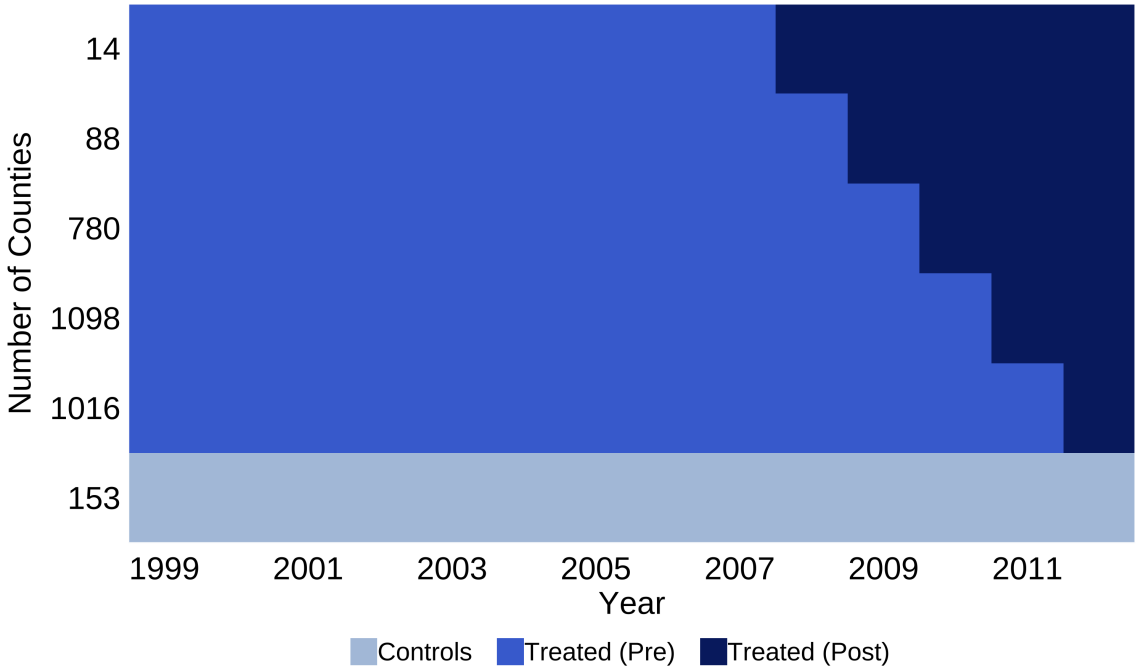
[2] Local jurisdictions consolidated by state; individual counties/cities separated by commas.

[3] Statewide policies apply to all jurisdictions within the state and may coexist with additional local measures.

[4] Sanctuary policies vary in scope: some limit ICE detainer cooperation, others have broader non-cooperation policies.

[5] List may not include all sanctuary jurisdictions nationwide; policies subject to change since data collection.

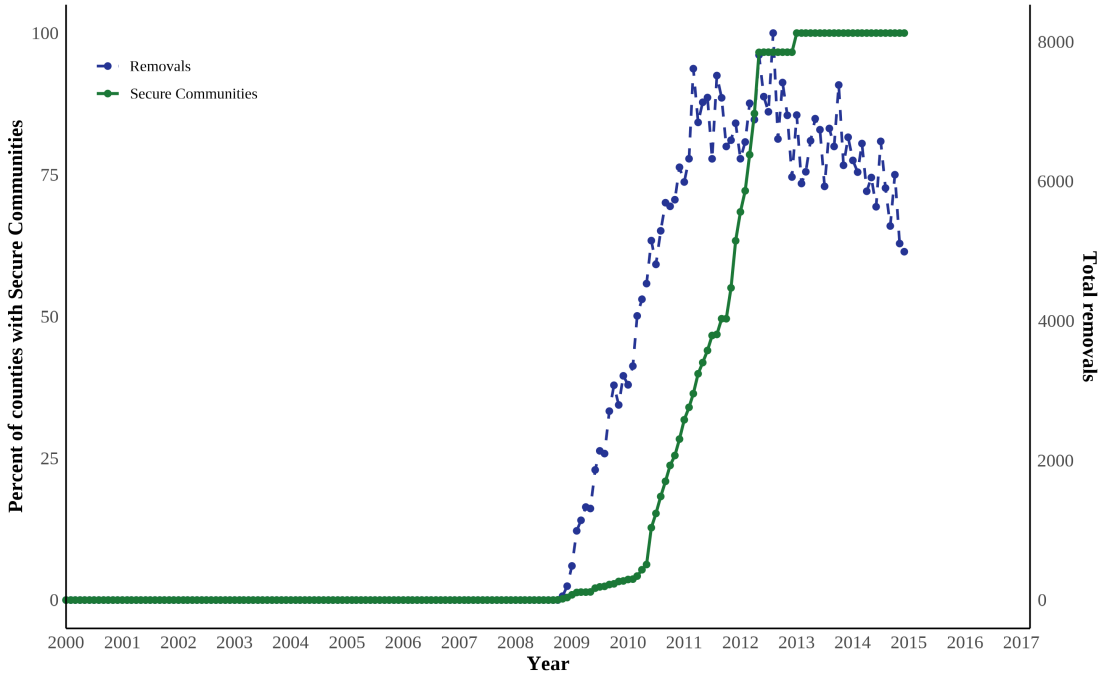
Figure 1: Staggered Adoption of Secure Communities Across US Counties



Notes: This figure illustrates the temporal and geographic variation in Secure Communities (SC) implementation across U.S. counties from 1999-2019. The staggered rollout provides the quasi-experimental variation necessary for causal identification, as counties were activated at different times based on administrative priorities rather than local suicide rates.

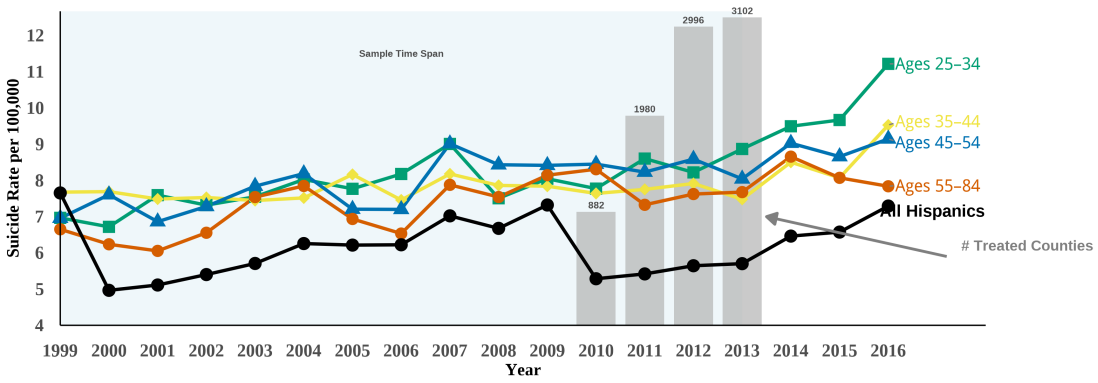
Source: Alsan and Yang (2024) collected records that are available to the public through FOIA requests to US Immigration and Customs Enforcement (ICE).

Figure 2: Staggered Adoption of Secure Communities Over Time



This figure shows the share of counties with Secure Communities and the Monthly Number of Removals (2008-2013).

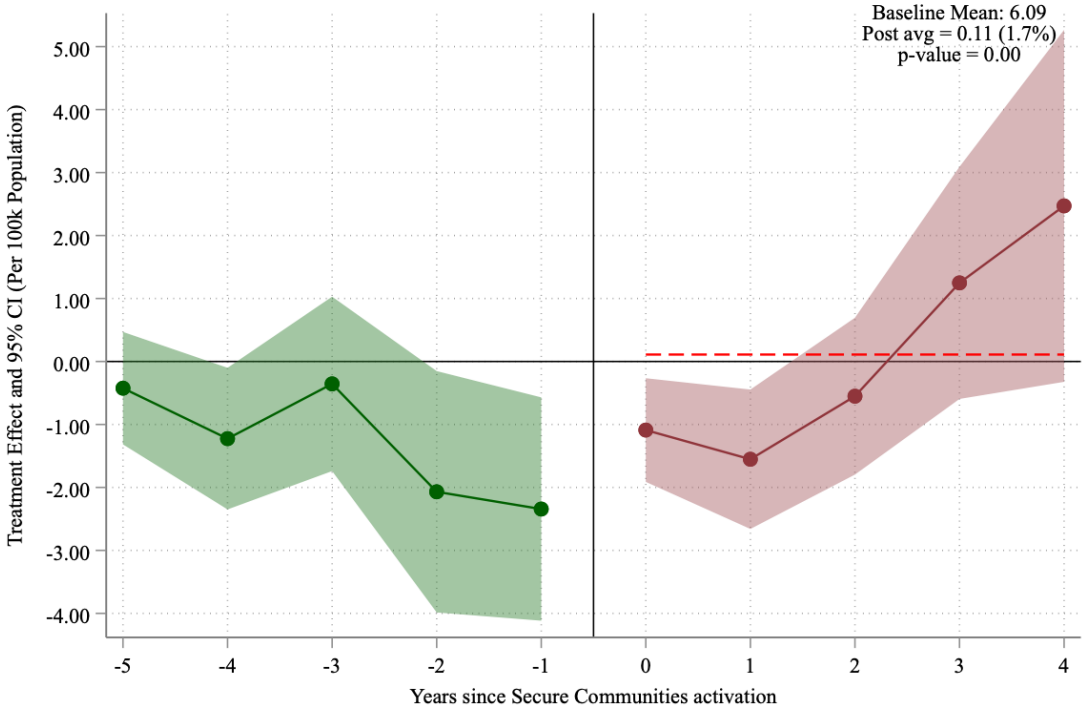
Figure 3: Suicides: By Age Groups



Notes: This descriptive figure shows the evolution of suicide rates among Hispanic adults aged 24–34, 35–44, 45–54, 55–84, and among all Hispanics over the study period. The shaded area is the study period from 1999 to 2013. I also include a histogram of the cumulative number of treated counties. For example, the total number of treated counties in 2011 was 882.

Source: National Vital Statistics System (NVSS) covering the years 1959 to 2019 (National vital statistics system 2007).

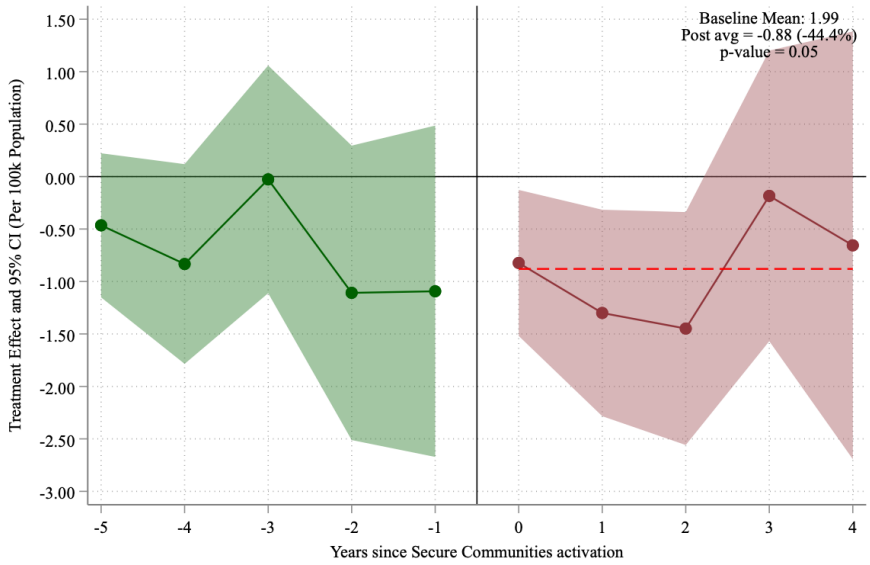
Figure 4: Triple Difference-in-Differences: Effect of Secure Communities on Hispanic vs White Suicide Rates Among Adults Aged 34 and Older



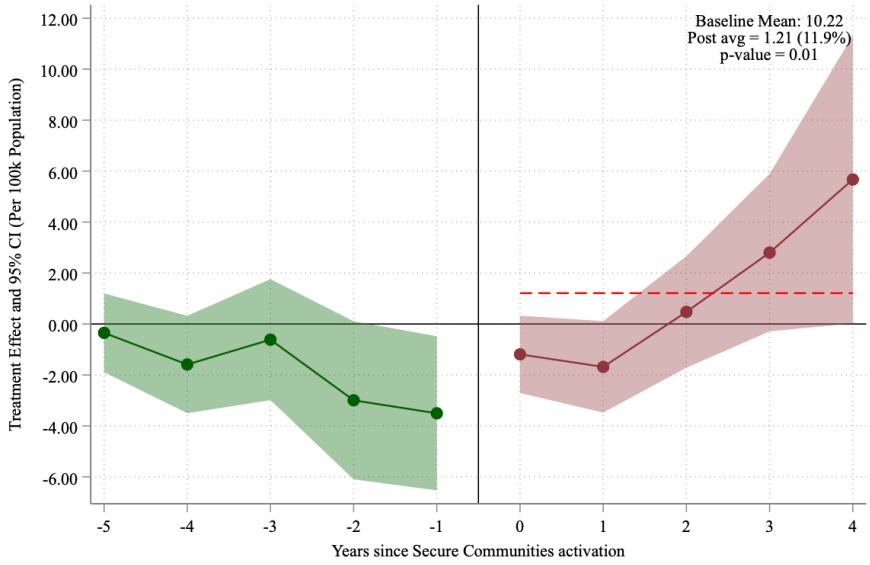
Notes: This figure estimates a triple difference-in-differences model comparing the differential impact of Secure Communities on Hispanic versus White suicide rates among adults aged 34 and older. The outcome variable is the suicide rate per 100,000 population. The specification includes county-race, county-year, and race-year fixed effects, using White suicide rates as a comparison group to control for common time-varying factors affecting suicide risk. Pre-treatment coefficients (β_l for $l < 0$) test the parallel trends assumption between Hispanic and White adults. Post-treatment coefficients (β_l for $l \geqslant 0$) capture the differential treatment effects of Secure Communities implementation on Hispanic versus White adults' suicide rates. The standard errors are clustered at the county level and the county population is used to weight the estimates.

Source: Alsan and Yang (2024) collected records that are available to the public through FOIA requests to US Immigration and Customs Enforcement (ICE). National Vital Statistics System (NVSS) covering the years 1959 to 2019 (National vital statistics system 2007).

Figure 5: Triple Difference-in-Differences: Effect of Secure Communities on Hispanic vs White Suicide Rates by Gender (Ages 34+)



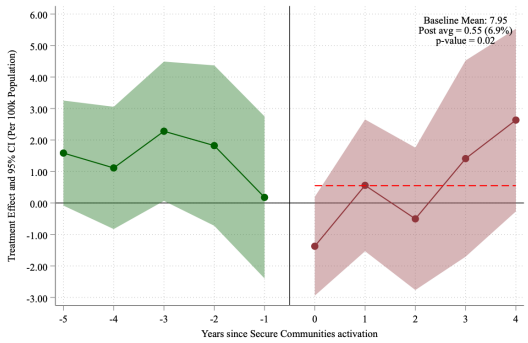
(a) Women Suicide Rates (Ages 34+)



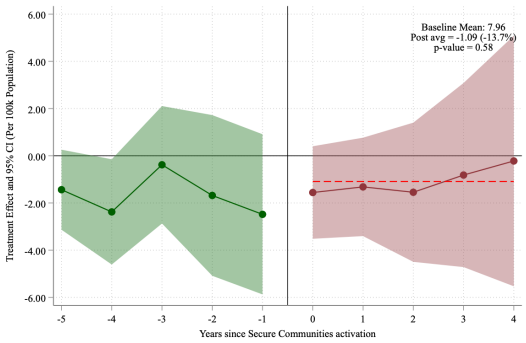
(b) Men Suicide Rates (Ages 34+)

Notes: See Figure 4 for more details. The analysis uses suicide rates per 100,000 among adults aged 34 and older by gender as the outcome variable.

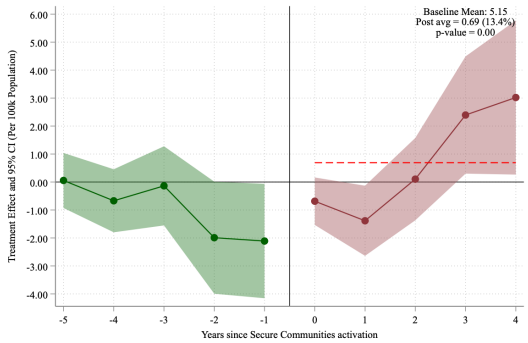
Figure 6: Triple Difference-in-Differences: Additional Adult Age Bands



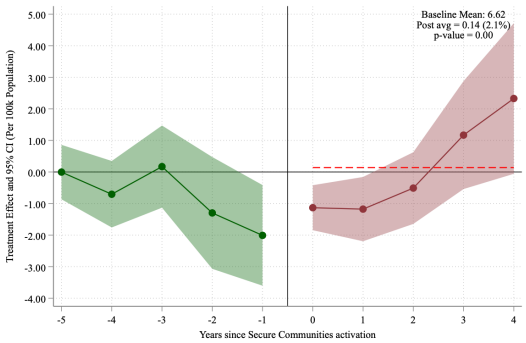
(a) Ages 25–34



(b) Ages 35–44



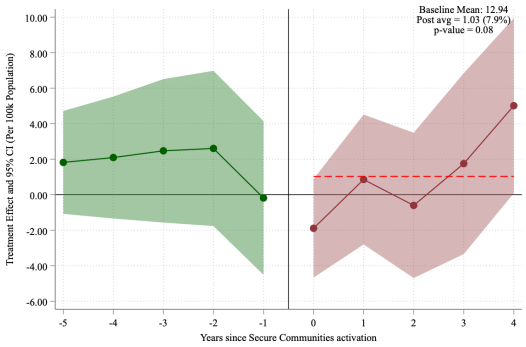
(c) Ages 45+



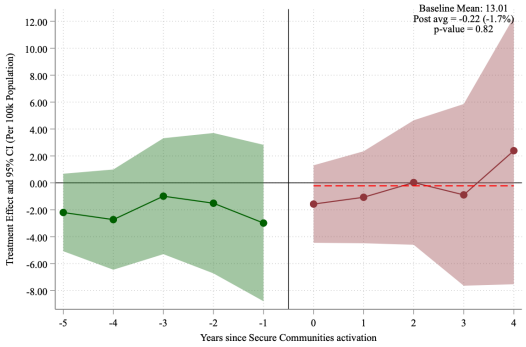
(d) Ages 25+

Notes: Additional triple difference estimates by adult age bands using per 100k suicide rates. Specification matches the main DDD model; see Figure 4 for details on controls, fixed effects, and weighting.

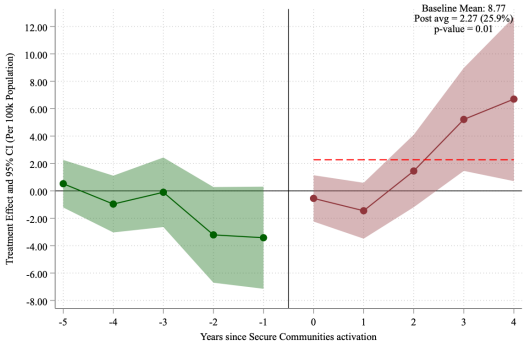
Figure 7: Triple Difference-in-Differences: Additional Adult Age Bands (Men)



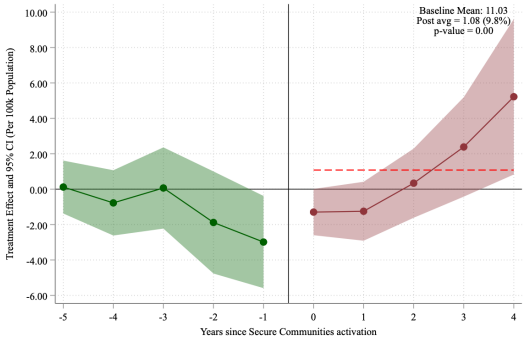
(a) Men 25–34



(b) Men 35–44



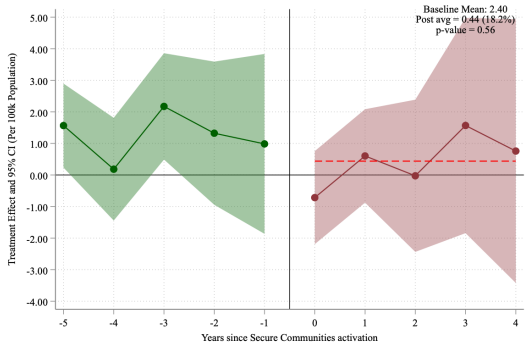
(c) Men 45+



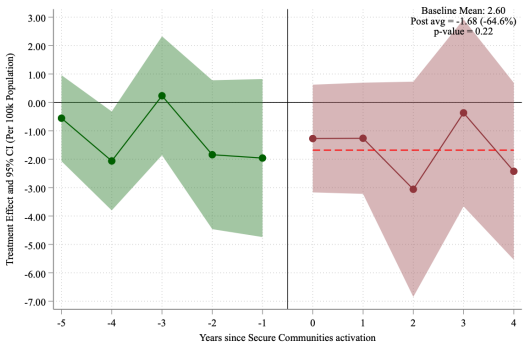
(d) Men 25+

Notes: Triple difference estimates for men suicide rates per 100k by adult age bands. Specification matches the main DDD model; see Figure 4 for details.

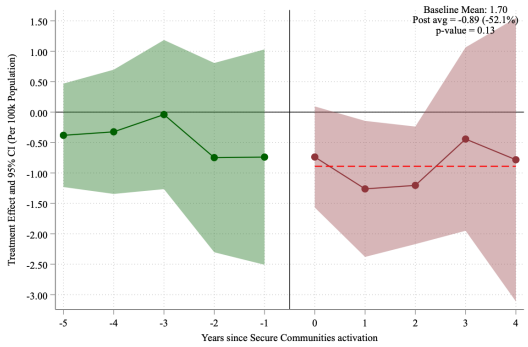
Figure 8: Triple Difference-in-Differences: Additional Adult Age Bands (Women)



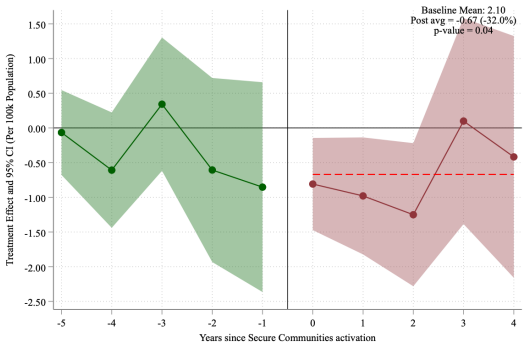
(a) Women 25–34



(b) Women 35–44



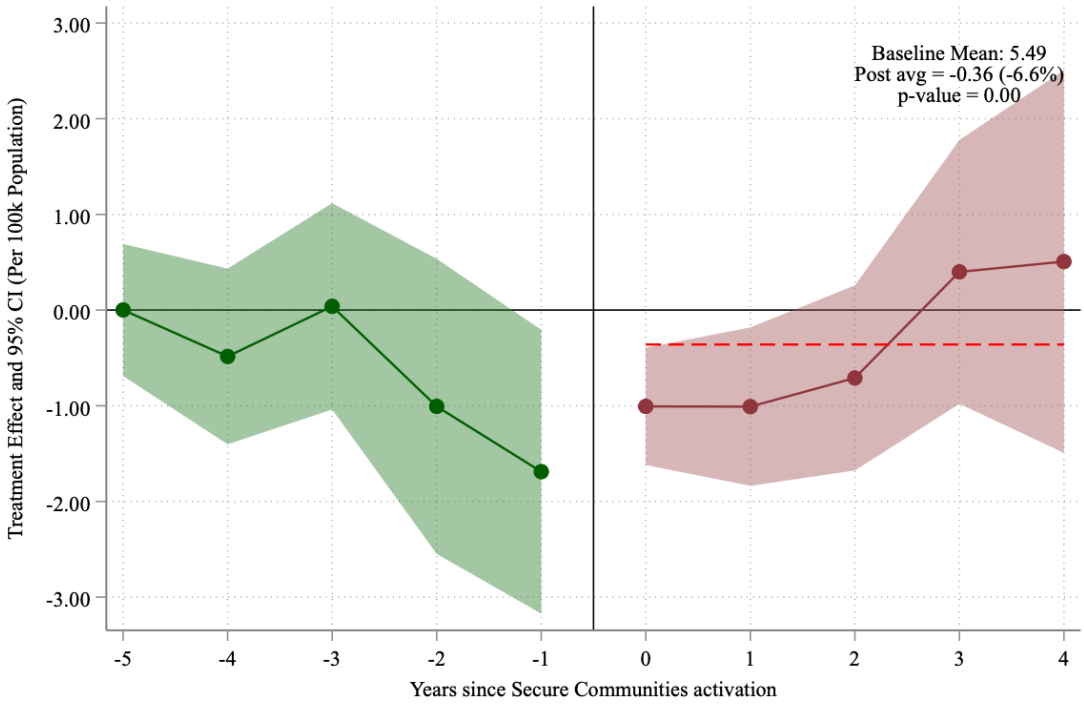
(c) Women 45+



(d) Women 25+

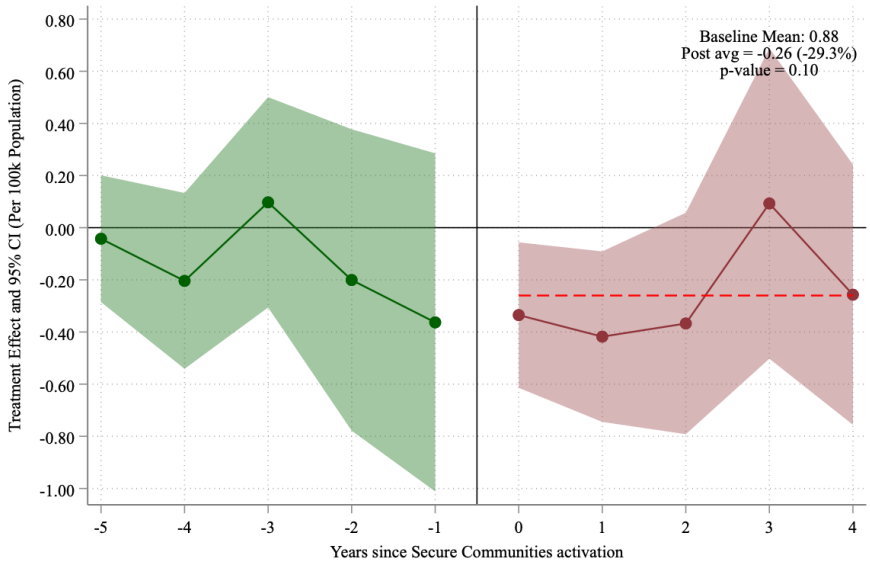
Notes: Triple difference estimates for woman suicide rates per 100k by adult age bands. Specification matches the main DDD model; see Figure 4 for details.

Figure 9: Triple Difference-in-Differences: Effect of Secure Communities on Hispanic vs White Suicide Rates Among All Individuals

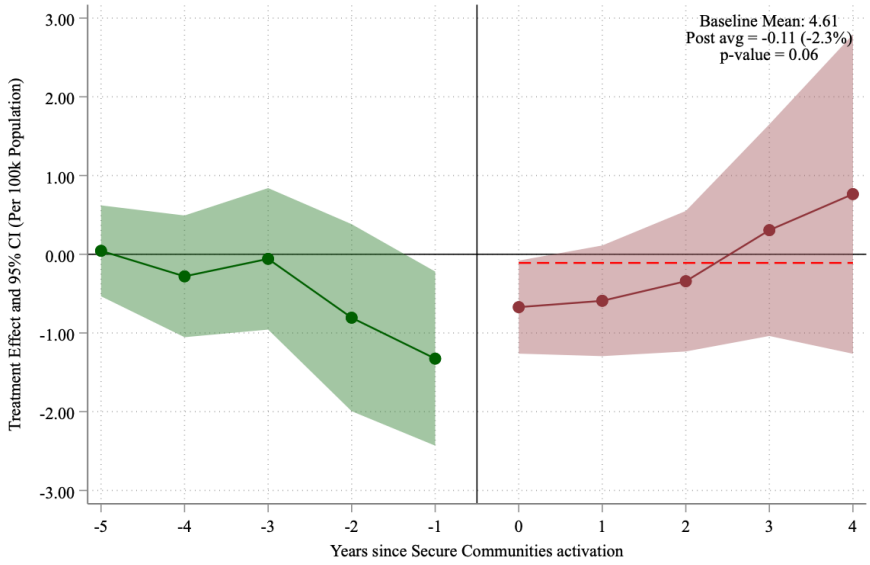


Notes: See the notes in Figure 4 for more details. The analysis uses suicide rates per 100,000 among all individuals as the outcome variable.

Figure 10: Triple Difference-in-Differences: Effect of Secure Communities on Hispanic vs White Suicide Rates by Gender (All Ages)



(a) Women Suicide Rates (All Ages)



(b) Men Suicide Rates (All Ages)

Notes: See Figure 4 for more details. The analysis uses suicide rates per 100,000 among all individuals by gender as the outcome variable.

ONLINE APPENDIX

Immigration Enforcement, Sanctuary Cities, and Rising Hispanic Suicide Rates

Hussain Hadah

A Tables

Table A.1: Spillover Effects of Secure Communities on Hispanic Suicide Rates

	Ages 34+	Ages 34+ (Intensity)	All Ages	All Ages (Intensity)
Direct Treatment	-0.04	-0.05	-0.06*	-0.06
	(0.05)	(0.06)	(0.04)	(0.05)
Neighboring Counties	-0.04		-0.06	
	(0.05)		(0.05)	
Neighboring Counties Intensity		0.01		0.01
		(0.01)		(0.01)
Observations	43,782	43,782	43,782	43,782
County FE	X	X	X	X
Year FE	X	X	X	X

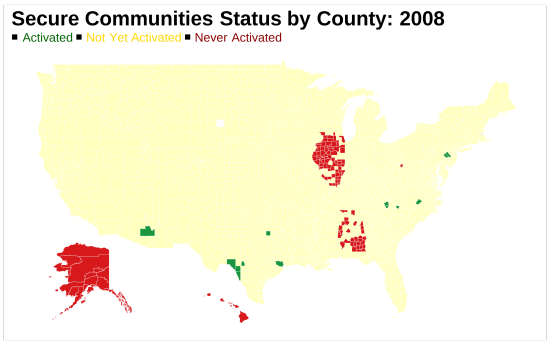
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] This table examines spillover effects on Hispanic suicide rates using two-way fixed effects regressions with county and year fixed effects. 'Direct Treatment' indicates counties that adopted Secure Communities. 'Neighboring Counties' is an indicator equal to 1 if a county borders a treated county in a given year but has not yet adopted the program itself. 'Neighboring Counties Intensity' counts the number of neighboring counties that have adopted Secure Communities by year t. Standard errors are clustered at the county level.

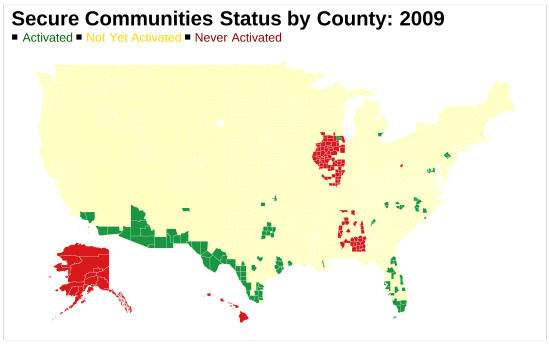
[2] Standard errors are clustered on the county level.

B Figures

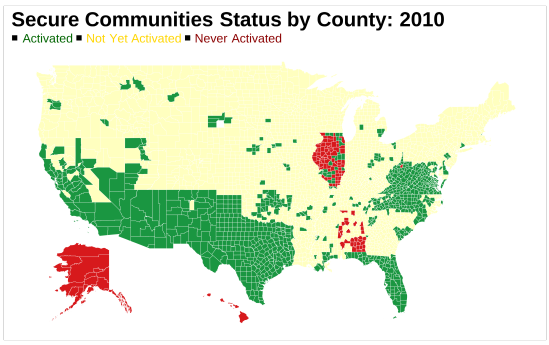
Figure A.1: Secure Communities Status by County



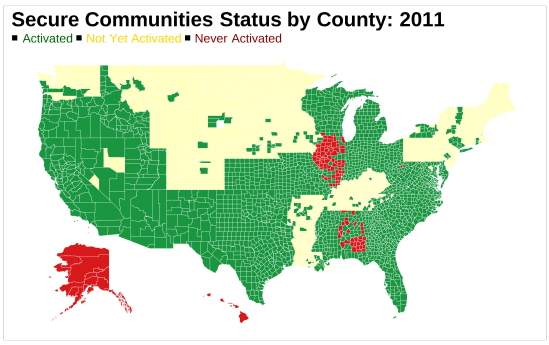
(a) 2008



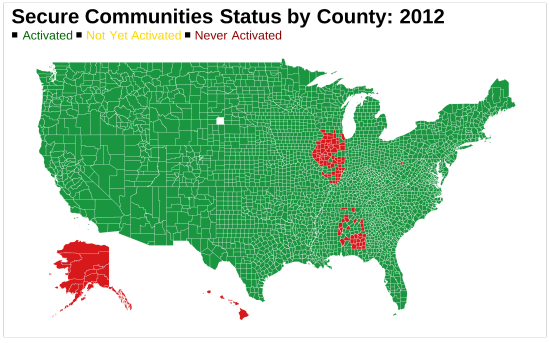
(b) 2009



(c) 2010



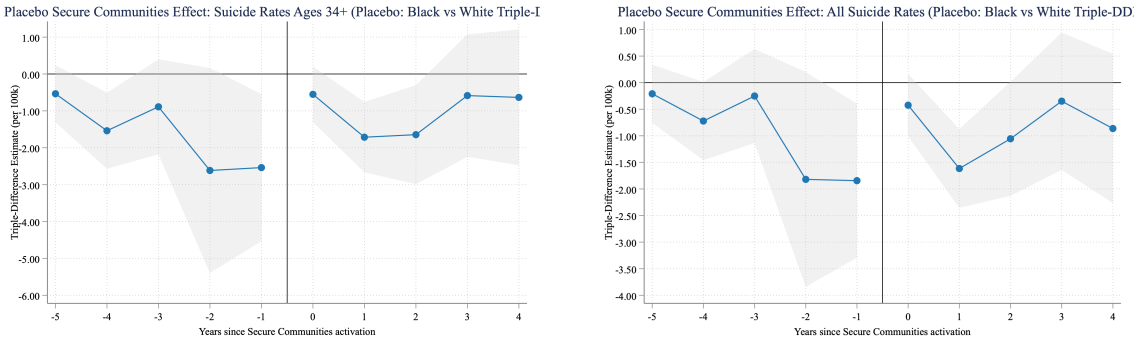
(d) 2011



(e) 2012

Notes: These maps illustrate the rollout of Secure Communities by county in selected years. Green counties had Secure Communities activated by that year, yellow counties not yet activated, and red counties never activated.

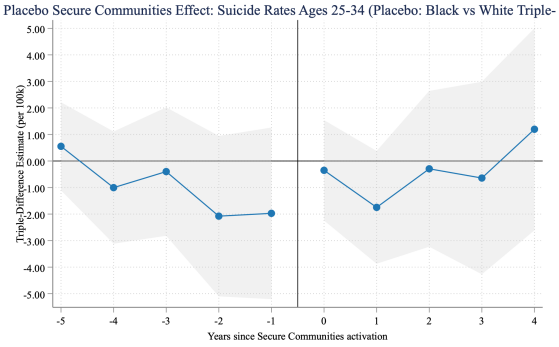
Figure A.2: Placebo Triple Difference-in-Differences: Effect on Black vs White Suicide Rates by Age Group



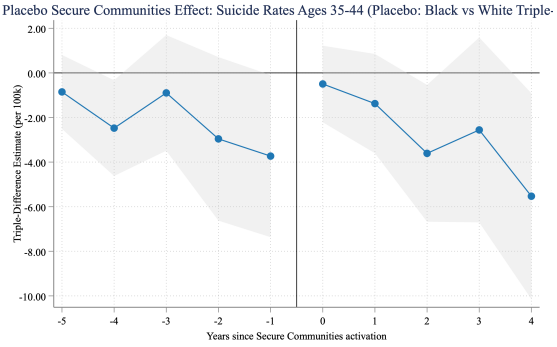
(a) Ages 34+ (b) All Ages

Notes: These placebo triple-difference event-study estimates mirror the baseline specification but assign Secure Communities activation five years prior to the actual rollout. The outcome variable y_{cst} is the difference in suicide rates per 100,000 between Black and White residents in county c, state s, at time t.

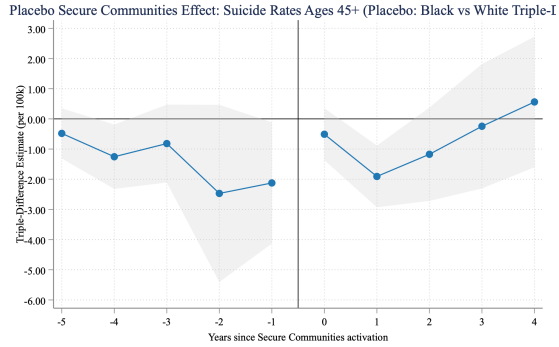
Figure A.3: Placebo Test: Black vs. White Suicide Rates



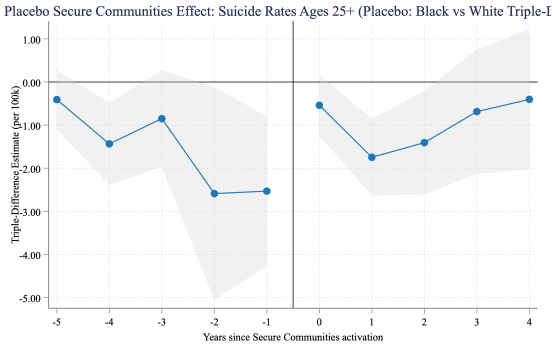
(a) Ages 25-34



(b) Ages 35-44



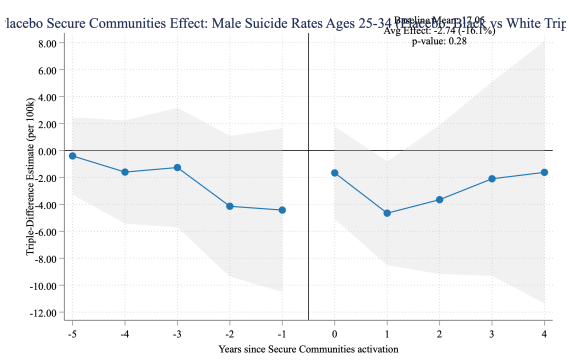
(c) Ages 45+



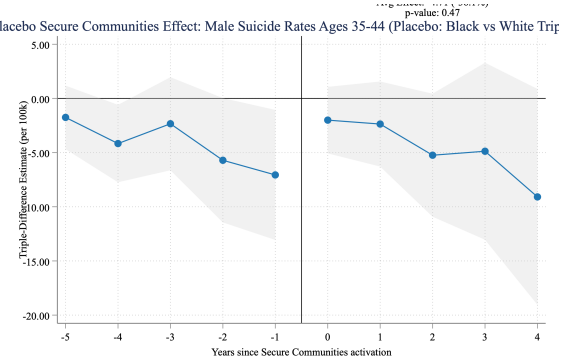
(d) Ages 25+

Notes: This figure displays event study estimates for a placebo test comparing Black and White suicide rates. The Secure Communities policy should not affect the suicide gap between these two groups. See Figure A.19 for more details.

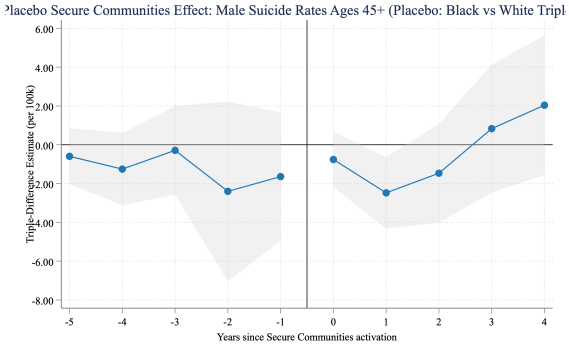
Figure A.4: Placebo Test: Black vs. White Suicide Rates: Men



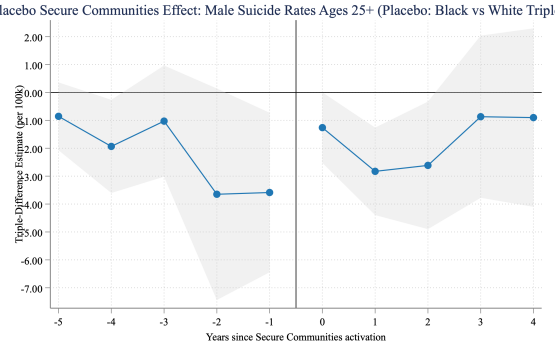
(a) Ages 25-34



(b) Ages 35-44



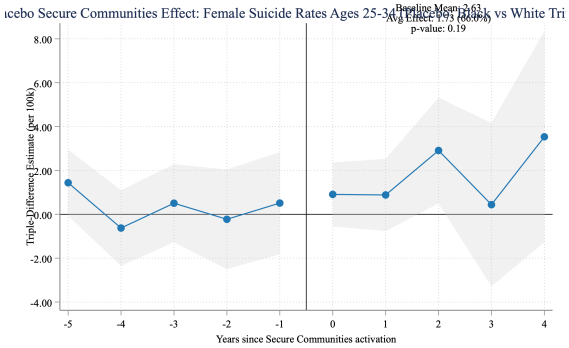
(c) Ages 45+



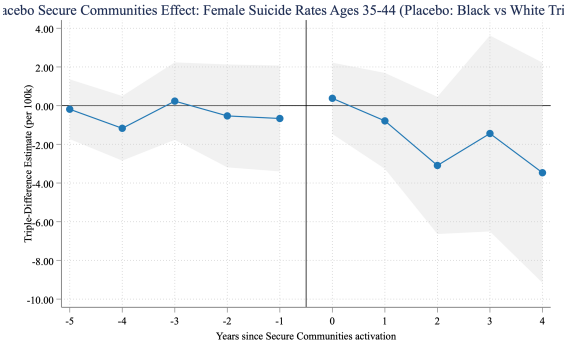
(d) Ages 25+

Notes: This figure displays event study estimates for a placebo test comparing Black and White suicide rates for men. The Secure Communities policy should not affect the suicide gap between these two groups. See Figure A.19 for more details.

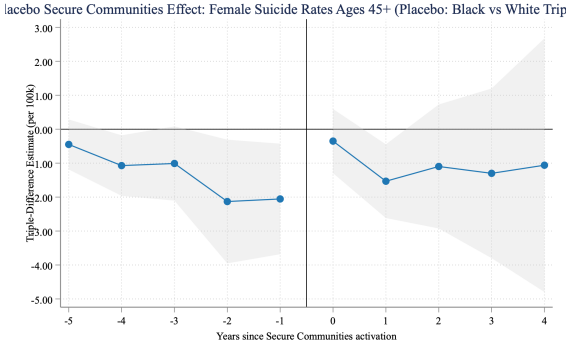
Figure A.5: Placebo Test: Black vs. White Suicide Rates: Women



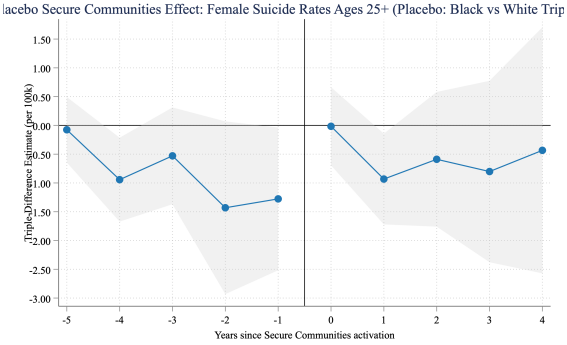
(a) Ages 25-34



(b) Ages 35-44



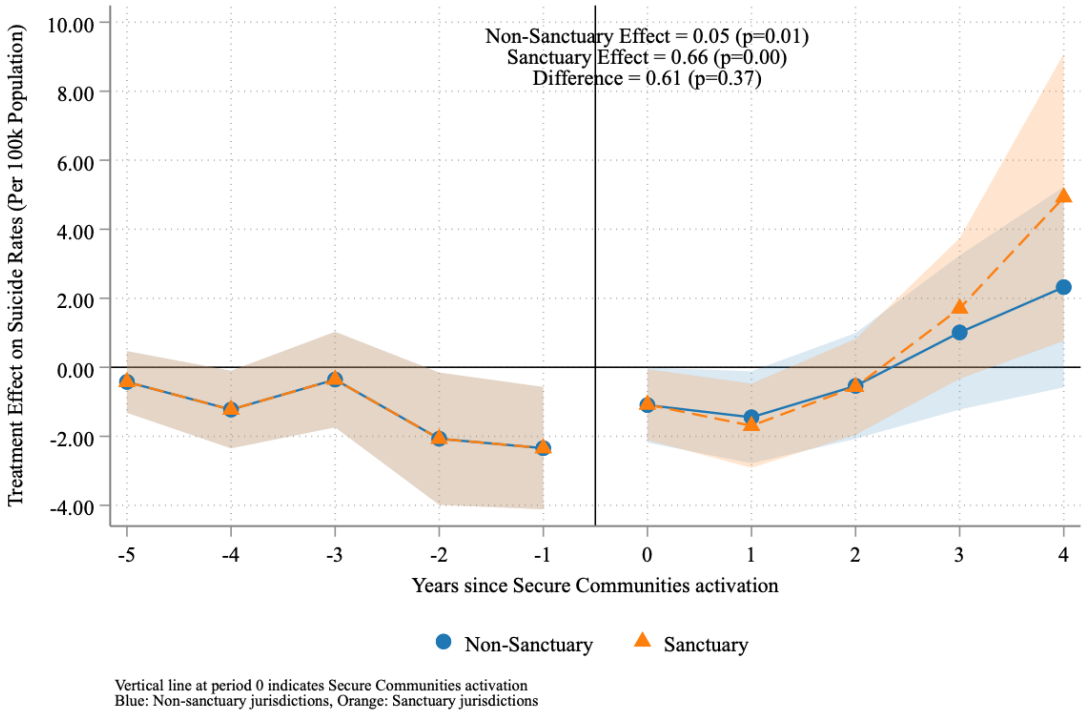
(c) Ages 45+



(d) Ages 25+

Notes: This figure displays event study estimates for a placebo test comparing Black and White suicide rates for women. The Secure Communities policy should not affect the suicide gap between these two groups. See Figure A.19 for more details.

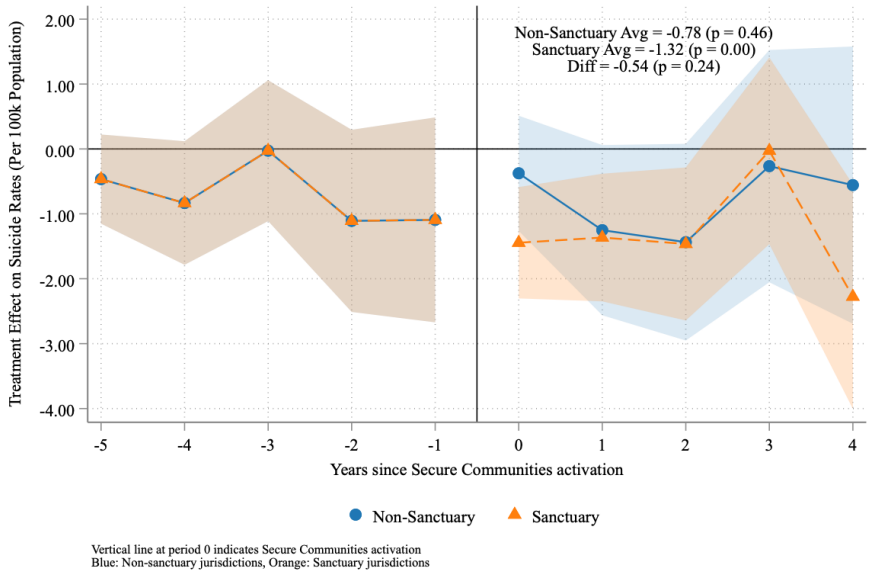
Figure A.6: Triple Difference-in-Differences with Sanctuary Heterogeneity: Effect of Secure Communities on Hispanic vs White Suicide Rates Among Adults Aged 34 and Older



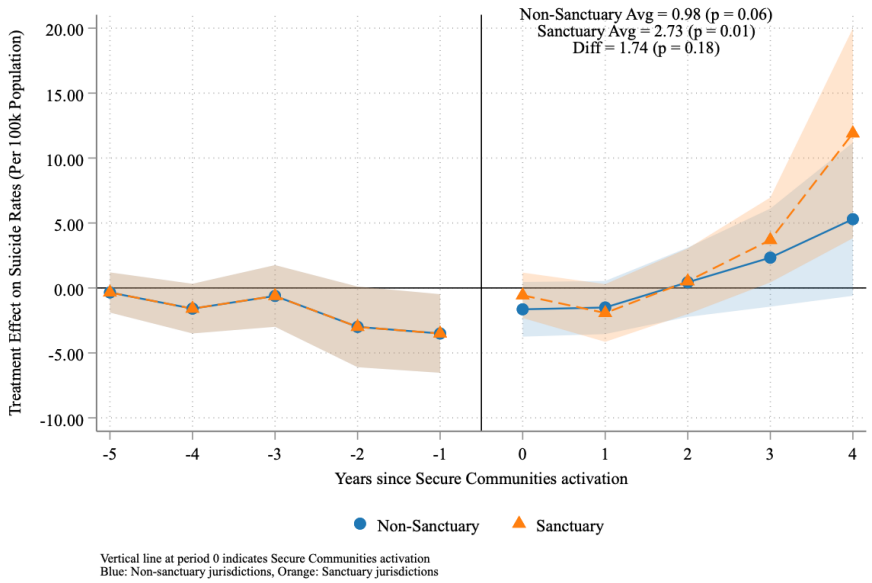
Notes: This figure estimates a triple difference-in-differences model with heterogeneous effects by sanctuary status, comparing the differential impact of Secure Communities on Hispanic versus White suicide rates among adults 34 and older. The outcome variable is the suicide rate per 100,000 population. The specification includes county-race, county-year, and race-year fixed effects, with separate treatment effects estimated for sanctuary and non-sanctuary counties. Pre-treatment coefficients test the parallel trends assumption between Hispanic and White adults in both county types. Post-treatment coefficients capture how sanctuary policies moderate the differential treatment effects of federal immigration enforcement. Sanctuary counties have local policies that limit cooperation with federal immigration enforcement, potentially buffering the psychological stress from immigration policy changes. The standard errors are clustered at the county level and the county population is used to weight the estimates.

Source: Alsan and Yang (2024) collected records that are available to the public through FOIA requests to US Immigration and Customs Enforcement (ICE). National Vital Statistics System (NVSS) covering the years 1959 to 2019 (National vital statistics system 2007).

Figure A.7: Triple Difference-in-Differences with Sanctuary Heterogeneity: Effect on Hispanic vs White Suicide Rates by Gender (Ages 34+)



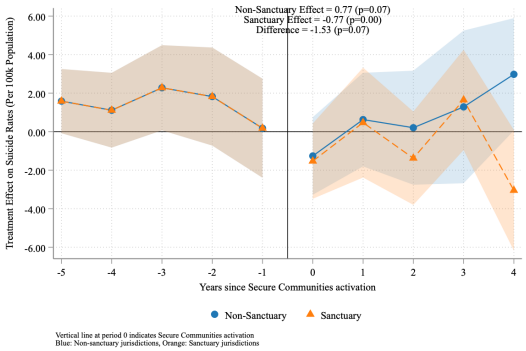
(a) Women Suicide Rates (Ages 34+)



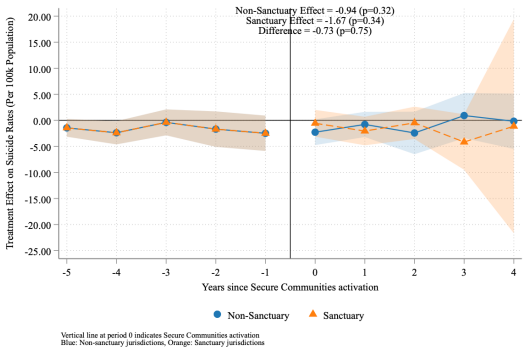
(b) Men Suicide Rates (Ages 34+)

Notes: See Figure A.6 for more details. The analysis uses suicide rates per 100,000 among adults aged 34 and older by gender as the outcome variable.

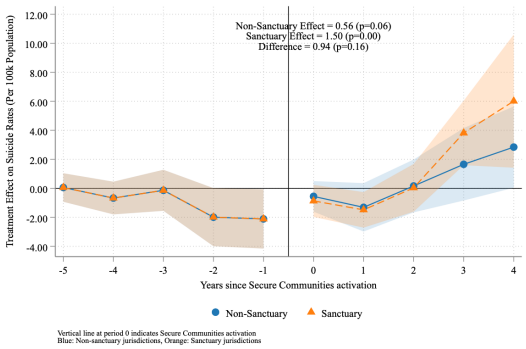
Figure A.8: Triple Difference-in-Differences with Sanctuary Heterogeneity: Additional Adult Age Bands



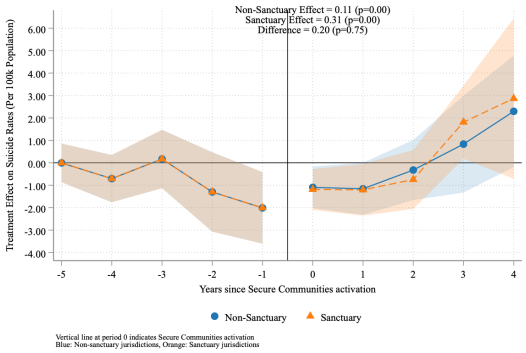
(a) Ages 25–34



(b) Ages 35–44



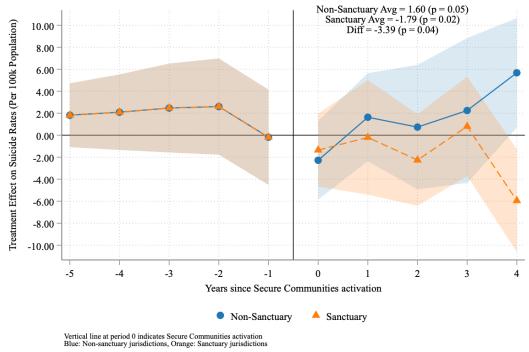
(c) Ages 45+



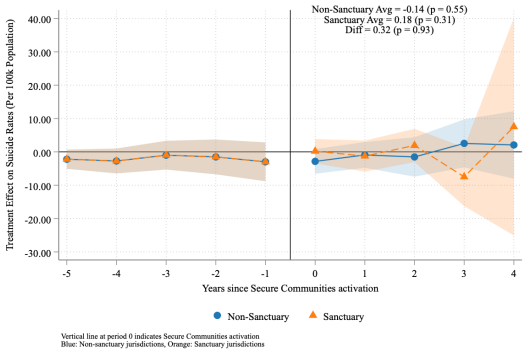
(d) Ages 25+

Notes: Additional triple difference estimates with sanctuary heterogeneity by adult age bands using per 100k suicide rates. Specification matches the main sanctuary DDD model; see Figure A.6 for details on controls, fixed effects, and weighting.

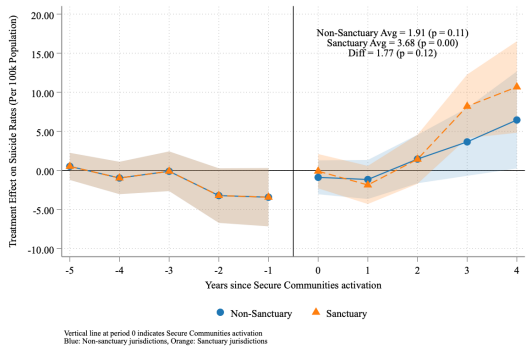
Figure A.9: Triple Difference-in-Differences with Sanctuary Heterogeneity: Additional Adult Age Bands (Men)



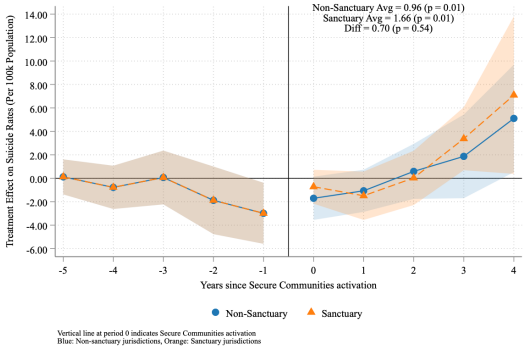
(a) Men 25–34



(b) Men 35–44



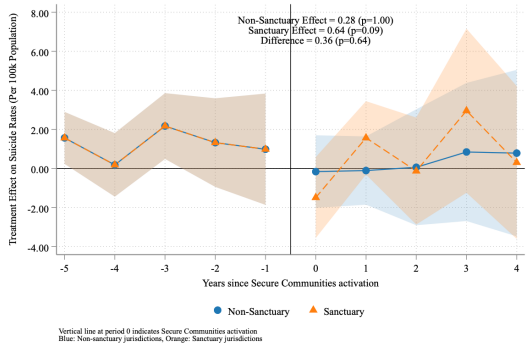
(c) Men 45+



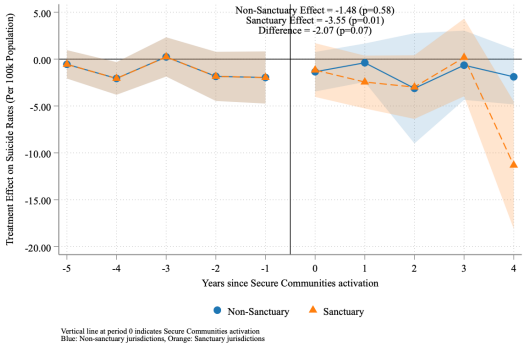
(d) Men 25+

Notes: Triple difference estimates with sanctuary heterogeneity for men suicide rates per 100k by adult age bands. Specification matches the main sanctuary DDD model; see Figure A.6 for details.

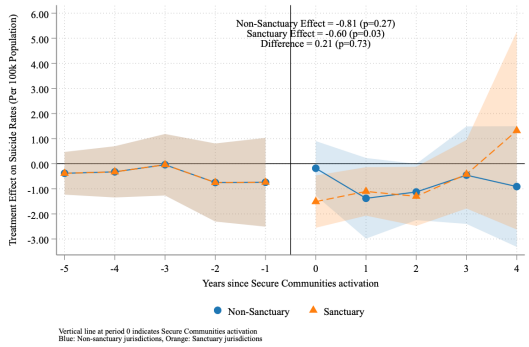
Figure A.10: Triple Difference-in-Differences with Sanctuary Heterogeneity: Additional Adult Age Bands (Women)



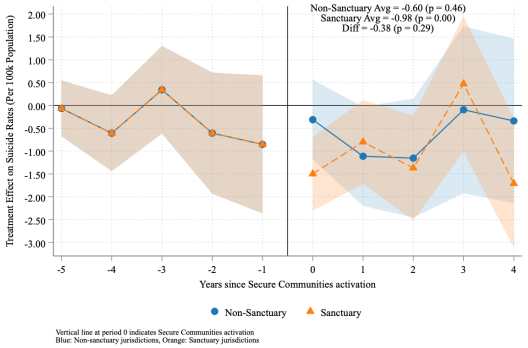
(a) Women 25–34



(b) Women 35–44



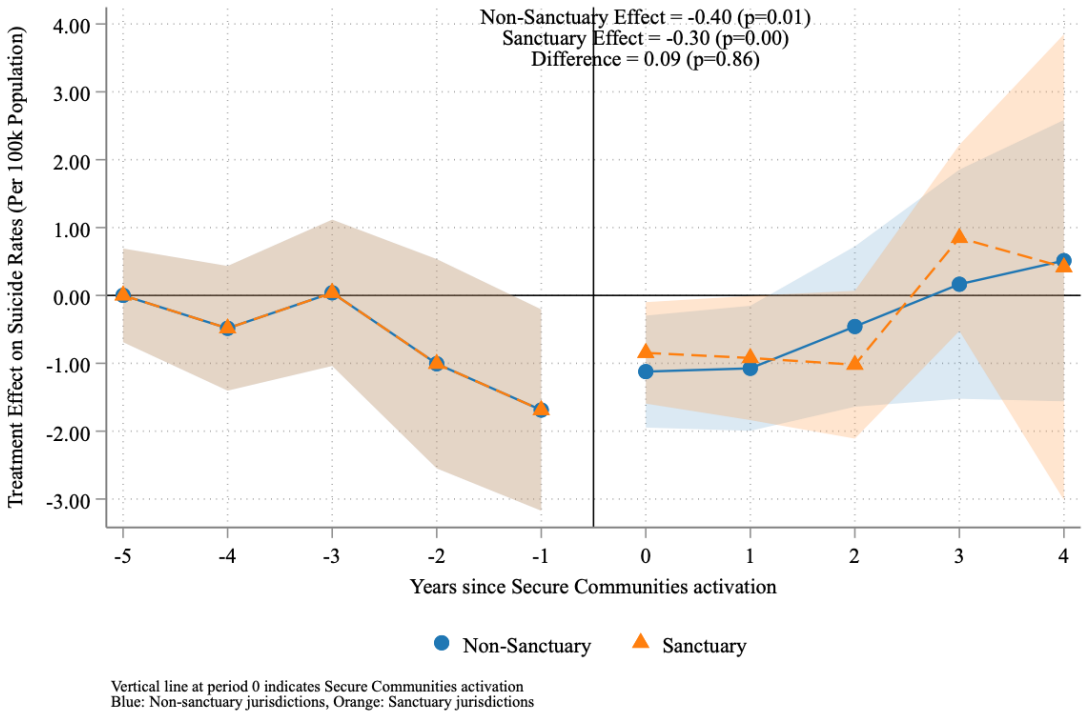
(c) Women 45+



(d) Women 25+

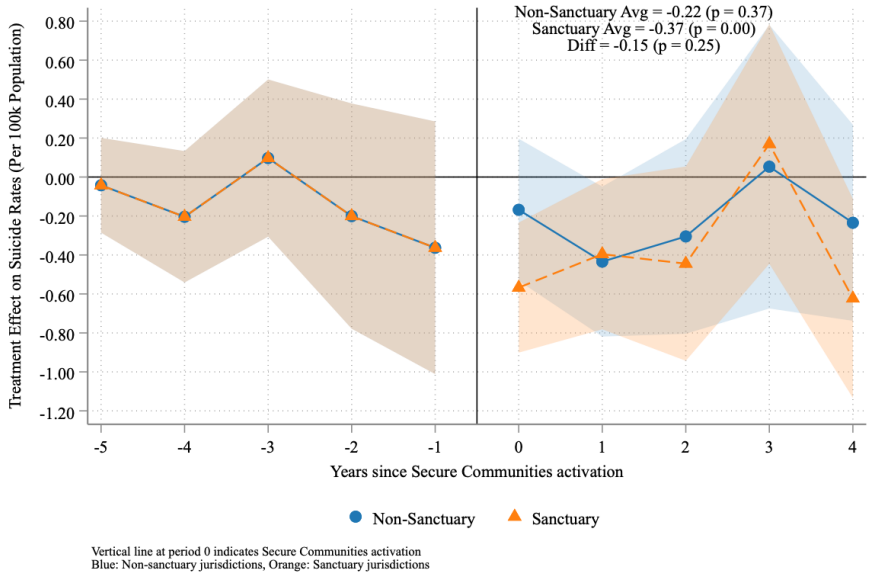
Notes: Triple difference estimates with sanctuary heterogeneity for women suicide rates per 100k by adult age bands. Specification matches the main sanctuary DDD model; see Figure A.6 for details.

Figure A.11: Triple Difference-in-Differences with Sanctuary Heterogeneity: Effect of Secure Communities on Hispanic vs White Suicide Rates Among All Individuals

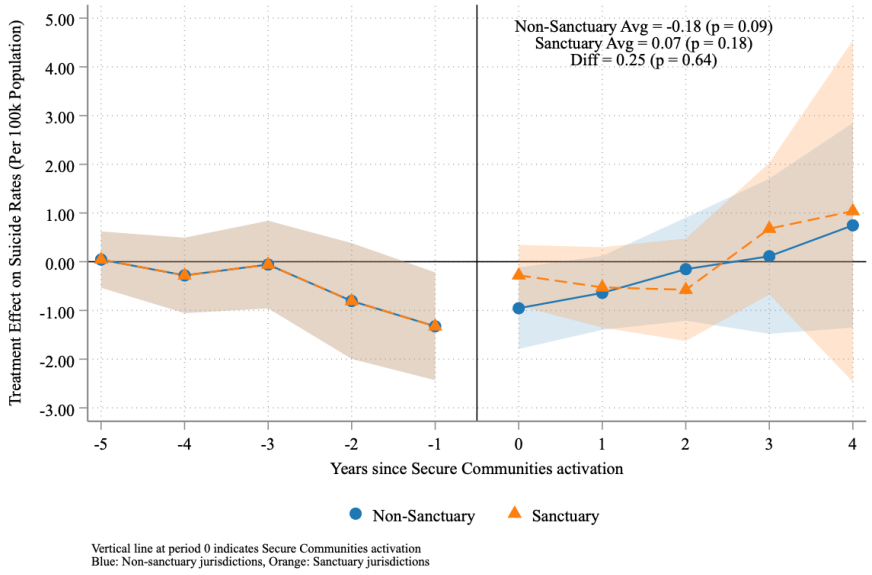


Notes: See Figure A.6 for more details. The analysis uses suicide rates per 100,000 among all individuals as the outcome variable.

Figure A.12: Triple Difference-in-Differences with Sanctuary Heterogeneity: Effect on Hispanic vs White Suicide Rates by Gender (All Ages)



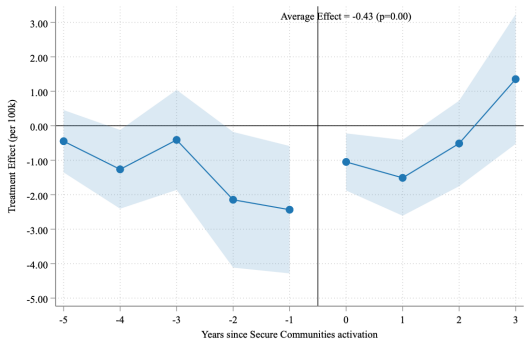
(a) Women Suicide Rates (All Ages)



(b) Men Suicide Rates (All Ages)

Notes: See Figure A.6 for more details. The analysis uses suicide rates per 100,000 among all individuals by gender as the outcome variable.

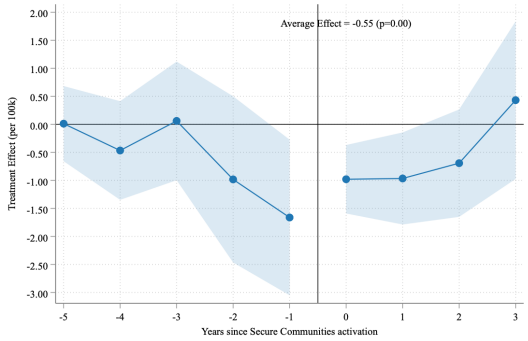
Figure A.13: Triple Difference-in-Differences with Removals as Control Group: Main Age Groups



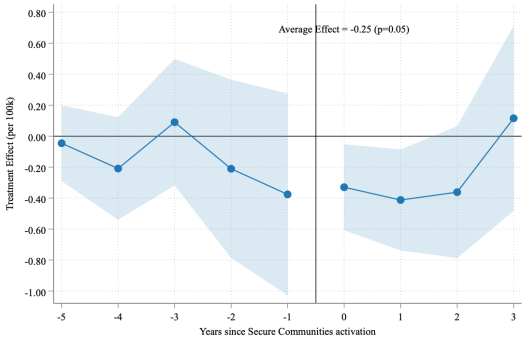
(a) Ages 34+ (Adults)

Notes: These results include county-level number of removals as a control. See Figure 4 for more details.

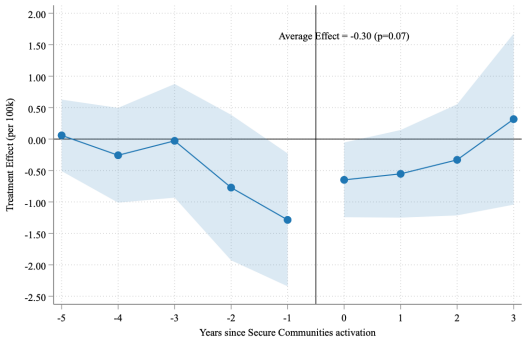
Figure A.14: Triple Difference-in-Differences with Removals as Control Group: All Ages and Gender-Specific Analysis



(a) All Ages



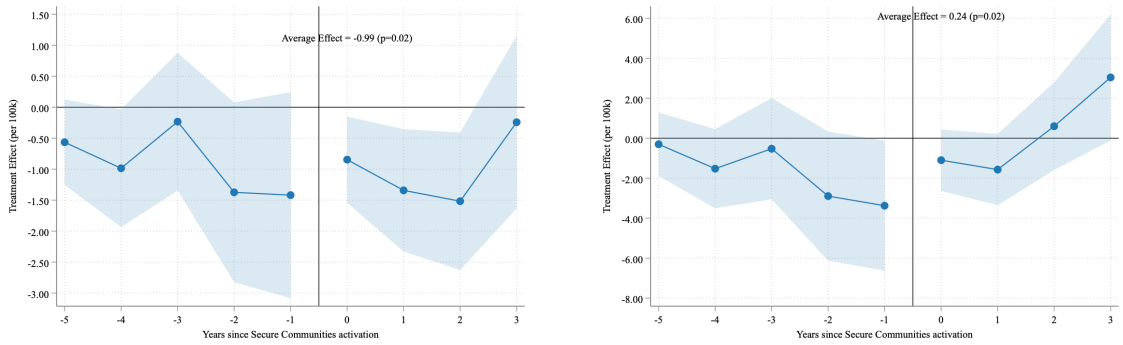
(b) Women (All Ages)



(c) Men (All Ages)

Notes: These results include county-level number of removals as a control. See Figure 4 for more details.

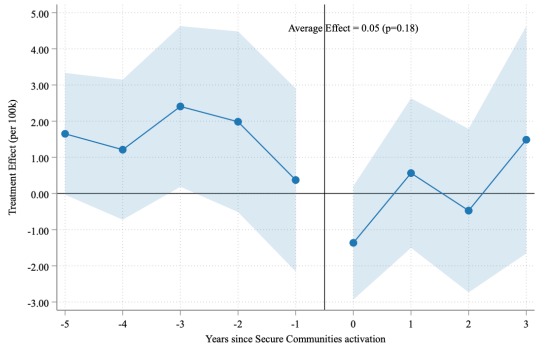
Figure A.15: Triple Difference-in-Differences with Removals as Control Group: Gender-Specific Analysis by Age Group (Ages 34+)



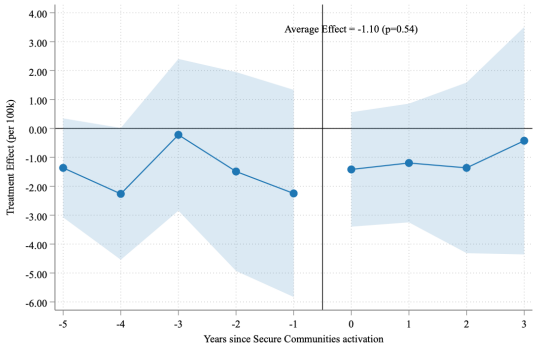
(a) Women Ages 34+ (b) Men Ages 34+

Notes: These results include county-level number of removals as a control. See Figure 4 for more details.

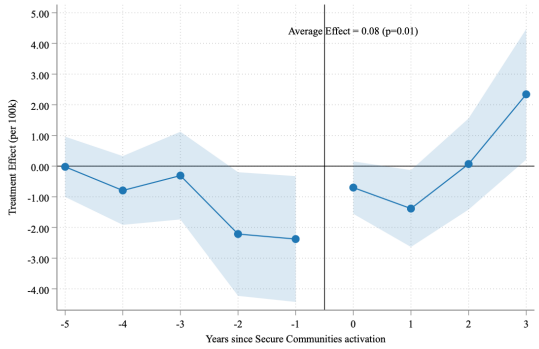
Figure A.16: Triple Difference-in-Differences with Removals as Control Group: By Age Group



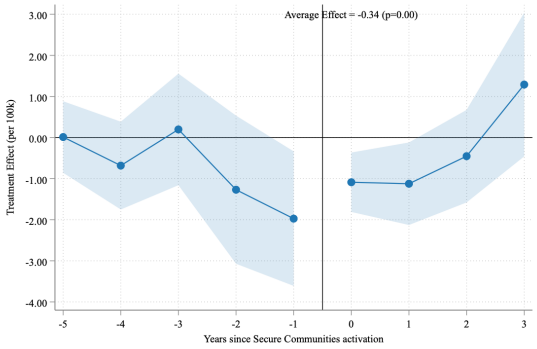
(a) Ages 25-34



(b) Ages 35-44



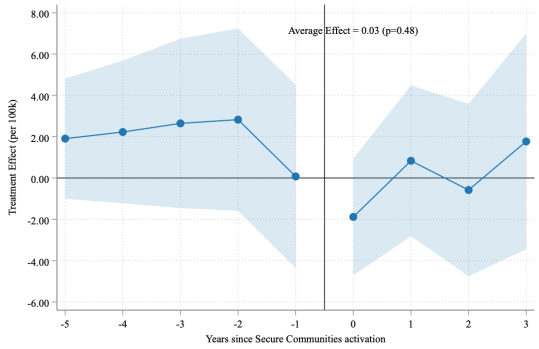
(c) Ages 45+



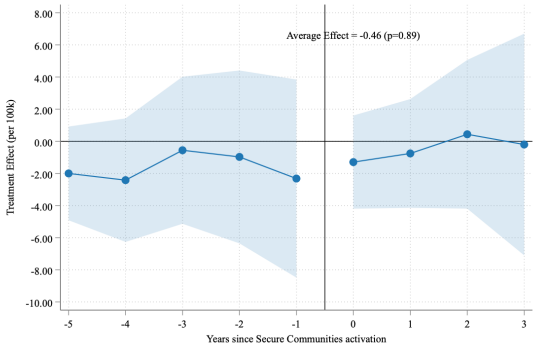
(d) Ages 25+

Notes: These results include county-level number of removals as a control. See Figure 4 for more details.

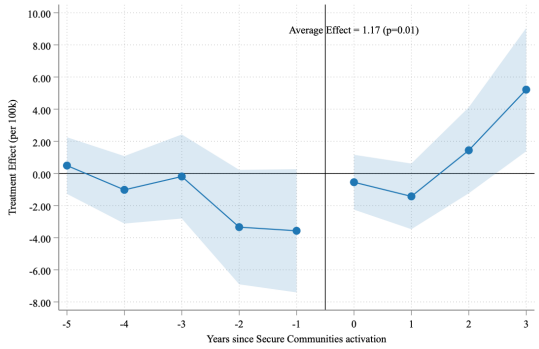
Figure A.17: Triple Difference-in-Differences with Removals as Control Group: Men by Age Group



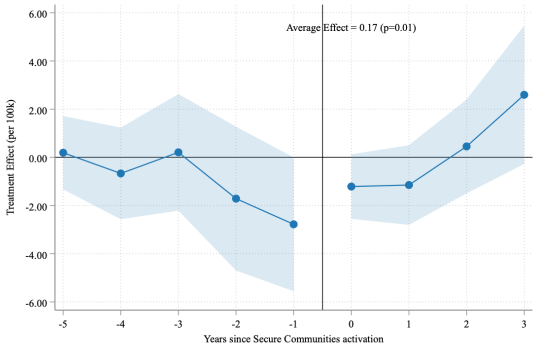
(a) Ages 25-34



(b) Ages 35-44



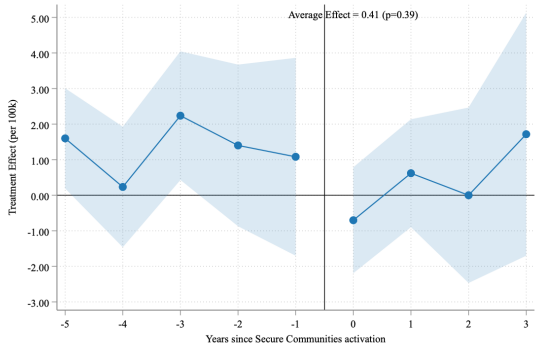
(c) Ages 45+



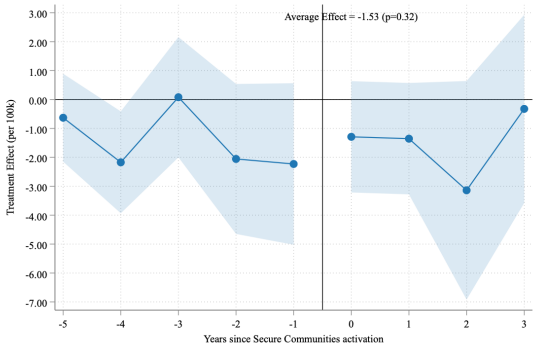
(d) Ages 25+

Notes: These results include county-level number of removals as a control. See Figure 4 for more details.

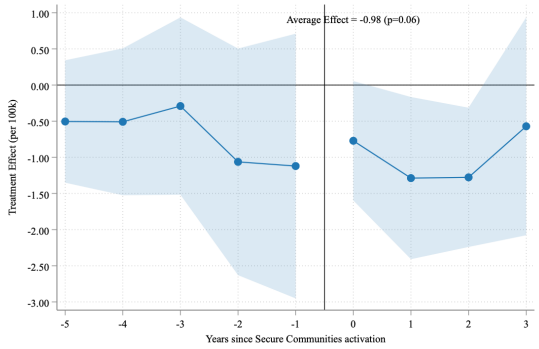
Figure A.18: Triple Difference-in-Differences with Removals as Control Group: Women by Age Group



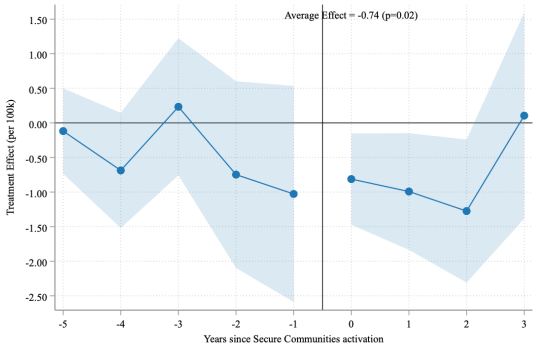
(a) Ages 25-34



(b) Ages 35-44



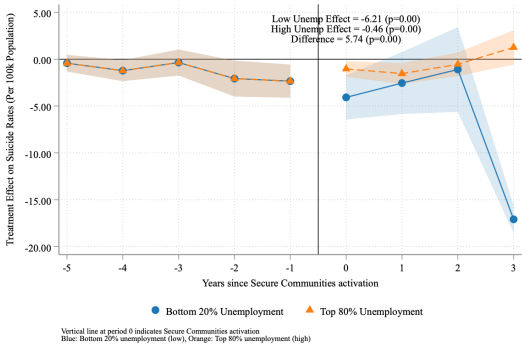
(c) Ages 45+



(d) Ages 25+

Notes: These results include county-level number of removals as a control. See Figure 4 for more details.

Figure A.19: Heterogeneous Effects by County-level Unemployment Rate

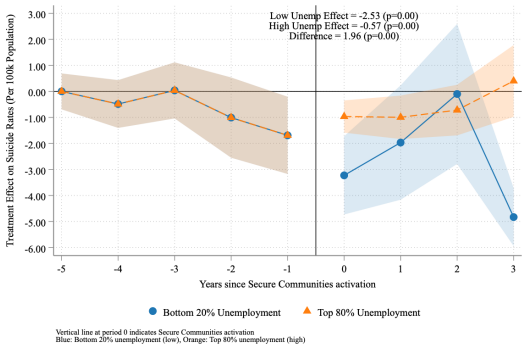


(a) Ages 34+ (Adults)

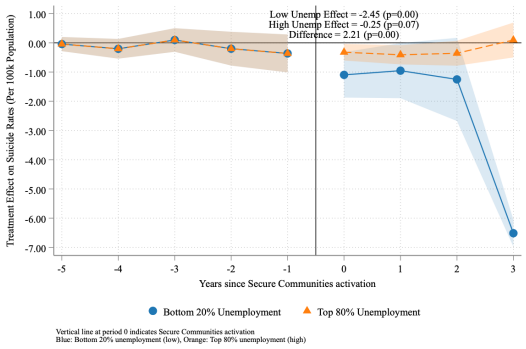
Notes: These figures estimate event study models for Hispanic suicide rates, comparing counties with bottom 20% ("Low Unemployment") versus top 80% ("High Unemployment") unemployment rates. The outcome variable y_{cst} is the suicide rate per 100,000 among Hispanics in the specified age group in county c, state s, at time t. Counties are classified by the unemployment rate percentile, with bottom 20% representing low unemployment areas and top 80% representing high unemployment areas. Pre-treatment coefficients (β_l for $l < 0$) test the parallel trends assumption for each unemployment group. Post-treatment coefficients (β_l for $l \geqslant 0$) capture how the mental health impact of Secure Communities varies by county-level unemployment conditions. All results are for Hispanic populations only; no comparison to White or other characteristics is made in these plots. The standard errors are clustered at the county level and the population weights are applied.

Source: County-level unemployment rate is from the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) (Flood, King, et al., Integrated Public Use Microdata Series, Current Population Survey).

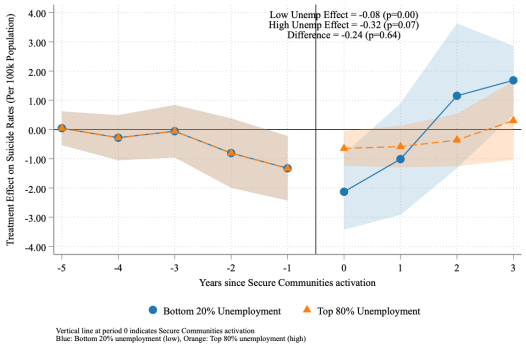
Figure A.20: Heterogeneous Effects by County-level Unemployment Rate: All Ages and Gender-Specific Analysis



(a) All Ages



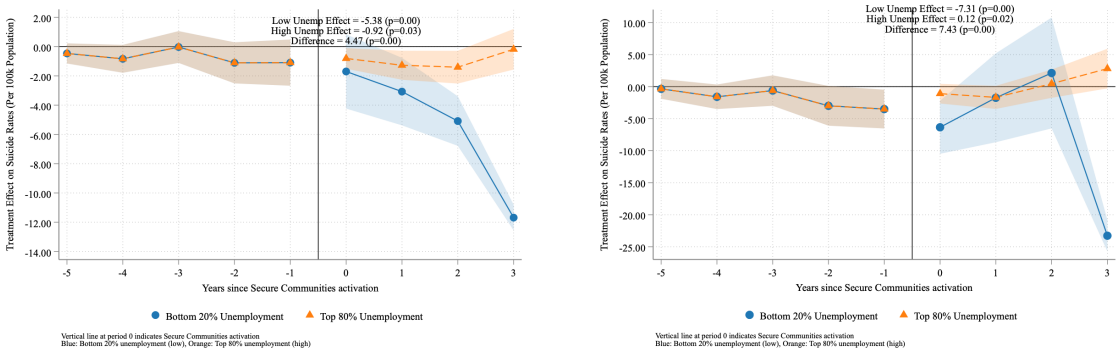
(b) Women (All Ages)



(c) Men (All Ages)

Notes: See Figure A.19 for more details. The analysis uses suicide rates per 100,000 among Hispanic individuals in the specified age group, with panels disaggregated by sex as labeled.

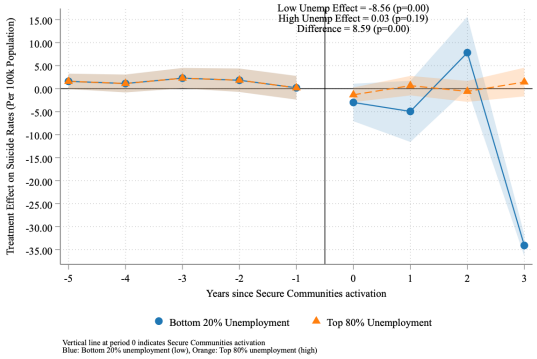
Figure A.21: Heterogeneous Effects by County-level Unemployment Rate: Gender-Specific Analysis by Age Group



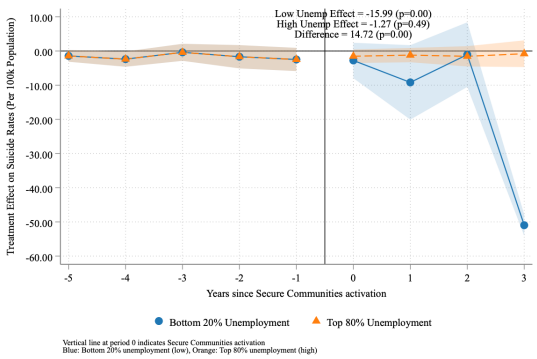
(a) Women Ages 34+ (b) Men Ages 34+

Notes: See Figure A.19 for more details. The analysis uses suicide rates per 100,000 among Hispanic individuals in the specified age group, with panels disaggregated by sex as labeled.

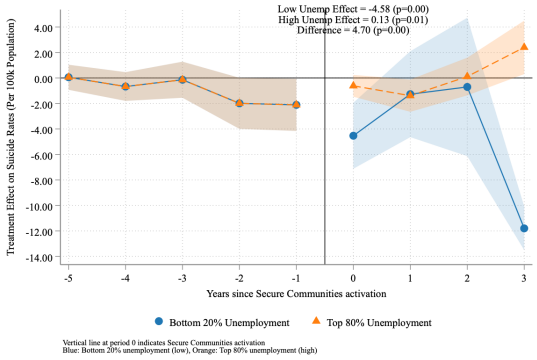
Figure A.22: Heterogeneity by Unemployment Rate (Bottom 20% vs. Top 80%)



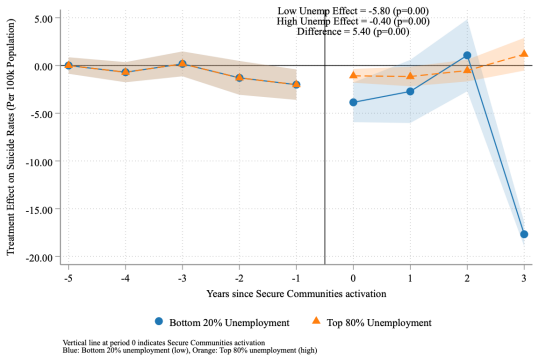
(a) Ages 25-34



(b) Ages 35-44



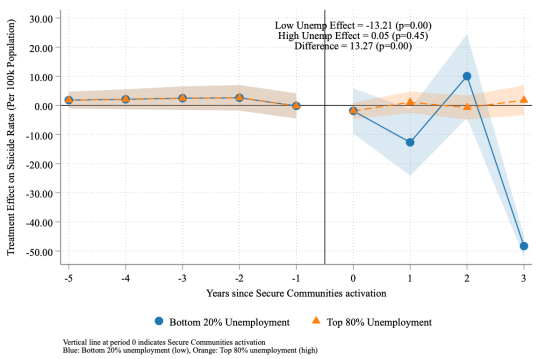
(c) Ages 45+



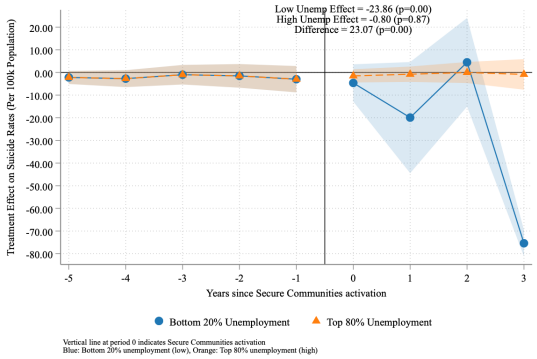
(d) Ages 25+

Notes: This figure displays event study estimates by unemployment rate (CPS data). Counties are split into bottom 20% (low unemployment) and top 80% (high unemployment) based on pre-treatment unemployment rates. See Figure A.19 for more details.

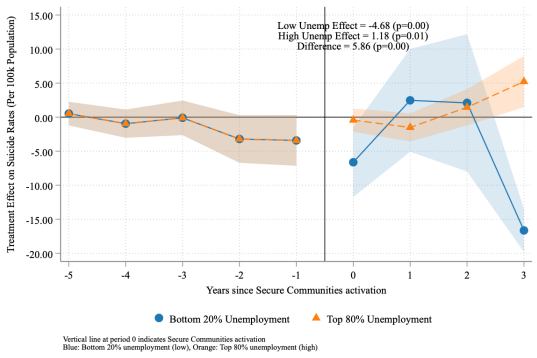
Figure A.23: Heterogeneity by Unemployment Rate (Bottom 20% vs. Top 80%): Men



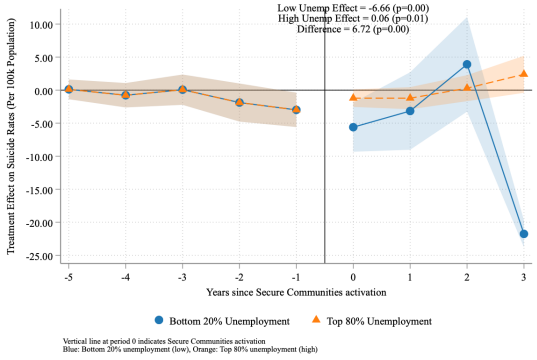
(a) Ages 25-34



(b) Ages 35-44



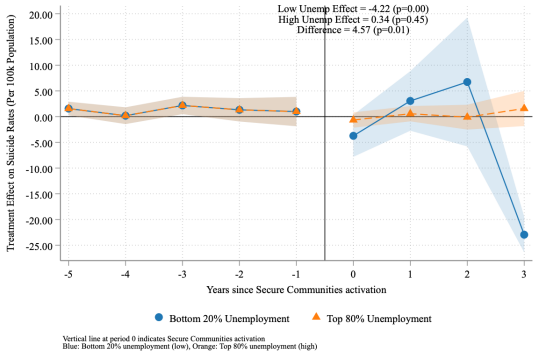
(c) Ages 45+



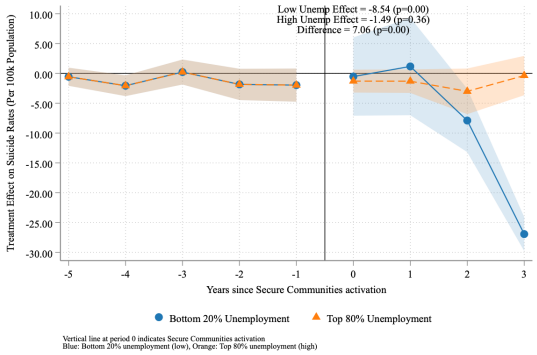
(d) Ages 25+

Notes: This figure displays event study estimates by unemployment rate (CPS data) for men. Counties are split into bottom 20% (low unemployment) and top 80% (high unemployment) based on pre-treatment unemployment rates. See Figure A.19 for more details.

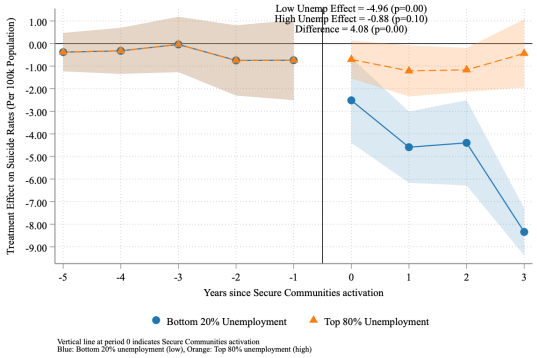
Figure A.24: Heterogeneity by Unemployment Rate (Bottom 20% vs. Top 80%): Women



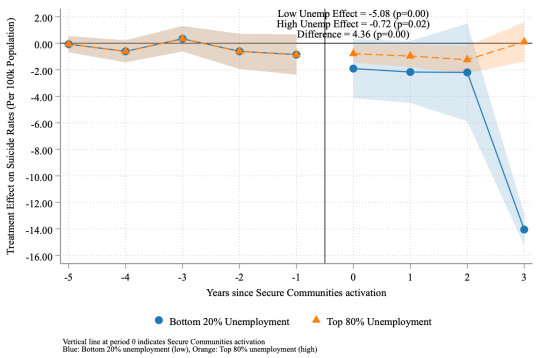
(a) Ages 25-34



(b) Ages 35-44



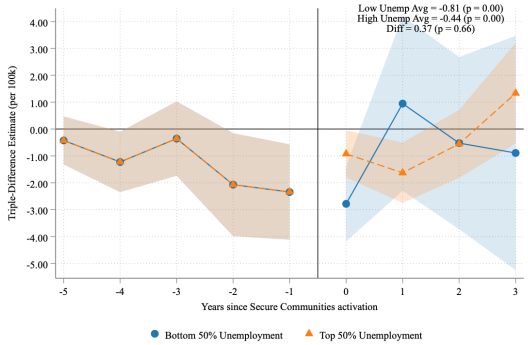
(c) Ages 45+



(d) Ages 25+

Notes: This figure displays event study estimates by unemployment rate (CPS data) for women. Counties are split into bottom 20% (low unemployment) and top 80% (high unemployment) based on pre-treatment unemployment rates. See Figure A.19 for more details.

Figure A.25: Heterogeneous Effects by County-level Unemployment Rate (LAUS)

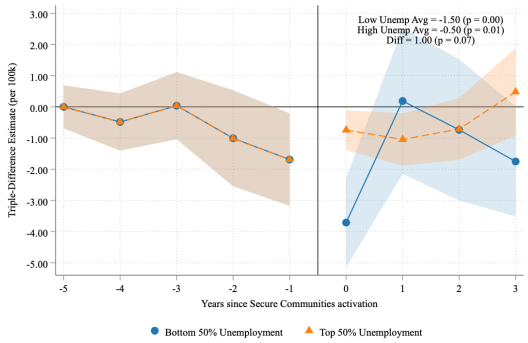


(a) Ages 34+ (Adults)

Notes: See Figure A.19.

Source: County-level unemployment rate is from the Local Area Unemployment Statistics (LAUS) (U.S. Bureau of Labor Statistics 2025).

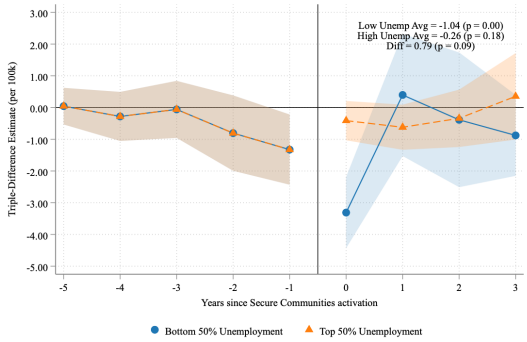
Figure A.26: Heterogeneous Effects by County-level Unemployment Rate (LAUS): All Ages and Gender-Specific Analysis



(a) All Ages



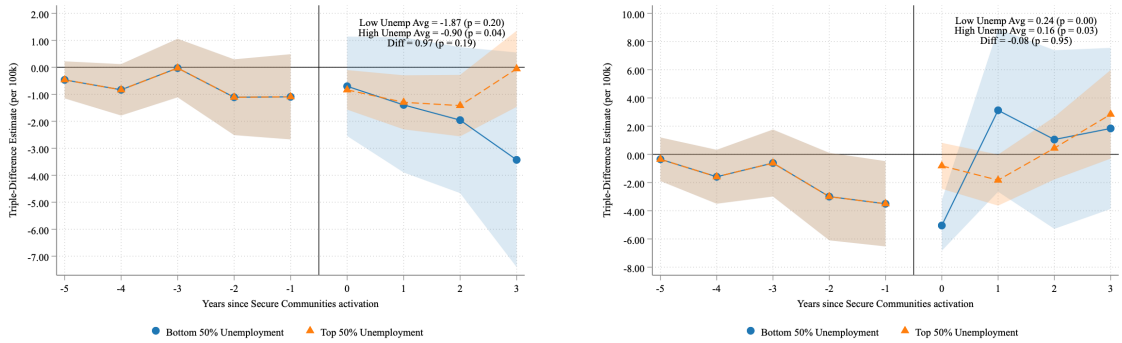
(b) Women (All Ages)



(c) Men (All Ages)

Notes: See Figure A.19 for more details. The analysis uses suicide rates per 100,000 among Hispanic individuals in the specified age group, with panels disaggregated by sex as labeled.

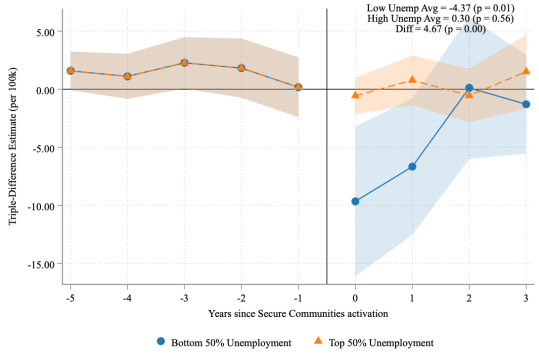
Figure A.27: Heterogeneous Effects by County-level Unemployment Rate (LAUS): Gender-Specific Analysis by Age Group



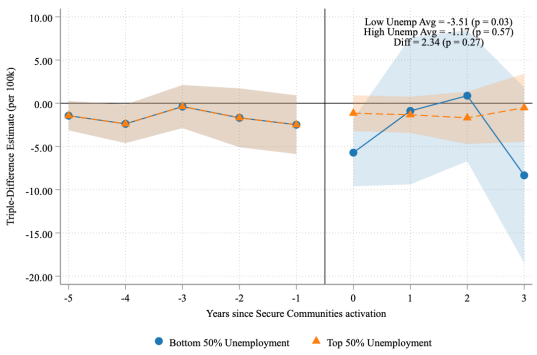
(a) Women Ages 34+ (b) Men Ages 34+

Notes: See Figure A.19 for more details. The analysis uses suicide rates per 100,000 among Hispanic individuals in the specified age group, with panels disaggregated by sex as labeled.

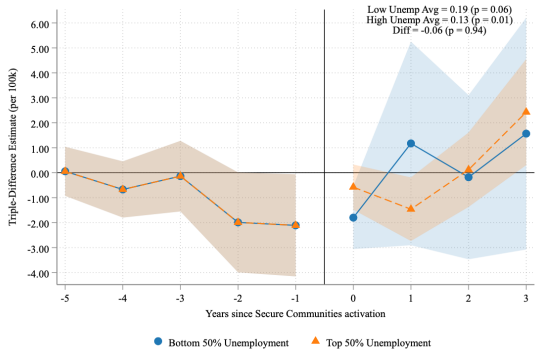
Figure A.28: Heterogeneity by Unemployment Rate (LAUS Data - 50% Split)



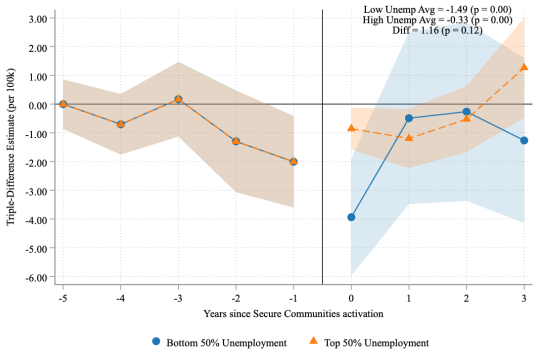
(a) Ages 25-34



(b) Ages 35-44



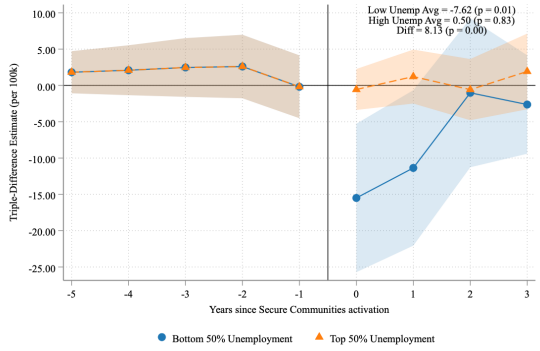
(c) Ages 45+



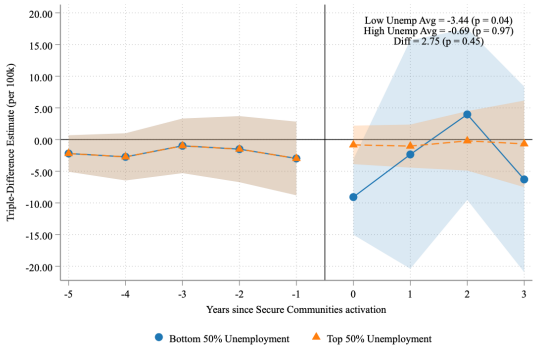
(d) Ages 25+

Notes: This figure displays event study estimates by unemployment rate (LAUS data). Counties are split at the median unemployment rate. See Figure A.19 for more details.

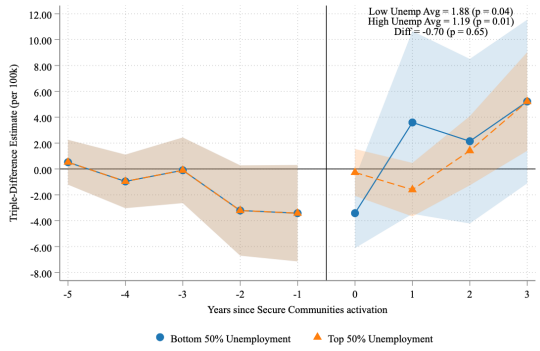
Figure A.29: Heterogeneity by Unemployment Rate (LAUS Data - 50% Split): Men



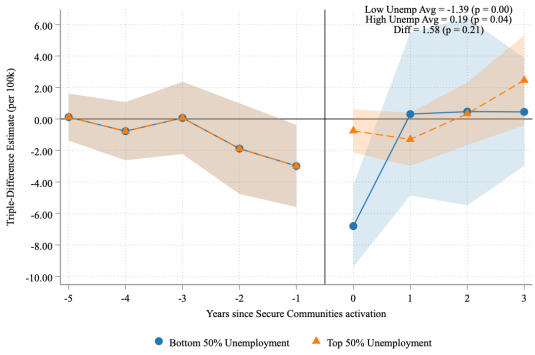
(a) Ages 25-34



(b) Ages 35-44



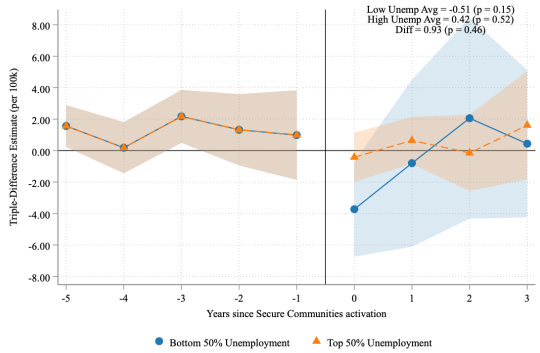
(c) Ages 45+



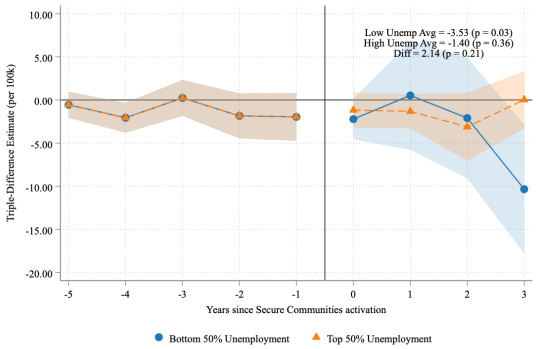
(d) Ages 25+

Notes: This figure displays event study estimates by unemployment rate (LAUS data) for men. Counties are split at the median unemployment rate. See Figure A.19 for more details.

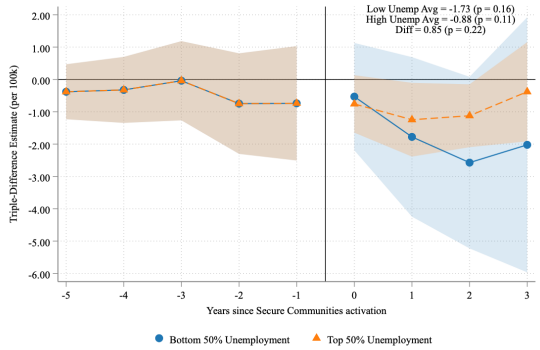
Figure A.30: Heterogeneity by Unemployment Rate (LAUS Data - 50% Split): Women



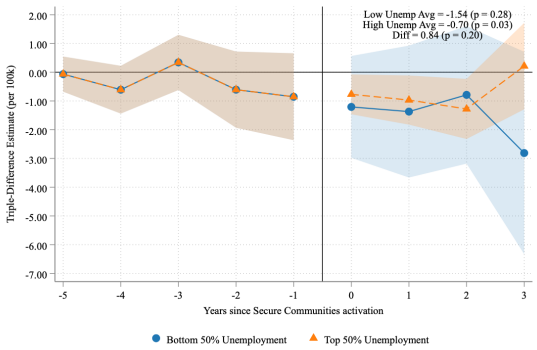
(a) Ages 25-34



(b) Ages 35-44



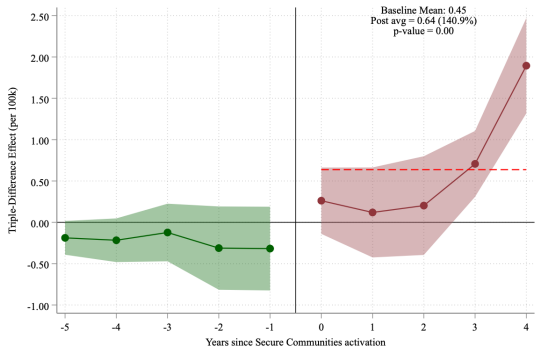
(c) Ages 45+



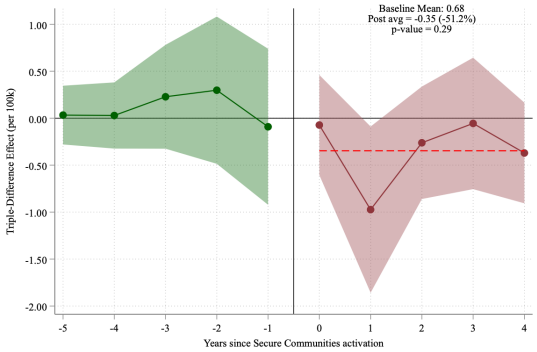
(d) Ages 25+

Notes: This figure displays event study estimates by unemployment rate (LAUS data) for women. Counties are split at the median unemployment rate. See Figure A.19 for more details.

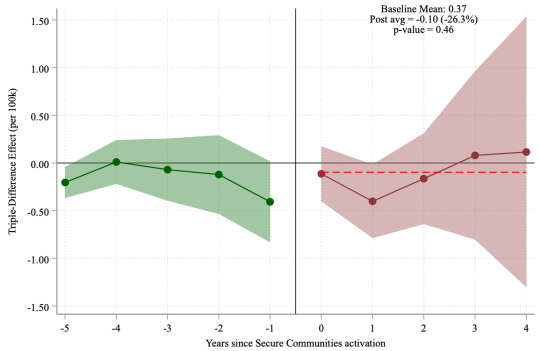
Figure A.31: Effect of Secure Communities on Alcohol-Related Deaths: All Age Groups



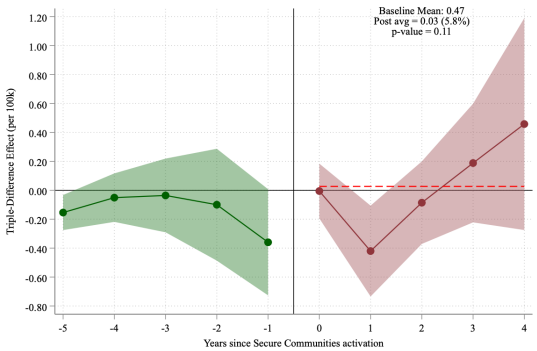
(a) Ages 25-34



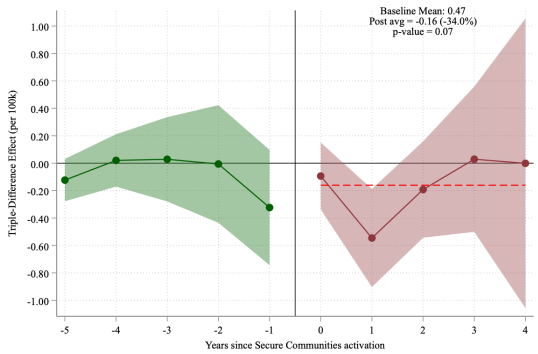
(b) Ages 35-44



(c) Ages 45+



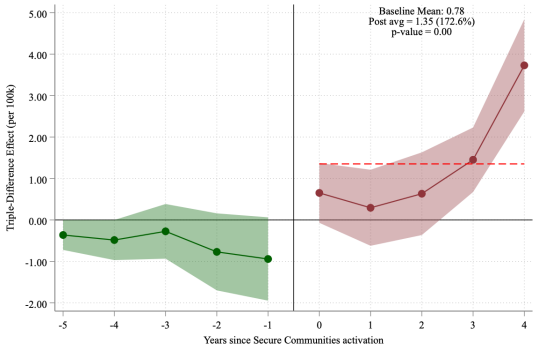
(d) Ages 25+



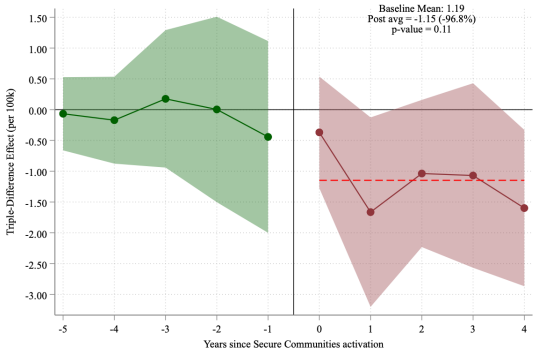
(e) Ages 34+

Notes: This figure displays event study estimates for alcohol-related deaths across different age groups.

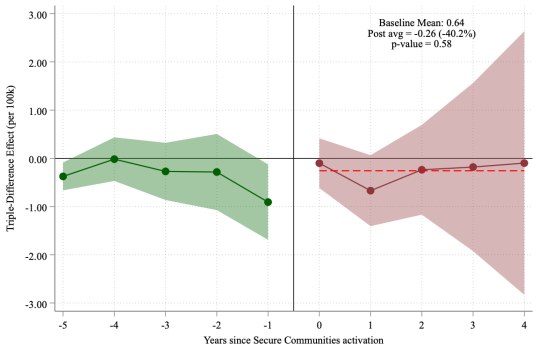
Figure A.32: Effect of Secure Communities on Alcohol-Related Deaths: Men



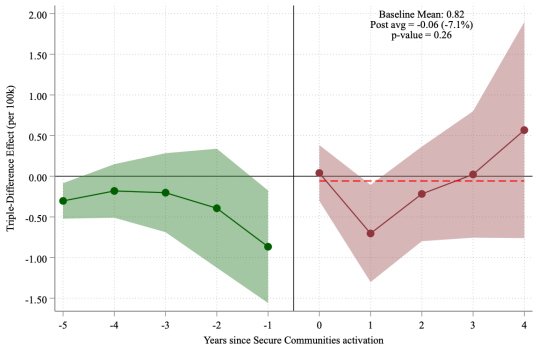
(a) Ages 25-34



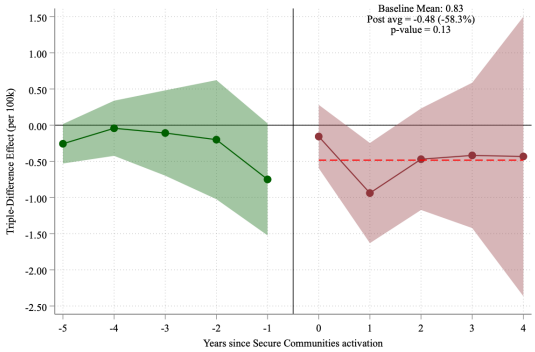
(b) Ages 35-44



(c) Ages 45+



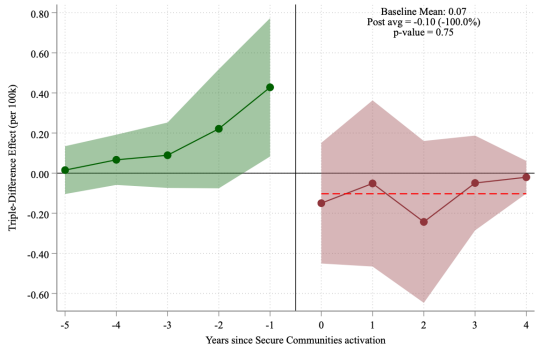
(d) Ages 25+



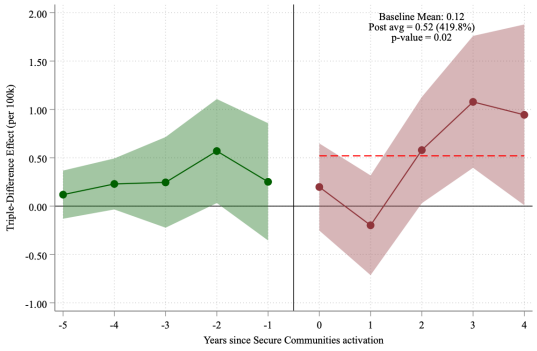
(e) Ages 34+

Notes: This figure displays event study estimates for alcohol-related deaths among men across different age groups.

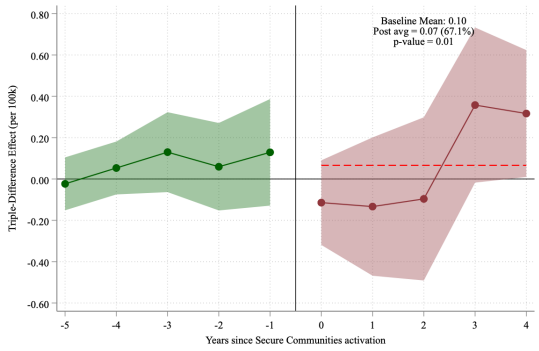
Figure A.33: Effect of Secure Communities on Alcohol-Related Deaths: Women



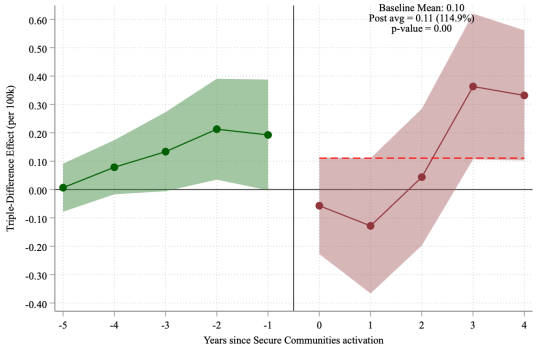
(a) Ages 25-34



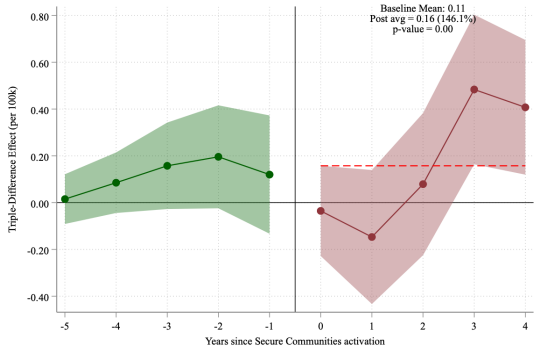
(b) Ages 35-44



(c) Ages 45+



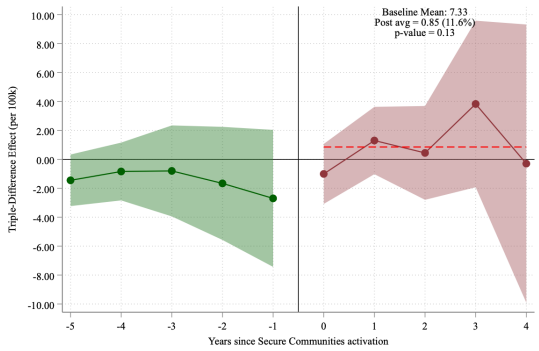
(d) Ages 25+



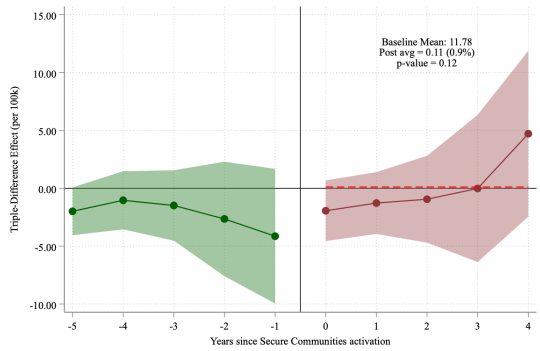
(e) Ages 34+

Notes: This figure displays event study estimates for alcohol-related deaths among women across different age groups.

Figure A.34: Effect of Secure Communities on Drug-Related Deaths: All Age Groups



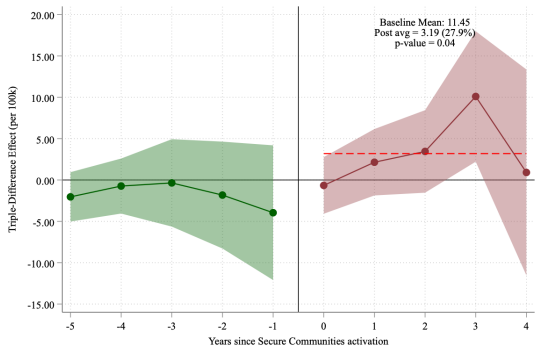
(a) Ages 25-34



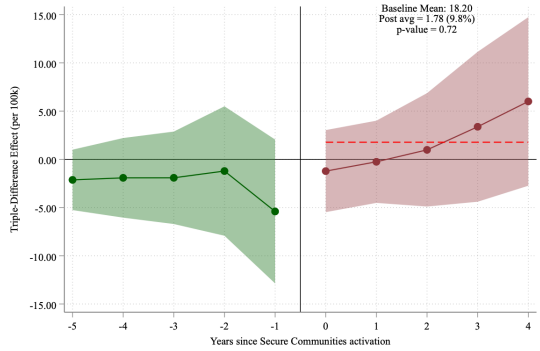
(b) Ages 35-44

Notes: This figure displays event study estimates for drug-related deaths across different age groups.

Figure A.35: Effect of Secure Communities on Drug-Related Deaths: Men



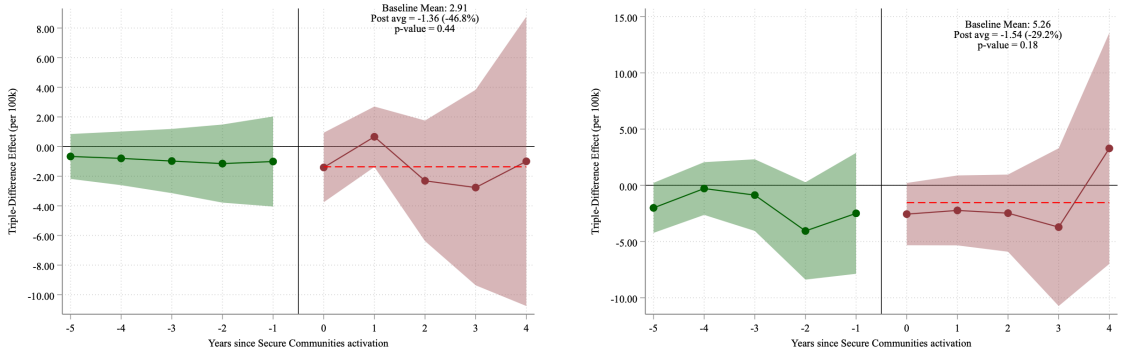
(a) Ages 25-34



(b) Ages 35-44

Notes: This figure displays event study estimates for drug-related deaths among men across different age groups.

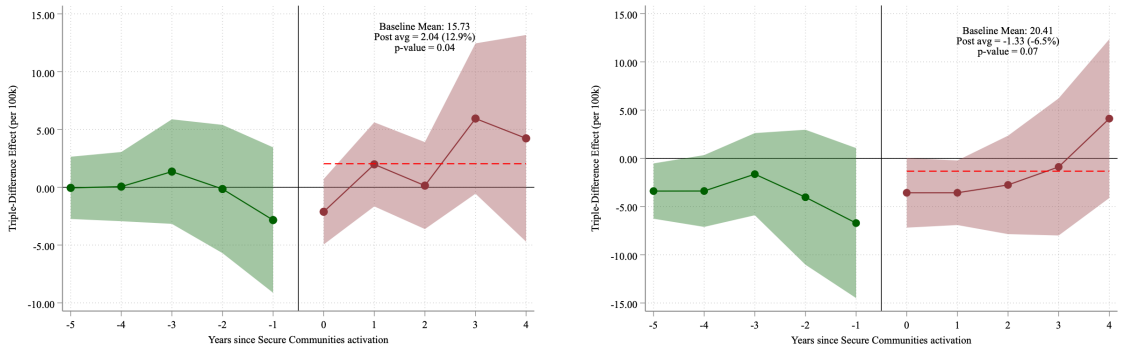
Figure A.36: Effect of Secure Communities on Drug-Related Deaths: Women



(a) Ages 25-34 (b) Ages 35-44

Notes: This figure displays event study estimates for drug-related deaths among women across different age groups.

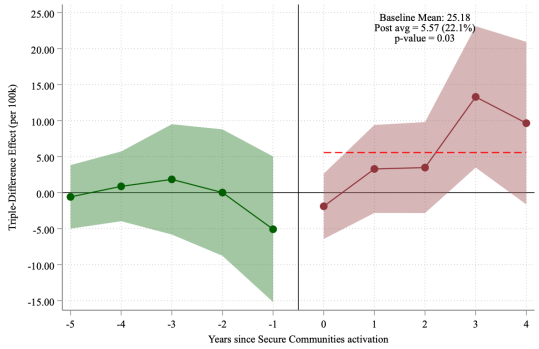
Figure A.37: Effect of Secure Communities on Deaths of Despair: All Age Groups



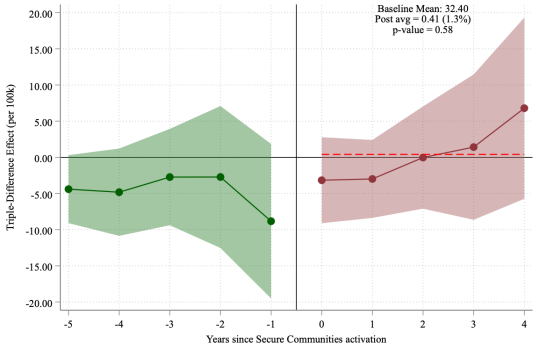
(a) Ages 25-34 (b) Ages 35-44

Notes: This figure displays event study estimates for deaths of despair (suicides, alcohol-related deaths, and drug-related deaths combined) across different age groups.

Figure A.38: Effect of Secure Communities on Deaths of Despair: Men



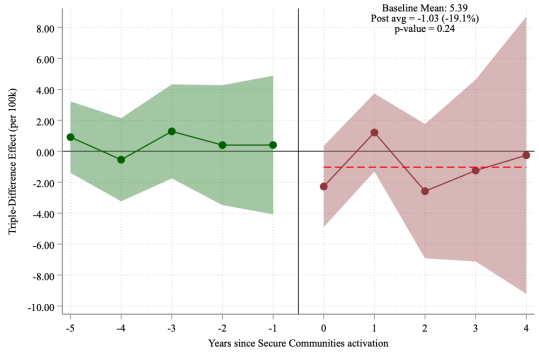
(a) Ages 25-34



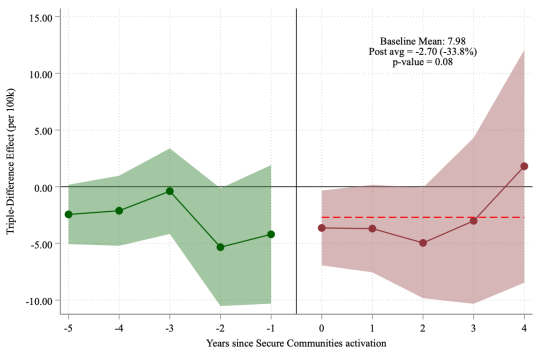
(b) Ages 35-44

Notes: This figure displays event study estimates for deaths of despair (suicides, alcohol-related deaths, and drug-related deaths combined) among men across different age groups.

Figure A.39: Effect of Secure Communities on Deaths of Despair: Women



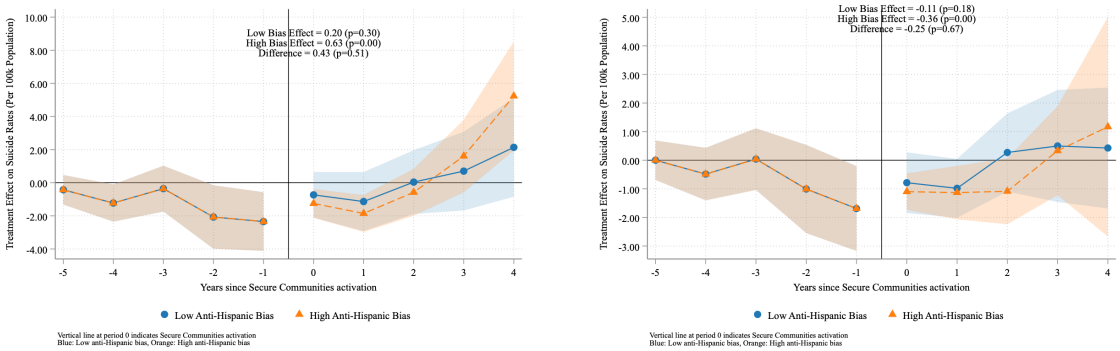
(a) Ages 25-34



(b) Ages 35-44

Notes: This figure displays event study estimates for deaths of despair (suicides, alcohol-related deaths, and drug-related deaths combined) among women across different age groups.

Figure A.40: Heterogeneous Effects by County-level Anti-Hispanic Bias



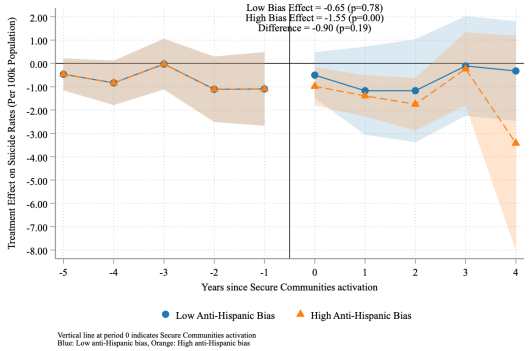
(a) Ages 34+ (Adults)

(b) All Ages

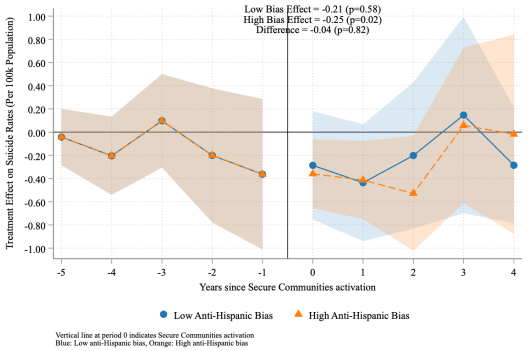
Notes: These figures estimate event study models for Hispanic suicide rates, comparing counties with above-median ("High Bias") versus below-median ("Low Bias") values of a composite anti-Hispanic bias index. The outcome variable y_{cst} is the number of suicides among Hispanics in the specified age group in county c, state s, at time t. The composite bias index incorporates implicit and explicit bias measures. Pre-treatment coefficients (β_l for $l < 0$) test the parallel trends assumption for each bias group. Post-treatment coefficients (β_l for $l \geqslant 0$) capture how the mental health impact of Secure Communities varies by county-level anti-Hispanic bias. All results are for Hispanic populations only; no comparison to White or sanctuary status is made in these plots.

Source: The bias index is constructed using Lubotsky and Wittenberg (2006) and incorporates measures of implicit association test (IAT) scores, hate crime rates, and explicit bias at the state level (American National Election Studies 2021; Bureau of Justice Statistics 2023a; Greenwald, McGhee, and Schwartz 1998).

Figure A.41: Heterogeneous Effects by County-level Anti-Hispanic Bias: Women Analysis



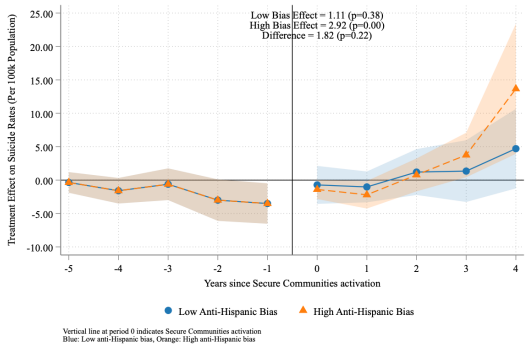
(a) Women Ages 34+



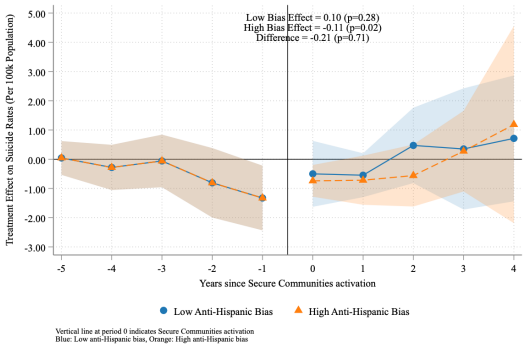
(b) Women (All Ages)

Notes: See Figure A.40 for more details. The analysis uses suicide rates per 100,000 among Hispanic women in the specified age group as the outcome variable.

Figure A.42: Heterogeneous Effects by County-level Anti-Hispanic Bias: Men Analysis



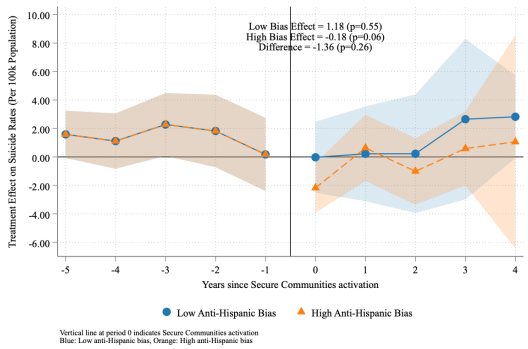
(a) Men Ages 34+



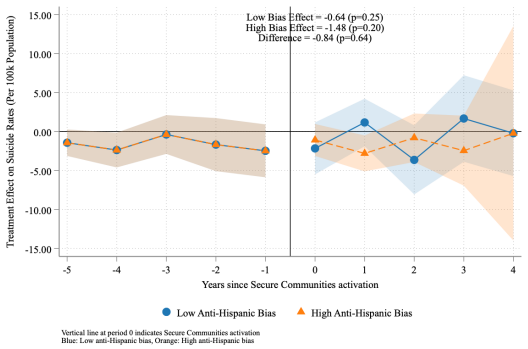
(b) Men (All Ages)

Notes: See Figure A.40 for more details. The analysis uses suicide rates per 100,000 among Hispanic mens in the specified age group as the outcome variable.

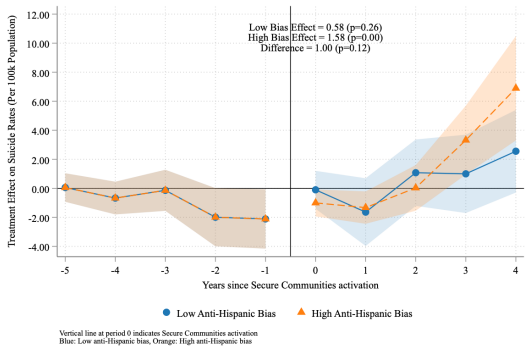
Figure A.43: Heterogeneous Effects by County-level Anti-Hispanic Bias: Additional Adult Age Bands



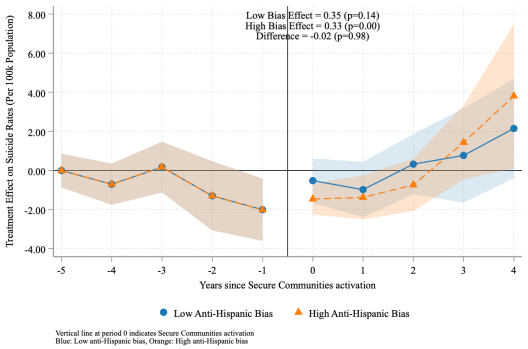
(a) Ages 25–34



(b) Ages 35–44



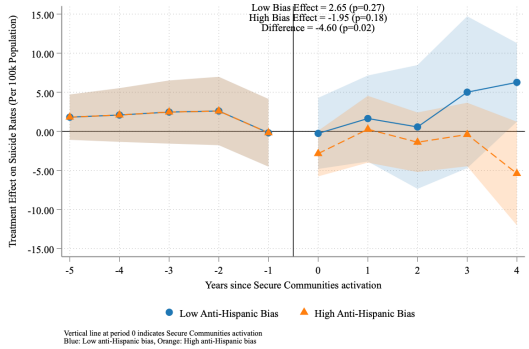
(c) Ages 45+



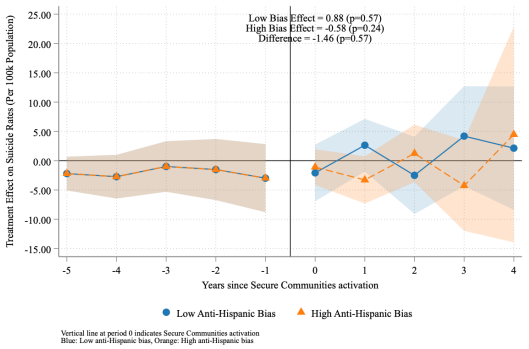
(d) Ages 25+

Notes: Additional heterogeneous effects by county-level anti-Hispanic bias for adult age bands using per 100k suicide rates. Specification matches the main bias heterogeneity model; see Figure A.40 for details on the composite bias index, controls, fixed effects, and weighting.

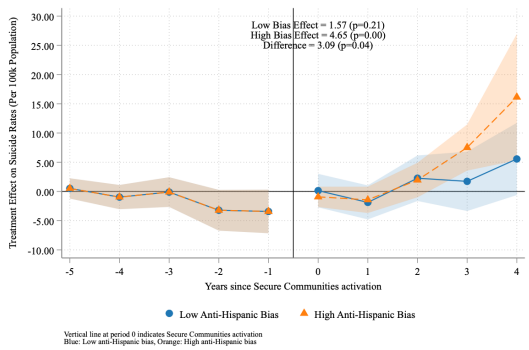
Figure A.44: Heterogeneous Effects by County-level Anti-Hispanic Bias: Additional Adult Age Bands (Men)



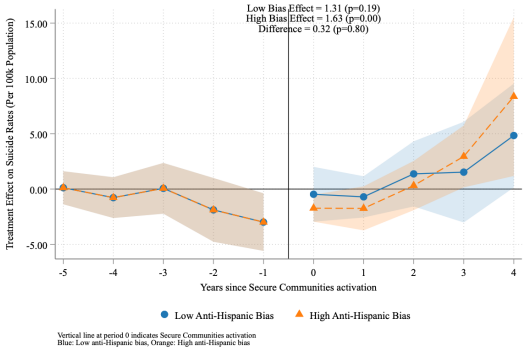
(a) Men 25–34



(b) Men 35–44



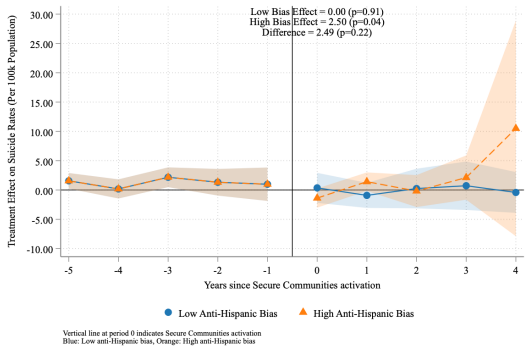
(c) Men 45+



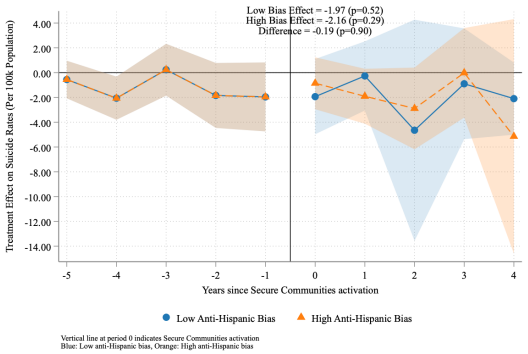
(d) Men 25+

Notes: Heterogeneous effects by county-level anti-Hispanic bias for men suicide rates per 100k by adult age bands. Specification matches the main bias heterogeneity model; see Figure A.40 for details.

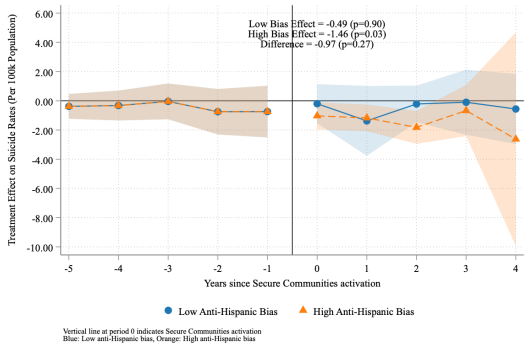
Figure A.45: Heterogeneous Effects by County-level Anti-Hispanic Bias: Additional Adult Age Bands (Women)



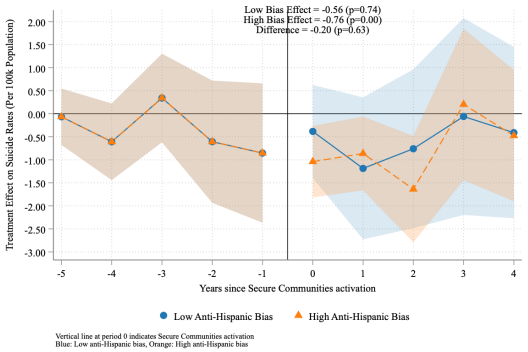
(a) Women 25–34



(b) Women 35–44



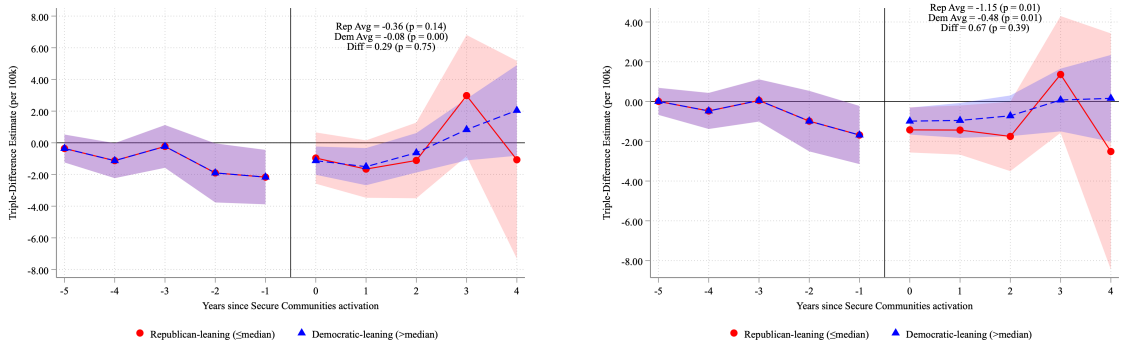
(c) Women 45+



(d) Women 25+

Notes: Heterogeneous effects by county-level anti-Hispanic bias for women suicide rates per 100k by adult age bands. Specification matches the main bias heterogeneity model; see Figure A.40 for details.

Figure A.46: Heterogeneous Effects by County-level Political Affiliation: Main Age Groups



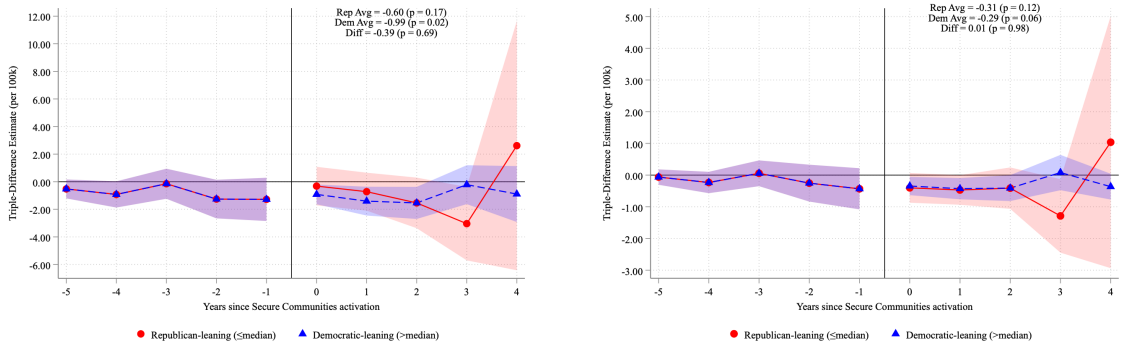
(a) Ages 34+ (Adults)

(b) All Ages

Notes: These figures estimate event study models for Hispanic suicide rates, comparing counties with Republican-leaning (below median Democratic vote share) versus Democratic-leaning (above median Democratic vote share) political affiliation. The outcome variable y_{cst} is the suicide rate per 100,000 among Hispanics in the specified age group in county c, state s, at time t. Counties are classified by Democratic vote share in presidential elections, with Republican-leaning counties expected to show different treatment effects if local political climate moderates community responses to federal immigration enforcement. Pre-treatment coefficients (β_l for $l < 0$) test the parallel trends assumption for each political group. Post-treatment coefficients (β_l for $l \geqslant 0$) capture how the mental health impact of Secure Communities varies by county-level political affiliation. All results are for Hispanic populations only; no comparison to White or other characteristics is made in these plots. The standard errors are clustered at the county level and the county population is used to weight the estimates.

Source: Voting data from Amlani and Algara (2021).

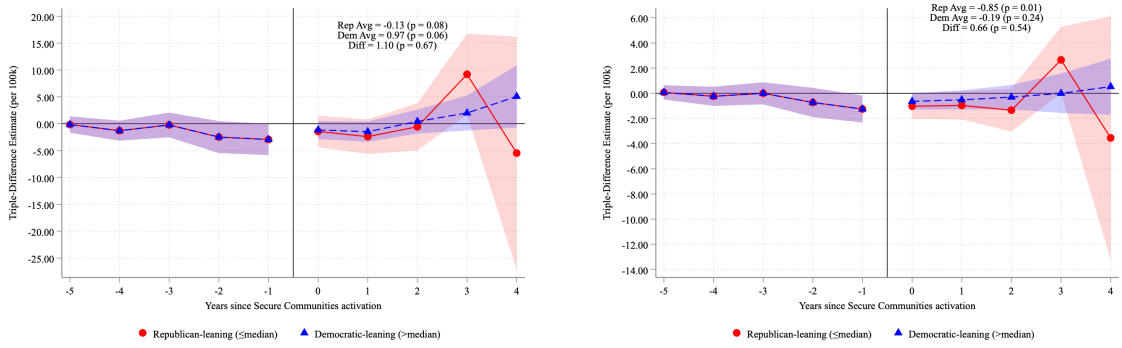
Figure A.47: Heterogeneous Effects by County-level Political Affiliation: Women Analysis



(a) Women Ages 34+ (b) Women (All Ages)

Notes: See Figure A.46 for more details. The analysis uses suicide rates per 100,000 among Hispanic women in the specified age group as the outcome variable.

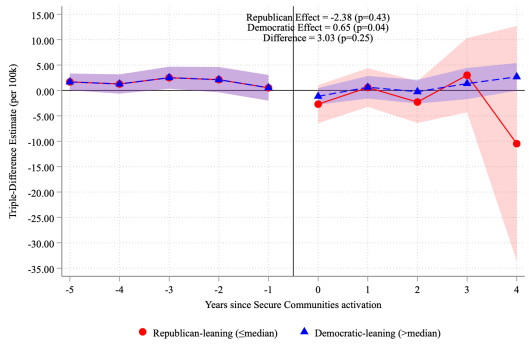
Figure A.48: Heterogeneous Effects by County-level Political Affiliation: Men Analysis



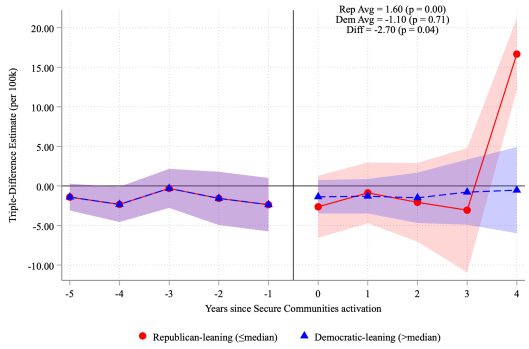
(a) Men Ages 34+ (b) Men (All Ages)

Notes: See Figure A.46 for more details. The analysis uses suicide rates per 100,000 among Hispanic mens in the specified age group as the outcome variable.

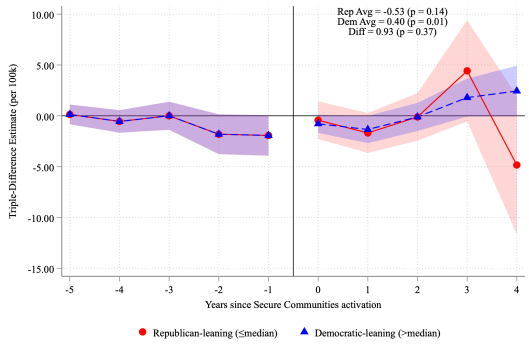
Figure A.49: Heterogeneous Effects by County-level Political Affiliation: Additional Adult Age Bands



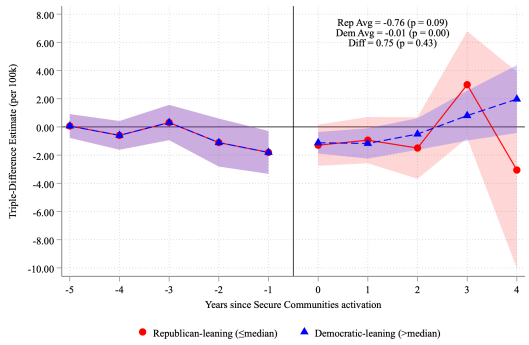
(a) Ages 25–34



(b) Ages 35–44



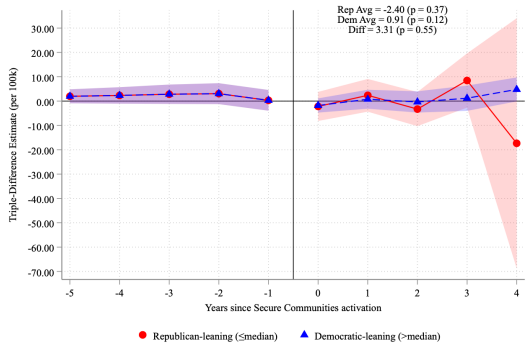
(c) Ages 45+



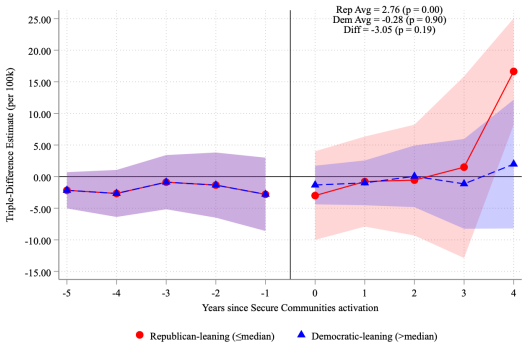
(d) Ages 25+

Notes: Additional heterogeneous effects by county-level political affiliation for adult age bands using per 100k suicide rates. Specification matches the main political heterogeneity model; see Figure A.46 for details on political classification, controls, fixed effects, and weighting.

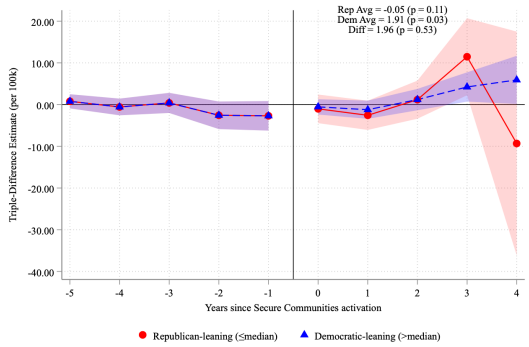
Figure A.50: Heterogeneous Effects by County-level Political Affiliation: Additional Adult Age Bands (Men)



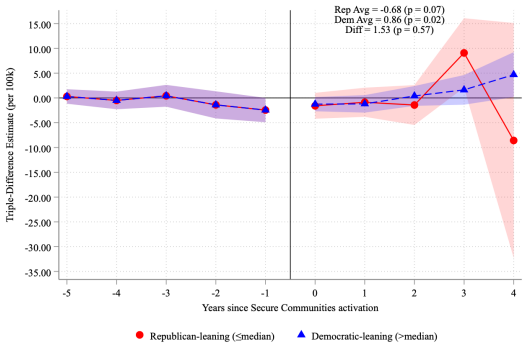
(a) Men 25–34



(b) Men 35–44



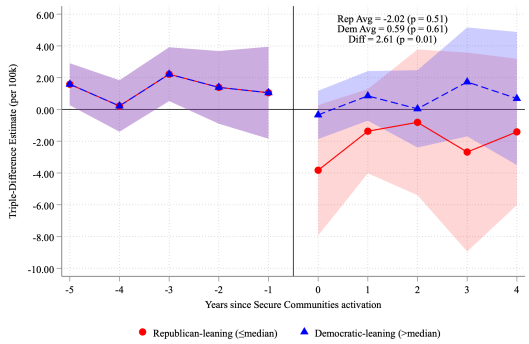
(c) Men 45+



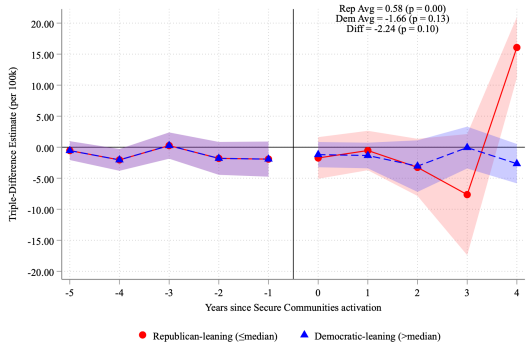
(d) Men 25+

Notes: Heterogeneous effects by county-level political affiliation for men suicide rates per 100k by adult age bands. Specification matches the main political heterogeneity model; see Figure A.46 for details.

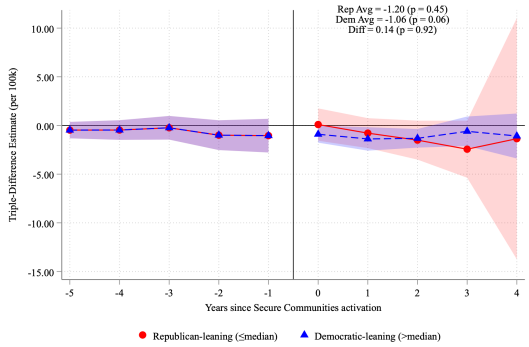
Figure A.51: Heterogeneous Effects by County-level Political Affiliation: Additional Adult Age Bands (Women)



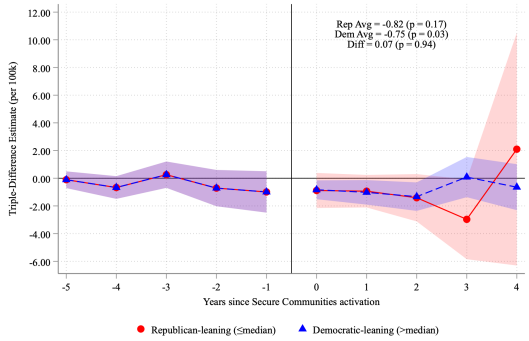
(a) Women 25–34



(b) Women 35–44



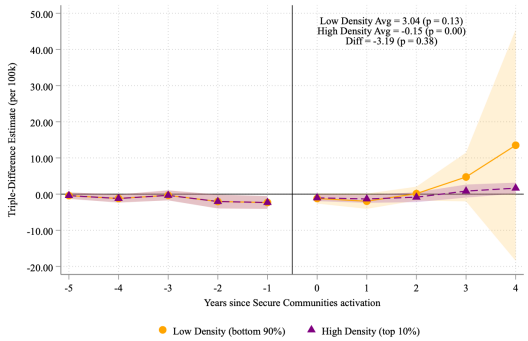
(c) Women 45+



(d) Women 25+

Notes: Heterogeneous effects by county-level political affiliation for women suicide rates per 100k by adult age bands. Specification matches the main political heterogeneity model; see Figure A.46 for details.

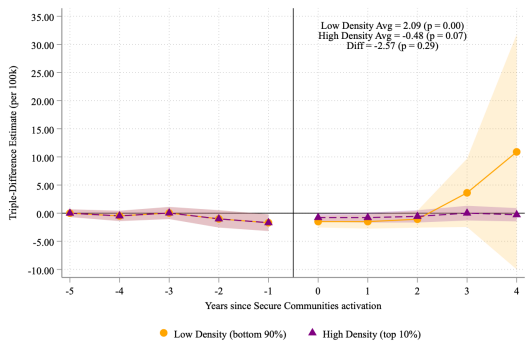
Figure A.52: Heterogeneous Effects by County-level Population Density



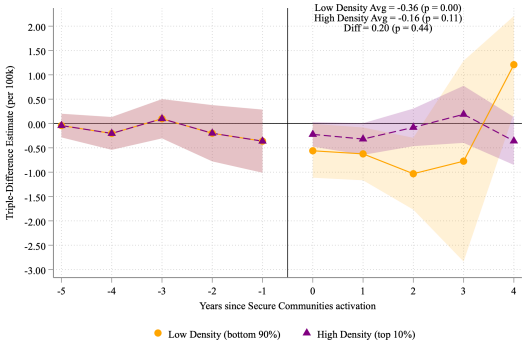
(a) Ages 34+ (Adults)

Notes: See Figure 4 for more details. Counties are classified by population density, with "Low Density" representing counties in the bottom 10% of population density and "High Density" representing counties in the top 90%.

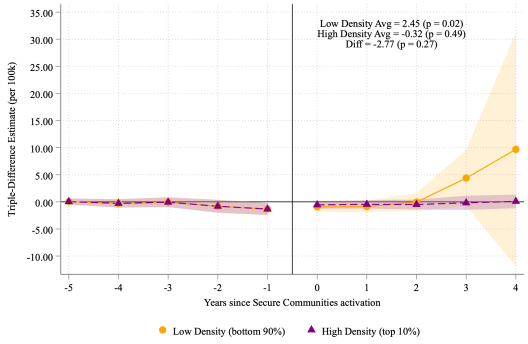
Figure A.53: Heterogeneous Effects by County-level Population Density: All Ages and Gender-Specific Analysis



(a) All Ages



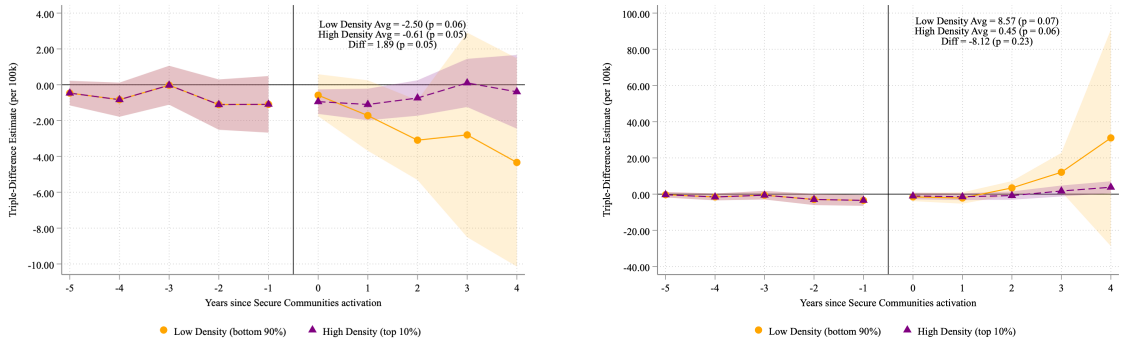
(b) Women (All Ages)



(c) Men (All Ages)

Notes: See Figure 4 for more details. Counties are classified by population density, with "Low Density" representing counties in the bottom 10% of population density and "High Density" representing counties in the top 90%.

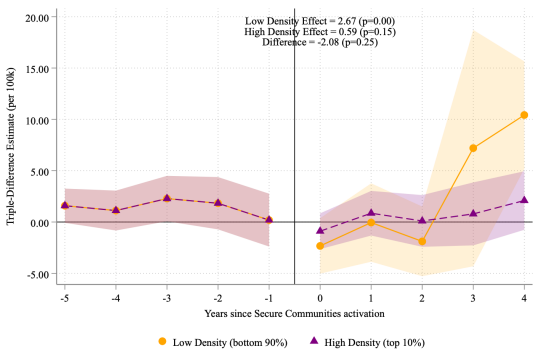
Figure A.54: Heterogeneous Effects by County-level Population Density: Gender-Specific Analysis by Age Group



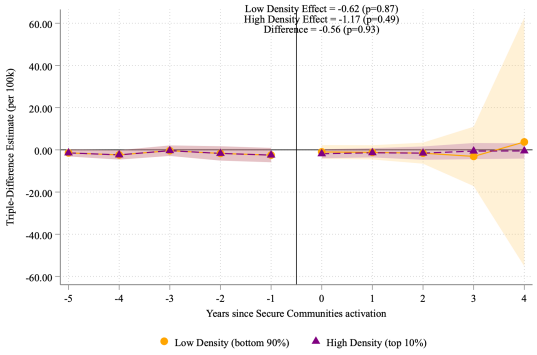
(a) Women Ages 34+ (b) Men Ages 34+

Notes: See Figure 4 for more details. Counties are classified by population density, with "Low Density" representing counties in the bottom 10% of population density and "High Density" representing counties in the top 90%.

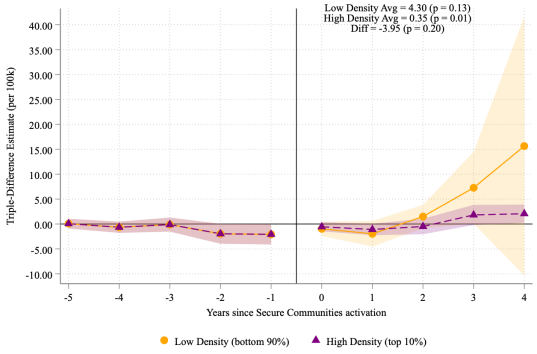
Figure A.55: Heterogeneity by Population Density (Top 10% vs. Bottom 90%)



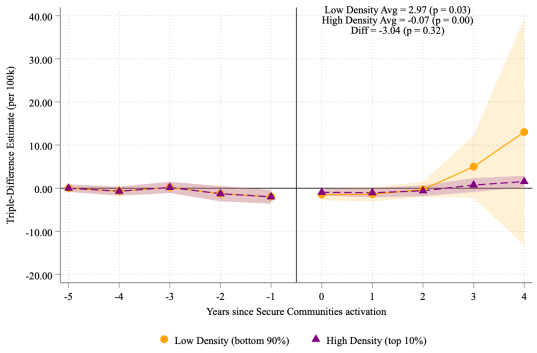
(a) Ages 25-34



(b) Ages 35-44



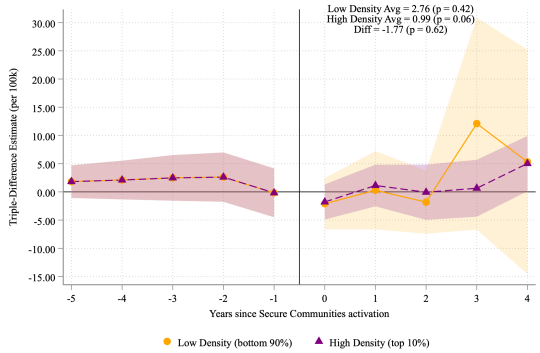
(c) Ages 45+



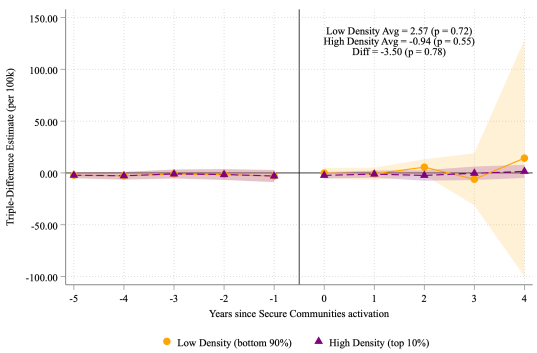
(d) Ages 25+

Notes: This figure displays event study estimates by population density. Counties are split into top 10% (high density) and bottom 90% (low density) based on pre-treatment population density. See Figure A.19 for more details.

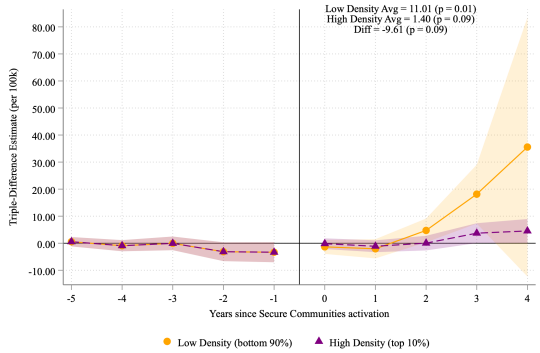
Figure A.56: Heterogeneity by Population Density (Top 10% vs. Bottom 90%): Men



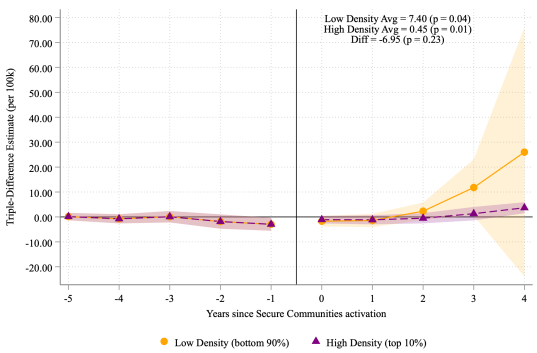
(a) Ages 25-34



(b) Ages 35-44



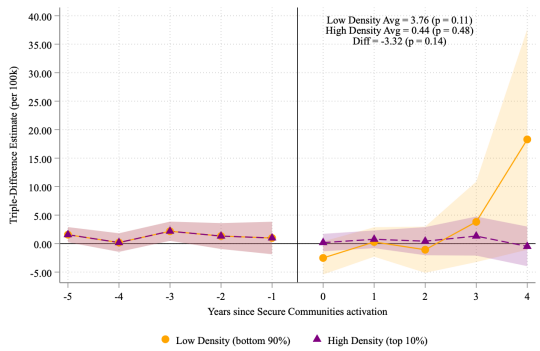
(c) Ages 45+



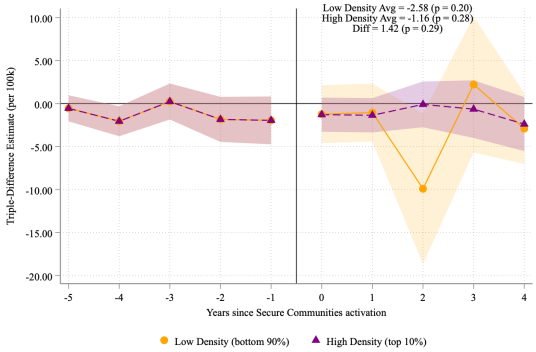
(d) Ages 25+

Notes: This figure displays event study estimates by population density for men. Counties are split into top 10% (high density) and bottom 90% (low density) based on pre-treatment population density. See Figure A.19 for more details.

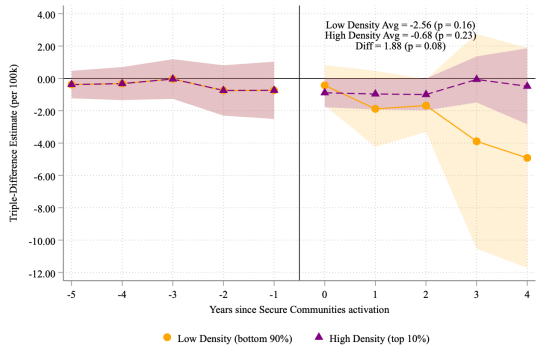
Figure A.57: Heterogeneity by Population Density (Top 10% vs. Bottom 90%): Women



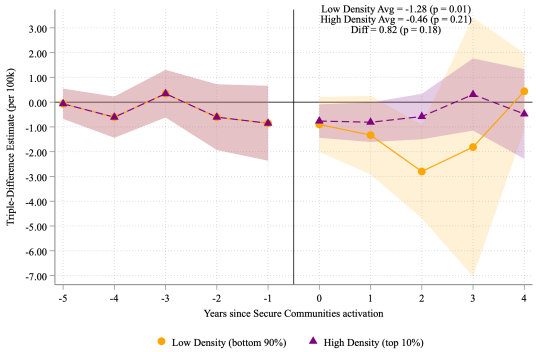
(a) Ages 25-34



(b) Ages 35-44



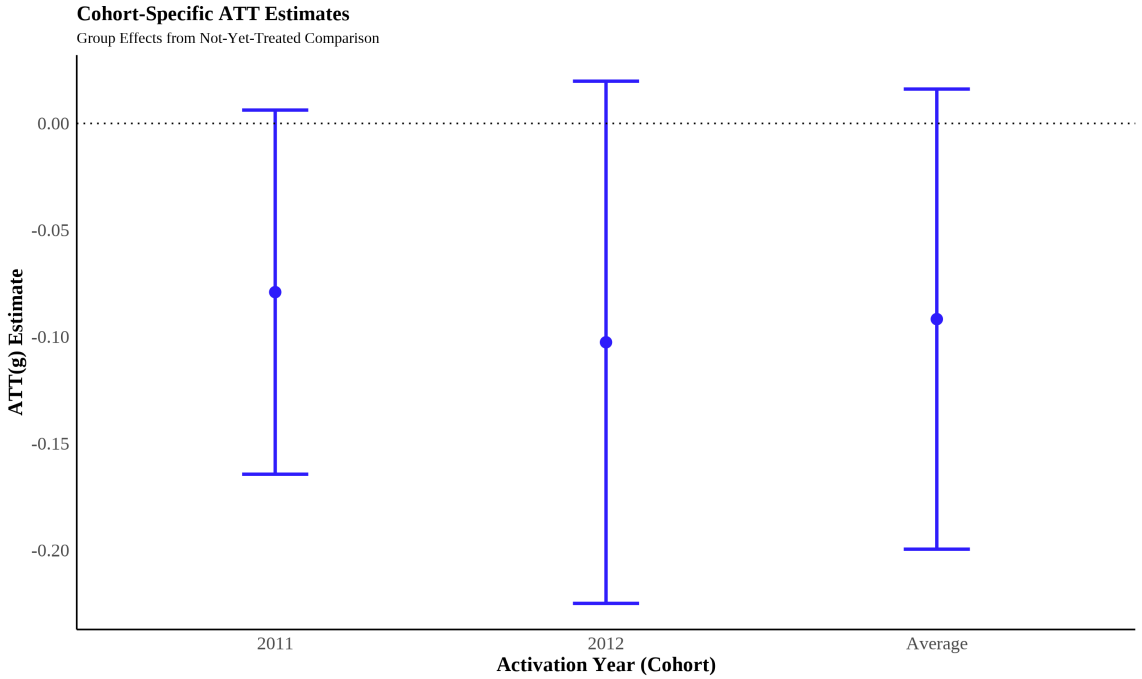
(c) Ages 45+



(d) Ages 25+

Notes: This figure displays event study estimates by population density for women. Counties are split into top 10% (high density) and bottom 90% (low density) based on pre-treatment population density. See Figure A.19 for more details.

Figure A.58: Effect of Secure Communities on Number of Day Reported Mental Unwellness



Notes: This figure shows the cohort specific effect of Secure Communities on the average number of days of reported mental unwellness in the past 30 days, using data from the County Health Rankings & Roadmaps. The outcome variable y_{ct} is the average number of days of poor mental health reported by adults in county c at time t.

Source: County Health Rankings & Roadmaps University of Wisconsin Population Health Institute (2025).