Immigration Enforcement and Child Maltreatment Reporting: Evidence from Secure Communities

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Abstract

I study the effects of a major immigration reform on the incidence and reporting of child maltreatment in Hispanic households. Secure Communities ties federal immigration enforcement to local law enforcement, effectively increasing the likelihood of deportation for undocumented immigrants who are arrested for a crime. I exploit the staggered rollout of Secure Communities across counties to estimate an event study triple differences model. I find that Secure Communities implementation decreased the rate of investigated child maltreatment cases involving Hispanic children, and increased the average severity of investigated cases. The effects are concentrated among referrals by non-mandated reporters, including family members, friends and neighbors.

1 Introduction

Child maltreatment in the U.S. is both prevalent and pernicious. More than one in three children growing up in the U.S. will be the subject of a Child Protective Services (CPS) investigation and one in eight children will be a confirmed victim of maltreatment by the time he or she reaches eighteen (Kim et al. 2017; Wildeman and Emanuel 2014). These hazard rates vary significantly across race and ethnicity, with Black and Hispanic children at higher risk than white children. Shocks in the early child environment can have important negative consequences for long-term outcomes (see Almond, Currie, and Duque (2018) for an overview), and child abuse and neglect are no exception. Victims of maltreatment obtain less education, are less likely to be employed, and have fewer earnings and assets as adults, compared to similar un-maltreated children (Currie and Spatz Widom 2010), and are more likely to themselves commit crime later in life (Currie and Tekin 2012).

CPS is responsible for investigating alleged cases of maltreatment, and determining whether allegations are true (substantiated). However, CPS relies on individuals outside of child welfare services to refer potential cases of abuse and neglect. Federal and state laws designate certain professionals as mandated reporters of abuse and neglect, and non-professionals such as parents, relatives, friends and neighbors may also make referrals to CPS. Although reports by professionals and community members are critical for CPS' detection of and response to child maltreatment, the factors that influence the decisions of potential reporters are not well known.

In this paper, I study the effects of a major immigration reform that may have differentially increased the (real or perceived) costs of interacting with CPS for Hispanic households. In particular, I ask whether and to what extent the rollout of Secure Communities impacted incidence and reporting of child maltreatment cases involving Hispanic children. Briefly, Secure Communities aimed to increase cooperation between local law enforcement and federal immigration enforcement, and served to increase both salience and likelihood of deportation for unauthorized immigrants.

Previous work has investigated the "chilling effect" of Secure Communities, and stricter immigration enforcement more broadly, on take up of social and medical services. Watson (2014) finds that enhanced immigration enforcement reduced participation in Medicaid for children of non-citizens, even when the children were themselves citizens. Similarly, Rhodes et al. (2015) find that stricter immigration enforcement led Hispanic mothers to seek pre-natal care later in their pregnancies, citing mistrust of health services. Alsan and Yang (2018) find that Secure Communities significantly decreased enrollment in SSI and SNAP by Hispanic citizens, who are themselves not eligible for deportation. The authors present evidence suggesting that their results are driven by Hispanic citizens' fear that by taking up social services, they will increase the risk of deportation for non-citizens in their social network. This body of work suggests that immigration enforcement has wide-ranging unintended consequences, including on activities which will likely not increase risk of deportation.

Law enforcement and immigration enforcement are institutions with distinct but overlapping goals. Although federal immigration enforcement aims primarily to identify and remove people who are in the country illegally, the Department of Homeland Security also claims to prioritize the removal of individuals who pose a threat to national security, border security or public safety. Promoting public safety is also a priority for local law enforcement. However, it is *a priori* not clear that policies which link these two institutions have a positive effect on this shared goal of public safety. On one hand, potential deportation increases the cost of committing crime for undocumented immigrants, in theory leading to a decrease in crime. However, the threat of deportation may also increase the cost of reporting crimes for undocumented immigrants, causing a decrease in reporting and potentially a decrease in public safety.

Anecdotal as well as empirical evidence ties fear of deportation to a reduction in the willingness of victims to report crimes.[1] Further, many have suggested that this connection has a negative impact on public safety.[2] However, despite much political debate over the effects of immigration

[1] Jácome (2022) studies the Priority Enforcement Program (PEP), which shifted ICE's enforcement efforts away from immigration-related offenses and towards immigrants convicted of serious crimes. She finds that PEP increased the number of incidents reported to the police by Hispanic (relative to non-Hispanic) individuals, and argues that the effects are due to an increased trust between immigrant communities and the police. See Engelbrecht (2018) and Clark (2018) for examples of news articles making similar arguments.

[2] For example, San Diego County Sheriff Bill Gore has said: "I think it makes our community less safe when people that might be in the country without documentation feel that they can't report crimes or be witnesses to crimes because they think the sheriff's deputy will turn them over to immigration." (Queally 2017).

enforcement policies on crime, relatively little robust academic evidence exists.[3] A key challenge in identifying the effects of any policy on crime is disentangling changes in reporting from changes in incidence of crime.

I overcome this challenge using case-level data from the National Child Abuse and Neglect Data System (NCANDS), and exploiting the staggered and quasi-random rollout of Secure Communities across U.S. counties. I estimate the effect of the policy on (1) the rate of investigated maltreatment reports per Hispanic child population and (2) the substantiation rate of child maltreatment cases involving Hispanic children. My empirical approach, an event study triple differences design, allows me to directly test for pre-trends and observe the timing of the effects relative to the policy implementation. I differentiate effects on reporting from effects on abuse rates by using substantiation rate as a measure of average severity of reported cases. Briefly, I suppose that the probability of reporting potential maltreatment is increasing in the severity of maltreatment and decreasing in cost of reporting. In this case, an increase in the cost of reporting would increase the average severity of reported cases, and thus the substantiation rate.

I find that, among cases referred by non-mandated reporters, Secure Communities decreased the rate of investigated cases involving Hispanic children by 3.2 percent relative to the sample mean, and had no statistically significant effect on the rate of investigated cases involving non-Hispanic Black or non-Hispanic white children. The effects are concentrated among allegations of neglect and deprivation, which decrease 4.8 percent relative to the sample mean, and physical abuse, which decrease 5.6 percent relative to the sample mean. Secure Communities also increased the substantiation rate of investigated cases involving Hispanic children by 6.6 percent overall, 8.1 percent for cases involving neglect and deprivation, and 26 percent for cases involving physical abuse (all measured relative to the sample mean). These results suggest that tying federal immi-

[3] Miles and Cox (2014) study the effect of Secure Communities on overall (observed) crime rates, and find a null effect. Wong (2017) examines the impact of sanctuary policies at the county level, and finds sanctuary counties have lower crime rates than matched non-sanctuary counties. (Sanctuary policies are essentially the opposite of Secure Communities, in that they aim to separate law enforcement from immigration enforcement activities.) However, Wong's analysis cannot distinguish correlations from the causal effect of sanctuary policies, as the unobserved characteristics driving counties to enact sanctuary policies may be the same characteristics that cause lower crime rates.

gration enforcement to local law enforcement had the unintentional consequence of reducing the willingness of Hispanic individuals to report crime, and, in particular, to report potential cases of child maltreatment. This paper also sheds light on the causes of racial and ethnic disparity within the child welfare system, and provides the first causal evidence of a policy which differentially impacts children's experience with CPS depending on their ethnicity.[4]

The paper proceeds as follows. In Section 2 I describe the policy context of Secure Communities, as well as the institutional context of Child Protective Services. Section 3 describes my data sources and presents summary statistics. Section 4 describes my empirical approach, Section 5 presents results, and Section 6 concludes.

2 Policy and Institutional Context

2.1 Secure Communities

Secure Communities is a program administered by the U.S. Immigration and Customs Enforcement (ICE), which aims to increase detection and deportation of unauthorized immigrants, and in particular of unauthorized immigrants convicted of a crime.[5] Specifically, this program has three main goals: (1) to identify criminal aliens, (2) to prioritize the apprehension and removal of dangerous criminal aliens, and (3) to transform criminal alien enforcement processes and systems (United States Immigration and Customs Enforcement, 2009). Prior to Secure Communities, local law enforcement had limited interaction with federal immigration enforcement. Potential unauthorized immigrants were identified primarily through biographic interviews, conducted either by federal officers under the Criminal Alien Program or law enforcement officers in jurisdictions with 287(g) agreements.[6] According to ICE, these "traditional processes of identification are labor-intensive,

[4]Note, an explicit analysis of the welfare consequences of these effects is outside the scope of this paper. The causal effects investigation for children on the margin of being reported are largely unstudied.

[5]For a detailed history of the institutional context of Secure Communities, see Alsan and Yang (2018), Online Appendix C.

[6]Section §287(g) of the Immigration and Nationality Act allows the Attorney General to authorize local law enforcement to assist with immigration enforcement. To enter such an agreement, jurisdictions must submit a request to ICE, and sign a Memorandum of Agreement (MOA) which defines the terms of the partnership. As of

time-consuming, and are often limited by the accuracy of the biographic information obtained from the subject" (United States Immigration and Customs Enforcement, 2009). Accordingly, prior to Secure Communities, prisoners were screened by immigration officials in only 14% of local jails and prisons (Cox and Miles 2013). Under Secure Communities, this process became automated and significantly less labor-intensive. When an individual is arrested and booked by state or local police, his fingerprints are automatically sent to the FBI, who uses them to conduct a criminal background check. Under Secure Communities, all fingerprints received by the FBI are automatically shared with the Department of Homeland Security (DHS). DHS then checks those fingerprints against a biometric database that stores information on non-citizens in the U.S.[7] Specifically, this database stores information on three categories of individuals: non-citizens who have violated immigration law (e.g., were previously deported or overstayed their visas), (2) non-citizens who are in the U.S. legally but who may be deported if convicted of a crime, and (3) citizens who naturalized after their fingerprints were included (Miles and Cox 2014; Alsan and Yang 2018). If there is a match between the arrested individual and the DHS database, ICE issues a "detainer," requesting that local law enforcement hold the individual in custody until ICE can begin deportation proceedings. Thus, under Secure Communities, individuals who might otherwise have been released by local law enforcement were instead held and turned over to federal immigration enforcement.

Secure Communities represented a major shift in U.S. immigration policy, and had a significant impact on the Hispanic community in particular. Over 93% of detainers issued by ICE were to Hispanic individuals (Alsan and Yang 2018). Between 2009 and 2014, almost 300,000 individuals were deported under Secure Communities, approximately 13% of all deportations from the U.S. during that time period. Moreover, although the program claimed to prioritize public safety and the removal of potentially dangerous individuals, ICE issued a large number of detainers for individuals arrested for low-level and non-violent offenses, and approximately 20% of those removed were never convicted of any crime, or were convicted only of illegal entry or re-entry into the country.[8]

November 2008 (the beginning of the rollout of Secure Communities), 67 jurisdictions had MOAs with ICE. See https://www.ice.gov/287g for more details.

[7] The Automated Biometric Identification System.

[8] Deportation statistics are from https://trac.syr.edu/immigration/

The program began in October 2008 and was rolled out across counties until it covered the entire country by January 2013. Resource and technological constraints were largely responsible for the county-by-county rollout.[9] The federal government was solely responsible for the pattern of staggered activation, and counties could not decline to participate.[10] Cox and Miles (2013) describe the rollout in detail, and test whether early activation was correlated with a number of county-level characteristics. Although a major priority of the program was to identify and remove potentially dangerous criminal aliens, they find that the timing of the rollout was not in fact correlated with crime rates. However, the timing *was* correlated with higher Hispanic population, shorter distance from the border and whether county law enforcement previously had a 287(g) agreement.[11] Secure Communities was discontinued in November 2014, and re-activated in January 2017.[12] Alsan and Yang (2018) verify that the rollout of the program was salient for individuals at the local level, using an event-study analysis of Google Trends data. In particular, they find that implementation of Secure Communities sharply increased normalized deportation-related search terms, by 25%.

Previous work has studied the effects of Secure Communities on a variety of outcomes. Miles and Cox (2014) and Hines and Peri (2019) each show a null effect of Secure Communities on reported local crime. Wang and Kaushal (2019) find that the implementation of Secure Communities had negative effects on the mental health of Latino immigrants. Alsan and Yang (2018) find decreased take up of safety net programs by Hispanic citizens. East et al. (Forthcoming) and East and Velásquez (2022) study the labor market effects of the policy. This work shows that Secure Communities decreased the employment share of likely undocumented immigrants, the employment rate of citizens (consistent with complementarities in production), and in particular labor supply of high-skilled citizen mothers (consistent with a decrease in undocumented women's labor

[9]As described by Cox and Miles (2013), these constraints included transportation and housing of those taken into custody, communicating with local law enforcement, and the lack of live-scan fingerprint machines in many jurisdictions.

[10]Several states (New York, New Jersey and Illinois) did resist the policy, and therefore I exclude them from my empirical analysis, following Alsan and Yang (2018).

[11]I will return to this point in discussing my empirical strategy in Section 4, below.

[12]In the interim, Secure Communities was replaced with a program called Priority Enforcement Program (PEP), which used similar methods to identify unauthorized immigrants, but under which only high-priority individuals were subject to detainer and removal.

supply and subsequent increase in cost of outsourcing household production). Finally, Grittner and Johnson (2021) find evidence that Secure Communities reduced reports of worker complaints and increased workplace injuries at workplaces with large shares of Hispanic workers.

2.2 Child Protective Services

In 2017, CPS agencies in the U.S. received over four million allegations of child maltreatment, involving over seven million children. Although CPS agencies are run at the state level, and thus specific policies and procedures are heterogeneous across the U.S., the general process for reporting and investigating child maltreatment is similar across states. In the first stage of the process, potential cases of abuse or neglect are referred to the child welfare office, either by mandated reporters (eg., teachers, police, physicians) or concerned members of the public (eg., friends, family or neighbors). Mandated reporters are required by law to refer suspected cases of maltreatment to CPS; specific regulations, penalties for non-compliance and mandated reporter categories vary by state. Once reported, CPS agencies must decide whether to screen in the referral for further investigation. Standards for which referrals warrant investigation differ somewhat across states, and in 2017 approximately 58% of referrals were screened in.[13] Once screened in, the case is assigned to an investigator charged with determining whether the allegations of abuse or neglect are true (substantiated) or likely true (indicated), what services to provide the family and whether to remove the child from their home. In 2017, 17% of investigations led to a substantiated or indicated disposition. Put differently, 9.1 children out of 1,000 children in the population were found to be victims of maltreatment. Of these confirmed victims, 23.7% were removed from their homes (Administration on Children and Families 2017).

The rate of investigated reports per child population and the rate of substantiated cases per reports both differ significantly across race and ethnicity (see Figures 1 and 2, respectively). In particular, Black and (to some extent) Hispanic children are more likely to be the subject of an

[13]The rate of screened-in referrals is calculated using data from the 42 states in my data that reported both screened-in and screened-out referral numbers for 2017.

investigated report than non-Hispanic white children. Further, allegations involving Hispanic children are more likely to be substantiated than allegations involving non-Hispanic children. These disparities have been raised as a significant concern by individual CPS agencies, scholars and child welfare experts alike.[14] However, the causes of racial and ethnic disparity at each stage are not well known. While differences may in part be explained by average differences across race/ethnicity in risk factors associated with maltreatment, bias may also play a part. In the first stage of the CPS process, bias may impact which cases of abuse are actually reported if, for example, a potential reporter is more suspicious of minority families, or alternatively less concerned with the welfare of minority children. Importantly for this paper, we would also expect to see differences in reporting rates across race and ethnicity if the costs associated with reporting child abuse are heterogeneous along this dimension. In subsequent stages, (either conscious or subconscious) bias may affect call screeners' and investigators' actions and decisions.

Previous work has made clear that removing a child from an abusive home may have significant and long-term consequences on that child's educational attainment, delinquency and earnings.[15] However, relatively little work has looked at the forces that bring cases of child maltreatment to the attention of the relevant authorities.[16] In addition, although the existence of racial and ethnic disparities in the child welfare system are well-established, the causes of these disparities are not well-understood. In this paper, I investigate the role of reporters in perpetuating the observed disparity in rates of victimization and substantiation across race and ethnicity, and in particular I will consider a barrier to reporting that may heterogeneously affect Hispanic children and families.

While the causes of child maltreatment are not fully understood, several risk factors at the individual, family and community level correlate with or predict abuse and neglect. At the individual

[14] See Gateway (2016) for an overview.

[15] See Doyle (2007, 2008), Gross and Baron (2022), and Bald, Chyn, et al. (2022). In each of these papers, the authors exploit random assignment of investigators to estimate the long-term effects of removal for children at the margin. Bald, Doyle, et al. (2022) provides an overview of the state of the economics literature as it relates to foster care.

[16] Exceptions include Fitzpatrick, Benson, and Bondurant (2020), and Baron, Goldstein, and Wallace (2020), which each investigate the role of educators in child abuse reporting. Fitzpatrick, Benson, and Bondurant (2020) find that reports by educators increase as children begin school, and that this increase is not offset by a decrease in reports from other sources. Baron, Goldstein, and Wallace (2020) show that school closures during the COVID-19 pandemic were the primary driver of a 27 percent drop in child maltreatment reports during March and April of 2020.

level, children under age four or with special needs are most at risk for maltreatment. Parents with substance abuse or mental health issues, parents who are young, low education, or low income, single parents and parents with many children are all more likely to be perpetrators of maltreatment. Children in families who are socially isolated, or dealing with stress, separation or divorce are more likely to be maltreated. Finally, children living in communities with violence, high poverty levels, high unemployment rates or poor social connections are at greater risk for maltreatment (Centers for Disease Control and Prevention). Several studies have suggested that employment and income are important determinants of maltreatment (Raissian and Bullinger 2017; Lindo, Schaller, and Hansen 2018; Berger et al. 2017).

CPS is inherently linked to law enforcement. In 2017, legal and law enforcement personnel were responsible for 18.3% of reports to CPS, second only to educators who reported 19.4% of cases. Confirmed cases of neglect and abuse can result in criminal convictions, and CPS notified police or prosecutors in over 27% of cases in 2017.

3 Data

I obtain data on child abuse and maltreatment reports from 2006 through 2016 from the National Child Abuse and Neglect Data System (NCANDS) Child Files. These data include information at the case-child level on all reports of child neglect or maltreatment that were investigated by CPS agencies in participating states.[17] Screening policies (i.e. the standards for deciding which referrals to investigate) vary across states, but referrals may be screened out for one or more of the following reasons: the referral does not concern child abuse or neglect; the referral does not contain enough information for CPS to respond; response by another agency is more appropriate; referred children are the responsibility of another agency/jurisdiction; children are older than 18 (US HSS 2017). Although data submission to NCANDS is voluntary for states, all states currently

[17] More information on the dataset and the process for obtaining it can be found at: https://www.ndacan.acf.hhs.gov/datasets/dataset-details.cfm?ID=220.

participate and most states have done so since 2006.[18] The data include information on reporter type (e.g., educator, relative, medical professional), allegation type (e.g., physical abuse, neglect), case disposition (i.e., whether the allegations were substantiated), services provided by CPS, and whether the child was removed from their home. Crucially, the data also include information on child demographics, including child race and ethnicity. In my main analysis, I consider three race/ethnicity groups: (1) Hispanic children, (2) non-Hispanic white children, and non-Hispanic black children. I leave out children whose ethnicity is unknown, and non-Hispanic children of other races. Importantly for my analysis, the data specify the county and the month of report.[19] One data limitation is important to note: county names are not provided for those counties with fewer than 1,000 child-reports in a given year. I use a balanced sample of counties that are uncensored in the 24 months prior to and 36 months after implementation of Secure Communities. Following Alsan and Yang (2018), I also exclude data from New York, Illinois and Massachusetts, as these three states actively resisted the rollout of Secure Communities. Finally, again following Alsan and Yang (2018), I exclude counties on the U.S. border with Mexico, to guard against endogenous rollout activity. This leaves me with a sample of 544 counties, accounting for approximately 17% of U.S. counties and 60% of investigated children. Figure 3 shows the sample of counties that I use, and Table 1 provides comparative summary statistics for the analysis sample relative to excluded counties. Note that the included counties have more cases involving minority children than excluded counties, with Hispanic children making up 23.1% of children in my sample, relative to 18.2% of observed children in excluded counties.[20]

Figure 4 shows shares of child reports by race/ethnicity and alleged maltreatment category in my sample. Note that the majority of reports involve allegations of neglect or deprivation of necessities, while allegations of physical, sexual and psychological/emotional abuse are relatively more rare.[21] Note also that, while there are not large differences in the breakdown of abuse category

[18] By 2005, the only states that did not regularly submit data were North Dakota and Oregon.

[19] The report date is is rounded to either the 8th of the month (for days 1-15) or the 23rd of the month (for days 16-31). In my analyses, I collapse the data to the monthly level.

[20] In 2016, Hispanic children made up 24.9% of the child population in the U.S.

[21] In the data a single child-report may involve multiple allegations of abuse (e.g. neglect/deprivation *and* physical abuse). In my main analysis, I use child-report level data, and define a child-report as "substantiated" if *any* of the

allegations by race or ethnicity, psychological/emotional maltreatment allegations are significantly more prevalent for Hispanic children than non-Hispanic children, making up 95% (49%) more of total reports than non-Hispanic Black (non-Hispanic white) children.[22] Figure 5 shows the shares of child-reports referred by different categories of reporters (mandated, non-mandated and unknown), separately by race/ethnicity. Note that, relative to cases involving non-Hispanic children, cases involving Hispanic children are less likely to be reported by non-mandated reporters, consistent with the hypothesis that Hispanic individuals face a greater cost of interacting with authorities.

I obtain annual child population by race, ethnicity and county from U.S. Census (2003-2017). I linearly interpolate child population to the monthly level, and merge at the county-month-race/ethnicity level with aggregate child-report counts to obtain rates of child abuse reports.

Finally, administrative data on the rollout of Secure Communities were generously shared with me by Drs. Marcella Alsan and Crystal Yang, who obtained the data via FOIA requests to ICE.[23] These data include the exact date on which Secure Communities was activated in each county in the U.S. Figure 6 shows the number of counties in my sample which activated Secure Communities in each month. I merge implementation dates at the county-month level with child-report rates. In my event study analysis, event time zero is equal to the month of Secure Communities activation, regardless of the exact day within that month the program was implemented.

4 Empirical Approach

In this paper I aim to answer the question: How did the rollout of Secure Communities impact incidence and reporting of child maltreatment cases involving Hispanic children? Given that I cannot observe true maltreatment rates (i.e., the true number of maltreated children divided by child population) or true reporting rates (i.e., the number of reported cases divided by the true

allegations in that report are substantiated. In heterogeneity analysis, I use allegation-level data. That is, a single child-report may be counted both in analysis of, e.g. effects on allegations and substantiations of neglect/deprivation *and* effects on allegations and substantiations of Physical abuse.

[22] While NCANDS does not provide a definition for psychological or emotional maltreatment, it does suggest mapping "threatened harm" and "domestic violence" to this category.

[23] More information on these data can be found in Alsan and Yang (2018) and the accompanying online appendix.

number of maltreated children), I make inferences using the number of investigated cases per child population, and the number of substantiated cases per investigated cases.

Assuming that CPS investigators are better able than reporters to determine if abuse or neglect is in fact taking place, the substantiation rate provides a measure of the accuracy of the referrals. If we further assume the probability that a given child is reported to child welfare is increasing in the severity and likelihood of abuse, and decreasing in the (perceived) cost to reporters of making a referral. That is, changes in the costs and benefits to reporters will change the distribution of accuracy/severity of reported cases. In particular, all else equal, reporters who perceive a higher cost will report on average more severe/accurate cases, while reporters facing lower costs will report on average less severe/accurate cases. Changes in the substantiation rate, i.e. the number of confirmed victims divided by the total number of investigated children, are thus likely to reflect changes in the reporting rate. In particular, a higher substantiation rate implies a lower reporting rate, while a lower substantiation rate implies a higher reporting rate.

To estimate the effect of Secure Communities on my outcomes of interest, I exploit the staggered rollout of the policy across counties and months. Specifically, I use a staggered rollout difference-in-differences design, comparing outcomes across counties before and after the implementation of Secure Communities. In particular, I estimate the following equation:

$$Y_{csmy} = \beta_1 Post_{csmy} + \gamma_{smy} + \gamma_{csm} + \varepsilon \tag{1}$$

Where: Y_{csmy} is either the rate of investigated reports involving Hispanic children per 1,000 Hispanic children in the population in county c within state s in year y and month-of-year m, or it is the number of substantiated cases involving Hispanic children divided by the number of investigated reports involving Hispanic children in county c, state s, year y and month-of-year m. Instead of the traditional county and month-year fixed effects, I include more restrictive state-month-year and county-month fixed effects, to respectively account for any state-level CPS policy changes which may affect the rates of investigated cases and substantiation, and differences across counties in the monthly variation in cases.[24] In all specifications, cells are weighted by the denominator (either Hispanic child population for reporting rate, or the total number of reports involving Hispanic children for the substantiation rate), and standard errors are clustered at the county level.

I then estimate these equations separately for cases involving non-Hispanic Black children and cases involving non-Hispanic white children. The effects of this policy are likely to be concentrated among Hispanic communities. Similar effects for non-Hispanic families might suggest that any results are driven by county-level trends or policy changes other than the implementation of Secure Communities.

A threat to my identification would be if the rollout of the policy change was not fully exogenous, and in particular if it was correlated with trends in abuse and neglect rates within the Hispanic community. For example, if Secure Communities was implemented first in places with rising rates of crime or poverty within Hispanic populations, one might expect that abuse and neglect rates would be higher in the post period, regardless of the effect of the policy.[25] Alternatively, treatment effects might be smaller in counties where the threat of deportation is already high, and if the rollout was correlated with existing immigration enforcement infrastructure one might expect results to be attenuated. Following Alsan and Yang (2018), I exclude border counties from my analysis to reduce bias caused by the potentially non-random rollout of the policy. I also directly test for pre-trends and explore the dynamic effects of the policy using an event study version of Eq. (1), shown below:

$$Y_{csmy} = \beta_1 Pre_{csmy} + \sum_{j=2}^{18} \beta_j I_{csmy}^{pre_j} + \sum_{j=0}^{24} \beta_{j+18} I_{csmy}^{post_j} + \beta_{44} Post_{csmy} + \gamma_{smy} + \gamma_{csm} + \varepsilon \tag{2}$$

Where: Y_{csmy}, γ_{smy} and γ_{csm} are each defined as in Eq. (1); $I_{csmy}^{pre_j}$ is an indicater equal to one

[24] Investigated case rates tend to spike during the school year, and dip during the summer and winter holidays. County-month fixed effects allow these seasonal effects to vary at the county level, for example with school district dates.

[25] Cox and Miles (2013) find that while the rollout was not correlated with crime rates, it was correlated with higher Hispanic population, shorter distance from the border and previous 287(g) agreements.

if county c will enact Secure Communities exactly j months from month m in year y, $I^{post_j}_{csmy}$ is an indicator equal to one if county c has enacted Secure Communities exactly j months before month m in year y, Pre_{csmy} is an indicator equal to one if county c will adopt Secure Communities more than 18 months after month m in year y, and $Post_{csmy}$ is an indicator equal to one if county c has adopted Secure Communities more than 24 months before month m in year y. The event time $j = -1$ is excluded from the regression, so coefficients are measured relative to the month prior to the implementation of the policy.

I also estimate Equations (1) and (2) separately by reporter category, to investigate the source of any changes in reporting behavior. In particular, I expect any increased cost of reporting would be more likely to influence individuals who are either Hispanic themselves, or who have many Hispanic people in their networks. Effects through this channel may thus be concentrated among non-mandated reporters.[26]

5 Results and Discussion

5.1 Main Results

Table 8 reports results from estimating Equation 1, where the outcome variable is the number of investigated child-reports per thousand children in the population. Results are shown separately by race/ethnicity in Panels A-C, and by reporter category (mandated v. non-mandated) in Columns (2) and (3). For reports involving Hispanic children, the estimated coefficient is negative in each column, suggesting that Secure Communities decreased the rate of reported cases involving Hispanic children. However, this result is statistically significant (at the 5% level) in only Column (3), suggesting that the effect is concentrated among cases reported by non-mandated reporters. Specifically, the results suggest that the rate of investigated cases reported by non-mandated reporters decreased by on average 3.78 per hundred thousand children per month, a 3.2 percent decrease rel-

[26]Recall that non-mandated reporters include parents, other relatives and friends/neighbors. In cases involving allegations of maltreatment for Hispanic children, this category of reporters may be more likely to themselves be Hispanic.

ative to the sample mean of 117.2 per hundred thousand Hispanic children. There is no significant effect on reporting rates for investigations involving non-Hispanic white or non-Hispanic Black children.

The corresponding event study results from estimating Equation 2 are shown graphically in Figures 7 (Hispanic only) and 9 (Hispanic, non-Hispanic white and non-Hispanic Black, separately), where the outcome is rate of investigated cases. In each of these event study plots, the outcome is limited to cases from non-mandated reporters.[27] That is, Figure 7 corresponds to Column (3) in Table 8, and Figure 9 corresponds to Column (3) in each of Table 8, Table S1, and Table S3. Figure 7 suggests that there may be a decreasing trend in the rate of Hispanic reports prior to the implementation of Secure Communities. However, comparing this with the results for cases involving non-Hispanic white and non-Hispanic Black children, in Figure 9, suggests that any decreasing trend is common among all races studied, while the negative effects in the post-period are unique to the rate of reported cases involving Hispanic children. I formalize this visual analysis of the pre-trends, using a triple-difference design to compare effects for cases involving Hispanic vs. non-Hispanic children. In particular, I estimate the following equation:

$$Y_{cth} = \beta_1 PostxHisp_{cth} + \gamma_{ct} + \gamma_{ch} + \gamma_{th} + \varepsilon \tag{3}$$

and the corresponding event study specification:

$$Y_{cth} = \beta_1 Pre_{ct} \cdot I_h + \sum_{j=2}^{18} \beta_j I_{ct}^{pre_j} \cdot I_h + \sum_{j=0}^{24} \beta_{j+18} I_{ct}^{post_j} \cdot I_h + \beta_{44} Post_{ct} \cdot I_h + \gamma_{ct} + \gamma_{ch} + \gamma_{th} + \varepsilon \tag{4}$$

Where: all is as defined in Equations 1 and 2, the subscript t indicates month-by-year, the subscript c indicates county, the subscript h indicates Hispanic ethnicity, and I_h is an indicator for Hispanic ethnicity. Fixed effects are included for county-by-month-by-year, county-by-ethnicity, and month-by-year-by-ethnicity. β_1 in Equation 3 captures the effect of Secure Communities im-

[27]Figure S1 shows the event study plot for mandated reporters, i.e. corresponding to Column (2) of Table 8.

plementation on reporting rates for cases involving Hispanic children, relative to reporting rates for cases involving non-Hispanic children. Results from estimating Equation 3 are shown in Table 11, and graphical results for Equation 4 are shown in Figure 10. This analysis suggests that, relative to reports involving non-Hispanic children, the rate of reported cases involving Hispanic children decreased after the implementation of Secure Communities, with the effect concentrated among cases referred by non-mandated reporters. The result for non-mandated reporters is significant at the 1% level, and is statistically indistinguishable from the difference-in-differences estimate. Figure 10 corresponds to Column (3) (non-mandated reporters), and suggests a lack of pre-trends in the triple difference specification (as expected from the informal graphical analysis of Figure 9, described above).

In sum, these results suggest that the rate of investigated cases of child abuse involving Hispanic children per child population decreased after the implementation of Secure Communities. However, this result may have two drastically different interpretations. The change in observed investigation rate could be due to either changes in the underlying abuse rate (i.e. fewer true cases of abuse), or changes in reporting behavior (i.e. reporters are less likely to refer suspected abuse cases). The fact that the effect is concentrated among cases referred by non-mandated reporters suggests that the change may be in reporting behavior rather than underlying abuse rates, although it is possible that there is a decrease in types of maltreatment that are more observable by non-mandated reporters. To distinguish between these avenues, I next turn to the results for rates of substantiation. Recall, under my conceptual framework, the likelihood of reporting a suspected case of maltreatment is increasing in case severity, and substantiation is a measure of a case's true severity. An increase in the average substantiation rate of investigated cases is thus consistent with a decrease in the rate of reporting.

Table 9 reports results from estimating Equation 1 where the outcome variable is the number of substantiated child-reports per investigated child-reports involving a Hispanic child. Again, results are shown separately by reporter category in Column (2) (mandated reporters) and (3) (non-mandated reporters). The coefficient of interest is positive in each column, suggesting that the policy increased the substantiation rate of cases involving Hispanic children. Again, this result is statistically significant (at the 10% level) only for cases referred by non-mandated reporters. Specifically, the results suggest that the share of substantiated cases increased in the post-period by 1.11 percentage points, a 6.6% increase relative to the sample mean of 16.8%. Corresponding event study results from estimating Equation 2, where the sample is limited to cases referred by non-mandated reporters, are shown graphically in Figure 11.[28] These figures do not suggest the existence of pretrends.

The decrease in the rate of reported cases involving Hispanic children, combined with the increase in substantiation rates of investigated cases, suggests that Secure Communities implementation had the unintentional consequence of reducing the willingness of non-mandated reporters to refer suspected cases of maltreatment to child welfare services. Note, it does not seem that this decrease is offset by an increase in reports from other sources. Although the results are not significant for mandated reporters, the sign of the effect is negative for reporting rate and positive for substantiation rate, suggesting directionally similar effects to those for non-mandated reporters. In the next section, I examine these effects separately for different maltreatment categories.

5.2 Maltreatment category

Tables 12 and 14 report results from Eq. (1), where the outcome variable is, respectively, rate of reports and rate of substantiation for cases involving Hispanic children and referred by non-mandated reporters. Event study plots corresponding to each column of Table 12 and Table 14 are shown in Figures 12a through 12e and Figures 14a through 14e, respectively. While β_1 is positive for each allegation category in Table 12 and negative for each allegation category in Table 14, the effects are concentrated among allegations and substantiations of Neglect/Deprivation, as well as Physical abuse. The rate of allegations of neglect or deprivation per Hispanic child population decreases by on average 4.01 per hundred thousand children per month in the post period, a reduction of 4.8% relative to the sample mean, while substantiation of those allegations increases

[28] Figures S2 shows the event study plot for mandated reporters, i.e. corresponding to Column (2) of Table 9.

by 1.06 percentage points (8.1% relative to the sample mean). The monthly rate of allegations of physical abuse decreases by 1.32 per hundred thousand children in the population, 5.6% relative to the sample mean, and substantiation of these allegations increases by 1.68 percentage points (26% relative to the sample mean). A visual analysis of the event studies suggest possible pre-trends for allegation rates, in particular for allegations of neglect and deprivation. Triple difference results from estimating Eq. (3) are shown in Table 13, and the corresponding event study figures from estimating Eq. (4) are shown in Figures 13a through 13e. These triple difference results confirm that, relative to allegations involving non-Hispanic children, the rate of allegations of neglect and deprivation and physical abuse involving Hispanic children decreased after the implementation of Secure Communities. Results are significant at the 1% level, and larger in magnitude although statistically indistinguishable from the difference-in-differences results reported in Table 12. A visual analysis of the triple difference event study plots (Figures 13a and 13b) does not suggest the existence of pre-trends. In the triple difference results, there is also a significant (at the 10% level) decrease in the rate of Sexual abuse and Psychological/Emotional maltreatment allegations (Columns 4 and 5 of Table 13).

6 Conclusion

In this paper I study the effects of Secure Communities on the incidence and reporting of child maltreatment. Using a case-level dataset that allows me to observe details about the universe of investigated child abuse and neglect cases in the U.S., I disentangle changes in reporting from changes in incidence of abuse. I find that Secure Communities had a significant negative effect on the reporting rate of abuse and neglect for cases involving Hispanic children, and no similar effect for cases involving non-Hispanic children. The effect is concentrated among cases referred by non-mandated reporters, for whom changes in the perceived cost of reporting are likely more salient. My results suggest an unintended consequence of immigration enforcement in the U.S., and provide evidence that tying immigration enforcement to law enforcement may have adverse consequences for public safety.

This paper also sheds light on a potential cause of ethnic disparities within CPS. In particular, my results suggest that potential reporters of maltreatment respond to changes in the perceived cost of interacting with CPS, and that policies or outreach which decrease this cost may be a potential solution.

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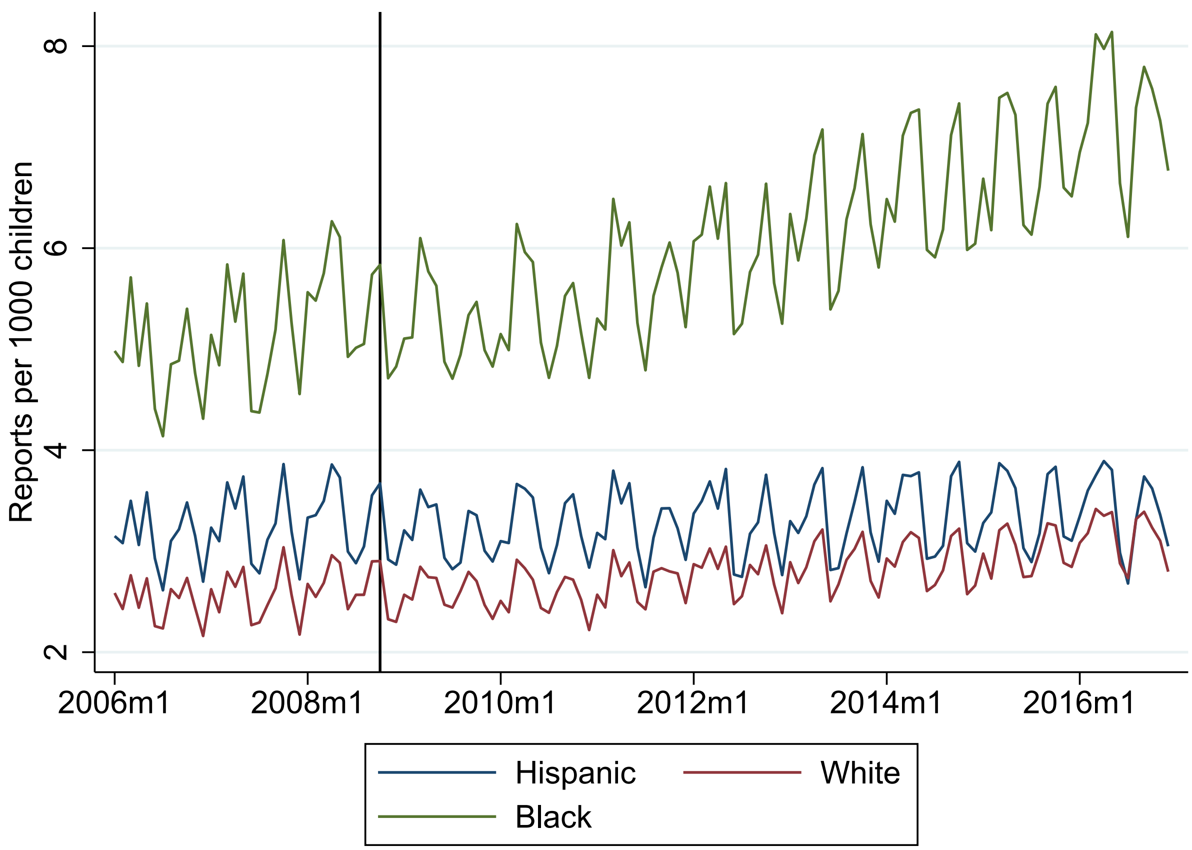
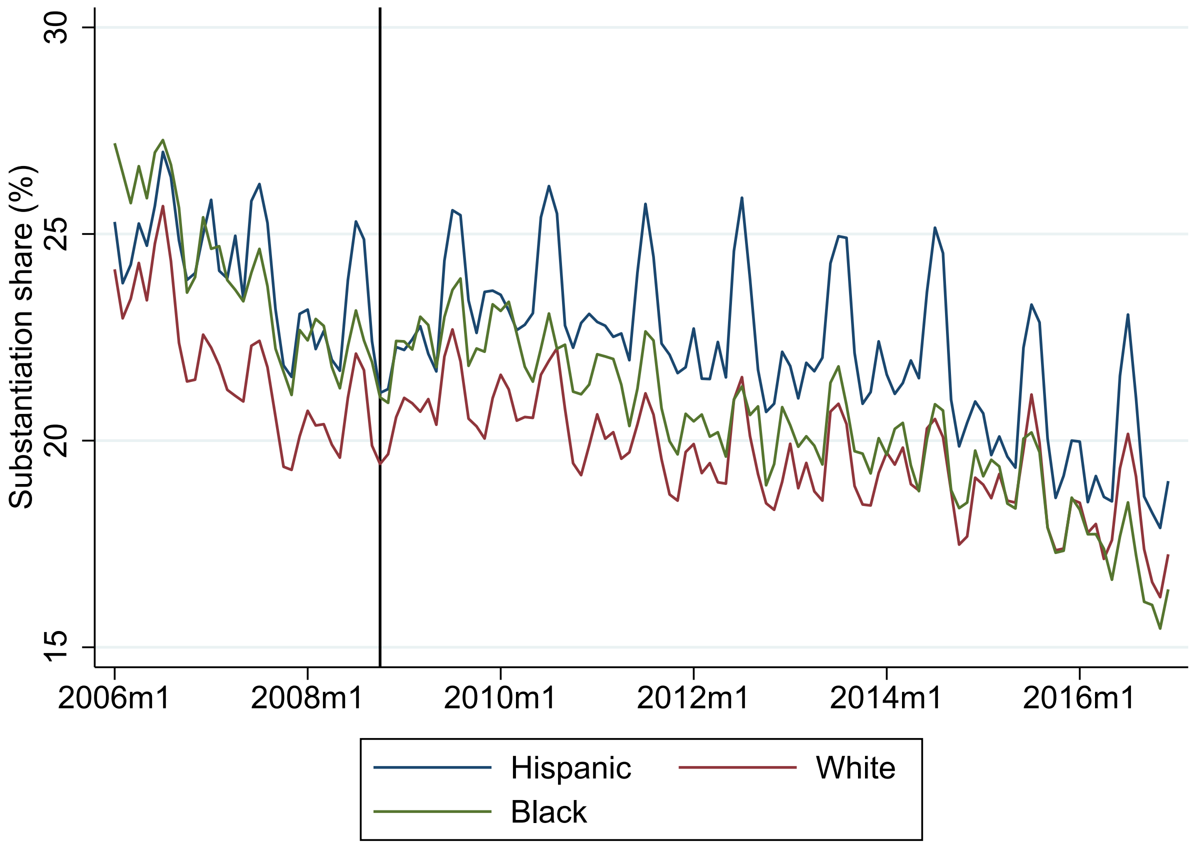
Figures

Figure 1: Child-reports per child population



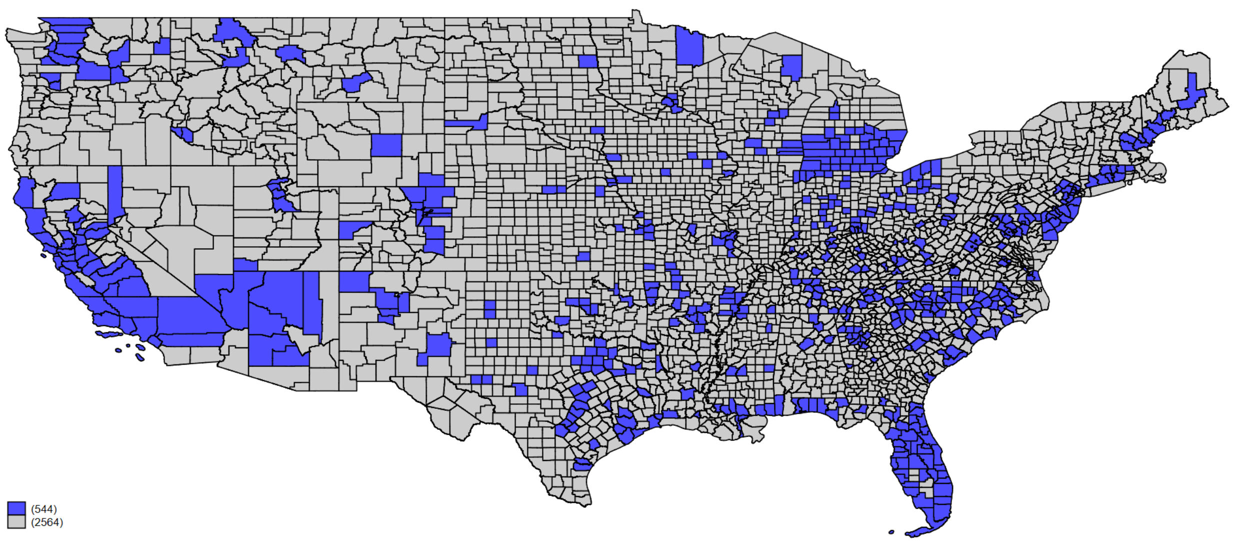
This figure reports monthly child reports per thousand children for cases involving Hispanic, non-Hispanic Black and non-Hispanic white children. The data used is limited to my analysis sample. The x-axis reports calendar time, and the black vertical line denotes the month that Secure Communities began rolling out.

Figure 2: Substantiated victims per reports



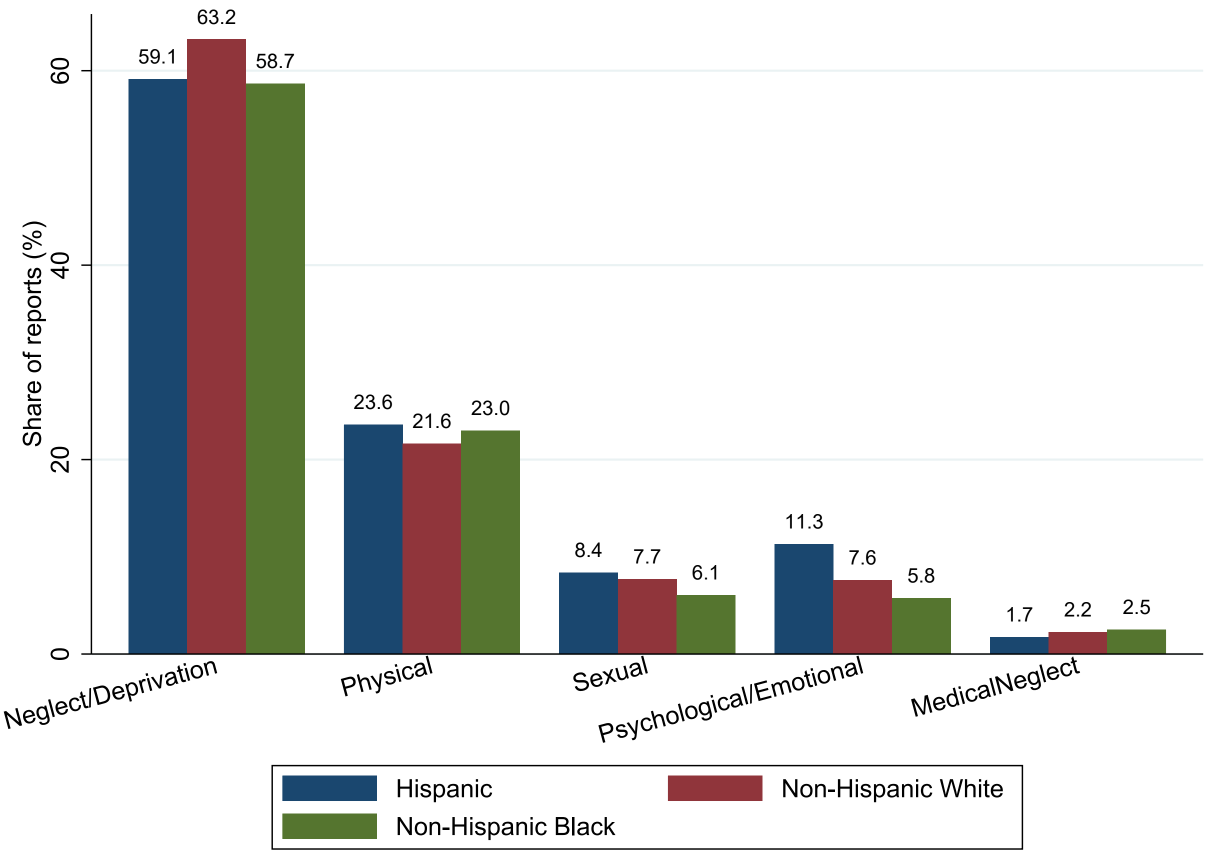
This figure reports monthly substantiated child reports per investigated child reports involving Hispanic, non-Hispanic Black and non-Hispanic white children. The data used is limited to my analysis sample. The x-axis reports calendar time, and the black vertical line denotes the month that Secure Communities began rolling out.

Figure 3: Analysis sample



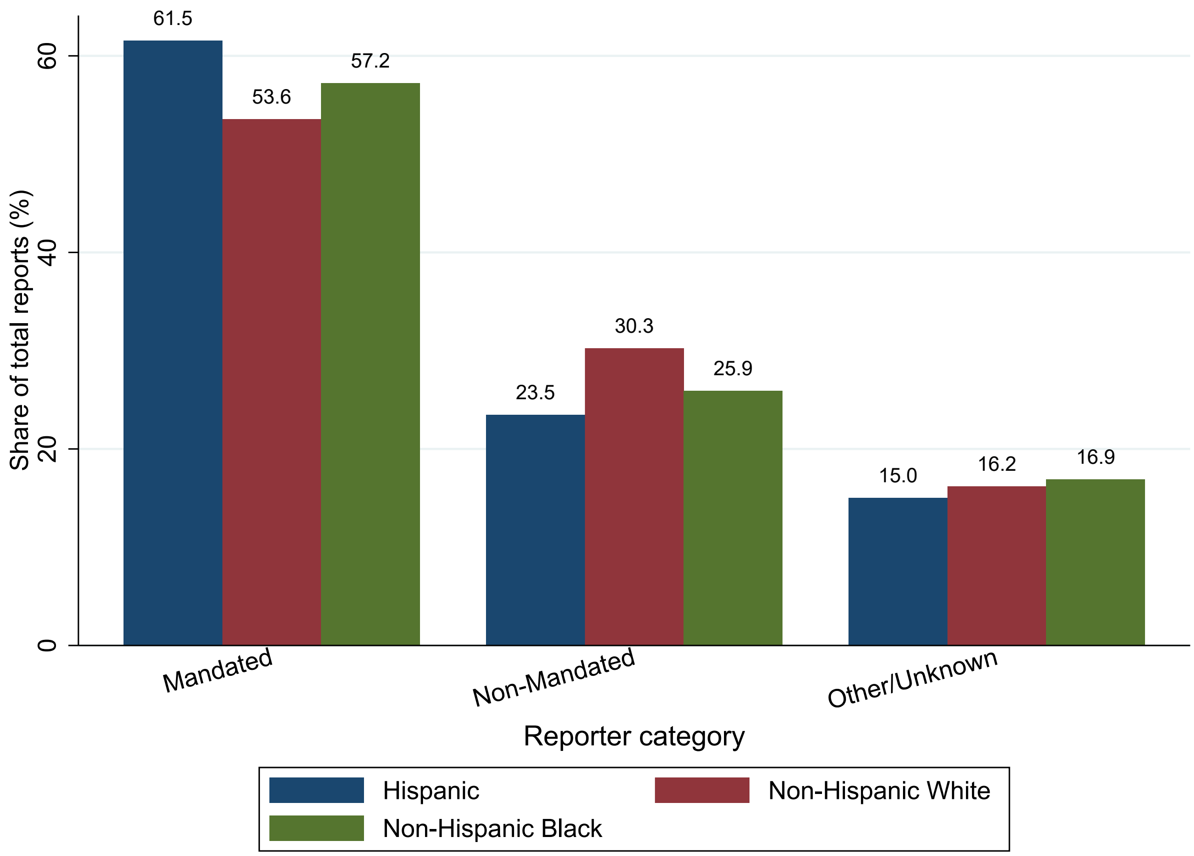
This figure highlights the 544 counties used in my analysis sample. Included counties are shaded in blue, while excluded counties are shaded in gray.

Figure 4: Alleged abuse category shares



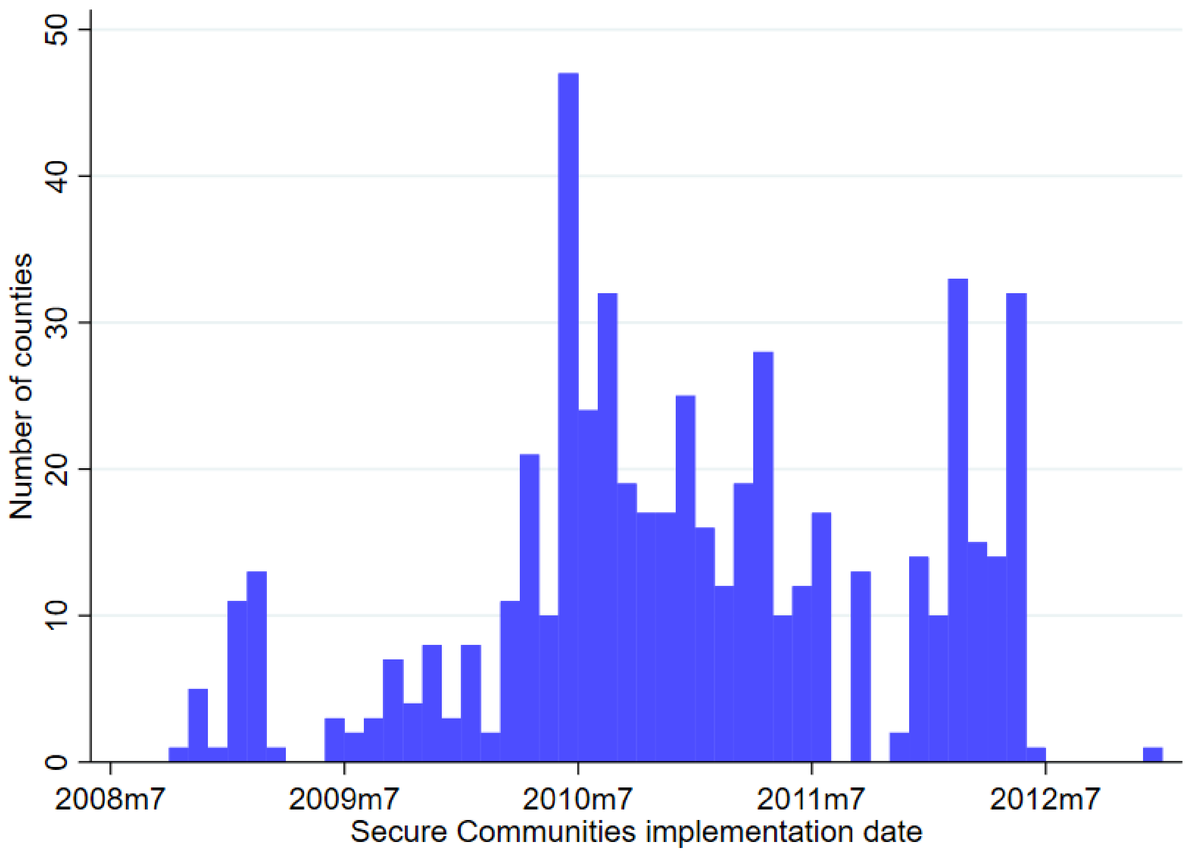
This figure reports shares of total child-reports which involve allegations of each category of maltreatment. The categories of maltreatment are reported on the horizontal axis, and the height of each bar (i.e. the percent of total reports for a given race/ethnicity) is reported above each bar. For example, 59.1 percent of child-reports involving a Hispanic child include an allegation of neglect or deprivation. Note, a single child-report may involve multiple allegations. The data used is limited to my analysis sample.

Figure 5: Reporter category shares



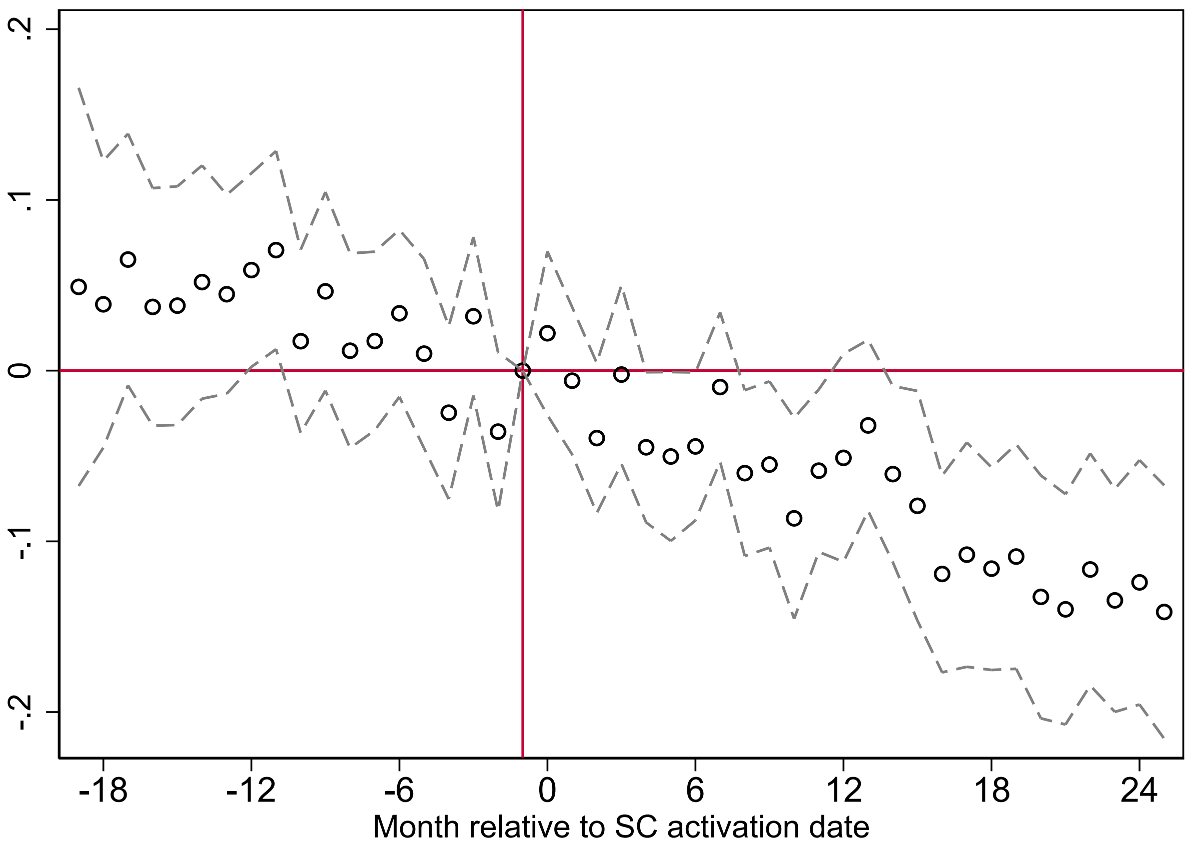
This figure reports shares of total child-reports which involve allegations of each category of reporter. The categories of reporters are shown on the horizontal axis, and the height of each bar (i.e. the percent of total reports for a given race/ethnicity) is reported above each bar. For example, 61.5 percent of child-reports involving a Hispanic child are referred by a mandated reporter. The data used is limited to my analysis sample.

Figure 6: Secure Communities Rollout



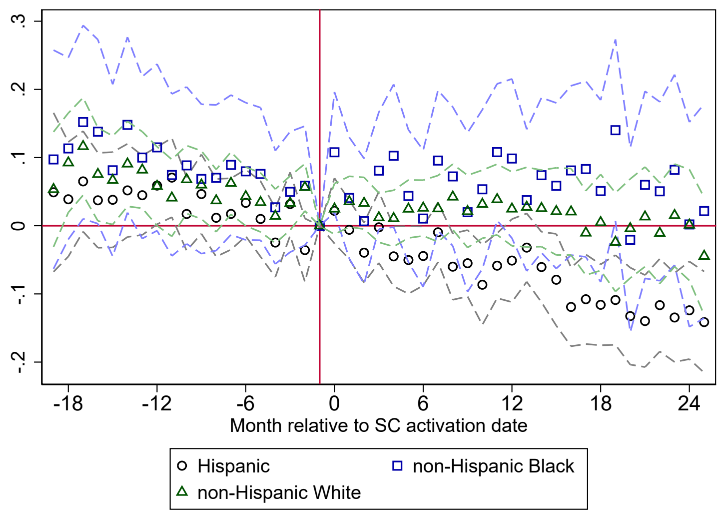
This figure reports the number of counties which activated Secure Communities in each calendar month. The data used is limited to my analysis sample (i.e. the 544 counties shaded in blue in Figure 3).

Figure 7: Reporting rate (Hispanic children, non-mandated reporters)

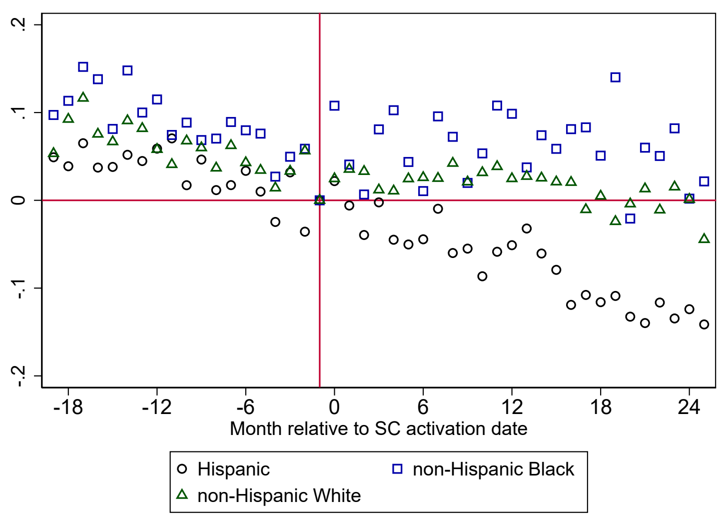


This figure reports results from estimating Equation 2, where the outcome variable is the number of child-reports referred by non-mandated reporters and involving Hispanic children per thousand Hispanic children in the population. The figure corresponds to Column (3) in Table 8. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

Figure 8: Reporting rate (non-mandated reporters)



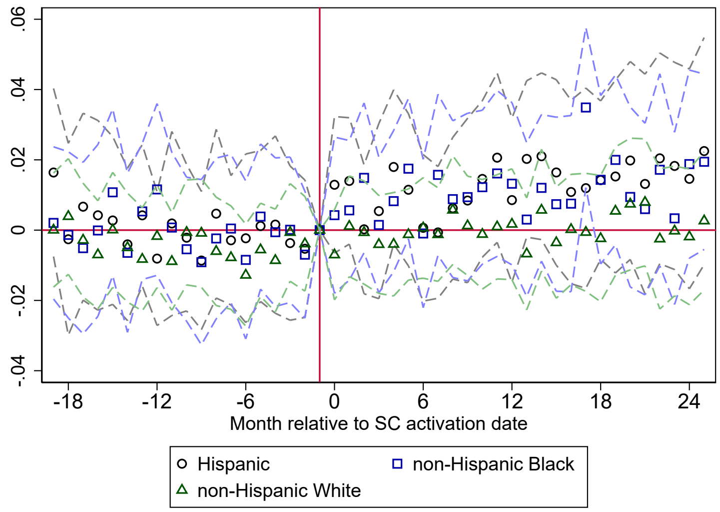
(a)



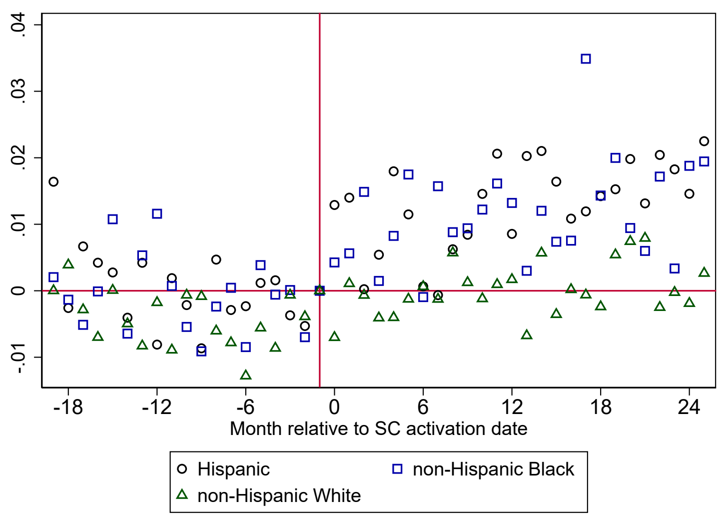
(b)

Each panel of this figure reports results from three separate regressions estimating Equation 2, where the outcome variable is the number of child-reports referred by non-mandated reporters per thousand children in the population, for each of Hispanic children, non-Hispanic Black children, and non-Hispanic white children. The figure corresponds to Columns (3) in Table 8, S3 and S1. Panels (a) and (b) are identical, but panel (b) removes confidence intervals, for clarity. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

Figure 9: Substantiation rate (non-mandated reporters)



(a)



(b)

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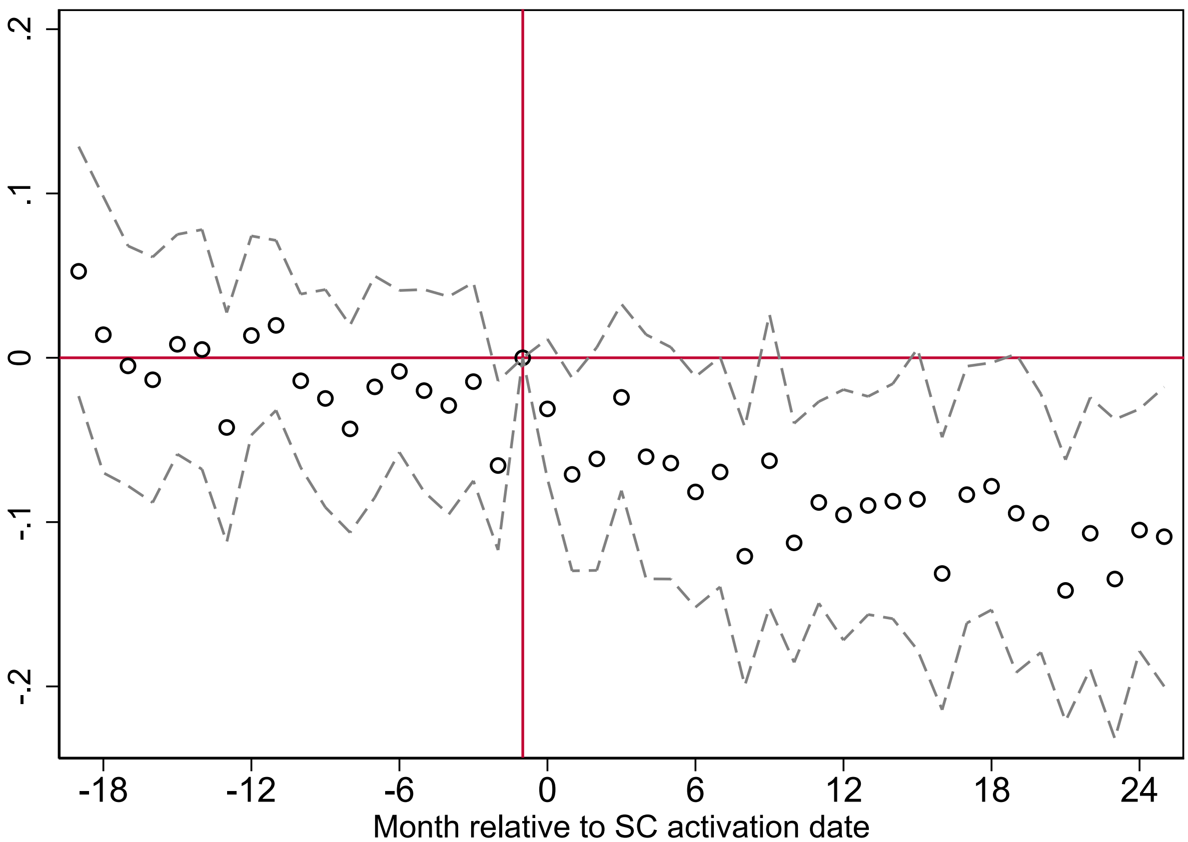
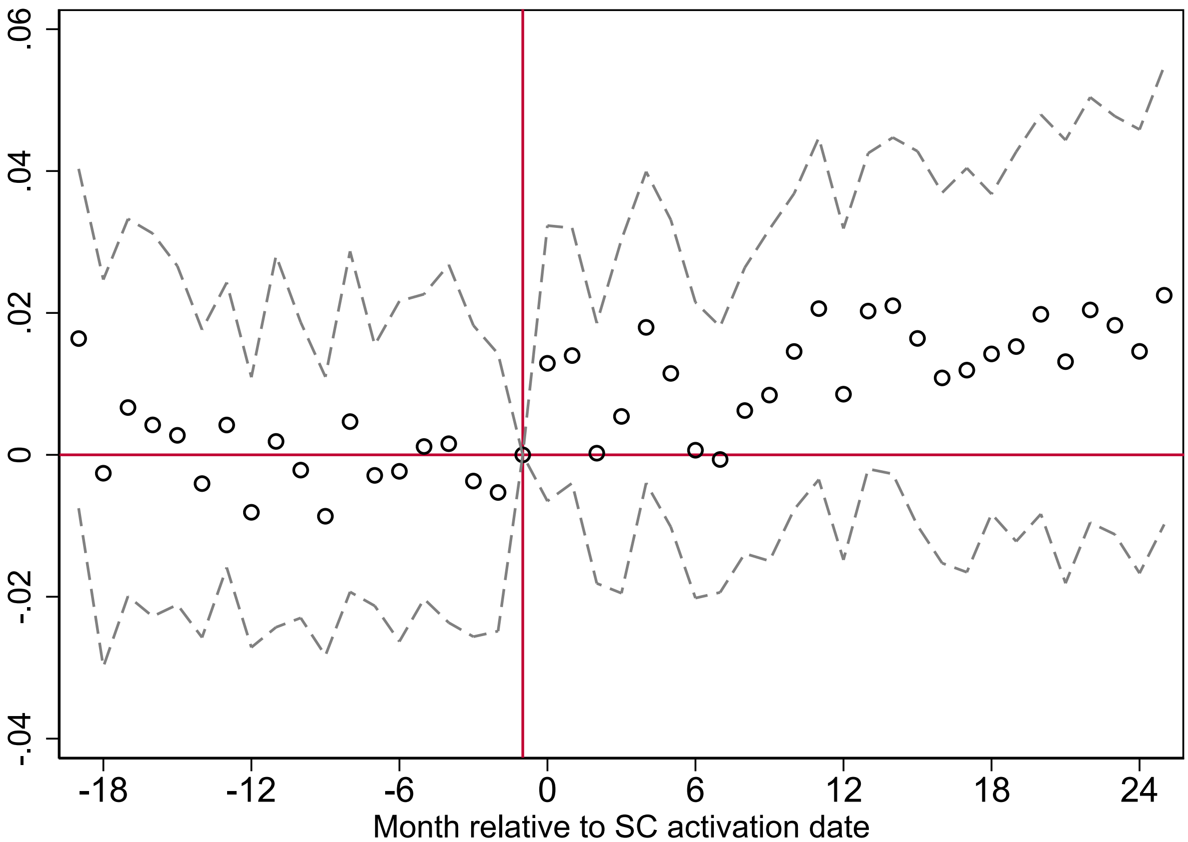
Figure 10: Reporting rate (Triple difference)



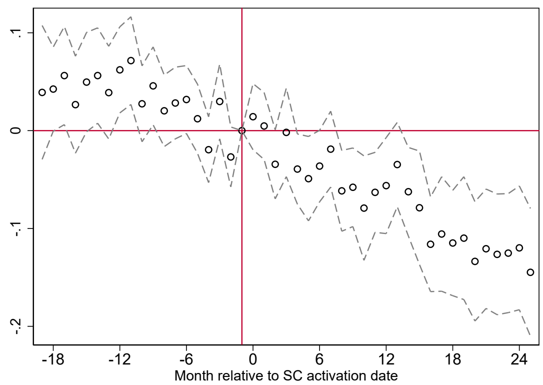
This figure reports results from estimating Equation 4, where the outcome variable is the number of child-reports referred by non-mandated reporters and involving Hispanic children per thousand Hispanic children in the population. The figure corresponds to Column (3) in Table 11. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

Figure 11: Substantiation rate (Hispanic children, non-mandated reporters)

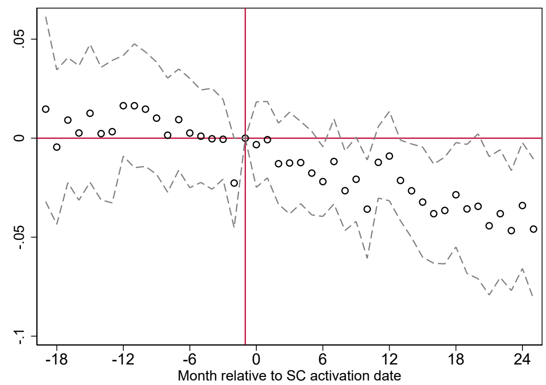


This figure reports results from estimating Equation 2, where the outcome variable is is the number of substantiated child-reports per investigated child-reports involving a Hispanic child and referred by a non-mandated reporter. The figure corresponds to Column (3) in Table 9. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

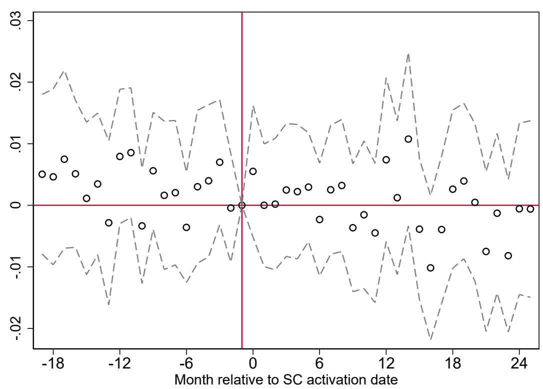
Figure 12: Reporting rate (non-mandated reporters)



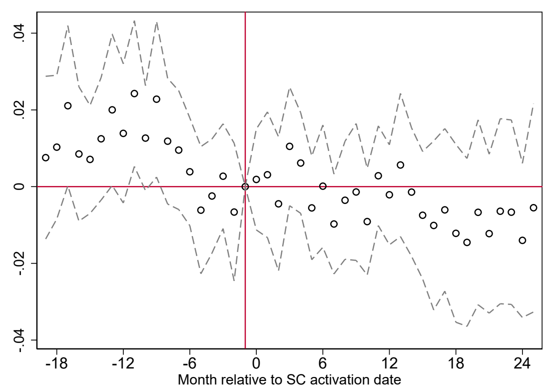
(a) Neglect and deprivation



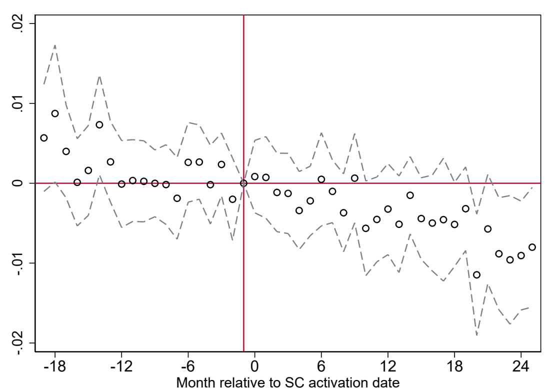
(b) Physical abuse



(c) Sexual abuse



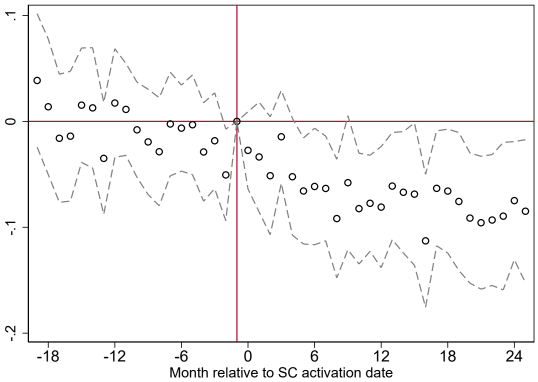
(d) Psychological/emotional abuse



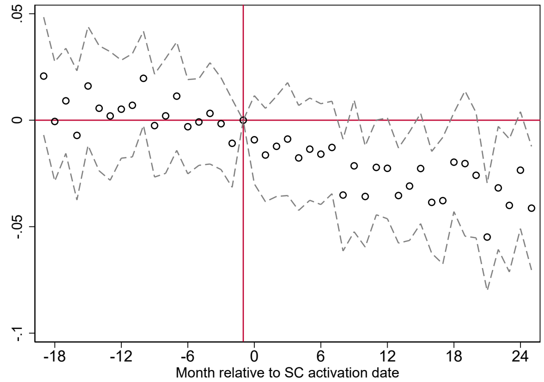
(e) Medical neglect

This figure reports results from estimating Equation 2, where the outcome variable is the number of child-reports involving an allegation of a particular maltreatment category referred by non-mandated reporters and involving a Hispanic child per thousand Hispanic children in the population. Each plot corresponds to one of Columns (1) through (5) in Table 12. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

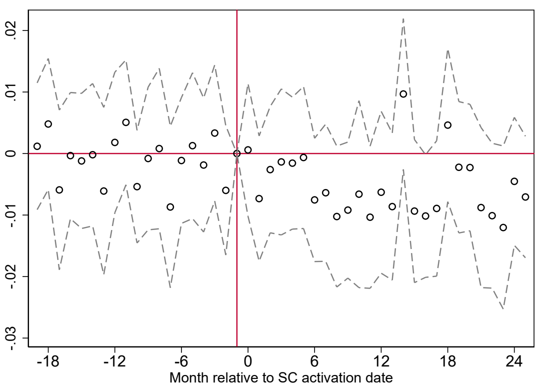
Figure 13: Reporting rate (Triple difference, non-mandated reporters)



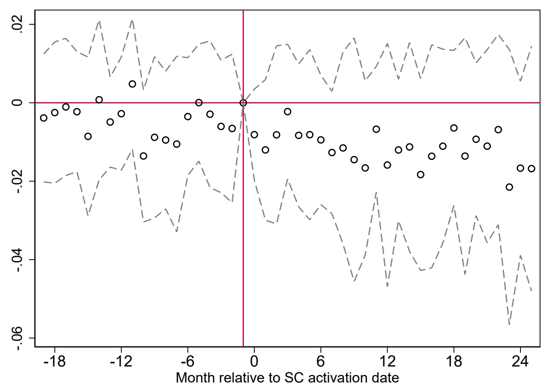
(a) Neglect and deprivation



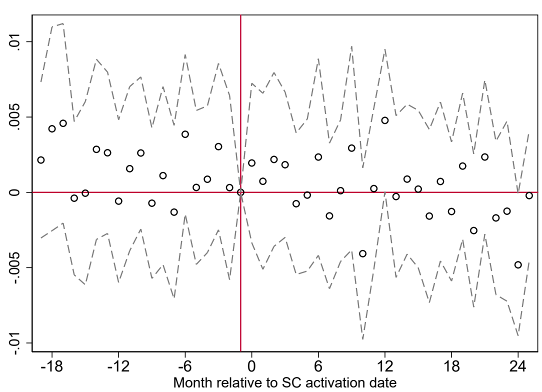
(b) Physical abuse



(c) Sexual abuse



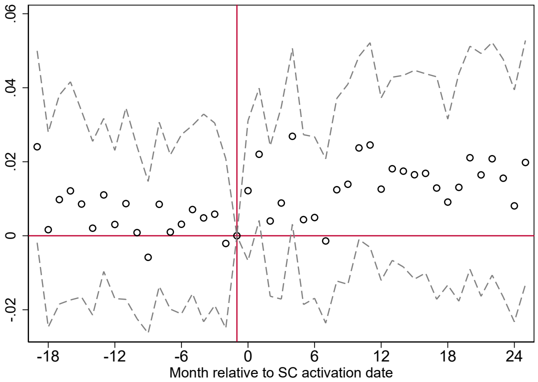
(d) Psychological/emotional abuse



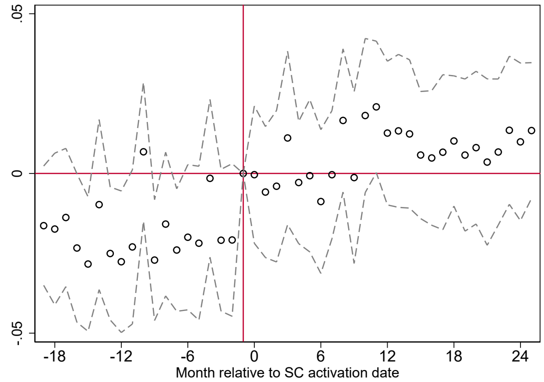
(e) Medical neglect

This figure reports results from estimating Equation 4, where the outcome variable is the number of child-reports involving an allegation of a particular maltreatment category referred by non-mandated reporters and involving a Hispanic child per thousand Hispanic children in the population. Each plot corresponds to one of Columns (1) through (5) in Table 13. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

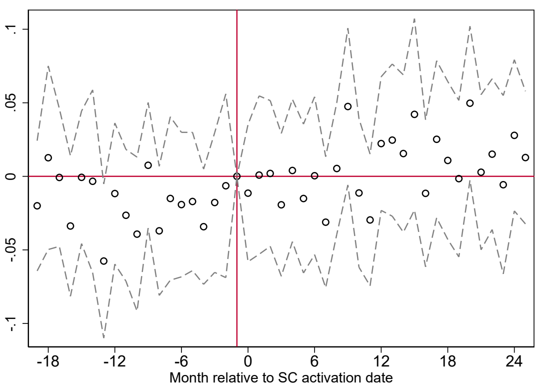
Figure 14: Substantiation rate (non-mandated reporters)



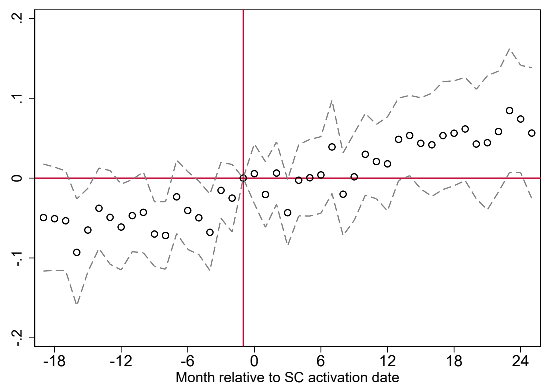
(a) Neglect and deprivation



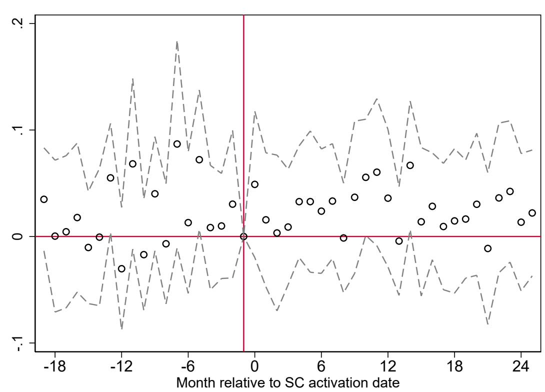
(b) Physical abuse



(c) Sexual abuse



(d) Psychological/emotional abuse



(e) Medical neglect

This figure reports results from estimating Equation 2. The outcome variable is the monthly number of substantiated allegations of a particular maltreatment category involving a Hispanic child in a given county divided by the monthly number of investigated allegations of that category involving a Hispanic child in that county. Each plot corresponds to one of Columns (1) through (5) in Table 14. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals include the red line are statistically indistinguishable from the pre-period, $t = -1$

Tables

Table 1: Comparative summary statistics

	Mean (Analysis Sample)	Mean (Excluded)	Diff
Male	0.497	0.493	0.004
Female	0.495	0.494	0.001
NonHispWhite	0.344	0.442	-0.097
NonHispBlack	0.242	0.151	0.090
Hispanic	0.231	0.182	0.050
OtherRace	0.205	0.242	-0.037
EthnicityUnknown	0.173	0.209	-0.036
Age18plus	0.001	0.002	-0.000
Age_min	7.099	7.152	-0.053
Age_max	7.994	8.146	-0.152
Reports	1.719	1.825	-0.105
ShareSubstantiated	0.194	0.243	-0.048
ShareRemoved	0.053	0.040	0.013
ShareServices	0.105	0.093	0.012
N	23535235		

This table reports comparative summary statistics for children included in my analysis sample vs. excluded from my sample.

Table 2: Reporting rate DD robustness to different sets of balanced counties

	(1)	(2)	(3)	(4)	(5)
	12 month	24 month	36 month	48 month	60 month
Post	-0.0367**	-0.0379**	-0.0385**	-0.0369**	-0.0375**
	(0.0172)	(0.0174)	(0.0175)	(0.0174)	(0.0177)
Mean	1.115	1.123	1.127	0.890	0.879
Counties	577	544	530	506	478
Obs.	95610	92451	90702	87387	83700

Standard errors in parentheses

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

This table....

Table 3: Reporting rate DDD robustness to different sets of balanced counties

	(1) 12 month	(2) 24 month	(3) 36 month	(4) 48 month	(5) 60 month
PostxHisp	-0.0448**	-0.0460**	-0.0460**	-0.0397*	-0.0368*
	(0.0195)	(0.0196)	(0.0198)	(0.0203)	(0.0204)
Mean	4.277	4.362	4.420	1.428	1.415
Counties	580	547	533	508	482
Obs.	288369	278892	273645	263385	253080

Standard errors in parentheses

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

This table....

Table 4: Reporting rate DD - Effects by race/ethnicity and reporter category

	(1) Hispanic	(2) Non-Hispanic White	(3) Non-Hispanic Black
Panel A: All			
Post	-0.00731	-0.00511	0.000499
	(0.0563)	(0.0833)	(0.0491)
Mean	4.409	33.35	3.722
Panel B: Mandated reporters			
Post	-0.00120	-0.0157	-0.00306
	(0.0335)	(0.0579)	(0.0278)
Mean	2.587	18.80	1.853
Panel C: Non-mandated reporters			
Post	-0.0385**	-0.0107	-0.0156
	(0.0175)	(0.0367)	(0.0200)
Mean	1.127	11.02	1.172

Standard errors in parentheses

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

This table....

Table 5: Reporting rate DDD

	(1) All reports
Panel A: All	
PostxHisp	-0.0259**
	(0.0114)
Mean	0.509
Panel B: Mandated reporters	
PostxHisp	-0.0193***
	(0.00675)
Mean	0.295
Panel C: Non-mandated reporters	
PostxHisp	-0.00547
	(0.00423)
Mean	0.157

Standard errors in parentheses

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

This table....

Table 6: Substantiation rate DD by ethnicity/reporter category

	(1) Hispanic	(2) Non-Hispanic White	(3) Non-Hispanic Black
Panel A: All			
Post	0.0131*	0.0129**	0.00836**
	(0.00742)	(0.00608)	(0.00398)
Mean	0.228	0.230	0.221
Panel B: Mandated reporters			
Post	0.00960	0.0174**	0.00811*
	(0.00756)	(0.00740)	(0.00430)
Mean	0.314	0.336	0.329
Panel C: Non-mandated reporters			
Post	0.0150**	0.00302	0.00844*
	(0.00728)	(0.00831)	(0.00440)
Mean	0.176	0.204	0.218

Standard errors in parentheses

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

This table....

Table 7: Substantiation rate DDD

	(1) All reports
Panel A: All	
PostxHisp	-0.00445
	(0.00728)
Mean	0.0721
Panel B: Mandated reporters	
PostxHisp	-0.00324
	(0.00659)
Mean	0.0720
Panel C: Non-mandated reporters	
PostxHisp	-0.00729
	(0.00912)
Mean	0.0291

Standard errors in parentheses

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

This table....

Table 8: Reporting rate (Hispanic children)

	(1) All reporters	(2) Mandated reporters	(3) Non-Mandated reporters
Post	-0.0452	-0.0344	-0.0378**
	(0.0456)	(0.0282)	(0.0156)
CountyxMonth	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes
Mean	4.555	2.695	1.172
Obs.	70068	70068	70068

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of investigated child-reports involving a Hispanic child in a given county divided by Hispanic child population in that month and county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the Hispanic child population at the county-month level), and standard errors are clustered at the county level.

Table 9: Substantiation rate (Hispanic children)

	(1) All reporters	(2) Mandated reporters	(3) Non-Mandated reporters
Post	0.0104	0.00692	0.0111*
	(0.00654)	(0.00693)	(0.00648)
CountyxMonth	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes
Mean	0.218	0.304	0.168
Obs.	63555	57760	47834

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of substantiated maltreatment child-reports involving a Hispanic child in a given county divided by the monthly number of investigated child-reports involving a Hispanic child in that county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the number of investigated child-reports involving a Hispanic child at the county-month level), and standard errors are clustered at the county level.

Table 10: Reporting rate (Triple difference)

	(1) All	(2) Mandated	(3) Non-Mandated
PostxHisp	-0.111**	-0.0453	-0.0598***
	(0.0507)	(0.0302)	(0.0191)
CountyxMonthxYear FE	Yes	Yes	Yes
CountyxHisp FE	Yes	Yes	Yes
MonthxYearxHisp FE	Yes	Yes	Yes
Mean	4.552	2.697	1.170
Obs.	205541	205541	205541

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 3. The outcome variable is the monthly number of investigated child-reports divided child population in that month and county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the Hispanic or non-Hispanic child population at the county-month level), and standard errors are clustered at the county level.

Table 11: Substantiation rate (Triple difference)

	(1) All	(2) Mandated	(3) Non-Mandated
PostxHisp	-0.00364*	-0.00573*	-0.00279
	(0.00197)	(0.00322)	(0.00294)
CountyxMonthxYear FE	Yes	Yes	Yes
CountyxHisp FE	Yes	Yes	Yes
MonthxYearxHisp FE	Yes	Yes	Yes
Mean	0.219	0.305	0.170
Obs.	190850	179121	157836

Standard errors in parentheses

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

This table...

Table 12: Reporting rate (Hispanic children, non-mandated reporters)

	(1) Neglect/Depr.	(2) Physical	(3) Sexual	(4) Psych/Emotional	(5) MedNeglect
Post	-0.0401***	-0.0132*	-0.000946	-0.00520	-0.00137
	(0.0127)	(0.00711)	(0.00256)	(0.00372)	(0.00126)
CountyxMonth	Yes	Yes	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes	Yes	Yes
Mean	0.839	0.234	0.0643	0.0782	0.0271
Obs.	70068	70068	70068	70068	70068

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of investigated allegations involving a Hispanic child in a given county divided by Hispanic child population in that month and county. The sample is limited to cases referred by a non-mandated reporter. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases which involve an allegation of neglect or deprivation; in Column (2) the sample includes all investigated cases which involve an allegation of physical abuse; in Column (3) the sample includes all investigated cases which involve an allegation of sexual abuse, in Column (4) the sample includes all investigated cases which involve an allegation of psychological or emotional abuse, and in Column (5) the sample includes all investigated cases which involve an allegation of medical neglect. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the Hispanic child population at the county-month level), and standard errors are clustered at the county level.

Table 13: Reporting rate (Triple difference, non-mandated reporters)

	(1) Neglect/Depr.	(2) Physical	(3) Sexual	(4) Psych/Emotional	(5) MedNeglect
PostxHisp	-0.0488***	-0.0221***	-0.00340*	-0.00550*	-0.000660
	(0.0156)	(0.00649)	(0.00202)	(0.00327)	(0.00109)
CountyxMonthxYear FE	Yes	Yes	Yes	Yes	Yes
CountyxHisp FE	Yes	Yes	Yes	Yes	Yes
MonthxYearxHisp FE	Yes	Yes	Yes	Yes	Yes
Mean (Hisp)	0.838	0.234	0.0641	0.0780	0.0270
Obs.	205541	205541	205541	205541	205541

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 3. The outcome variable is the monthly number of investigated child-reports divided child population in that month and county. The sample is limited to cases referred by a non-mandated reporter. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases which involve an allegation of neglect or deprivation; in Column (2) the sample includes all investigated cases which involve an allegation of physical abuse; in Column (3) the sample includes all investigated cases which involve an allegation of sexual abuse, in Column (4) the sample includes all investigated cases which involve an allegation of psychological or emotional abuse, and in Column (5) the sample includes all investigated cases which involve an allegation of medical neglect. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the number of investigated child-reports involving a Hispanic child at the county-month level), and standard errors are clustered at the county level.

Table 14: Substantiation rate (Hispanic children, non-mandated reporters)

	(1)	(2)	(3)	(4)	(5)
	Neglect/Depr.	Physical	Sexual	Psych/Emotional	MedNeglect
Post	0.0106*	0.0168***	0.0117	0.0361**	0.00604
	(0.00636)	(0.00339)	(0.00990)	(0.0143)	(0.0112)
CountyxMonth	Yes	Yes	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes	Yes	Yes
Mean	0.131	0.0657	0.131	0.0878	0.0794
Obs.	42306	27667	15445	13047	6595

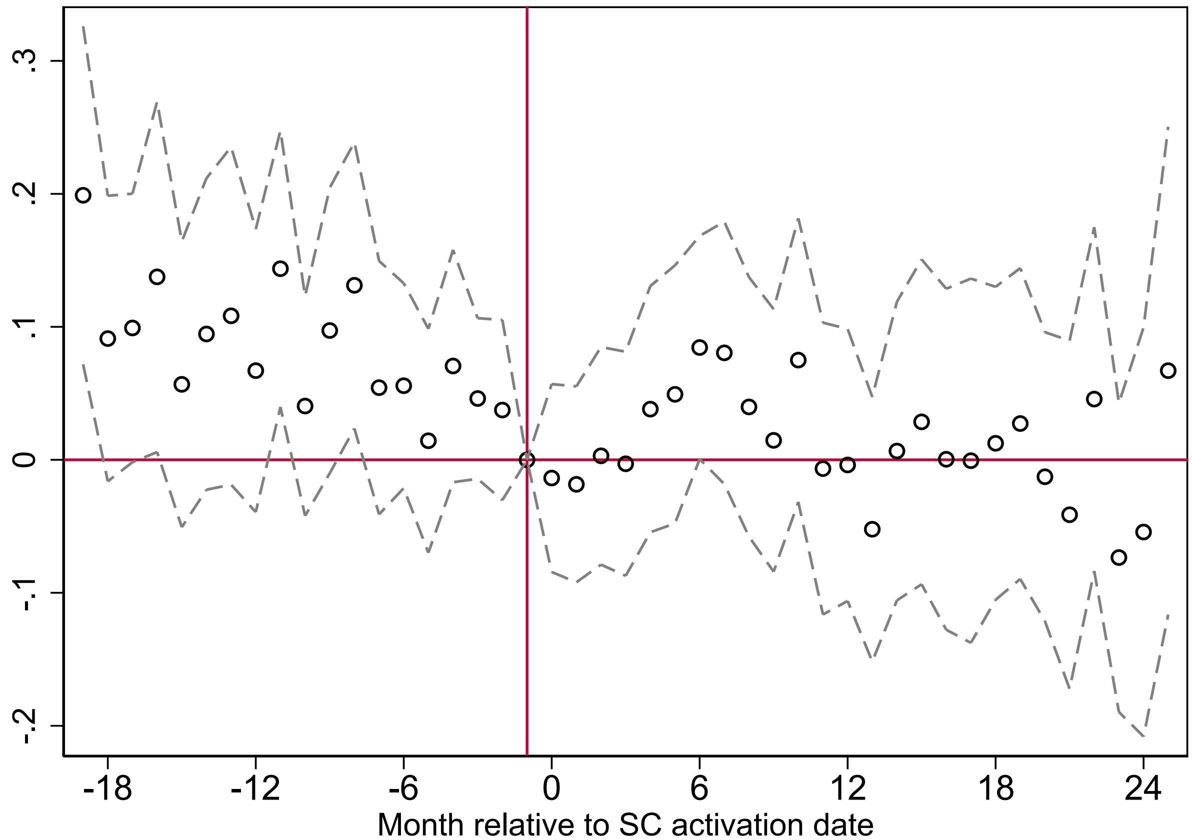
Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of substantiated allegations involving a Hispanic child in a given county divided by monthly number of investigated allegations involving a Hispanic child in that county. The sample is limited to cases referred by a non-mandated reporter. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases which involve an allegation of neglect or deprivation; in Column (2) the sample includes all investigated cases which involve an allegation of physical abuse; in Column (3) the sample includes all investigated cases which involve an allegation of sexual abuse, in Column (4) the sample includes all investigated cases which involve an allegation of psychological or emotional abuse, and in Column (5) the sample includes all investigated cases which involve an allegation of medical neglect. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the number of investigated child-reports involving a Hispanic child at the county-month level), and standard errors are clustered at the county level.

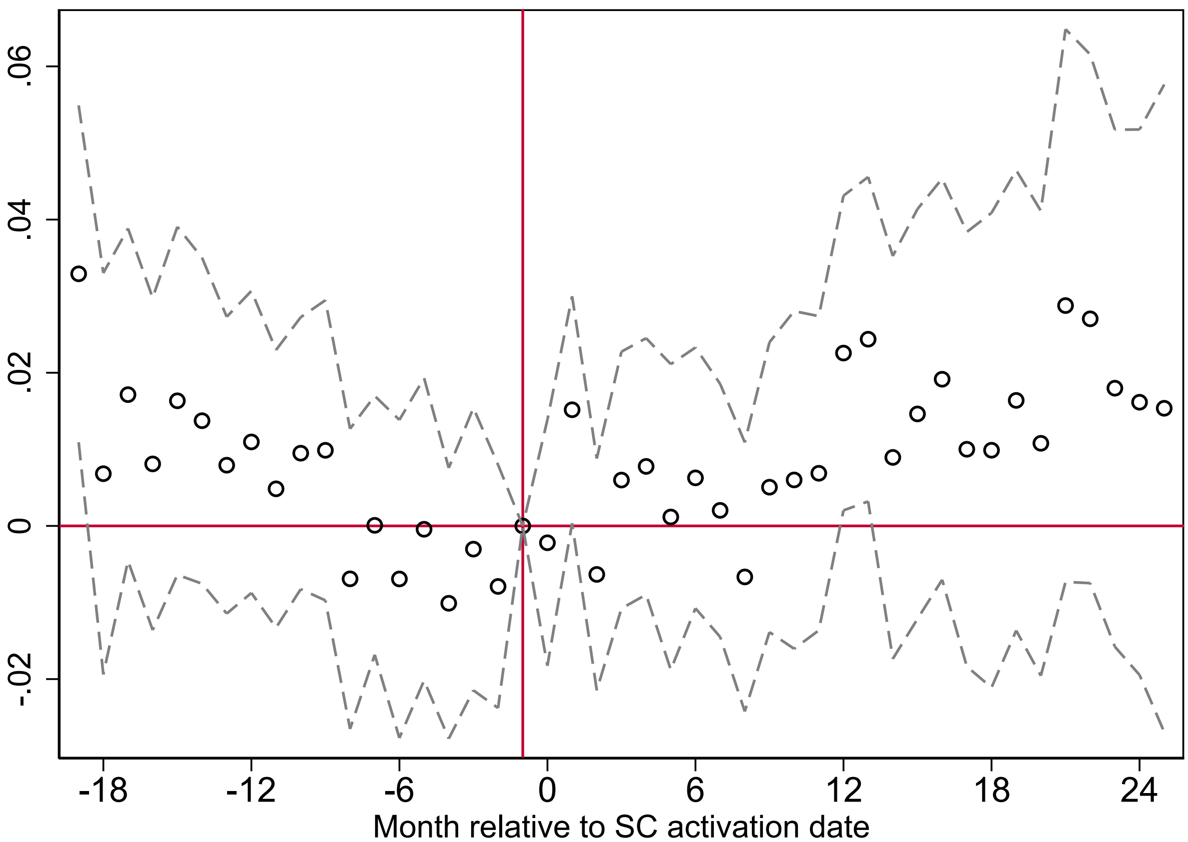
Supplementary Tables and Figures

Figure S1: Reporting rate (Hispanic children, mandated reporters)



This figure reports results from estimating Equation 2, where the outcome variable is the number of child-reports referred by mandated reporters and involving Hispanic children per thousand Hispanic children in the population. The figure corresponds to Column (2) in Table 8. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals touch the red line are statistically indistinguishable from the pre-period, $t = -1$

Figure S2: Substantiation rate (Hispanic children, mandated reporters)



This figure reports results from estimating Equation 2, where the outcome variable is is the number of substantiated child-reports per investigated child-reports involving a Hispanic child and referred by a mandated reporter. The figure corresponds to Column (2) in Table 9. The x-axis shows the month relative to Secure Communities activation in event time, and the y-axis reports the effect, relative to time period $t = -1$. Each hollow marker reports one of the coefficients β_1 through β_{44} from Equation 2, and dashed lines represent 95% confidence intervals. The vertical red line shows the event time $t = 0$ (i.e. the month in which Secure Communities is activated), and the horizontal red line shows the level $y = 0$ (that is, dots whose confidence intervals touch the red line are statistically indistinguishable from the pre-period, $t = -1$

Table S1: Reporting rate (non-Hispanic White children)

	(1) All reporters	(2) Mandated reporters	(3) Non-Mandated reporters
Post	0.0399	0.0275	-0.0114
	(0.0464)	(0.0258)	(0.0186)
CountyxMonth	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes
Mean	3.840	1.933	1.201
Obs.	70068	70068	70068

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of investigated child-reports involving a non-Hispanic white child in a given county divided by non-Hispanic white child population in that month and county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the non-Hispanic white child population at the county-month level), and standard errors are clustered at the county level.

Table S2: Substantiation rate (non-Hispanic White children)

	(1) All reporters	(2) Mandated reporters	(3) Non-Mandated reporters
Post	0.00472	0.00553	0.00347
	(0.00345)	(0.00430)	(0.00385)
CountyxMonth	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes
Mean	0.211	0.320	0.210
Obs.	67612	66537	64923

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of substantiated maltreatment child-reports involving a non-Hispanic white child in a given county divided by the monthly number of investigated child-reports involving a non-Hispanic white child in that county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the number of investigated child-reports involving a non-Hispanic white child at the county-month level), and standard errors are clustered at the county level.

Table S3: Reporting rate (non-Hispanic Black children)

	(1) All reporters	(2) Mandated reporters	(3) Non-Mandated reporters
Post	0.0173	0.00820	-0.000494
	(0.0755)	(0.0547)	(0.0313)
CountyxMonth	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes
Mean	29.77	17.60	9.003
Obs.	70068	70068	70068

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of investigated child-reports involving a non-Hispanic black child in a given county divided by non-Hispanic black child population in that month and county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the non-Hispanic black child population at the county-month level), and standard errors are clustered at the county level.

Table S4: Substantiation rate (non-Hispanic Black children)

	(1) All reporters	(2) Mandated reporters	(3) Non-Mandated reporters
Post	0.00675	0.00649	0.00965*
	(0.00515)	(0.00661)	(0.00498)
CountyxMonth	Yes	Yes	Yes
StatexMonthxYr	Yes	Yes	Yes
Mean	0.220	0.327	0.195
Obs.	64749	61052	53875

Standard errors in parentheses

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

This table reports coefficients and standard errors from estimating Equation 1. The outcome variable is the monthly number of substantiated maltreatment child-reports involving a non-Hispanic black child in a given county divided by the monthly number of investigated child-reports involving a non-Hispanic black child in that county. Each column reports results from a separate regression. In Column (1) the sample includes all investigated cases; in Column (2) the sample includes all investigated cases referred by mandated reporters; in Column (3) the sample includes all investigated cases referred by non-mandated reporters. The sample mean for each sample is also reported. Cells are weighted by the denominator (i.e. the number of investigated child-reports involving a non-Hispanic white child at the county-month level), and standard errors are clustered at the county level.