

Immigration Enforcement and Student Achievement: the Negative Spillover of Secure Communities

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ABSTRACT

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VERSION

December 2018

Suggested citation: Bellows, L. (2018). Immigration Enforcement and Student Achievement: the Negative Spillover of Secure Communities. Retrieved from Stanford Center for Education Policy Analysis: <https://stanford.io/2RLa4wk>

Immigration Enforcement and Student Achievement: the Negative Spillover of Secure Communities

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Abstract

Over the past decade, U.S. immigration enforcement policies have increasingly targeted unauthorized immigrants residing in the U.S. interior, many of whom are the parents of U.S.-citizen children. Heightened immigration enforcement may affect student achievement through stress, income effects, or student mobility. I use one such immigration enforcement policy, Secure Communities, to examine how immigration enforcement affects student achievement. I use the staggered activation of Secure Communities across counties between 2008 and 2013 to measure its impact on average achievement for Hispanic students, as well as non-Hispanic black and white students. My results suggest that the implementation of Secure Communities decreased average achievement for Hispanic students in English Language Arts (ELA), although not in math. I also find that Secure Communities negatively affected the performance of non-Hispanic black students in ELA. Similarly, I find that increases in county removals due to Secure Communities are associated with decreased achievement for both Hispanic and non-Hispanic black students in ELA.

This work has been supported (in part) by (award #83-17-01) from the Russell Sage Foundation and the W.T. Grant Foundation. Any opinions expressed are those of the author alone and should not be construed as representing the opinions of either foundation.

Introduction

Between 2007 and 2013, immigration enforcement increased dramatically in the U.S. interior (Figure 1). From 2003 to 2006, an average of 9000 individuals were removed from the U.S. interior each month. Between 2007 and 2013, that average nearly doubled: nearly 17,000 individuals were removed from the U.S. interior each month. This increase was accomplished primarily through partnerships between local law enforcement and Immigrations and Custom Enforcement (ICE) targeting criminal aliens. In 2003 through 2006, ICE issued fewer than 1000 detainers per month, or immigration holds for individuals in law enforcement custody. Between 2007 and 2013, ICE issued an average of 19,000 detainers per month (Figure 2). Between FY 2008 and 2011, transfers from local and state law enforcement custody accounted for 85 percent of ICE arrests in the U.S. interior (Capps et al., 2018).

One partnership between local law enforcement and ICE was the Secure Communities program, “the largest expansion of local involvement in immigration enforcement in the nation’s history” (Cox and Miles, 2013, 93). Despite Secure Communities’ stated purpose to reduce crime by removing criminal aliens, two previous evaluations found no effects of Secure Communities on crime rates in activated jurisdictions (Miles and Cox, 2014; Treyger et al., 2014). However, the rollout of Secure Communities did impact children, increasing parent-child separations among deportees from Guatemala, Honduras, and El Salvador (Amuedo-Dorantes et al., 2015). Indeed, approximately 37 percent of individuals arrested via Secure Communities report having U.S. citizen children (Kohli et al., 2011). It is likely, however, that the enactment of Secure Communities affected the well-being of children who did not experience parent-child separations. Residing in a community with rising levels of detentions and removals increases stress and fear for both unauthorized parents and their children. These rising levels of stress and fear are likely to impact other child outcomes, including children’s performance in school.

Stress and fear associated with immigration enforcement are likely greatest for the 5.1 million U.S.-resident children who are estimated to have at least one unauthorized immigrant parent (Passel and Taylor, 2010). Beyond children of unauthorized immigrants, the

children of authorized immigrants may also feel stress and fear if these policies increase hostility towards immigrants. A broader population of children may be affected if they are exposed to immigration enforcement: although the extent of children’s exposure to immigration enforcement is unknown, nearly 40 percent of respondents in a recent survey of Latino adults reported knowing someone who had been detained or removed (Vargas et al., 2018). Hispanic children are the largest subgroup likely affected: about one quarter of Hispanic children are estimated to have an unauthorized parent (Clarke and Guzman, 2016), and Hispanic children with foreign-born parents account for 53 percent of the 17.5 million Hispanic children in the U.S. (Murphey et al., 2014).

This paper is the first to examine the impact of immigration enforcement on student achievement using administrative test score data from all U.S. counties. I use the staggered rollout of Secure Communities to examine the effects of immigration enforcement policy on county-level average Hispanic achievement during the 2008-2009 through 2012-2013 school years. I find that Secure Communities decreased the average achievement of Hispanic students in English Language Arts (ELA), although not in math. Additionally, Secure Communities also decreased the average achievement of non-Hispanic black students in ELA. I also examine how increases in removals affect student achievement and find that, as removals increased in a county, the average achievement of both Hispanic and non-Hispanic black students also declined in ELA.

Theoretical Framework

Hispanic students enter school over half a standard deviation below white students in reading and approximately 70 to 80 percent of a standard deviation below white students in math (Fryer and Levitt, 2006; Stiefel et al., 2007; Reardon and Galindo, 2009; Reardon and Ho, 2015). As students progress through school, Hispanic students improve in performance relative to white students (Stiefel et al., 2007; Clotfelter et al., 2009; Reardon and Galindo, 2009; Reardon and Ho, 2015). However, most of that progress appears to be concentrated in early grades and may be related to improvements in English language

skills (Reardon and Galindo, 2009); gaps are about 50 to 60 percent of a standard deviation by fifth grade (Clotfelter et al., 2009; Reardon and Galindo, 2009) and about 40 percent of a standard deviation by eighth grade (Clotfelter et al., 2009). As students typically gain between 1.2 and 1.5 standard deviations in math and reading from fourth to eighth grade and 0.6 and 0.7 standard deviations from eighth to twelfth grade, these gaps represents multiple years of learning (Reardon, 2011).

Immigration enforcement policies may decrease achievement for Hispanic students through several mechanisms. Most prominently, immigration enforcement policies likely affect the academic performance of children of immigrants by increasing child and parent fear and stress. Immigration enforcement increases child stress: both children experiencing a parental detention or removal as well as children not experiencing a parental detention or removal but with an unauthorized parent exhibit higher levels of child distress and anxiety (Allen et al., 2015; Zayas et al., 2015). Unauthorized parents describe constant worry over detection by immigration officials (Menjívar and Abrego, 2012; Nguyen and Gill, 2015), worry which is likely translated to children. Additionally, children of authorized immigrants may experience an increase in stress and anxiety. First, some children of authorized immigrant parents may be confused over their parents' immigration status (Dreby, 2012). Second, authorized immigrants are subject to removal in certain circumstances. Secure Communities specifically increased mental health distress among Hispanic immigrants living with non-citizen family members (Wang and Kaushal, 2018). Both child and parent stress negatively affect children's academic achievement.

Increases in immigration enforcement also could impact student achievement through losses of income and benefits. Families experiencing a detention or removal also typically lose family income (Capps et al., 2007; Dreby, 2012, 2015; Koball et al., 2015). This negative income shock spills over to create housing and childcare instability (Dreby, 2012, 2015; Rugh and Hall, 2016). However, families with unauthorized members not experiencing a detention or removal may also experience a decrease in resources if members reduce employment (Amuedo-Dorantes et al., 2018; East et al., 2018) or their interaction with social service agencies (Watson, 2014; Vargas, 2015; Vargas and Pirog, 2016;

Potochnick et al., 2016; Alsan and Yang, 2018). Recent work finds that Secure Communities decreased families' participation with the Supplemental Nutrition Assistance Program (SNAP) and the Affordable Care Act (ACA), as well as reduced employment for Hispanic men with lower levels of education (East et al., 2018). Decreases in resources affect children's educational achievement by reducing families' ability to invest in children or further increasing family stress (Conger and Donnellan, 2007).

Additionally, newly enacted immigration enforcement policies may increase community stress, which could affect Hispanic and non-Hispanic students. An emerging body of research suggests that increases in community-level stress reduce test performance. Studies in Mexico, Brazil, New York City, Chicago, and Washington D.C. all suggest that exposure to community violence lowers student test scores (Sharkey, 2010; Michaelsen and Salardi, 2013; Monteiro and Rocha, 2013; Sharkey et al., 2014; Orraca Romano, 2015; Burdick-Will, 2018; Gershenson and Tekin, 2018). Increases in certain activities by local law enforcement, particularly "broken windows" style policing, also have negative effects on student achievement, although these effects have been previously found only for black boys (Legewie and Fagan, 2018). Since the main targets of Secure Communities were Hispanic immigrants, increases in racial profiling by local law enforcement may affect Hispanic as well as non-Hispanic black youth.

However, immigration enforcement policies may also increase average achievement by Hispanic students if newly implemented immigration enforcement policies lead to families with unauthorized members migrating or withdrawing children from school. Following increases in immigration enforcement, children of unauthorized immigrants are more likely to leave school (Amuedo-Dorantes and Lopez, 2015) and the activation of a different type of partnership between ICE and local law enforcement, 287(g) programs, decreased Hispanic enrollment in affected counties (Dee and Murphy, 2018). Considering that the children of unauthorized parents likely perform below other Hispanic children, in part because they belong to a more vulnerable, lower-income population, removing them from the school system may increase the average levels of performance for Hispanic students. However, this increase would be artificial because the most vulnerable Hispanic children

are no longer being tested.

Background

Secure Communities required law enforcement agencies to automatically submit fingerprints of arrested individuals to the Department of Homeland Security's (DHS) Automated Biometric Identification System (IDENT). If a potential match was identified, additional data matching and prioritization occurred at the Law Enforcement Support Center (LESC), a centralized ICE location. If the match was determined to be a potentially removable alien, LESL notified an ICE field office within four hours and then could issue a detainer against the individual (Kohli et al., 2011; Rosenblum and Kandel, 2011). A detainer requests that local law enforcement hold the arrested individual for up to 48 hours for transfer into ICE custody. According to data from Syracuse's Transitional Records Access Clearinghouse (TRAC), Secure Communities was responsible for over 600,000 removals from the United States between 2009 and 2018.

Secure Communities was rolled out county-by-county across the U.S. between 2008 and 2013, as shown in Figure 3. Timing of rollout has previously been shown to relate to the size of the Hispanic population as well as distance from the Mexican border. However, Secure Communities was also implemented gradually because of resource constraints (Cox and Miles, 2013).

Although Secure Communities was eventually activated in all U.S. counties, local law enforcement responded to the program in different ways. In early activating counties, ICE originally established memorandums of understanding with local law enforcement. Some states and counties asked to opt out of participation, which originally appeared to be an option. However, in January of 2012, an internal ICE memo was released, making explicit that Secure Communities was a mandatory program. By 2014, increasing criticism by immigration advocates resulted in the Obama administration halting Secure Communities in order to implement programs that better targeted serious criminal offenders (Capps et al., 2018).

Data

I use newly available measures of average county achievement for Hispanic, white, and black students from the Stanford Education Data Archives (SEDA) (Reardon et al., 2016). These data were constructed using the results of federally mandated grade 3-8 math and English Language Arts (ELA) tests in school years 2008-2009 through 2012-2013. Under No Child Left Behind (NCLB), all states are required to test grade 3-8 students annually in reading and math. However, as each state is allowed to designate its own test, results were not previously comparable across states. As described in Reardon et al. (2017), SEDA has linked state achievement tests to states' National Assessment of Educational Progress (NAEP) results, which allows researchers to directly contrast student achievement in counties and districts across the United States for the first time.

Average achievement for student subgroups is measured for a particular grade, year, county, and subject if there are at least 20 students in that subgroup tested (in that grade, year, county, and subject). SEDA provides several different versions of county averages; I use estimates of county averages standardized within subject and grade, measured in national student-level SD units. Additionally, SEDA also provides estimates of standard errors of average achievement measures, which I use to calculate precision weights.

One concern might be that first and second generation Hispanic students are less likely to take state tests and that state test results therefore do not capture the scores of students most likely to be affected by immigration enforcement policies. Indeed, NCLB exempts English Language Learner (ELL) students from testing in ELA during their first year in school; however, ELL students are required to test in math during their first year. After the first year, states are required to include ELL students in state tests, but ELL students are allowed to test in their own language. In 2012-2013, ten states allowed ELL students to test in a language other than English for accountability purposes, with nine of those states allowing Spanish-speaking ELL students to test in Spanish for math and five states allowing Spanish-speaking ELL students to test in Spanish for ELA (Boyle et al., 2015). In SEDA, all state assessments, including Spanish-language assessments, are included in calculations used to estimate county averages. SEDA also makes available

counts of students who took achievement tests by different subgroups.

Estimating the effect of Secure Communities on student achievement requires an indicator for whether the program was activated prior to the beginning of the state's testing window for a particular year. Information on precise testing dates is unavailable in SEDA. Therefore, I collected state testing windows for the 2008-2009 through 2012-2013 school years using state department of education websites and through communication with state education administrators. State testing windows vary widely in length: although some states prescribe that all students test on a single day in a particular subject, other states allow school districts to schedule tests at any point over several months. The majority of testing windows begin in spring; however, a few states test in the fall on material that students covered in the previous academic year (Personal communication with education officials in Maine, Michigan, and Vermont). I combine information on state testing windows with publicly available information from ICE on the dates of Secure Communities activation to create my main variable of interest.

The effect of Secure Communities may vary based on the operation of the program within a particular county. Through a Freedom of Information Act request to ICE, I also obtained counts of submissions, matches, and removals associated with Secure Communities by county and month. Submissions refers to the number of fingerprint submissions to IDENT per month, indicating the number of individuals arrested per month in a particular county. Matches refers to the number of fingerprint submissions identified as potentially removable aliens per month in a particular county. Data on monthly removals by county are available from the 2009-2010 school year through the 2012-2013 school year, whereas data on monthly submissions and matches are available from the 2010-2011 through 2012-2013 school years.

Analytic Plan

To estimate the effects of increased immigration enforcement via Secure Communities on average achievement, I use ordinary least squares (OLS) models with county, year,

and grade fixed effects to account for any persistent differences between counties, nationwide policy changes in particular years, and performance differences between grades. Additionally, prior work suggests that the timing of Secure Communities implementation was correlated with the size of the Hispanic population (Cox and Miles, 2013). Therefore, I include a time-varying control for the size of the Hispanic population. My regression model is summarized below:

$$\text{Avg}_{ijt} = \alpha + \beta_1 \text{SC}_{jt} + \beta_2 \text{Num}_{ijt} + \beta_3 \text{Tot}_{ijt} + \phi_j + \gamma_i + \eta_t + \epsilon \quad (1)$$

where Avg is the average achievement of Hispanic students in grade i in county j in year t ; SC is an indicator for the activation of Secure Communities prior to the beginning of the testing window in that county in year t ; Num is the number of tested Hispanic students; Tot is the total number of tested students; ϕ is a county fixed effect; γ is a grade fixed effect; and η is a year fixed effect. I cluster standard errors at the county level. I weight by the precision of the estimated county averages ($\frac{1}{SE^2}$). I run separate models for average achievement in ELA and math.

I estimate the same models with different dependent variables, substituting the average achievement of non-Hispanic white students and the average achievement of non-Hispanic black students in ELA and math for the average achievement of Hispanic students. In all models, I include only counties that have measures of average achievement for Hispanic students, non-Hispanic black students, and non-Hispanic white students in that grade, year, and subject.

I also examine the relationship between removals per school year and student achievement. Models are similar to my main models, except that the main predictor variable of interest is logged removals that school year prior to the beginning of the testing window. I use logged removals because the distribution of removals across counties and years is positively skewed. I again cluster standard errors at the county level and weight by the precision of the estimated county average.

Because I only have information on average achievement at the county-level, any effects may result from shifts in student enrollment as well as effects on testing students.

I therefore construct “cohorts” to examine the effect of Secure Communities on cohort sizes of Hispanic, non-Hispanic black, and non-Hispanic white students, using the number of tested students in each subgroup per grade. Otherwise, models are similar to those examining achievement, except that I substitute a cohort fixed effect for the grade fixed effect and do not control for enrollment variables. I again cluster standard errors at the county level.

Results

Descriptive Statistics

Table 1 presents descriptive information on academic test-taking for the subset of counties used in the main analysis. Average ELA and math achievement for all students, as measured in standard deviation units, is only slightly above 0 at 0.03. Average ELA achievement for Hispanic students is about a third of a standard deviation below average ELA achievement for all students, and average math achievement for Hispanic students is about a quarter of a standard deviation below average math achievement for all students. Average ELA achievement for non-Hispanic black students is 42 percent of a standard deviation lower than average ELA achievement for all students, and average math achievement for non-Hispanic black students is 46 percent of a standard deviation below average math achievement for all students. In contrast, average ELA and math achievement for non-Hispanic white students is about a quarter of a standard deviation above average ELA and math achievement for all students. As shown in Figures 4-6, average achievement for Hispanic, non-Hispanic white, and non-Hispanic black students is relatively normally distributed.

Figure 7 shows the number of removals resulting from Secure Communities for each county between October 2008 and September 2013. Although a few areas had high numbers of removals associated with the program, the majority of counties had fewer than 100 removals between 2008 and 2013. High levels of removals were concentrated in more populous areas; high levels of removals were also more common in southern and

western states. The 49 counties with over 1000 removals during this time period are in California, Arizona, Texas, Florida, Georgia, Nevada, North Carolina, Utah, Virginia, Oklahoma, and Tennessee, with the majority in California and Texas.

Main Findings

As shown in Table 2, I find that the activation of Secure Communities reduced average achievement for Hispanic students in English Language Arts (ELA). I find no change to average achievement for Hispanic students in math. The activation of Secure Communities decreased academic achievement in ELA for a county's Hispanic students by approximately 0.85 percent of a standard deviation.

Table 2 also presents results for non-Hispanic white and black students. I find no impact of Secure Communities on non-Hispanic white students. For ELA, the coefficient is also negative and about 40 percent of the size of measured impact for Hispanic students. However, I do find that the activation of Secure Communities reduced non-Hispanic black students' average achievement in ELA, by 1.48 percent of a standard deviation. Secure Communities does not significantly affect the average math achievement of non-Hispanic black students.

Robustness and Specification Checks

It is possible that other changes in counties implementing Secure Communities affected students' test scores, unrelated to the rollout of the program. I check for this possibility by running a specification in which I pretend Secure Communities was activated a year prior to its true activation date. Significant estimates from these regressions would suggest that any effects I previously attributed to the activation of Secure Communities were instead the result of differing pre-trends between activating and non-activating counties. As shown in Table 3, I observe no effects of the year prior to activation of Secure Communities on the achievement of Hispanic or non-Hispanic black students.

In alternate models, I include county time trends, as well as county fixed effects. County time trends also control for differences in trends between counties activating

and not activating Secure Communities. Activation of Secure Communities continues to reduce average achievement for Hispanic and non-Hispanic black students in ELA, but not in math (Table 4). In these models, activation of Secure Communities also reduces average achievement for non-Hispanic white students in ELA, although the effect is smaller than the effects for Hispanic and non-Hispanic black students.

In another set of models, I include state-by-year fixed effects, to control for any state-wide policy change occurring in a particular year. As shown in Table 5, activation of Secure Communities continues to reduce achievement for Hispanic and non-Hispanic black students in ELA. Following Alsan and Yang (2018), I also exclude all border counties, as border counties were purposely activated at the beginning of the rollout. Although results are measured less precisely for Hispanic students, effects are approximately the same size and direction (Table 6).

I also obtain similar coefficient estimates using the Stata command `metareg`, which better accounts than weighted least squares for the portion of error attributable to measurement error in the dependent variable. Because `metareg` does not allow for clustering standard errors, I do not use this command in my main set of analyses. In my main set of models using weighted least squares, clustering standard errors at the county level inflates standard errors by factors ranging from 1.235 to 2. I therefore inflate standard errors obtained through `metareg` by a factor of two and continue to reach similar results (all `metareg` results available upon request).

Potential Mechanisms

The activation of Secure Communities might affect average achievement by either affecting students' performance on tests or changing the composition of students within schools. As shown in Table 7, I see no effect on the number of Hispanic students in a testing cohort. Similarly, cohort sizes for black and white students did not change with the activation of Secure Communities.

If Secure Communities affected performance on exams rather than changing the population of Hispanic students, one mechanism through which it likely operated was by

increasing stress in a community. I would expect stress to increase as removals increase within a community. Table 8 presents models using removals as the key predictor of interest. Increases in removals within a county are associated with reduced average achievement in ELA for both Hispanic and non-Hispanic black students. A one percent increase in removals in a county decreased average Hispanic achievement in ELA by 1.8 percent of a standard deviation and decreased average achievement in ELA for non-Hispanic black students by 1.4 percent of a standard deviation. Removals did not affect the average math achievement of students in any group.

Higher numbers of removals could indicate that law enforcement was cooperating with ICE by honoring detainers issued. Although I do not observe how many detainers were honored per county, I do observe both fingerprint match and removal counts, which allows me to construct the rate of removals per fingerprint match. Counties that have higher rates of removals per fingerprint match likely have higher cooperation rates with ICE (Pedroza, 2017). Because removals are not immediate, I look at the rate of removals per fingerprint matches through 2013. Instead of controlling for county and year fixed effects, I use grade fixed effects and control for 2009 test scores. Although evidence is only suggestive, Table 9 shows that counties with higher rates of removals per fingerprint match over the course of Secure Communities experienced larger declines in ELA test scores by 2012-2013. With every 1 percent increase in removals per fingerprint matches, test scores for Hispanic students in ELA are predicted to decline by 0.1 percent of a standard deviation.

Another pathway through which Secure Communities might affect achievement could be increased absences. If parents or children are afraid of arrest, they might more frequently miss school. Although it was not possible to examine absences in this paper, future research should examine how immigration enforcement affects student absences.

Discussion

In qualitative work, increases in immigration enforcement appear to have strong effects on children's performance in schools (Capps et al., 2007); parental unauthorized status and experiences with immigration enforcement have also been associated with parental reports of lower academic achievement (Brabeck and Xu, 2010; Brabeck et al., 2015). I find that immigration enforcement decreases average Hispanic achievement, as well as average non-Hispanic black achievement, in ELA.

These findings build on prior work in multiple ways. First, this paper is the first to use administrative test score data for all counties across the United States to examine the effects of immigration enforcement on student achievement. Second, I use the rollout of Secure Communities and control for consistent characteristics of counties that might be correlated with lower student achievement. Students with unauthorized parents are more vulnerable in multiple ways and may perform below students with authorized immigrant or U.S.-born parents because of these other sources of disadvantage. Similarly, removals are not a random process: for example, individuals are more likely to be removed if they have contact with the criminal justice system, which might also separately affect student achievement. Therefore, isolating the effects of immigration enforcement policies requires a strategy that controls for pre-existing differences.

These results add to a growing body of literature on immigration enforcement's multi-generational consequences. Since only a small proportion of Hispanic students are likely unauthorized immigrants themselves, the majority of affected Hispanic students are either authorized immigrants or, most likely, U.S. citizens. By lowering Hispanic students' ELA test scores, immigration enforcement may decrease students' access to future opportunities, further calcifying stratification based on ethnicity.

Although some effects may be driven by stress associated with the activation of the program alone, program activation is unlikely to be as salient as exposure to family and friends who have experienced removal. Indeed, it is unclear that Secure Communities would have strong effects within counties in which law enforcement were reluctant collaborators with ICE. I find some evidence for an interaction effect between Secure

Communities' activation and cooperation by local law enforcement: first, increases in removals in a county are associated with drops in student achievement in ELA for Hispanic and non-Hispanic black students. Second, counties with higher rates of removals per fingerprint matches experience larger declines in ELA test scores for Hispanic students. Conversely, counties that were more likely to cooperate with ICE may have higher pre-existing levels of anti-immigrant bias.

Interestingly, I also find effects of Secure Communities on the ELA test scores of non-Hispanic black students. Although this could be driven by black students with immigrant family members, it could also reflect that Secure Communities was implemented by local law enforcement agencies. One objection raised to "crimmigration" policies that combine elements of immigration enforcement and criminal justice has been that they encourage local law enforcement to engage in racial profiling. If Secure Communities encouraged law enforcement agents to engage in racial profiling, this could affect non-Hispanic black community members, as well as Hispanic community members. Aggressive policing reduces academic achievement for black male youth, with larger effects on ELA than math (Legewie and Fagan, 2018).

Throughout, I find effects of Secure Communities and removals on average ELA achievement but not on math achievement. These findings are consistent with some research on neighborhood and community stressors' effects on student achievement. For example, neighborhood disadvantage appears particularly associated with reductions in reading performance (Burdick-Will et al., 2011). In New York City, community violence affects reading, but not math, test scores (Sharkey et al., 2014). In Chicago, although peer exposure to neighborhood violence has slightly stronger effects on math than reading scores, individual child exposure to neighborhood violence has a detectable effect on reading but not math scores (Burdick-Will, 2018). Across the country, reductions in crime impact average ELA, not math, test scores (Torrats-Espinosa, 2018). Therefore, my findings suggest that effects operate through exposure to stress outside of school.

I find no effect of Secure Communities on student enrollment; similarly, East et al. (2018) find that Secure Communities did not have migration effects. However, these re-

sults contrast with previous work finding that immigration enforcement increases dropout rates (Amuedo-Dorantes and Lopez, 2015), as well as concurrent work finding that activation of 287(g) programs decreased student enrollment (Dee and Murphy, 2018). These results are not inconsistent: although 287(g) programs were never active in as many counties as Secure Communities, the local effects of these programs are likely to be more intense than effects of Secure Communities. First, law enforcement agencies had to apply to participate in 287(g) programs; therefore, all participating agencies had some motivation to cooperate with ICE. Second, ICE provided participating agencies with training and, in turn, local law enforcement agents could act as immigration enforcement agents. For these reasons, effects of Secure Communities on student achievement also likely differ from effects of 287(g) programs on student achievement.

Conclusion

The Obama administration halted Secure Communities in favor of the Priority Enforcement Program, partially in response to criticism that Secure Communities did not achieve its stated purpose of targeting serious criminal offenders. However, the current administration has revived Secure Communities, as well as proposed redefining criminal alien to include a broader population of immigrants (Capps et al., 2018). Most recently, federal officials have been examining the citizenship of some naturalized citizens for potential fraud, leaving naturalized citizens also vulnerable to removal. In this climate, understanding the multiple impacts of intensified immigration enforcement is increasingly important.

My results suggest that immigration enforcement has negative consequences for Hispanic and non-Hispanic black students, primarily by reducing achievement in ELA. For Hispanic children, these effects may be a result of stress for the children of unauthorized immigrants, estimated to be a quarter of Hispanic children. The effects on non-Hispanic black children, however, suggest that policies targeting one marginalized group may increase stress for other marginalized groups.

My results also suggest that effects depend on the level of cooperation between the

local law enforcement agency and ICE. This is particularly important in the current immigration enforcement context, in which local jurisdictions differ dramatically in the extent to which they are collaborating with ICE (Capps et al., 2018). School personnel who are concerned about the spillover effects of immigration enforcement within the classroom may want to work with local law enforcement agencies to discourage collaborations with ICE.

Future research using individual-level education data may be able to better identify whether effects vary for different groups of Hispanic and non-Hispanic black students. My results likely understate the effect of Secure Communities on Hispanic students with unauthorized immigrant parents, as I cannot separate those students from the larger group of Hispanic students. Research using individual-level data may be able to better track students' school enrollment patterns, as well as explore potential mechanisms. The result on ELA, rather than math, suggests that students are primarily affected by stress outside of school.

As prior scholars have emphasized, immigration enforcement affects not only immigrants but also their families. Students' performance in school affects their future trajectory: children with higher test scores are more likely to attend college, graduate from college, and earn more in the workforce. An increasing climate of fear has long-term consequences for the futures of those children affected but also for the United States workforce.

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Appendix

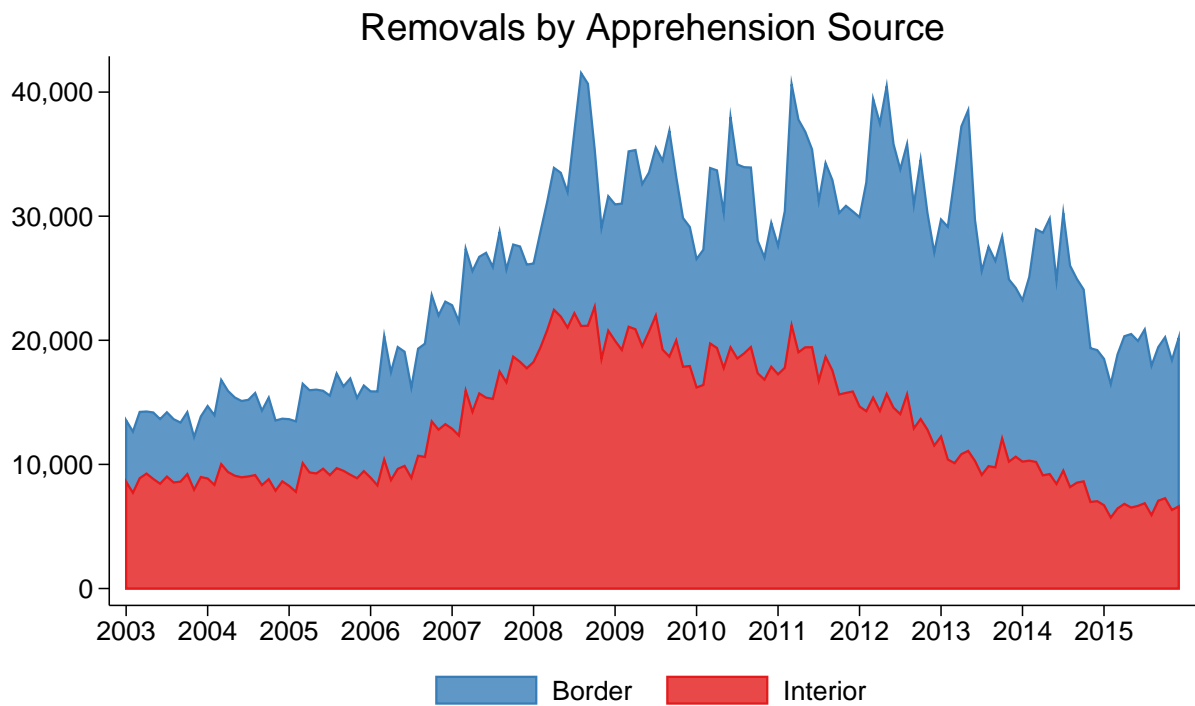


Figure 1: Pattern of Removals
Source: Transitional Records Access Clearinghouse (TRAC), Syracuse University

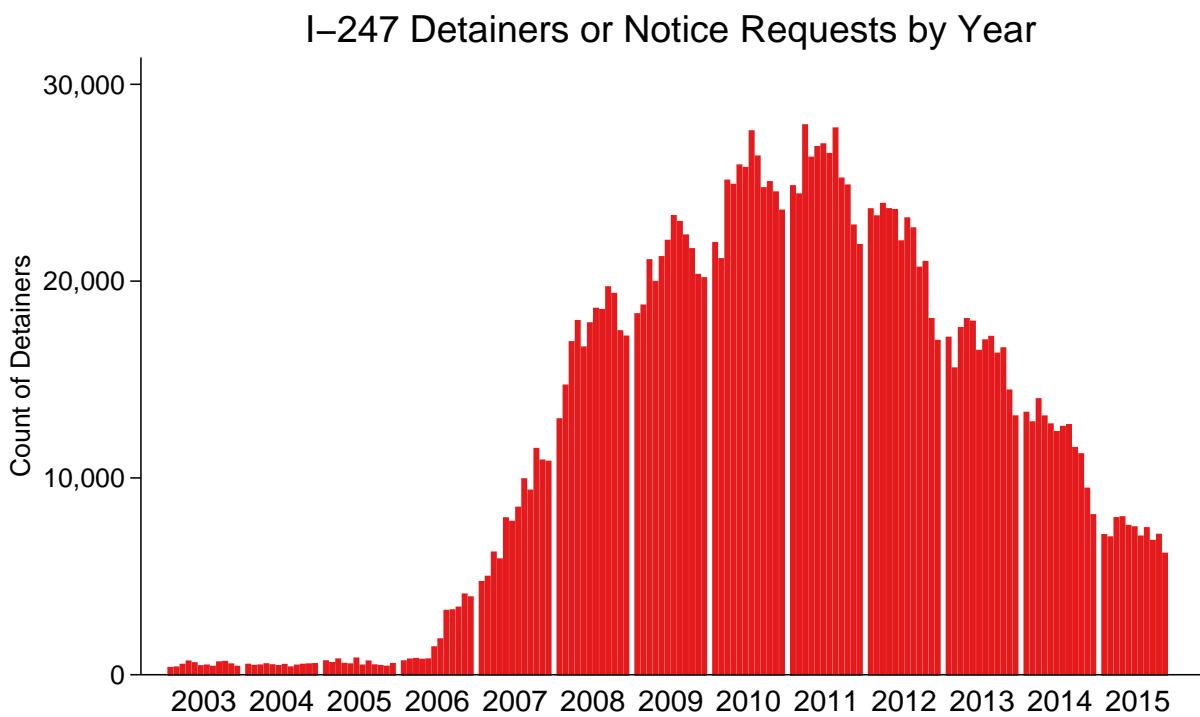
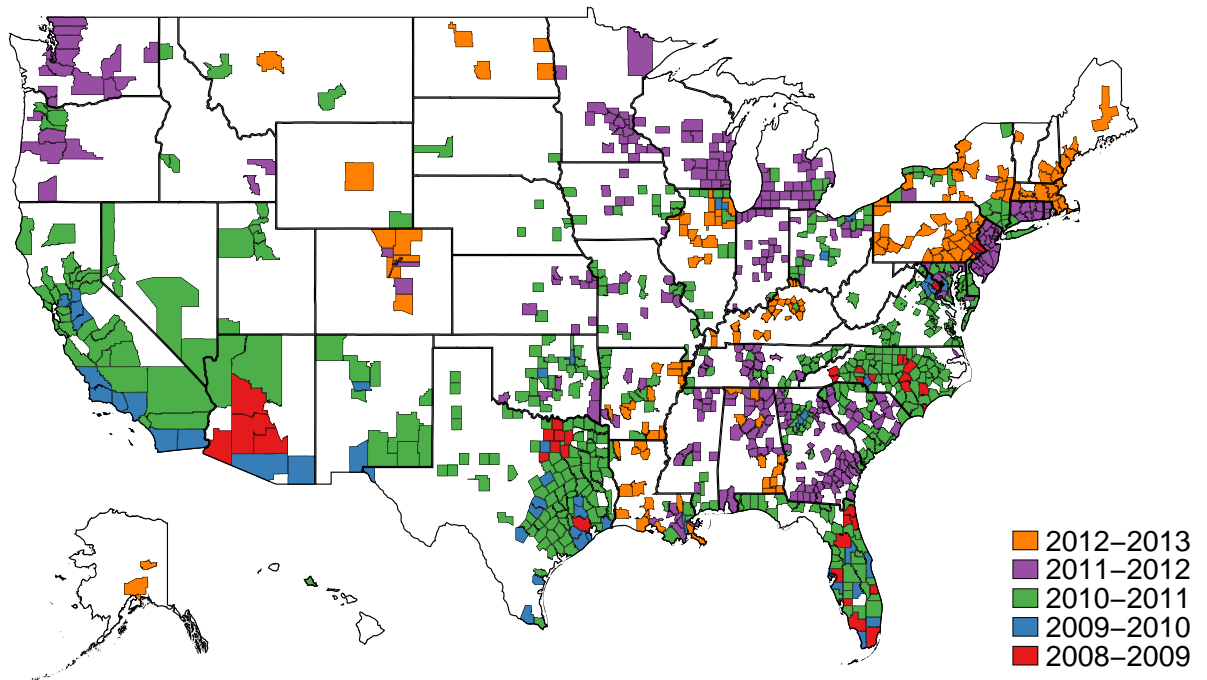


Figure 2: Pattern of Detainers Issued
Source: Transitional Records Access Clearinghouse (TRAC), Syracuse University

School Year of Secure Communities Implementation



Including only counties containing districts with Hispanic, non-Hispanic white, and non-Hispanic black measures of average achievement

Figure 3: Staggered Implementation of Secure Communities

Source: Immigration and Customs Enforcement (2013, January 22). Activated jurisdictions. U.S. Department of Homeland Security.

	ELA			Math		
	Mean	Std. Dev.	Range	Mean	Std. Dev.	Range
Average Achievement						
All	0.0303	0.2437	-1.2437-0.8941	0.0356	0.0263	-1.3403-1.4042
Hispanic	-0.3292	0.2286	-1.5150-0.9996	-0.2516	0.2314	-1.4923-1.4618
White	0.2697	0.2099	-1.0185-1.6460	0.2553	0.2425	-1.1301-1.6164
Black	-0.4167	0.2136	-2.0553-0.8578	-0.4619	0.2302	-1.8931-0.9701
Number of Students Testing						
All	3505	7042	95-127,083	3400	6586	95-122,066
Hispanic	900	3706	20-80,484	820	3331	20-77,932
White	1662	2082	21-23,733	1658	2051	21-23,728
Black	620	1513	20-22,636	619	1519	20-22,678
Counties	1054			1054		
Observations	25,155			23,984		

All test score calculations precision-weighted.

Table 1: Descriptives of Counties

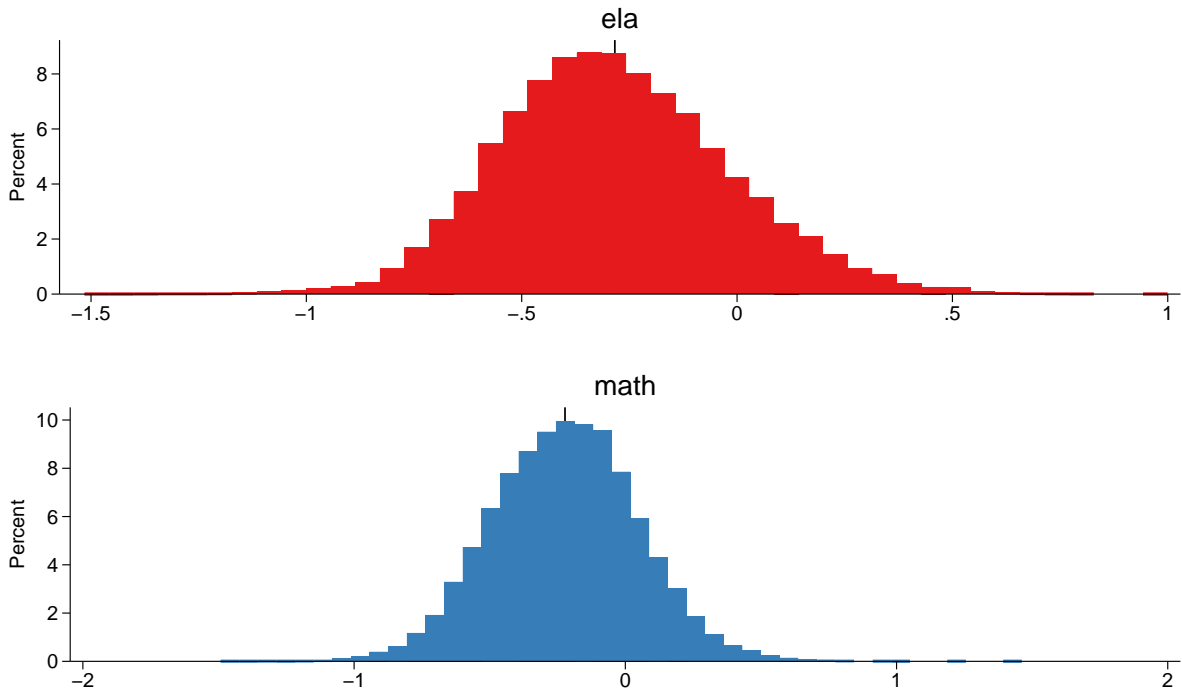


Figure 4: Distribution of ELA and Math County Grade-Level Average Achievement for Hispanic Students
 Source: Stanford Education Data Archive (SEDA)

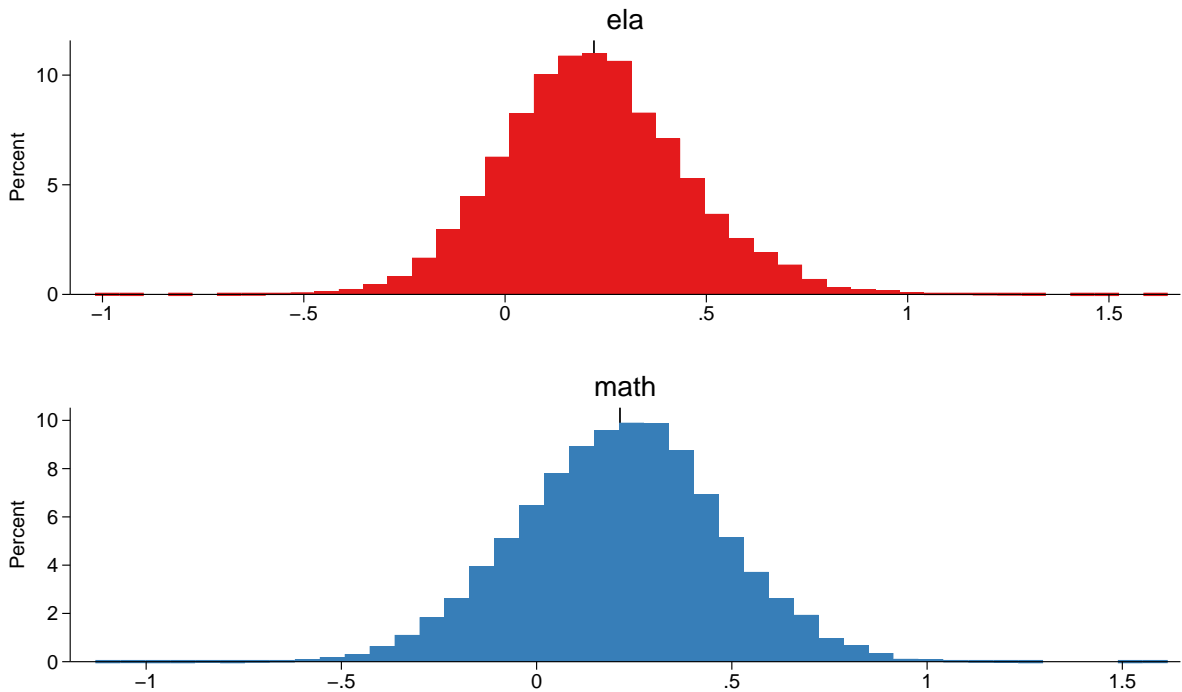


Figure 5: Distribution of ELA and Math County Grade-Level Average Achievement for Non-Hispanic White Students
 Source: Stanford Education Data Archive (SEDA)

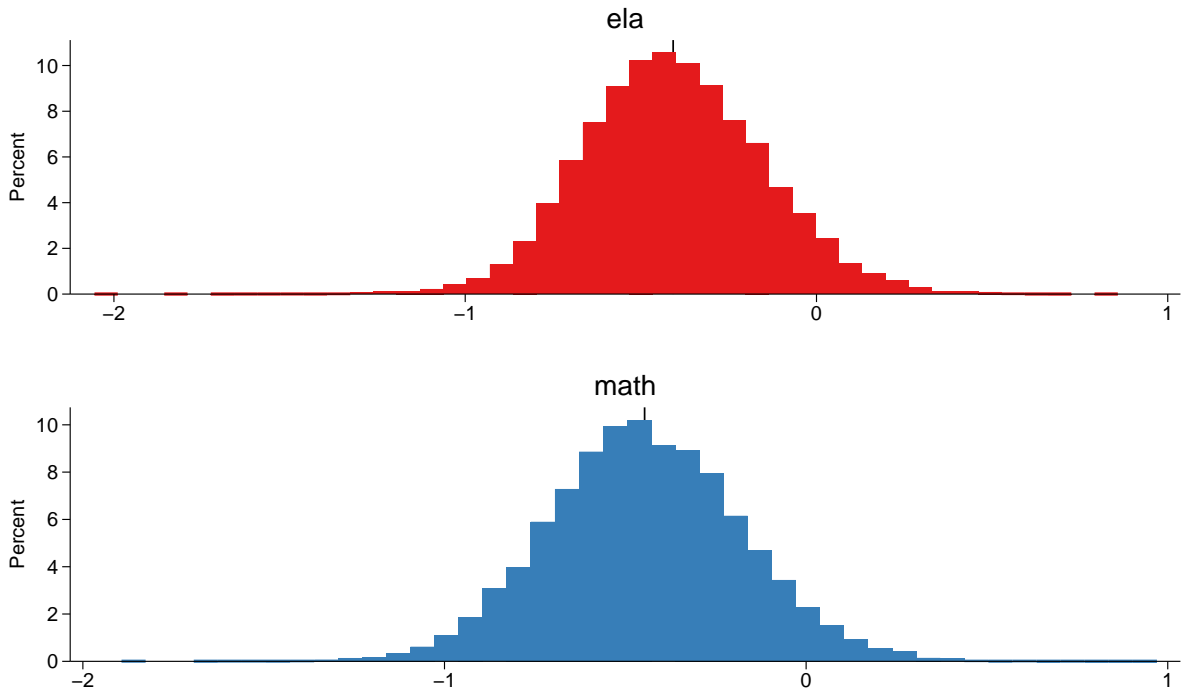


Figure 6: Distribution of ELA and Math County Grade-Level Average Achievement for Non-Hispanic Black Students
 Source: Stanford Education Data Archive (SEDA)

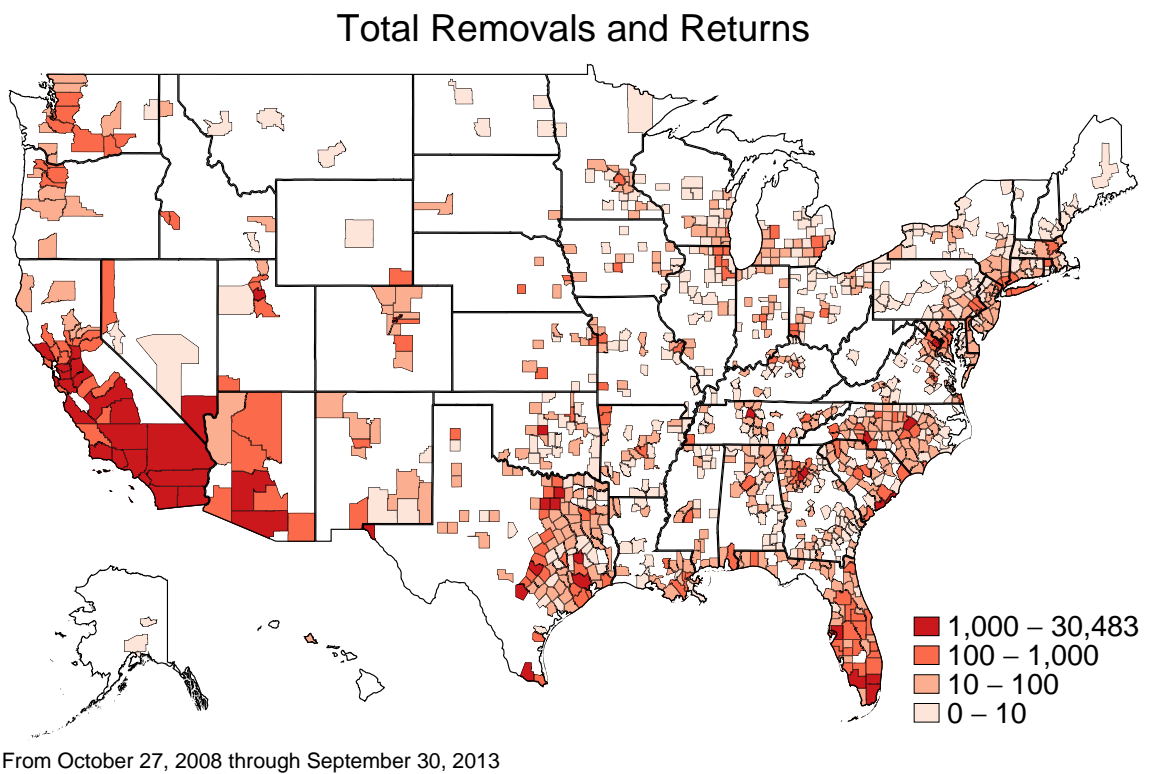


Figure 7: Removals Associated with Secure Communities
 Source: Immigration and Customs Enforcement. Secure Communities: Monthly statistics through September 30, 2013. U.S. Department of Homeland Security.

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
Secure Communities	-0.0085* (0.0042)	-0.0017 (0.0052)	-0.0033 (0.0021)	0.0029 (0.0029)	-0.0148** (0.0041)	-0.0059 (0.0048)
Observations	25,155	23,984	25,155	23,984	25,155	23,984
R-squared	0.8294	0.7987	0.8884	0.8739	0.8003	0.7810

Precision-weighted regressions control for grade, year, and county fixed effects
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 2: Effect of Secure Communities on Average Achievement

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
Year Prior	0.0011 (0.0048)	-0.0043 (0.0060)	0.0025 (0.0027)	0.0055 (0.0031)	-0.0054 (0.0046)	-0.0007 (0.0060)
Observations	25,155	23,984	25,155	23,984	25,155	23,984
R-squared	0.8293	0.7987	0.8884	0.8739	0.8000	0.7810

Precision-weighted regressions control for grade, year, and county fixed effects
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 3: Effect of Year Prior to Secure Communities Activation on Average Achievement

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
Secure Communities	-0.0115** (0.0036)	0.0071 (0.0039)	-0.0077** (0.0020)	0.0049 (0.0025)	-0.0108** (0.0034)	0.0013 (0.0040)
Observations	25,155	23,984	25,155	23,984	25,155	23,984
R-squared	0.8505	0.8279	0.9046	0.8948	0.8299	0.8145

Precision-weighted regressions control for all fixed effects as well as county trends
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 4: Effect of Secure Communities on Average Achievement Using County Time Trends

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
Secure Communities	-0.0098* (0.0042)	-0.0067 (0.0044)	-0.0029 (0.0023)	-0.0003 (0.0033)	-0.0116** (0.0040)	-0.0094 (0.0048)
Observations	25,155	23,984	25,155	23,984	25,155	23,984
R-squared	0.8428	0.8142	0.8884	0.8739	0.8159	0.7948

Precision-weighted regressions include grade, year, state-by-year, and county fixed effects
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 5: Effect of Secure Communities on Average Achievement Using State by Year Fixed Effects

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
Secure Communities	-0.0085 (0.0043)	0.0001 (0.0051)	-0.0031 (0.0021)	0.0034 (0.0029)	-0.0148** (0.0041)	-0.0057 (0.0049)
Observations	24,849	23,704	24,849	23,704	24,849	23,704
R-squared	0.8294	0.7950	0.8887	0.8741	0.8007	0.7810

Precision-weighted regressions control for grade, year, and county fixed effects
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 6: Effect of Secure Communities on Average Achievement Excluding All Border Counties

VARIABLES	(1) Hispanic	(2) Black	(3) White
Secure Communities	-4.9953 (8.5136)	7.8944 (6.1606)	1.0574 (4.0766)
Observations	25,346	25,346	25,346
R-squared	0.9982	0.9974	0.9966

Regressions control for cohort, year, and county fixed effects
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 7: Effect of Secure Communities on Number of Hispanic, Black, and White Students per Cohort

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
Logged Removals	-0.0181** (0.0053)	-0.0128 (0.0090)	0.0032 (0.0041)	-0.0015 (0.0065)	-0.0144* (0.0058)	-0.0057 (0.0069)
Observations	8,433	7,790	8,433	7,790	8,433	7,790
R-squared	0.8708	0.8431	0.8964	0.8851	0.8349	0.8182

Precision-weighted regressions control for grade, year, and county fixed effects
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 8: Effect of Removals on Average Achievement

VARIABLES	(1) Hispanic ELA	(2) Hispanic Math	(3) White ELA	(4) White Math	(5) Black ELA	(6) Black Math
% Matches Removed	-0.0010* (0.0004)	0.0011 (0.0006)	-0.0001 (0.0003)	0.0001 (0.0004)	-0.0003 (0.0006)	0.0007 (0.0007)
Observations	4,149	3,785	4,149	3,785	4,149	3,785
R-squared	0.6376	0.5704	0.7689	0.7196	0.6025	0.5445

Precision-weighted regressions control for grade fixed effects and 2009 test scores
Robust standard errors, clustered at the county-level, in parentheses
** p<0.01, * p<0.05

Table 9: Association Between Local Cooperation with ICE and Test Scores