ANNENBERG
BROWN UNIVERSITY

EdWorkingPaper No. 21-366

The Effect of Immigration Enforcement on School Engagement: Evidence from 287(g) Programs in North Carolina

Laura Bellows
University of Virginia

During the past fifteen years, immigration enforcement increased dramatically in the U.S. interior. There is a growing recognition that immigration enforcement in the U.S. interior has spillover effects onto U.S. citizens. I examine the impacts of a type of partnership between Immigration and Customs Enforcement (ICE) and local law enforcement, 287(g) programs, on school engagement within North Carolina. In North Carolina, nine counties were approved to establish 287(g) programs, and another fifteen applied but were not approved to participate. I use a triple difference strategy in which I compare educational outcomes for different groups of students in these two sets of counties before and after activation of 287(g) programs. I find that 287(g) programs decrease school engagement by decreasing attendance. This effect appears to be driven by increases in chronic absenteeism (missing 15 or more days per year). In contrast, I observe no effect of 287(g) programs on achievement.

VERSION: March 2021

Suggested citation: Bellows, Laura . (2021). The Effect of Immigration Enforcement on School Engagement: Evidence from 287(g) Programs in North Carolina. (EdWorkingPaper: 21-366). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/3b23-4e84

The Effect of Immigration Enforcement on School Engagement: Evidence from 287(g) Programs in North Carolina

Laura Bellows
University of Virginia

Abstract

During the past fifteen years, immigration enforcement increased dramatically in the U.S. interior. There is a growing recognition that immigration enforcement in the U.S. interior has spillover effects onto U.S. citizens. I examine the impacts of a type of partnership between Immigration and Customs Enforcement (ICE) and local law enforcement, 287(g) programs, on school engagement within North Carolina. In North Carolina, nine counties were approved to establish 287(g) programs, and another fifteen applied but were not approved to participate. I use a triple difference strategy in which I compare educational outcomes for different groups of students in these two sets of counties before and after activation of 287(g) programs. I find that 287(g) programs decrease school engagement by decreasing attendance. This effect appears to be driven by increases in chronic absenteeism (missing 15 or more days per year). In contrast, I observe no effect of 287(g) programs on achievement.

This work has been supported (in part) by the Horowitz Foundation. Any opinions expressed are those of the author alone and should not be construed as representing the opinions of the foundation. This research was also supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305B170002 to the University of Virginia (PI: Sara Rimm-Kaufman). The opinions expressed are those of the author and do not represent views of the Institute or the U.S. Department of Education. Thanks to Stephanie Potochnick and Juan Pedroza, who made available data on 287(g) program applications and statuses. Thanks to the organizers and participants at the Summer Institute in Migration Research Methods (SIMRM); they were essential to developing this project. Thanks to participants at the annual conference of the Association for Education Finance and Policy (AEFP), and the annual conference of the Association for Public Policy Analysis and Management (APPAM) for their many helpful comments on early iterations of this paper (particularly Carolyn Heinrich, who served as a discussant for this paper twice). Many thanks to Anna Gassman-Pines, Liz Ananat, and Seth Sanders for reading and providing comments on multiple drafts of this paper. Finally, thanks to Daphna Bassok, Lucy Sorensen, and Ying Shi for their helpful comments on final iterations.

INTRODUCTION

During the past fifteen years, partnerships between local law enforcement and Immigration and Customs Enforcement (ICE) greatly expanded the reach of immigration enforcement into the U.S. interior (Capps et al., 2018). The best known of these partnerships between ICE and local law enforcement, 287(g) programs, give authority to local law enforcement to act as immigration enforcement agents. When asked about their experiences with 287(g) programs, immigrants express high awareness of these programs, describing increases in contact with local law enforcement following program activation (Nguyen and Gill, 2015). In response, unauthorized immigrants, and immigrant communities more generally, may reduce their contact with public institutions to avoid exposing themselves, their friends, or their family members to detection by immigration enforcement. In deterring families from accessing public services to which they are entitled, immigration enforcement represents a form of administrative burden (Heinrich, 2018). Although prior work finds that immigration enforcement consistently decreases affected families' engagement with social services and other public institutions (Hagan et al., 2010; Watson, 2014; Vargas, 2015; Vargas and Pirog, 2016; Alsan and Yang, 2018), less work has examined the effects of immigration enforcement on youth engagement with public institutions.

Most youth have substantial contact with public institutions via public schools; one measure of their engagement with schools is attendance. Beyond its usefulness as a measure of short-term engagement, school attendance also affects a variety of other student outcomes. Each day of increased absence per year is associated with lower achievement (Gershenson et al., 2017, 2019). Chronic absenteeism, defined by the U.S. Department of Education's Office of Civil Rights as missing fifteen or more days per school year, is negatively associated with longer-term student outcomes. Students who are chronically absent for multiple years in early elementary school are less likely to read on grade level by third grade (Ehrlich et al., 2018). Middle school and high school students with high levels of absenteeism have greatly increased risk of dropping out of high school (Balfanz et al., 2007; Schoeneberger, 2012).

This paper adds to the extant literature by examining the effect of immigration enforcement, via the activation of 287(g) programs, on school engagement via student attendance. In North Carolina, nine counties established 287(g) programs in different years, whereas another 15 counties applied for 287(g) programs but were denied. To isolate the causal effect of 287(g) programs on student attendance, I use a triple differences strategy in which I compare attendance for different groups of students in these two sets of counties before and after activation of 287(g) programs. I find that 287(g) programs increase absences for Hispanic students ever classified as Limited English Proficient (LEP).[1] I also find that 287(g) programs increase the likelihood that students will be chronically absent, a probable sign of school disengagement. I also examine the impact of 287(g) programs on academic achievement for students in grades 3 through 9 but find no effects.

BACKGROUND ON 287(g) PROGRAMS

287(g) programs refer to Section 287(g) of the Immigration and Nationality Act (INA) and were first authorized as part of the 1996 Illegal Immigration Reform and Immigrant Responsibility Act (Rosenblum and Kandel, 2011). In 287(g) programs, ICE enters into agreements allowing state and local law enforcement to act as immigration enforcement agents. Under these arrangements, ICE provides training and other capacities to state and local law enforcement agents. In return, state and local law enforcement agents question individuals about their immigration status and issue detainers, or holds of up to 48 hours to transfer individuals into ICE custody.

Between 2005 and 2012, 70 county and city local law enforcement agencies implemented 287(g) programs; another 142 local law enforcement agencies submitted applications or inquiries to the Department of Homeland Security (DHS) but did not implement a 287(g) program under the Obama administration (Pedroza, 2018).[2] Of those that did

[1] I use Hispanic rather than Latino/a/x throughout because students are classified as Hispanic or non-Hispanic in my source data. Similarly, Limited English Proficient (LEP) is the classification used in my source data to refer to students who speak another language (or languages) and are learning English.

[2] Several state-wide entities also either implemented 287(g) programs or applied to implement 287(g) programs; these are not included.

not implement a 287(g) program, about half (71) had the application denied by DHS, whereas another 52 withdrew the application.[3]

ICE reported that applications were denied for multiple reasons, mostly related to internal ICE capacity but also related to characteristics of the applying agency. According to a 2010 DHS report, of the 51 applications that had been denied at that time, about three-quarters were denied because ICE either had insufficient field staff or insufficient funding for training or other requirements (Skinner, 2010). The remaining applications were denied if ICE determined that the agency did not have sufficient need for the program, if ICE believed another program could better suit community needs, or if the agency had insufficient detention space. Notably, the early application process did not require that law enforcement agencies submit any information related to potential effects on civil rights and civil liberties, such as agencies' past history with civil rights complaints. Therefore, sites were unlikely to be denied for this reason (Skinner, 2010). Early comparisons of counties that were approved versus not approved to participate in a 287(g) program indicate that approved counties are larger and have higher shares of Hispanic residents (Wong, 2012).

Approved 287(g) programs follow the task-force model, the jail model and a combined hybrid model. Under the task-force model, 287(g) officers can ask individuals about their immigration status and issue detainers in the community. Under the jail model, individuals are first arrested for a nonimmigration offense; inquiries into their immigration status under the 287(g) program occur after they are booked (Rosenblum and Kandel, 2011). However, particularly in early years of 287(g) programs, there may have been little practical distinction between models: Police reports in North Carolina counties, for example, suggest that law enforcement in some counties with jail models questioned individuals about immigration status prior to arrest (Nguyen and Gill, 2010, 2015).

The express purpose of partnerships with local law enforcement agencies is to target noncitizens who have committed crimes (Rosenblum and Kandel, 2011). However, critics have noted that many of the individuals who are identified as a result of 287(g) programs

[3]The majority of the remaining applications were listed as "pending."

have only low-level offenses, such as traffic violations. Therefore, it is unclear whether these programs are targeting immigrants who have committed crimes or unauthorized immigrants, regardless of criminal status.[4]

As a "new destination" for Hispanic immigrants, North Carolina has been at the forefront of immigration enforcement (Nguyen and Gill, 2010). In 2006, Mecklenburg County became one the first U.S. counties to establish a 287(g) agreement. Mecklenburg County was also the first county to implement a "universal" model, in which local law enforcement did not specifically target serious criminal offenders but identified as many unauthorized immigrants as possible (Capps et al., 2011). As shown in Table 1, between 2006 and 2009, eight more local law enforcement agencies in North Carolina established 287(g) agreements. Law enforcement agencies in another fifteen counties attempted to establish agreements during this time period but were rejected by ICE (Capps et al., 2011; Potochnick et al., 2016; Rugh and Hall, 2016).

In December of 2012, ICE scaled back on 287(g) programs by not renewing any agreements for task force programs.[5] In 2013, ICE created a new MOA, and jail programs continued to operate.

THEORETICAL FRAMEWORK

Increases in immigration enforcement via 287(g) programs may affect student attendance through several mechanisms. Although the largest driver of absences is illness, other causes of absences include chronic health conditions, family responsibilities (such as caring for younger siblings or working), transportation issues, housing instability, exclusionary discipline, and bullying, as well as students not wanting to attend school (Balfanz and Byrnes, 2012). Immigration enforcement may increase student absences by leading families to disengage with public institutions, increasing parents' reluctance to venture into public spaces, or increasing the likelihood of students experiencing poor physical or

[4]Unauthorized presence in the United States, absent other factors, is a civil, not criminal, offense.

[5]FY 2012: ICE announces year-end removal numbers, highlights focus on key priorities and issues new national detainer guidance to further focus resources (2012, December 20). Retrieved from `https://www.ice.gov/news/releases/fy-2012-ice-announces-year-end-removal-numbers-highlights-focus-key-priorities-and`.

mental health.

Under conditions of heightened immigration enforcement, families are less likely to engage with public institutions. Immigration enforcement produces a chilling effect on public benefit receipt, leading families to be less likely to apply or recertify for public benefits to which they are entitled (Watson, 2014; Vargas, 2015; Vargas and Pirog, 2016; Alsan and Yang, 2018). Immigration enforcement also reduces engagement with public safety units, via reductions in crime reporting, and use of other public services, such as libraries and parks (Hagan et al., 2010; Nguyen and Gill, 2015; Dhingra et al., 2021). These effects all appear to be driven by fear around possible detection by immigration authorities (Nguyen and Gill, 2015; Alsan and Yang, 2018). Schools represent another government institution that could pose a danger to families with unauthorized members: Families may fear school authorities' potential cooperation with ICE.[6] Under conditions of increased immigration enforcement, families may be less likely to bring children to schools because of fear of detection by immigration authorities.

Unauthorized immigrants' reluctance to be in public spaces in which there is a chance of detection by immigration authorities may have secondary effects on children's attendance. First, the majority of offenses for which unauthorized immigrants were arrested under partnerships between local law enforcement and ICE were traffic offenses. If parents are more afraid to drive children to school, children may end up missing school; this might just be a small increase in marginal absences if, for example, children typically take the bus but miss the bus a few days a year. Second, employment by noncitizen men with lower levels of education decreases when immigration enforcement increases, likely due to fear over potential detection (East et al., 2018). Older students may therefore leave school in order to supplement their families' incomes (Martinez, 2016).

Immigration enforcement may increase student absences through negative effects on mental or physical health. Partnerships between local law enforcement and ICE increase mental health distress for Latino immigrants (Wang and Kaushal, 2019). To my knowledge, no studies have examined the effects of immigration enforcement on children's

[6]Several school districts have released statements emphasizing that school personnel would not report students to ICE for this reason.

physical health or pediatric care, but immigration enforcement appears to worsen birth outcomes through expectant mothers receiving less prenatal care (Rhodes et al., 2015; Tome et al., 2021). Although ICE policy designates health care facilities as sensitive locations, this does not prevent cooperating local law enforcement from conducting arrests near health care facilities. In North Carolina, sheriff's deputies have been reported waiting outside of migrant health clinics (Arriaga, 2017). Illness is the main reason students are absent from school, so even small declines in children's health are likely to increase absenteeism.

Immigration enforcement may also affect child health through reductions in health care coverage. Multiple studies have found that increases in immigration enforcement reduce families' likelihood of healthcare coverage via Medicaid and the Affordable Care Act (ACA) (Vargas, 2015; Alsan and Yang, 2018). Children with breaks in health insurance coverage are less likely to receive preventive care and prescriptions (Olson et al., 2005), which is particularly likely to create a detrimental effect for children with chronic conditions. Approximately 29 percent of school-age children have chronic conditions, with 8.8 percent suffering from asthma and 7.9 percent suffering from attention deficit disorder (ADD) or attention deficit hyperactivity disorder (ADHD), both of which require ongoing care and medication.[7] If immigration enforcement increases the likelihood of breaks in insurance coverage, children with chronic health conditions will be more likely to miss school.

PRIOR RESEARCH

Prior research on the effects of immigration enforcement on student attendance reaches mixed conclusions. In one study, first and second generation Kindergarten through third grade immigrant students attend school at higher rates in Enforcement and Removal Operations (ERO) areas with higher numbers of ICE apprehensions (Sattin-Bajaj and Kirksey, 2019). However, there are only 24 ERO offices that cover relatively large geo-

[7] National Survey of Children's Health. NSCH 2011/12. Data query from the Child and Adolescent HealthMeasurement Initiative, Data Resource Center for Child and Adolescent Health website. Retrieved [08/07/2016]from www.childhealthdata.org.

graphic areas, and it is unclear that apprehensions are evenly geographically distributed across areas covered.

In contrast, immigration raids conducted by ICE agents, whether at worksites or in the community, have negative impacts on student attendance and Head Start enrollment. Following worksite raids, children with an arrested parent are likely to miss school (Chaudry et al., 2010). Reports of immigration enforcement activities have large immediate effects on daily high school attendance, with declines up to 11 percentage points for migrant students (Kirksey, 2020). In the wake of immigration raids, county Head Start enrollment declines for Hispanic children. Although some of this effect is potentially driven by migration, the majority appears to be driven by deterrence, in that families are no longer enrolling children in Head Start (Santillano et al., 2020).

Results described above may vary because of differences in immigration enforcement policies. ICE raids are a traumatic and salient form of immigration enforcement that may produce larger effects than partnerships between local law enforcement and ICE. Worksite raids, in particular, appear to have large negative effects on student achievement (Zuniga, 2018). In contrast, the relationship between another partnership between ICE and local law enforcement, Secure Communities, and student achievement is negative but small (Bellows, 2019). Understanding the effects of both types of enforcement is important in part because ICE raids represent a fraction of immigration enforcement activity in the U.S. interior: The majority of ICE arrests derive from transfers into ICE custody from federal, state, or local custody, not from community arrests made by ICE (TRAC Immigration, 2018).

Apart from student achievement and attendance, a few prior studies have examined the effects of partnerships between ICE and local law enforcement on other measures of student engagement. In qualitative studies, fear of parental detention and removal under these policies reduces reported participation in extracurricular educational activities (Hagan et al., 2010; Koball et al., 2015). Using an index of policies, including 287(g) programs and Secure Communities, Amuedo-Dorantes and Lopez (2015) find that intensified immigration enforcement increases dropout rates and grade retention rates among the children of likely unauthorized immigrants. Comparing counties that activated 287(g) programs with counties that applied to participate but were not approved by ICE, Dee and Murphy (2019) find that Hispanic student enrollment declined in activating counties. The authors are unable to distinguish between increases in student mobility and increases in student dropout rates, although they find that effects are driven by younger students.

This project builds on previous work by examining the effects of immigration enforcement on student attendance and uses a quasi-experimental design to recover plausibly causal estimates. This design addresses endogeneity arising from local conditions that would motivate local officials to participate in partnerships with ICE. I also use administrative education data covering the entire student population of North Carolina over the course of nearly a decade. Unlike much work in this area, which uses data at a more aggregated level, I am able to track individual students from grade to grade, as well as identify their location prior to the activation of 287(g) programs. I am also able to identify a more narrowly defined treatment group, Hispanic students ever classified as Limited English Proficient (LEP). I ask how 287(g) programs affect absences for a group of students likely affected by immigration enforcement (Hispanic students ever classified as LEP), as compared with a group of students less likely affected (White students never classified as LEP). Finally, I explore whether effects on attendance translate to declines in academic achievement.

DATA

Data for this paper come from two sources. First, from Immigration and Customs Enforcement (ICE), I use publicly available data on the dates of North Carolina 287(g) programs, as well as more detailed information on historical 287(g) agreements and applications made available to me by Stephanie Potochnick and Juan Pedroza (used in Potochnick et al. (2016); Rugh and Hall (2016); Dee and Murphy (2019)). Second, I match this information with individual-level student data on attendance for the 2003/2004 through 2012/2013 school years from the North Carolina Education Research Data Center (NCERDC), housed at Duke University. NCERDC maintains all of the administrative records on North Carolina public school students that are collected by the state Department of Public Instruction and makes them available to researchers.

Measures

In primary analyses, I use information on days absent, as well as days in school membership, which is available for every student in grades 3 through 12 on a yearly (and later semesterly) basis from 2003/2004 forward. Although attendance is sometimes recorded for students in grades PK-2 in later years of data, this information is not required to be collected and is unavailable prior to the 2005/2006 school year. I therefore exclude students in pre-Kindergarten through second grade in all analyses. Because students switch schools during the year, I total days in membership and days absent over all schools. If a student was absent from school because they had not yet been enrolled in a new school, however, that absence is not included. I also exclude students who have unrealistic values of days in membership or days absent (more days than in the year or more days in absenteeism than in membership).

I also use information on end-of-grade (EOG) test scores in reading and math and end-of-course (EOC) test scores in English 1 and Algebra 1 from the 2003/2004 through 2010/2011 academic years. All 3rd- through 8th-grade students in North Carolina are required to take EOG achievement tests in both reading and math.[8] Most students take the EOC achievement test in English 1 in 9th grade, and many also test that year in Algebra 1 (although some students test in earlier years and many test in tenth grade). I use any student with a valid first (regular administration) test score in either math or reading. I exclude retest scores, as well as students who had only retest scores, because students were scheduled to take retests nonrandomly (students who took retests were mostly students who scored at not proficient levels on the regular administration). I

[8] In October 2010, the State Board of Education stopped requiring schools' use of EOG scores in student promotion decisions in Grades 3, 5, and 8. However, EOG scores continued to be used to compute school growth and performance as required by North Carolina's ABCs Accountability Program and to determine adequate yearly progress (AYP). EOG tests in reading comprehension measure the ability to demonstrate understanding of a written passage and knowledge of vocabulary. EOG tests in math measure proficiency in numbers and operations, measurement, geometry, data analysis and probability, and algebra. EOG test score files include raw test scores, as well as students' race/ethnicity, sex, grade level, and school.

standardize test scores using the entire population of students within the same grade and subject.

Defining Student Treatment Status

NCERDC also contains information about student demographics, which I use to define which students are most likely to be affected by immigration enforcement policies (the "treatment group"). In main analyses, I use Hispanic students ever classified as LEP as the treatment group, with White students never classified as LEP as the control group. I focus on this group as the treatment group for several reasons. First, immigration enforcement largely affects Hispanic immigrants (Rosenblum and Soto, 2015). Second, students' English proficiency may serve as a proxy for parental nativity. Among Mexican-origin kindergarteners, 95 percent of first generation and 75 percent of second generation students spoke only Spanish or predominantly Spanish at home, whereas 85 percent of third generation students spoke only English or predominantly English at home (Reardon and Galindo, 2009).

I focus on White students never classified as LEP as the control group because White students are the largest subgroup in North Carolina and White students are less likely than Black students to be affected by potential spillover effects of immigration enforcement, such as increases in racial animus. However, I also present robustness checks using Black students never classified as LEP and all non-Hispanic students never classified as LEP as the control group.

In NCERDC, race and ethnicity are captured in most years by a single categorical variable, in which students are identified as American Indian, Asian-American, Black, Hispanic, Multiracial, or White (in some years, students are identified as Pacific Islander). I identify students' modal race and/or ethnicity, or the race and/or ethnicity category they are recorded as most frequently across years.[9]

[9] Overall, about three percent of students are recorded in multiple race and/or ethnicity categories, with the majority who have more than one race and/or ethnicity recorded in two. This is most common for students who are recorded most frequently as Multiracial: Approximately 34 percent of students identified most frequently as Multiracial have been identified in a different category during another year. However, it is also quite common for American Indian students, 22 percent of whom have been identified as a different race/ethnicity in another year. The three groups that I use in my analyses, Hispanic,

I define whether a student was classified as LEP using information on students' current Limited English Proficiency (LEP) status and year exiting LEP. I find that, during my study period, a majority of Hispanic students in North Carolina (over 70%) are classified as LEP or identified as having previously exited LEP status in at least one school year.

Families may migrate in response to 287(g) programs (Capps et al., 2011). Using NCERDC data, I am able to track these migrating families, as long as they remain in North Carolina.[10] Therefore, in these models I treat students' county as observed in the 2005/2006 school year as their "permanent county." In robustness checks, I investigate effects for non-migratory students as well as effects based on assigning students to the county observed in the 2004/2005 school year. In mapping students to counties, I use the substantial overlap between North Carolina district boundaries and county lines. I exclude students who were located at charter schools.[11]

Control Variables

I control for certain student characteristics, particularly grade and gender.[12] I also control for other county-level immigration enforcement policies. Between 2008 and 2011, ICE activated Secure Communities, another type of partnership between ICE and local law enforcement, in all counties in North Carolina. 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 match was determined to be a potentially removable individual, ICE might issue a detainer against that individual, or a request to local law enforcement to hold that

White, and Black students, have lower rates (all under 3%) of being identified in multiple race/ethnicity classifications.

[10]According to the American Community Survey 5-year estimates for 2005/2009, approximately 2 percent of school-aged children living within North Carolina the previous year were living in another state during the following year. This does not include children who moved abroad in the following year.

[11]Between 2003/2004 and 2012/2013, approximately one percent of students in North Carolina (and half a percent of Hispanic students) were located in charter schools in any given year.

[12]Gender is collected in every year; however, students may differ in terms of recorded gender across years. I observe that approximately 0.5 percent of students have more than one recorded gender across years. Although I treat these as misclassifications and use students' most frequently recorded gender, these students may be transgender: Indeed, recent estimates suggest that about 0.6 percent of the adult population identify as transgender. To my knowledge, the North Carolina Department of Public Instruction collects no additional information on students' sexual orientation or gender identity.

individual for up to 48 hours for transfer into ICE custody (Kohli et al., 2011; Rosenblum and Kandel, 2011). I control for Secure Communities activation in a particular county school-year using publicly available data on Secure Communities' activation from ICE. In North Carolina, all 287(g) programs were active in approved counties prior to Secure Communities' activation.

Sample

Overall, I identify 1,032,136 students in grades 3 through 12 whom I can observe in a North Carolina county during the spring of 2005/2006. In most models, I restrict my sample to 540,180 unique students who were located in a county that applied to participate in a 287(g) program. I only include student-year observations if the student has information on spring absences in that year; I therefore exclude student-year observations where the student is only observed in the fall.[13] If students subsequently move (post 2005/2006) to another county in North Carolina, they remain in my sample. However, if students leave North Carolina, I am unable to observe them.

ANALYTIC PLAN

To estimate the effects of increased immigration enforcement via 287(g) programs on student attendance and achievement, I compare students before and after activation of a 287(g) program. The activation of 287(g) programs is an endogenous policy change: Local law enforcement may have applied to host a 287(g) programs because of increases in violence in local immigrant communities or because of increases in anti-immigrant animus, both of which would negatively impact student attendance. Therefore, I compare only counties that applied to participate in 287(g) programs. This controls for unobserved time-varying factors related to the local county's desire to participate in 287(g) programs. This approach of comparing individuals in counties that were approved for 287(g) programs only to individuals in counties that were not approved for 287(g) programs is similar to that used in several prior nationwide studies to estimate the effects of

[13] I am only able to observe students recorded only in fall beginning in 2005/2006.

287(g) programs on food insecurity, foreclosure rates, and school enrollment (Potochnick et al., 2016; Rugh and Hall, 2016; Dee and Murphy, 2019).

Although I show results for Hispanic students ever classified as LEP and all Hispanic students alone in a difference-in-difference specification, my preferred approach introduces a third difference, in most cases comparing Hispanic ever classified as LEP to White students never classified as LEP. This third difference accounts for any trends in participating and non-participating counties affecting all students. In alternate specifications, I compare all Hispanic students to all White students and show a falsification check comparing all Black and White students.

The difference-in-difference-in-differences specification uses the following equation:

$$\begin{aligned}\mathrm{Y}_{ict} = \alpha + \beta_1 \mathrm{T}_i + \beta_2 \mathrm{A}_c + \beta_3 \mathrm{P}_{ct} + \beta_4 \mathrm{T}_i \times \mathrm{A}_c + \beta_5 \mathrm{T}_i \times \mathrm{P}_{ct} + \beta_6 \mathrm{A}_c \times \mathrm{P}_{ct} \\ + \beta_7 \mathrm{T}_i \times \mathrm{A}_c \times \mathrm{P}_{ct} + \beta_m \mathrm{Student}_i + \phi_c + \gamma + \eta_t + \mathrm{T}_i \times \eta_t + \epsilon\end{aligned} \tag{1}$$

Here, Y is the number of absences for an individual student i in county c in school year t. T is the treatment group of Hispanic students ever identified as LEP, with White students never identified as LEP serving as the control group. A is an indicator variable that is 0 if a county applied but was not approved for a 287(g) program and 1 if a county applied and was approved for a 287(g) program, and P is an indicator variable representing post-287(g) implementation. For counties that are rejected from 287(g) programs, P represents what would likely have been the post-287(g) implementation period, beginning a year following the application, if the application had been approved. This roughly approximates implementation timing for counties that were approved for participation. Four out of nine 287(g) programs ended prior to the final year of my data, 2012/2013: The programs in Cumberland and Guilford discontinued after a single year, and the programs in Durham and Alamance ended in 2013. I continue to treat those counties as activated but show robustness checks in which I drop 2012/2013 entirely (effects remain similar).

As described earlier, I control for student gender and county-level Secure Communities activation. I also use several layers of fixed effects, including permanent county fixed effects (ϕ); grade fixed effects (γ); year fixed effects (η); and treatment group by year fixed effects. These layers of fixed effects control for time-invariant characteristics of counties that affect attendance, persistent differences in attendance between grades, and any state-wide or national policy changes in a particular year. To examine effects on achievement, I substitute test scores as the dependent variable but otherwise maintain the same approach.

In specification checks for effects of 287(g) programs on absences, I estimate negative binomial regressions.[14] Because I reach similar results using all approaches, I use OLS in additional robustness and falsification checks. Since restricting only to counties that applied for a 287(g) program drastically reduces the number of counties in my analysis, I use a wild cluster bootstrap (user-written `boottest` in Stata) to account for clustering at the county-level as well as small numbers of counties (Roodman et al., 2019).

RESULTS

Descriptive Statistics

Table 2 shows descriptive statistics for the three groups of counties in North Carolina, which are counties that did not apply to host a 287(g) program (76), counties that did apply but were not approved to host a 287(g) program (15), and counties that were approved for 287(g) program (9). Counties that were approved to host a 287(g) program are much larger, on average, than counties that did not apply to host a 287(g) program and counties that were not approved for a 287(g) program. Two of the most populous counties in North Carolina, Mecklenburg and Wake, activated 287(g) programs.

Counties also differ in terms of racial/ethnic makeup. Counties that were approved for 287(g) programs have the highest percentage of Hispanic students ever classified as LEP (5.92%), and counties that did not apply for 287(g) programs have the lowest percentage of Hispanic students ever classified as LEP (4.74%). A much larger share of students in counties not approved for 287(g) programs are White, relative to students in either

[14] I use negative binomial rather than Poisson models because there is substantial overdispersion of the dependent variable (Ryan et al., 2018).

counties that did not apply to host 287(g) programs and counties that were approved for 287(g) programs. Nearly three-quarters of students in counties not approved for 287(g) programs are White, as compared with half of students in counties approved for 287(g) programs. Correspondingly, in counties approved for 287(g) programs, approximately 36 percent of students are Black, whereas only 16 percent of students are Black in counties not approved. Counties that did not apply to host 287(g) programs fall in between counties that were approved or not approved. Very few students are identified as Asian-American, American Indian, or Multiracial, although a higher share of Asian-American students reside in approved counties as compared with both counties that did not apply and counties that were not approved. In all counties, the majority of White students are never identified as LEP (99% across all counties), whereas the majority of Hispanic students are identified as LEP (73% across all counties).

Table 2 shows average days absent and absence rates (number of absences divided by days in membership) for counties by 287(g) application and approval status. In counties that did not apply to host 287(g) programs, students are absent an average of 8.03 days per year, with an absence rate of 4.85 percent. In approved counties, students are absent slightly less, with an average of 7.82 days per year and an absence rate of 4.81 percent. In denied counties, students are absent the least, with an average of 7.34 days a year and an absence rate of 4.41 percent. Overall, nearly 90 percent of students have at least one absence during a school year, and nearly half of students are absent at least six days. A large number of students are absent ten or more (28%), fifteen or more (14%), or twenty or more days (8%). Differences begin to emerge between counties by approval status in terms of high numbers of absences: Counties approved for 287(g) programs have higher percentages of students who are absent for larger numbers of days than counties not approved for 287(g) programs. Once I control for student demographics (grade, gender, and race/ethnicity), these differences shrink but are still significant (not shown).

Main Findings

I first present difference-in-differences results for Hispanic students ever classified as LEP and all Hispanic students, comparing students in counties activating 287(g) programs to students in counties not activating 287(g) programs prior to and following activation. As shown in Table 4, the activation of a 287(g) program appears to increase absences for Hispanic students ever classified as LEP by about a day. The effect size appears slightly smaller for the entire population of Hispanic students, but the activation of a 287(g) program also increases absences for all Hispanic students by nearly a day (91%).

As falsification checks, I estimate similar models with White students never classified as LEP, White students regardless of LEP classification, and Black students, again comparing students in counties activating 287(g) programs to students in counties not activating 287(g) programs prior to and following activation. White and Black students are less likely to be directly affected by 287(g) programs than Hispanic students, as few White and Black students in North Carolina are immigrants or the children of immigrants. Although 287(g) programs may affect Black students indirectly through increases in racial animus, all evidence in North Carolina suggests that both law enforcement and community members were aware that 287(g) programs were focused on the identification and removal of Hispanic immigrants. As expected, I find that the activation of 287(g) programs has no effect on attendance for White students never classified as LEP, the larger group of White students, or Black students.

I then introduce the third difference, comparing Hispanic students ever classified as LEP to White students never classified as LEP. As expected, I continue to find that the activation of 287(g) programs increases the number of days absent for Hispanic students ever classified as LEP by about a day (Table 5). Results are, again, similarly sized if slightly attenuated when I compare all Hispanic students to all White students. When I estimate a similar triple difference model comparing Black to White students, I find no effect of 287(g) programs on absences, as suggested by the previous results from Table 4.

The lack of results for White and Black students, as compared to the increase in absences for Hispanic students ever classified as LEP and all Hispanic students, gives me greater confidence that increases in absences for Hispanic students ever classified as LEP and all Hispanic students are due to the activation of 287(g) programs, rather than any other simultaneous policy change.

I employ an event study analysis in which I interact indicators for my treatment group and approved counties with a series of leading and lagged indicators, with the period one year prior to activation serving as the base group. As shown in Figure 1, I see no effect of 287(g) activation on leading indicators of program activation, giving me greater confidence that effects do not arise solely from prior trends in counties activating 287(g) programs. Although not all effects remain significant at conventional levels once I interact year of activation and year lags with program approval and treatment group, estimates of the effects of year of activation and lagging indicators appear fairly consistent over the course of the program. However, they do appear much larger for programs that have been active for four years or more.

Robustness Checks

In addition to the event history analysis and falsification checks, I conduct a variety of specification, robustness, and placebo checks. As shown in Table 6, results are similar for days absent when I use negative binomial models rather than OLS. The activation of a 287(g) program increases absences for both Hispanic students ever classified as LEP and all Hispanic students by about half a day, lower than the sizes of the estimated increases from OLS models. Results are also similar when I substitute absence rate for days absent, calculated as the percent of absences out of days in membership (Table 7). The activation of a 287(g) program increases the absence rate by approximately 0.5 percentage points. This is equivalent to an increase of one day per year.

In Table 8, I show results when I vary control variables and fixed effects, vary control group, and vary sampling decisions. Estimates for the effects of 287(g) programs on Hispanic students ever classified as LEP range from about two-thirds of a day to slightly more than a day when I include or exclude different combinations of control variables and fixed effects. Estimates are similarly sized when I switch control groups, comparing

Hispanic students ever classified as LEP to either Black students never classified as LEP or to all non-Hispanic students never classified as LEP. Estimates are also robust to different data decisions. First, I exclude 2013, in which Durham and Alamance had deactivated their 287(g) programs. Second, I include only students who do not move from their permanent county. Finally, I use students' county as identified in the 2004/2005 school year. In main models, I use students' county as identified in the 2005/2006 school year; Mecklenburg activated their 287(g) program in February of 2006, which is immediately before information on attendance for the year was collected but might have led to some student mobility. In all robustness checks, I reach very similar results: The activation of 287(g) programs increases absences for Hispanic students ever classified as LEP by about a school day.

Counties vary dramatically in population size, with Mecklenburg and Wake together accounting for approximately a third of all students. In order to determine whether one county is driving results, I iteratively drop counties (both approved and denied) and reestimate models using my preferred triple difference specification. As shown in Figure 2, results are largely robust to this test. When I drop Mecklenburg, the triple difference estimate is similar in size but does not reach conventional levels of statistical significance. Similarly, excluding Wake or Durham county does not reduce the estimated size of the effect but does reduce precision so that effects are only marginally significant.

I additionally run two separate placebo tests. In the first, I randomly assign Hispanic ever classified as LEP and White students never classified as LEP from my main models to treatment or control condition and estimate my main specification over one thousand simulations. In the second, I randomly assign students from my main models to approved or denied counties and again estimate my main specification over one thousand simulations. In results from these two placebo tests (shown in Figures 3 and 4), I find that estimated coefficients from my main results (shown with red lines) are much larger than any estimates from placebo tests.[15]

[15]In addition to the specification checks using Hispanic students as the treatment group and White students as the control group shown in Tables 6 and 7, I have conducted all robustness and placebo checks from Table 8 and Figures 2-4 using entire populations of Hispanic and White students and reach similar conclusions. Results are available upon request.

Varying Effects Based on Number of Days Absent

Effects on number of days absent may result from increases in a few days absent or increases in many days absent. To identify where in the distribution of absences increases occur, I therefore estimate a series of linear probability models, using the same triple difference approach, in which the outcomes are indicators for number of absences. I divide these into one or more absences, two or more absences, three or more absences, six or more absences, ten or more absences, fifteen or more absences, twenty or more absences, or fifty or more absences.

As shown in Figure 5, I find that increases in absences are driven by increases in chronic absenteeism. There are no effects of the activation of 287(g) programs on the likelihood that students will have up to ten absences. However, the activation of 287(g) programs appears to increase the likelihood that Hispanic students ever classified as LEP will have fifteen or more, twenty or more, or fifty or more absences, relative to White students never classified as LEP (or, as shown in orange, Hispanic students relative to White students). The activation of a 287(g) program appears to increase the probability that Hispanic students ever classified as LEP will be absent fifteen or more days by about two percentage points, with a similarly sized increase in the probability that Hispanic students ever classified as LEP will be absent twenty or more days. As shown in Table 3, across all counties, about 14 percent of students are absent fifteen or more days, and eight percent of students are absent 20 or more days. The activation of a 287(g) program also increases the probability Hispanic students will be absent fifty or more days by about one percentage point; this represents a doubling in the likelihood of missing fifty or more days from the baseline rate of 0.78 percent of students overall who are absent 50 or more days.

Varying Effects Based on Grade Level and Gender

When I split models by students identified as female or male, estimates appear larger for male students, although the difference is not significant. For age, I split models by school level (grades 3 through 5, grades 6 through 8, and grades 9 through 12). Although all estimates are imprecisely measured, coefficients for elementary and middle school students are negative, suggesting that results are primarily driven by high school students. Indeed, most observations are for students in upper grades because absence data are not available for students in grades K through 2 and because I restrict to students who were observed in the spring of 2005/2006.[16]

Student Achievement

Increases in absences are likely to decrease student achievement. Additionally, student achievement seems likely to be affected by increases in immigration enforcement through mechanisms other than increases in absences: Students may experience increases in stress or worry, which may decrease their ability to focus in school. However, as shown in Table 9, I find no effect of the activation of 287(g) programs in North Carolina for Hispanic students in either math or reading achievement. I also find no effects on English I or Algebra I test scores (Table 10). I additionally split models of effects on math and reading achievement by age and gender and continue to find no separate effects (results available upon request).

DISCUSSION

In prior studies, immigration raids have been found to decrease student attendance (Chaudry et al., 2010; Kirksey, 2020); no prior research has examined the effects of partnerships between local law enforcement and ICE on school attendance. Work on achievement suggests that immigration raids appear to have stronger effects on schooling outcomes than partnerships between ICE and local law enforcement. However, prior studies suggest that partnerships between ICE and local law enforcement may decrease school engagement, via an increase in student dropout rates (Amuedo-Dorantes and Lopez, 2015). My results also suggest the immigration enforcement decreases student engagement, via decreases in student attendance. Overall, I find that these partnerships increase absences for Hispanic students ever classified as LEP by a day per year. This

[16] All results from this section available upon request.

increase is primarily driven by an increase in chronic absenteeism, as defined by the U.S. Department of Education's Office of the Civil Rights as missing fifteen or more days of school. I find significant increases in the number of Hispanic students ever classified as LEP absent from school fifteen or more, twenty or more, and even fifty or more days.

Attendance is a marker of school engagement (Fredricks et al., 2004). My findings confirm a general pattern of disengagement with public institutions in the wake of immigration enforcement. Increases in absences appear to be driven by high school students, who have greater control over their own school attendance. Therefore, a decrease in attendance may represent decreased engagement with public institutions amongst youth. Although this increase in disengagement following the activation of partnerships between local law enforcement and ICE has been documented for adults, this study demonstrates the same pattern amongst youth.

Decreasing school attendance has ramifications for students and families. Although I detect no impact of 287(g) programs on achievement, overall, most evidence suggests that absences decrease student achievement (Gottfried, 2011; Aucejo and Romano, 2016; Goodman, 2014; Gershenson et al., 2017; Liu et al., 2019). High rates of absenteeism have long been associated with increased risk of dropping out of high school (Balfanz et al., 2007; Schoeneberger, 2012). Here, increases in chronic absenteeism may be a precursor to students leaving school entirely.

Decreasing school attendance also has implications for schools. When students are absent, schools lose federal and state education funding based on daily attendance. Recently, schools' accountability for attendance has increased. Under the Every Student Succeeds Act (ESSA), states are also required to report chronic absenteeism, or the rate of students absent fifteen or more days. Thirty-seven states and the District of Columbia have also incorporated chronic absenteeism into their additional "school quality or student success" (SQSS) accountability indicator required under the Every Student Succeeds Act (ESSA) of 2015, which revised the structure of No Child Left Behind (NCLB). Districts and schools in these states are now held accountable for chronic absenteeism rates.[17] Al-

[17] North Carolina happens to be one of the thirteen states not using chronic absenteeism in its "non-academic" accountability.

though several promising practices suggest that in-school interventions can reduce chronic absenteeism rates (Cook et al., 2017), out-of-school policies may also be drivers of chronic absenteeism and can also be addressed via policy.

The mechanism through which 287(g) programs affect attendance is unclear, although results for chronic absenteeism suggest that increases in episodic illness are not the cause (although the worsening of chronic health conditions could be). However, there are still multiple potential mechanisms. First, students may simply feel less motivated to attend school. Second, students may need to work more or assist their parents with childcare. Third, older students may be more likely to be at risk themselves for immigration enforcement.

Despite this increase in absences, I find no effect of 287(g) programs on achievement in either math or reading in elementary or middle school; I also find no effects on ninth grade test scores in English 1 or Algebra 1. In contrast, as previously noted, large worksite raids appear to have large negative effects on math and reading achievement for grade 3 through 8 students in the same vicinity (Zuniga, 2018). Although I find effects on attendance, I find an increase in absences of only a day per year, a smaller effect than increases in absences following raids (Kirksey, 2020).

Because school attendance is mandatory, any effect I detect on student attendance is likely larger for non-mandatory educational programming. Under conditions of increased immigration enforcement, students in families with unauthorized members are less likely to attend after-school programs or enroll in early childhood education programs (Santillano et al., 2020). One limitation is that North Carolina does not consistently collect data on attendance for children in grades PK-2. Future work should focus on the effects of different immigration enforcement policies on non-mandatory educational programming.

CONCLUSION

During the second term of the Obama administration, immigration enforcement activity deescalated, as the administration put a stronger focus on identifying and removing serious criminal offenders. In contrast, the Trump administration adopted a universal approach to immigration enforcement, with the goal to identify and remove as many unauthorized immigrants as possible, regardless of criminal status. From 2017 to 2018, the number of active 287(g) agreements grew from 30 to 76, the most in the history of the program (Capps et al., 2018). The Biden administration has again reversed course and proposed an array of more immigrant-friendly policies, including a pathway to citizenship for unauthorized immigrants residing in the United States. However, the country remains divided on many questions around immigration policy, including on how to treat unauthorized immigrants living in the U.S. interior.

My results add to a growing body of literature suggesting that harsh immigration enforcement policies have negative consequences for the children of unauthorized immigrants. In this specific case, school attendance is necessary for other positive schooling outcomes, and chronic absenteeism is linked particularly to increases in school dropout rates. Reducing overall levels of educational attainment will negatively impact the U.S. economy, as well as reduce the likelihood of political engagement.

In Plyler v. Doe, the Supreme Court overturned a Texas law withholding state funds for the education of unauthorized immigrant children and authorizing school districts to disenroll unauthorized immigrant children. In the opinion for the majority, Justice Brennan wrote, "It is difficult to understand precisely what the State hopes to achieve by promoting the creation and perpetuation of a subclass of illiterates within our boundaries, surely adding to the problems and costs of unemployment, welfare, and crime" (Plyler v Doe, 1982, p.230). Although immigration enforcement is a more subtle form of administrative burden than laws restricting access to education based on immigration status, it also has negative spillover effects on access to education for both children who are unauthorized immigrants themselves and for the larger population of children of unauthorized immigrants. When considering the full costs of immigration enforcement, policymakers should consider Justice Brennan's implied question from nearly fifty years ago: Are the costs associated with leading multiple generations of individuals to disengage from U.S. society really worth the benefits?

REFERENCES

Alsan, M. and Yang, C. (2018). Fear and the safety net: Evidence from Secure Communities. Working Paper 24731, National Bureau of Economic Research.

Amuedo-Dorantes, C. and Lopez, M. J. (2015). Falling through the cracks? Grade retention and school dropout among children of likely unauthorized immigrants. *The American Economic Review*, 105(5):598–603.

Arriaga, F. (2017). Relationships between the public and crimmigration entities in North Carolina: A 287(g) program focus. *Sociology of Race and Ethnicity*, 3(3):417–431.

Aucejo, E. M. and Romano, T. F. (2016). Assessing the effect of school days and absences on test score performance. *Economics of Education Review*, 55:70–87.

Balfanz, R. and Byrnes, V. (2012). Chronic absenteeism: Summarizing what we know from nationally available data. Baltimore, MD: Johns Hopkins University Center for Social Organization of Schools.

Balfanz, R., Herzog, L., and Iver, D. J. M. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: Early identification and effective interventions. *Educational Psychologist*, 42(4):223–235.

Bellows, L. (2019). Immigration enforcement and student achievement in the wake of Secure Communities. *AERA Open*, 5(4).

Capps, R., Chishti, M., Gelatt, J., Bolter, J., and Ruiz Soto, A. G. (2018). Revving up the deportation machinery: Enforcement and pushback under Trump. Washington, D.C.: Migration Policy Institute.

Capps, R., Rosenblum, M. R., Rodriguez, C., and Chishti, M. (2011). Delegation and divergence: A study of 287 (g) state and local immigration enforcement. Washington, D.C.: Migration Policy Institute.

Chaudry, A., Capps, R., Pedroza, J., Castaneda, R., Santos, R., and Scott, M. (2010). Facing our future: Children in the aftermath of immigration enforcement. Washington, D.C.: Urban Institute.

Cook, P. J., Dodge, K. A., Gifford, E. J., and Schulting, A. B. (2017). A new program to prevent primary school absenteeism: Results of a pilot study in five schools. *Children and Youth Services Review*, 82:262–270.

Dee, T. S. and Murphy, M. (2019). Vanished classmates: The effects of local immigration enforcement on school enrollment. *American Educational Research Journal*, 57(2):694–727.

Dhingra, R., Kilborn, M., and Woldemikael, O. (2021). Immigration policies and access to the justice system: The effect of enforcement escalations on undocumented immigrants and their communities. *Political Behavior*: 1–29.

East, C. N., Hines, A. L., Luck, P., Mansour, H., and Velasquez, A. (2018). The labor market effects of immigration enforcement. Discussion Paper 11486, IZA.

Ehrlich, S. B., Gwynne, J. A., and Allensworth, E. M. (2018). Pre-kindergarten attendance matters: Early chronic absence patterns and relationships to learning outcomes. *Early Childhood Research Quarterly*, 44:136–151.

Fredricks, J. A., Blumenfeld, P. C., and Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, 74(1):59–109.

Gershenson, S., Jacknowitz, A., and Brannegan, A. (2017). Are student absences worth the worry in U.S. primary schools? *Education Finance and Policy*, 12(2):1–47.

Gershenson, S., McBean, J. R., and Tran, L. (2019). The distributional impacts of student absences on academic achievement. In Gottfried, M. A. and Hutt, E. L., Editors, *Absent from School* (pp. 101–120). Harvard Education Press.

Goodman, J. (2014). Flaking out: Student absences and snow days as disruptions of instructional time. Working Paper 20221, National Bureau of Economic Research.

Gottfried, M. A. (2011). The detrimental effects of missing school: Evidence from urban siblings. *American Journal of Education*, 117(2):147–182.

Hagan, J., Castro, B., and Rodriguez, N. (2010). The effects of U.S. deportation policies on immigrant families and communities: Cross–border perspectives. *North Carolina Law Review*, 88:1799–1824.

Heinrich, C. J. (2018). "A thousand petty fortresses": Administrative burden in U.S. immigration policies and its consequences. *Journal of Policy Analysis and Management*, 37(2):211–239.

Kirksey, J. J. (2020). Weeks after the raid: The immediate and sustained changes in student attendance rates following immigration arrests. Available from EdArXiv.

Koball, H., Capps, R., Perreira, K., Campetella, A., Hooker, S., Pedroza, J. M., Monson, W., and Huerta, S. (2015). Health and social service needs of U.S.-citizen children with detained or deported immigrant parents. The Urban Institute, Washington, D.C.

Kohli, A., Markowitz, P. L., and Chavez, L. (2011). Secure Communities by the numbers: An analysis of demographics and due process. Berkeley, CA: Chief Justice Earl Warren Institute on Law and Social Policy.

Liu, J., Lee, M., and Gershenson, S. (2019). The short-and long-run impacts of secondary school absences. Discussion Paper 12613, IZA.

Martinez, I. (2016). Supporting two households: Unaccompanied Mexican minors and their absences from U.S. schools. *Journal of Latinos and Education*, 15(3):229–243.

Nguyen, M. T. and Gill, H. (2015). Interior immigration enforcement: The impacts of expanding local law enforcement authority. *Urban Studies*: 1–22.

Nguyen, M. T. and Gill, H. E. (2010). The 287 (g) program: The costs and consequences of local immigration enforcement in North Carolina communities. Latino Migration Project.

Olson, L. M., Tang, S. S., and Newacheck, P. W. (2005). Children in the United States with discontinuous health insurance coverage. *New England Journal of Medicine*, 353(4):382–391.

Pedroza, J. (2018). Where immigration enforcement agreements stalled: The location of local 287 (g) program applications and inquiries (2005-2012). Available from SocArXiv.

Potochnick, S., Chen, J.-H., and Perreira, K. (2016). Local-level immigration enforcement and food insecurity risk among Hispanic immigrant families with children: National-level evidence. *Journal of Immigrant and Minority Health*, 19(5):1–8.

Reardon, S. F. and Galindo, C. (2009). The Hispanic-white achievement gap in math and reading in the elementary grades. *American Educational Research Journal*, 46(3):853–891.

Rhodes, S. D., Mann, L., Simán, F. M., Song, E., Alonzo, J., Downs, M., Lawlor, E., Martinez, O., Sun, C. J., O'Brien, M. C., Reboussin, B. A., and Hall, M. A. (2015). The impact of local immigration enforcement policies on the health of immigrant Hispanics/Latinos in the United States. *American Journal of Public Health*, 105(2):329–337.

Roodman, D. M., MacKinnon, J. G., Nielsen, M. Ø., and Webb, M. (2019). Fast and wild: Bootstrap inference in Stata using boottest. *The Stata Journal*, 19(1):4–60.

Rosenblum, M. R. and Kandel, W. (2011). Interior immigration enforcement: Programs targeting criminal aliens. Washington, D.C.: Congressional Research Service.

Rosenblum, M. R. and Soto, A. G. R. (2015). An analysis of unauthorized immigrants in the United States by country and region of birth. Washington, D.C.: Migration Policy Institute.

Rugh, J. S. and Hall, M. (2016). Deporting the American dream: Immigration enforcement and Latino foreclosures. *Sociological Science*, 3:1053–1076.

Ryan, W., Evers, E., and Moore, D. A. (2018). False positive Poisson. Available from PsyArXiv.

Santillano, R., Potochnick, S., and Jenkins, J. (2020). Do immigration raids deter Head Start enrollment? *American Economic Association Papers and Proceedings*, 110:419–423.

Sattin-Bajaj, C. and Kirksey, J. J. (2019). Schools as sanctuaries? Examining the relationship between immigration enforcement and absenteeism rates for immigrant-origin children. In Gottfried, M. A. and Hutt, E. L., Editors, *Absent from School* (pp. 101–120). Harvard Education Press.

Schoeneberger, J. A. (2012). Longitudinal attendance patterns: Developing high school dropouts. *The Clearing House: A Journal of Educational Strategies, Issues and Ideas*, 85(1):7–14.

Skinner, R. (2010). The performance of 287(g) agreements. U.S. Department of Homeland Security.

Tome, R., Rangel, M. A., Gibson-Davis, C. M., and Bellows, L. (2021). Heightened immigration enforcement impacts US citizens' birth outcomes: Evidence from early ICE interventions in North Carolina. *PLOS ONE*, 16(2):1–15.

TRAC Immigration (2018). Tracking over 2 million ICE arrests: A first look. Transactional Records Access Clearinghouse (TRAC), Syracuse University. Retrieved from https://trac.syr.edu/immigration/reports/529/.

Vargas, E. D. (2015). Immigration enforcement and mixed-status families: The effects of risk of deportation on Medicaid use. *Children and Youth Services Review*, 57:83–89.

Vargas, E. D. and Pirog, M. A. (2016). Mixed-status families and WIC uptake: The effects of risk of deportation on program use. *Social Science Quarterly*, 97(3):555–572.

Wang, J. S.-H. and Kaushal, N. (2019). Health and mental health effects of local immigration enforcement. *International Migration Review*, 53(4):970–1001.

Watson, T. (2014). Inside the refrigerator: Immigration enforcement and chilling effects in Medicaid participation. *American Economic Journal: Economic Policy*, 6(3):313–338.

Wong, T. K. (2012). 287 (g) and the politics of interior immigration control in the United States: Explaining local cooperation with federal immigration authorities. *Journal of Ethnic and Migration Studies*, 38(5):737–756.

Zuniga, R. (2018). The chilling effect of ICE: An examination of student achievement following a large worksite raid. Annual conference of the Association for Education Finance and Policy, Portland, OR.

TABLES AND FIGURES

Table 1: 287(g) Programs in North Carolina Requested, by Application Status

Law Enforcement Agency	Date Requested	Date Signed	Application Status
Alamance County Sheriff's Office	8/21/2006	1/10/2007	Approved
Alexander County Sheriff's Office	2/9/2007		Denied
Buncombe County Sheriff's Office	8/23/2007		Denied
Bunswick County Sheriff's Office	6/4/2007		Denied
Cabarrus County Sheriff's Office	11/8/2006	8/2/2007	Approved
Carteret County Sheriff's Office	12/3/2007		Denied
Catawba County Sheriff's Office	10/16/2006		Denied
Columbus County Sheriff's Office	6/22/2007		Denied
Cumberland County Sheriff's Office	5/16/2007	6/25/2008	Approved
Duplin County Sheriff's Office	2/7/2007		Denied
Durham Police Department	1/25/2007	2/1/2008	Approved
Gaston County Sheriff's Office	2/3/2006	02/22/2007	Approved
Guilford County Sheriff's Office	3/21/2007	10/15/2009	Approved
Henderson County Sheriff's Office	4/9/2007	06/25/2008	Approved
Iredell County Sheriff's Office	2/23/2007		Denied
Lee County Sheriff's Office	3/15/2007		Denied
Lincoln Sheriff's Office	6/28/2007		Denied
Mecklenburg County Sheriff's Office	11/3/2005	02/27/2006	Approved
New Hanover County (Wilmington Police Department)	4/5/2007		Denied
Randolph County Sheriff's Office	5/10/2007		Withdrew
Stokes County Sheriff's Office	5/16/2007		Denied
Surry County Sheriff's Office	5/1/ 2007		Denied
Union County Sheriff's Office	4/17/2007		Denied
Wake County Sheriff's Office	11/28/2007	06/25/2008	Approved
Yadkin County Sheriff's Office	5/10/2007		Denied

Table 2: Demographic Information, by 287(g) Application and Approval Status

	Did Not Apply	Not Approved	Approved	Total
White, Never LEP	58.53%	72.02%	48.26%	57.02%
Hispanic, Ever LEP	4.74%	5.82%	5.92%	5.34%
Hispanic	6.38%	7.41%	8.51%	7.32%
White	58.81%	72.49%	48.78%	57.42%
Black	28.86%	15.50%	35.92%	29.23%
Asian-American*	1.25%	1.74%	3.41%	2.10%
American Indian*	2.37%	0.48%	0.50%	1.39%
Multiracial*	2.19%	2.26%	2.71%	2.39%
Female	49.17%	49.07%	49.20%	49.17%
Total Student-Year Observations	3,079,874	1,057,879	2,269,917	6,407,670
Total Unique Students	491,956	168,103	372,077	1,032,136

*I exclude Asian-American, American Indian, and multiracial students in all analyses.

Table 3: Descriptive Statistics on Absences, by 287(g) Application and Approval Status

	Did Not Apply	Not Approved	Approved	Total
Average Days Absent	8.03	7.34	7.82	7.84
Average Absence Rate	4.85%	4.41%	4.81%	4.76%
No Absences	10.68%	10.75%	11.34%	10.93%
Absent 1 or More Days	89.32%	89.25%	88.66%	89.07%
Absent 2 or More Days	81.49%	81.08%	80.01%	80.90%
Absent 3 or More Days	73.23%	72.30%	71.09%	72.32%
Absent 6 or More Days	50.42%	48.03%	47.71%	49.06%
Absent 10 or More Days	29.15%	26.08%	27.10%	27.92%
Absent 15 or More Days	14.70%	12.18%	13.86%	13.99%
Absent 20 or More Days	7.97%	6.24%	7.81%	7.63%
Absent 50 or More Days	0.77%	0.50%	0.93%	0.78%
Total Student-Year Observations	3,079,874	1,057,879	2,269,917	6,407,670
Total Unique Students	491,956	168,103	372,077	1,032,136

Table 4: Effect of 287(g) Programs on Absences, Difference-in-Differences Models

Variables	(1) Hispanic Students Classified Ever LEP	(2) Hispanic Students	(3) White Students Classified Never LEP	(4) White Students	(5) Black Students
Post (P)	-0.9969*	-0.8601*	0.2808	0.2804	0.1054
	(0.0731)	(0.0741)	(0.2683)	(0.2623)	(0.5826)
	[-1.8267, 0.0723]	[-1.5217, 0.0637]	[-0.1773, 0.9845]	[-0.1980, 0.9025]	[-0.2958, 0.6560]
A X P	1.0971***	0.9115***	-0.0706	-0.0696	0.0134
	(0.0020)	(0.0090)	(0.7327)	(0.7277)	(0.9650)
	[0.4408, 1.7110]	[0.3489, 1.4963]	[-0.4559, 0.3602]	[-0.4626, 0.4172]	[-0.5866, 0.5703]
Observations	203,473	271,744	1,855,102	1,871,741	979,169
R-squared	0.0427	0.0357	0.0055	0.0055	0.0207
Grade and Gender	Yes	Yes	Yes	Yes	Yes
Secure Communities	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes

P-values (in parentheses) and confidence intervals (in brackets) obtained through wild cluster bootstrap, with clustering at the county-level (999 replications)
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 5: Effect of 287(g) Programs on Absences, Difference-in-Difference-in-Differences Models

Variables	(1) Hispanic Ever LEP Compared to White Never LEP Students	(2) Hispanic Compared to White Students	(3) Black Compared to White Students
Treatment Group (T)	-1.0121***	-0.7208**	-0.5337
	(0.0060)	(0.0140)	(0.1431)
	[-1.7201, -0.3412]	[-1.3321, -0.1474]	[-1.3258, 0.1969]
Post (P)	0.2558	0.2326	0.1703
	(0.3924)	(0.4605)	(0.7207)
	[-0.3024, 0.9884]	[-0.3280, 0.9906]	[-0.5782, 1.2474]
T X A	1.6860***	1.4207**	0.9853
	(0.0070)	(0.0160)	(0.1592)
	[0.5286, 2.7566]	[0.2436, 2.4111]	[-0.4420, 2.2040]
T X P	-1.0450*	-0.8050	0.1395
	(0.0821)	(0.1542)	(0.8639)
	[-2.5162, 0.1273]	[-2.0494, 0.2694]	[-1.2939, 1.3729]
A X P	-0.0475	-0.0584	-0.1062
	(0.8038)	(0.7467)	(0.5616)
	[-0.4021, 0.3548]	[-0.4130, 0.3344]	[-0.4648, 0.3186]
T X A X P	0.9827**	0.9002***	0.1258
	(0.0130)	(0.0070)	(0.5966)
	[0.3042, 1.6226]	[0.2928, 1.4241]	[-0.3948, 0.6006]
Observations	2,058,575	2,143,485	2,850,910
R-squared	0.0117	0.0114	0.0116
Grade and Gender	Yes	Yes	Yes
Secure Communities	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
T X Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

P-values (in parentheses) and confidence intervals (in brackets) obtained through wild cluster bootstrap, with clustering at the county-level (999 replications)
*** p<0.01, ** p<0.05, * p<0.10

Figure 1: Event Study for Effects on Absences, Comparing Hispanic Students Ever Classified as LEP to White Students Never Classified as LEP

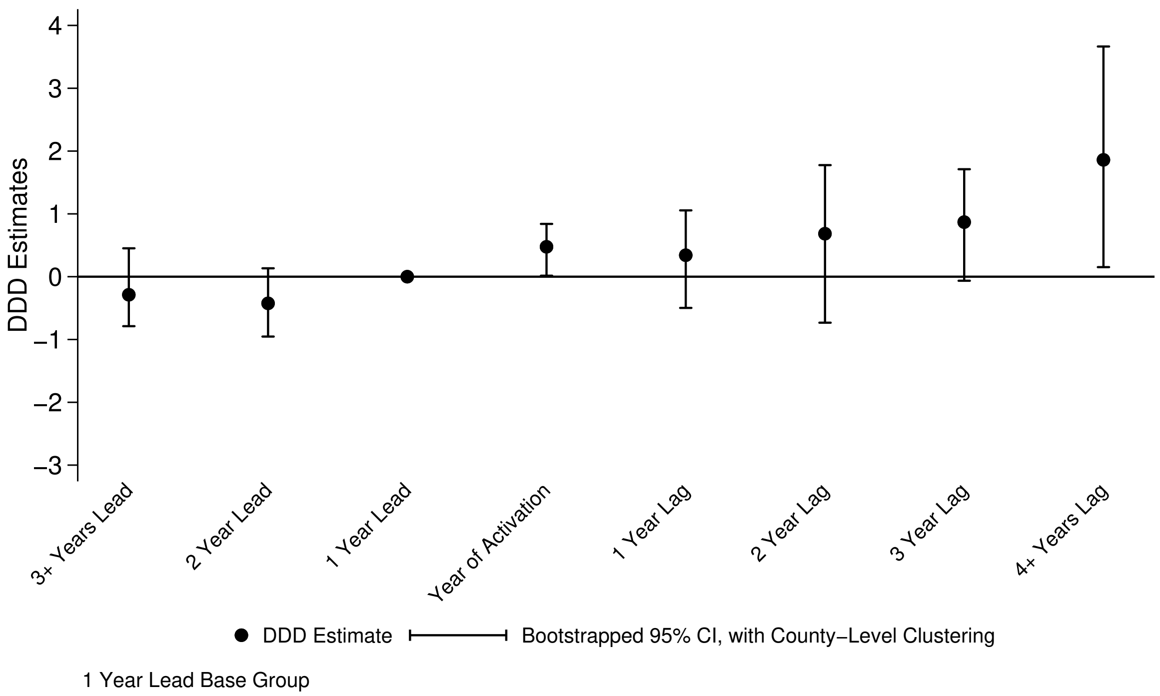


Table 6: Effect of 287(g) Programs on Absences, Negative Binomial Models

Variables	(1) Hispanic Ever LEP Compared to White Never LEP Students	(2) Hispanic Compared to White Students
Treatment Group (T)	-0.1533***	-0.1095***
	(0.0000)	(0.0000)
Post (P)	0.0272	0.0248
	(0.4000)	(0.3700)
T X A	0.2418***	0.2040***
	(0.0000)	(0.0000)
T X P	-0.0850	-0.0690
	(0.2200)	(0.3200)
A X P	-0.0082	-0.0092
	(0.7300)	(0.6700)
T X A X P	0.0680**	0.0734***
	(0.0400)	(0.0000)
Observations	2,058,575	2,143,485
R-squared	0.0050	0.0049
Grade and Gender	Yes	Yes
Secure Communities	Yes	Yes
Year FE	Yes	Yes
T X Year FE	Yes	Yes
County FE	Yes	Yes

P-values (in parentheses) obtained through score cluster bootstrap, with clustering at the county-level (100 replications)
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 7: Effect of 287(g) Programs on Absence Rate

Variables	(1) Hispanic Ever LEP Compared to White Never LEP Students	(2) Hispanic Compared to White Students
Treatment Group (T)	-0.0044**	-0.0027
	(0.0260)	(0.1401)
	[-0.0087, -0.0005]	[-0.0065, 0.0010]
Post (P)	0.0015	0.0013
	(0.3794)	(0.4675)
	[-0.0019, 0.0058]	[-0.0021, 0.0061]
T X A	0.0115***	0.0096**
	(0.0040)	(0.0130)
	[0.0039, 0.0188]	[0.0021, 0.0164]
T X P	-0.0060	-0.0045
	(0.1081)	(0.2012)
	[-0.0151, 0.0013]	[-0.0131, 0.0022]
A X P	-0.0004	-0.0005
	(0.7207)	(0.6637)
	[-0.0025, 0.0021]	[-0.0026, 0.0019]
T X A X P	0.0054**	0.0050***
	(0.0130)	(0.0040)
	[0.0012, 0.0090]	[0.0017, 0.0085]
Observations	2,058,575	2,143,485
R-squared	0.0118	0.0114
Grade and Gender	Yes	Yes
Secure Communities	Yes	Yes
Year FE	Yes	Yes
T X Year FE	Yes	Yes
County FE	Yes	Yes

P-values (in parentheses) and confidence intervals (in brackets) obtained through wild cluster bootstrap, with clustering at the county-level (999 replications)
*** p<0.01, ** p<0.05, * p<0.10

Table 8: Robustness Checks for Difference-in-Difference-in-Differences Estimates

Robustness Check	DDD Estimate	95% CI	Obs.
Main Models	0.9827***	[0.2916, 1.5996]	2,058,575
Varying Control Variables			
No Controls	0.6424**	[0.0329, 1.2361]	2,058,575
Controls for Gender, Grade, Year, County, and SC	0.6969**	[0.1334, 1.2042]	2,058,575
Interacting All Controls with Treatment Group	1.1677***	[0.4034, 1.8982]	2,058,575
Adding Grade by County and Grade by Year FE	0.7650**	[0.1920, 1.2986]	2,058,575
Varying Control Group			
Using Black Never LEP Students	0.8810***	[0.3417, 1.4716]	1,171,451
Using All Non-Hispanic and Never LEP Students	0.7169**	[0.1806, 1.2119]	3,183,045
Varying Sampling Decisions			
Excluding 2013	1.0392**	[0.2911, 1.7269]	1,980,923
Excluding Mobile Students	1.2250***	[0.4066, 1.9836]	1,881,449
2005 County	1.2680***	[0.5272, 1.9972]	1,871,201

Confidence intervals obtained through wild cluster bootstrap, with clustering at the county-level (999 replications)
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Figure 2: Effect of 287(g) Programs on Absences, Dropping Counties Iteratively

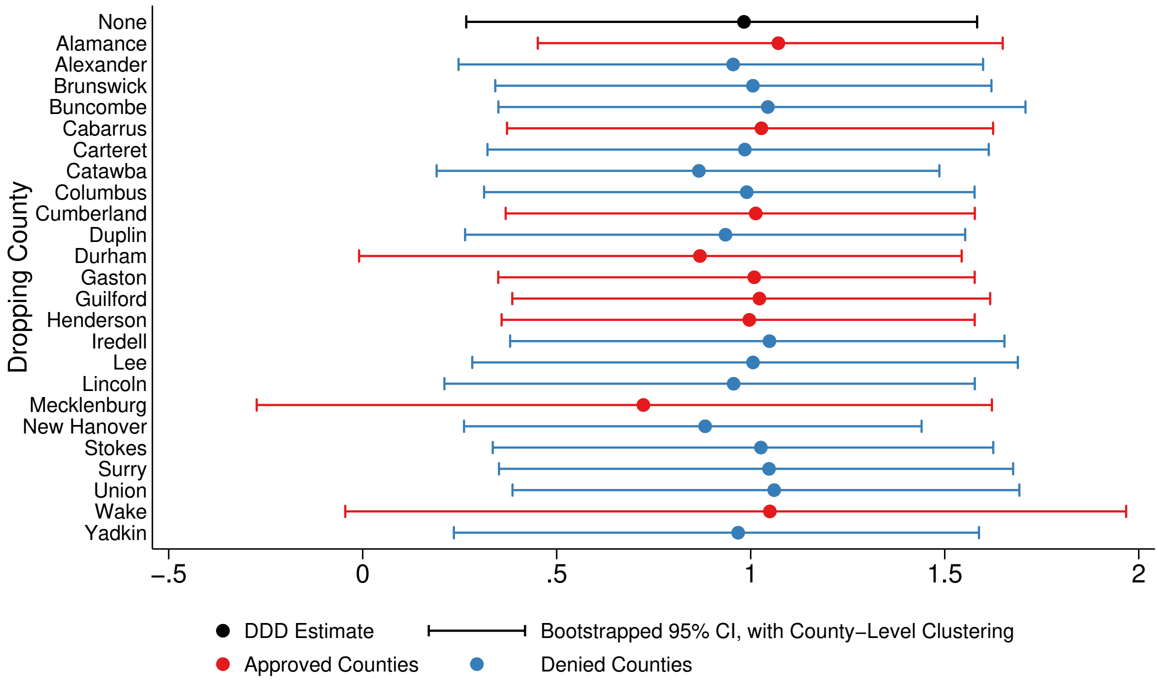
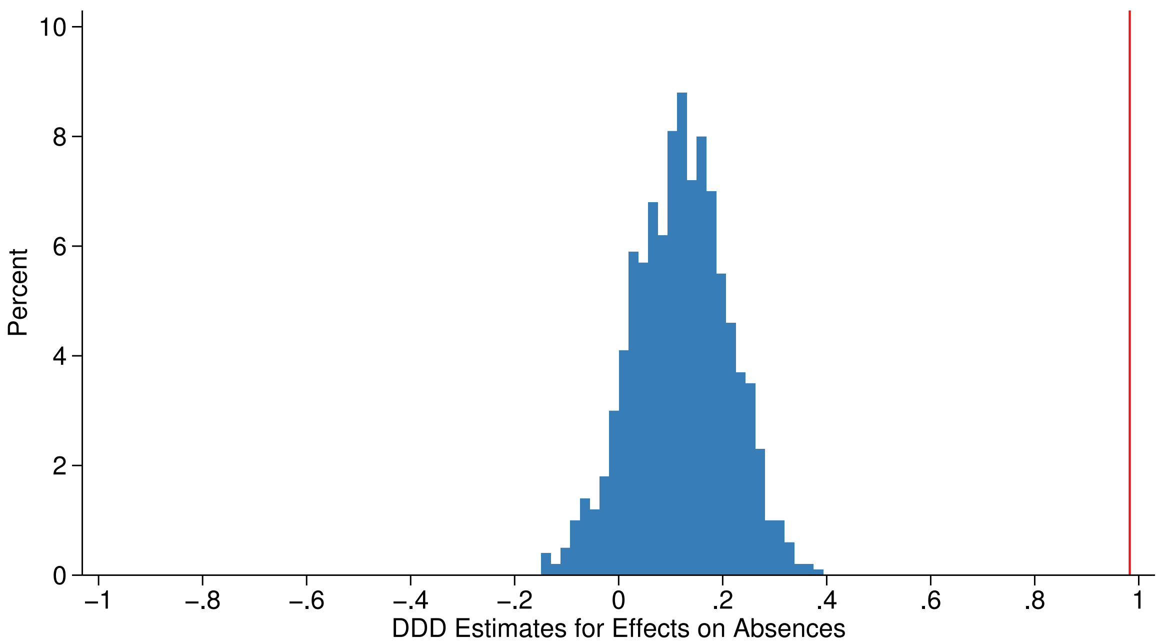
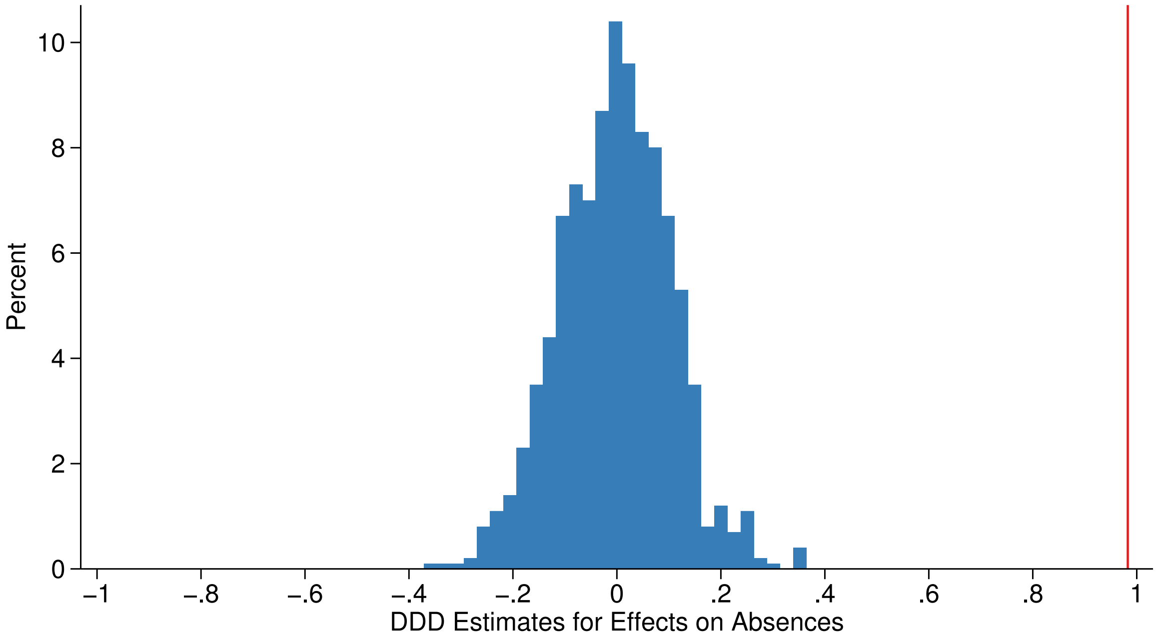


Figure 3: Randomly Assigning Students to Treatment Group



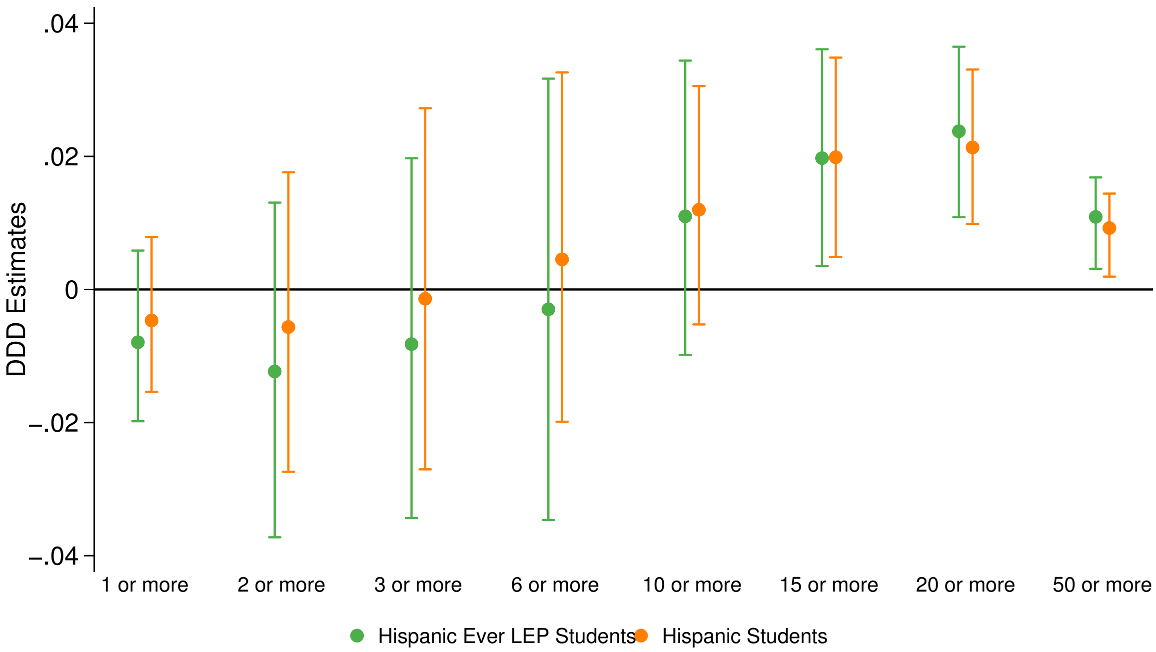
Results from 1000 simulations randomly assigning students to treatment or control group.
DDD estimate from main model shown in red for comparison.

Figure 4: Randomly Assigning Hispanic Ever LEP and White Never LEP Students to Counties



Results from 1000 simulations randomly assigning students to counties.
DDD estimate from main model shown in red for comparison.

Figure 5: Effects of 287(g) Programs on a Series of Absence Indicators



Includes bootstrapped 95% confidence intervals, with county−level clustering.

Table 9: Effect of 287(g) Programs on Achievement in Grades 3-8

Variables	(1) Math	(2) Reading
Hispanic Ever LEP Students (T)	-0.5169***	-0.6501***
	(0.0000)	(0.0000)
	[-0.6301, -0.4111]	[-0.7803, -0.5417]
Post (P)	0.0311	-0.0071
	(0.1812)	(0.5385)
	[-0.0225, 0.0737]	[-0.0317, 0.0172]
T X A	-0.3647***	-0.3349***
	(0.0030)	(0.0040)
	[-0.5700, -0.1396]	[-0.5274, -0.1137]
T X P	-0.0162	-0.0052
	(0.8498)	(0.9419)
	[-0.1515, 0.1624]	[-0.1378, 0.1740]
A X P	-0.0742**	-0.0259
	(0.0280)	(0.2583)
	[-0.1351, -0.0119]	[-0.0690, 0.0216]
T X A X P	0.0298	0.0309
	(0.6296)	(0.4535)
	[-0.0931, 0.1553]	[-0.0583, 0.1156]
Observations	893,307	890,070
R-squared	0.0662	0.0940
Grade and Gender	Yes	Yes
Secure Communities	Yes	Yes
Year FE	Yes	Yes
T X Year FE	Yes	Yes
County FE	Yes	Yes

P-values (in parentheses) and confidence intervals (in brackets) obtained through wild cluster bootstrap, with clustering at the county-level (999 replications)
*** p<0.01, ** p<0.05, * p<0.10

Table 10: Effect of 287(g) Programs on Achievement in Grade 9

Variables	(1) Algebra I	(2) English I
Hispanic Ever LEP Students (T)	-0.4961***	-0.9682***
	(0.0000)	(0.0000)
	[-0.6851, -0.2813]	[-1.1496, -0.7936]
Post (P)	-0.1754	-0.0166
	(0.4044)	(0.4214)
	[-0.5196, 0.1206]	[-0.0642, 0.0302]
T X A	-0.2793**	-0.4361***
	(0.0360)	(0.0030)
	[-0.5085, -0.0192]	[-0.6654, -0.1810]
T X P	-0.0695	-0.0340
	(0.6476)	(0.7818)
	[-0.4347, 0.2873]	[-0.2616, 0.2877]
A X P	0.1313	-0.0101
	(0.2693)	(0.7097)
	[-0.0925, 0.4117]	[-0.0658, 0.0409]
T X A X P	0.0964	0.1086
	(0.3313)	(0.1041)
	[-0.1099, 0.2815]	[-0.0275, 0.2452]
Observations	141,996	253,246
R-squared	0.0252	0.1072
Grade and Gender	Yes	Yes
Secure Communities	Yes	Yes
Year FE	Yes	Yes
T X Year FE	Yes	Yes
County FE	Yes	Yes

P-values (in parentheses) and confidence intervals (in brackets) obtained through wild cluster bootstrap, with clustering at the county-level (999 replications)
*** p<0.01, ** p<0.05, * p<0.10