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The Effects of Exposure to Community Gun-Violence on the High School Dropout Rates of California Public School Students

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The Effects of Exposure to Community Gun-Violence on the High School Dropout Rates of California Public School Students

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Sociology

by

Ravaris LaDale Moore

2018

ABSTRACT OF THE DISSERTATION

The Effects of Exposure to Community Gun-Violence

on the High School Dropout Rates of

California Public School Students

by

Ravaris LaDale Moore

Doctor of Philosophy in Sociology

University of California, Los Angeles, 2018

Professor Jennie Elizabeth Brand, Chair

I constructed a unique set of data from over 300 California law enforcement agencies, in conjunction with large-scale education microdata covering the high school outcomes of over 3.8 million California ninth-graders from the classes of 2003 to 2014 to examine the extent to which estimated effects of violence exposure, coupled with significant differences in violence exposure rates, contribute to population-level differences in educational attainment. I find evidence for two important processes linking violence exposure and educational attainment. [1] High school dropout rates significantly respond to gun violence only if exposure exceeds a certain threshold. This threshold rule, coupled with differential exposure rates across student subgroups, leads to significant exposure effects on the dropout rates of black and Hispanic students, and no significant effects for white and Asian students. [2] Learning loss does not appear to be the

primary mediator of exposure effects on dropout rates. This suggests that dropouts in high violence areas often have the academic capacity for educational attainment beyond realized levels.

The dissertation of Ravaris LaDale Moore is approved.

Robert Denis Mare

Patrick Clement Heuveline

Moshe Buchinsky

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University of California, Los Angeles

2018

To my wife, Letecia,

thank you for supporting my pursuit of the work that I love.

To my parents, Alfred and Bobbie Moore, and my brother, Starcy Moore,

thank you for a lifetime of support and encouragement.

To my son, Elias, and my daughters, Geneva and Estelle,

may you also find success pursuing work that you love.

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1. INTRODUCTION AND OVERVIEW

1.1. Introduction

A great deal of research has found that violence exposure and victimization have well documented psychological, physiological, and behavioral effects on children. Violence exposure is associated with the onset of post-traumatic stress disorder symptomology (PTSD) (Berman et al. 1996; Berton and Stabb 1996), depression (Moses 1999; Freeman, Mokros, and Poznanski 1993), and anxiety (Pynoos 1994; Hill et al. 1996)). There is evidence of nightmares and other anxiety related sleep disturbances (Pynoos 1994). Children report feeling unsafe, "jumpy", and "scared" (Richters and Martinez 1993; Osofsky et al 1993). Young children are less likely to explore their environment (Osofsky and Fenechel 1994), and may have difficulty paying attention or concentrating due to intrusive thoughts (Pynoos 1994). Among young children, regression in developmental achievements such as toileting and language is common (Drell et al. 1993). There is also evidence of cumulative effects of trauma (Cummings et al. 1994; Cummings and Zahn-Waxler 1992), suggesting that traumatic events early in childhood may compound the negative effects of later life difficulty. In adolescence, violence exposure is associated with greater risks of running away from home, attempting suicide, and encountering the criminal justice system (Haynie 2009). Violence also affects a parent's ability to protect their child. Parents who are living with violence frequently express feelings of helplessness and frustration due to an inability to safeguard their children (Osofsky 1995 ; Garbarino et al. 1992; Lorion and Saltzman 1993; Osofsky et al 1993; Richters and Martinez 1993).

All of these effects offer clear mechanisms and pathways that may mediate the estimated effects of exposure and victimization on the education, and adult outcomes, of children. There is evidence of short-term (Sharkey 2010) exposure effects that lower exam performance in the weeks that immediately follow an incident, as well as cumulative effects (Burdick-Will 2016) of violence exposure due to learning losses over time. Beyond test score effects, violence exposure and victimization can undermine one's fundamental need to feel safe, which must be met before prioritizing higher needs, such as education (Maslow1954). In agreement, MacMillan and Hagan (2004, pp. 127) argue that, "…victimization diminishes educational self-efficacy, which subsequently undermines educational performance and attainment".

Evidence of negative causal effects of violence exposure on child outcomes is further supported by experimental evidence showing gains from moving to safer neighborhoods. Sharkey and Sampson (2010) found that Chicago residents who moved to safer neighborhoods beyond the city were less likely to become violent offenders. Positive effects were mediated by increased school quality, the change in neighborhood racial and economic makeup, and increased feelings of control over a new and safer environment. Also, evidence from a reanalysis of Moving to Opportunity (MTO) intervention data highlighted larger relocation effects for kids who moved out of neighborhoods in the study's most violent cities (Baltimore and Chicago). Data shows an inverse correlation between beat-level crime, and reading and math test scores (Burdick-Will et al. 2011), as well as psychological benefits for a parents and children of living in safer neighborhoods (Katz et al. 2001; Goering and Feins 2003). Violence exposure is thus viewed as a key causal pathway linking neighborhood context, and individual behavioral and health outcomes (Galster 2012).

The literature referenced above offers clear evidence of psychological, physiological, and behavioral effects of violence exposure on kids, and resulting indirect effects on a range of educational outcomes. Evidence in these studies was generally derived from microdata samples among subpopulations of children who are exposed to elevated violence levels. This work shows significant effects among the sample of children in each study who are exposed to abnormally high levels of violence. However, less is known about the implications of these effects across a population of children with varied levels of exposure. This work takes a logical next step by considering whether the education effects identified above are reflective of significant gun-violence exposure effects at the population level.

This work aims to understand how gun-violence exposure impacts the educational outcomes of a population. I construct a unique large dataset and employ quantitative analyses to understand the population-level effects of gun-violence exposure. I also exploit a policy change over the sample period that aids in discerning whether gun-violence exposure suppresses educational attainment by eroding the gains to learning and limiting cognitive growth and performance.

1.2. Overview of Chapters

Chapter two investigates the bivariate relationship between gun-violence and exposure and the dropout rates of California public high school students. The chapter begins with detail on the construction of a unique set of data from over 300 California law enforcement agencies, in conjunction with large-scale education microdata covering the high school outcomes of over 3.8 million California ninth-graders from the classes of 2003 to 2014. I introduce the main independent and dependent variables (gun-violence exposure and high school dropout rates, respectively), and show trends in each. From here I employ a fixed effects model to determine whether dropout rates among student subgroups of a fixed race/ethnicity classification who attend the same school at different points in time are significantly associated with gun-violence exposure levels experienced by the cohort. Results show that cohorts who experience higher gun-violence exposure levels register high dropout rates. Results also offer evidence that dropout effects are larger for the black and Hispanic student subgroups, and smaller among white and Asian student subgroups.

Chapter three examines the extent to which estimated effects of violence exposure, coupled with significant differences in violence exposure rates, contribute to population-level differences in educational attainment. I find that gun-violence exposure rates have significant effects on the dropout rates of California's Black and Hispanic students, but no significant effect for White and Asian students. This is driven by a non-linearity in the effects of gun-violence exposure, coupled with differences in the distribution of exposure intensity across student subgroups. Dropout rates significantly respond to gun-violence exposure only when exposure levels exceed a certain threshold. Differential dropout effects arise because Black and Hispanic student are more densely represented above this exposure threshold than White and Asian students. Gun-violence exposure effects on high school completion are not primarily mediated by learning loss, suggesting that dropouts have the cognitive capability to excel beyond their realized levels of educational attainment. Estimates suggest that the Black-White (Hispanic-White) difference in gun-violence exposure levels is associated with 16 (19) percent of the Black-White (Hispanic-White) difference in California dropout rates over the last decade.

Chapter four investigates whether cumulative learning loss leads to cognitive performance constraints that mediate the elevated dropout rates of black and Hispanic youth who were exposed to elevated levels of gun-violence. Results suggest that cognitive performance constraints from learning loss are not closely tied to higher dropout rates for black and Hispanic youth. After a policy change that raised the cognitive requirements for high school completion, the dropout rates of Black and Hispanic students in areas with higher levels of gun-violence showed no differential short-term response to the policy relative to the same groups in low gun-violence exposure areas. The absence of a differential response among black and Hispanic students in high crime areas suggests that there was not a significant mass of students near the previous cognitive threshold for high school graduation. Thus, cognitive constraints from learning loss are likely not a limiting factor mediating the elevated black and Hispanic dropout rates in high gun-violence exposure areas. The dropout rates of White and Asian students in the same areas, however, had a short-term differential increase after the policy change relative to the same groups in low gun-violence exposure areas. This suggests that cognitive performance constraints from learning loss may affect high school completion for these groups. The differential responses of black and Hispanic versus white and Asian students are likely due to differences in other factors that affect academic success, and lead low performing black and Hispanic youth to leave school before cognitive performance constraints become limiting.

Chapter five offers a summary of results, and discusses directions for further research.

1.3. Organization of the Dissertation

This dissertation is organized as one cohesive work. At present, the substantive chapters are not formatted as stand-alone articles. I made this decision to avoid repeating the details of the data work multiple times. Chapter 2 describes data sources, dataset construction, variable construction, assumptions and known limitations of the data. These data are employed in all substantive chapters. Additional details about the data, such as new sample restrictions and control measures, are mentioned throughout the work as needed. Along all other dimensions beyond data (i.e. contribution, theory, analysis, and results), the chapters are written to stand alone. The data component will be added to each chapter with minor edits for journal submission.

2. The Bivariate Relationship Between Gun-Violence Exposure and High School Dropout Rates

2.1 Introduction

It is well-documented that gun-violence exposure is associated with a range of negative schooling outcomes (Sharkey 2010; Burdick-Will 2016; Burdick-Will et al. 2011; Chen 2013) including elevated dropout rates (Fry et al. 2018; Boynton et al. 2013). Furthermore, there is evidence that the effect of exposure depends in part on the intensity of exposure which suggests a presence of effect heterogeneity. To the best of my knowledge we have yet to discern whether the effects identified in high exposure subpopulations translate into significant effects across the full student population.

This chapter aims to characterize the population level bivariate relationship between gun-violence exposure and high school dropout rates. I employ data data that covers the full population of California public high school students from the graduating classes of 2003 through 2014. Relative to smaller data samples, this statewide extract offer the advantage of including the outcomes of all students instead of restricting to a subsample that experienced extreme exposure levels. This facilitates an assessment of whether gun-violence exposure significantly affects the average outcomes of all students.

This question is important for several reasons. The effects of gun-violence are often conceptualized only from the standpoint of those who are directly involved in a particular incident. Beyond the physical, emotional, and economic toll of victimization, there are also significant measurable effects of indirect exposure that are rarely mentioned in discourse on gun-violence. Indirect violence exposure can yield psychological, physiological, and emotional responses in children. These may translate into poorer schooling outcomes, which have implications for a range of individual outcomes across the life course including labor market outcomes, family formation decisions, and health outcomes. There are also significant fiscal implications associated with eroding early education success. Specifically, increased high school dropout rates have clear implications for future employment rates, wage expectations, and levels of taxable incomes. This work aims to discern whether gun-violence exposure levels are associated with measurable changes in the overall state dropout rate, suggesting the possibility of sizeable indirect fiscal gun-violence effects.

The chapter proceeds as follows. I start with a presentation of the data sources and the approach employed to merge multiple data sources into an analysis file that fits the needs of this study. Next, I briefly analyze the univariate trends in gun-violence exposure and high school dropout rates, which are the independent and dependent variables of interest. Afterwards, I explore the bivariate relationship between these measures and assess what patterns begin to emerge. I pursue a bivariate analyses directed towards characterizing differences in the effects of gun-violence exposure on the dropout rates of student subgroups.

2.2 Data and Measures

This chapter explains the construction of a micro-level dataset that facilitates a study of the relationship between gun-violence exposure and student outcomes across the state of California. I construct a dataset that incorporates data from all police and sheriff agencies in the state of California with data on population density to construct a measure of gun-violence exposure rates. This independent measure is related to dropout rate measure that incorporates the outcomes of all California public high school students from the classes of 2003 to 2014. Additional control measures are incorporated from the American Community Survey.

The sections below describe individual data sources, key variable constructs, assumptions imposed on the data, and the process through which the various datasets were joined. From here I look at descriptive statistics, trends over time in the independent (gun-violence exposure) and dependent (high school dropout rates) variables, and the bivariate relationship between the two.

2.2.1 Education Data

I employ education data that was collected and compiled by the California Department of Education (CDE). These data describe the performance of all ninth-graders who would have graduated from a California public high school between the years of 2003 and 2014, assuming a typical four-year high school plan. After restricting to observations with valid data for outcomes, gun-violence measures, and control variables, the data contain 280 California school districts, covering 756 California schools, and roughly 3.9 million[1] ninth-graders within the window of observation.

This work is primarily interested in understanding effects of gun-violence exposure on high school dropout rates. These data report grade-specific enrollment and dropout counts for grades 9 through 12. I divide grade-specific dropout counts by grade-specific enrollment counts to calculate grade-specific dropout rates. These grade-specific rates are used to calculate cohort-level dropout rates, d_{cohort}, according to:

1 There are 3,877,529 students enrolled in grade 9 between the years 2000 and 2015 among the subset of observations that have valid dropout and CAHSEE data. Enrollment counts were taken at the beginning of each school year on a day in early October known as, “information day”.

$$d_{cohort} = 100 \cdot \sum_{g=9}^{12} \frac{d_g}{1-d_g} \cdot \left[\prod_{k=0}^{g} (1-d_k)\right]$$

This four-year calculation is equivalent to the "Four-year derived Rate Formula" employed by the CDE.

Education data are observed at the $year \times school \times race \times grade$ level of observation. This means that I do not observe outcomes for individual students. However, I do observe the group level outcomes for all students in a designated racial group and grade at a chosen high school in a given year. For this reason, I do not observe the heterogeneity in outcomes between students in the same the $year \times school \times race \times grade$ designated group. However, I do observe differences in student outcomes and control measures between student groups. Since the treatment of interest (exposure to gun-violence) conceptually occurs at the $year \times school$ level, the loss of intragroup variance does not sacrifice any variance component that is correlated with the treatment. Thus, the remaining between group variance is sufficient for identifying the effect of interest.

2.2.2 Gun-Violence Data

Data on the gun-violence were collected and provided by the California Office of the Attorney General. These data list counts of specific classes of crimes at the agency level for all law enforcement agencies in the state of California. I only employ data from local police and county sheriff's offices as they are most likely to respond to gun-related crimes of interest to this research[2]. This leaves data from 314 California local law enforcement agencies.

The analysis focusses on three types of firearm related events: (1) Firearm related robbery; (2) Firearm related assault, and (3) Homicide. Homicide totals include both firearm related homicides, and those from other causes. These data do not allow isolating firearm related homicides. The CDC estimates that 69% of murders are firearm related (CDC 2014A). For this reason, I use counts of all homicides as an instrument to gauge the effect of gun-related homicide with the implicit assumption that the proportion of gun-related homicides is fairly constant over the sample period.

Incident counts are translated into incident risk rates per 100,000 residents for the purpose of analysis. I employ agency level population estimates from the 2012 Law Enforcement Agency Identifier Crosswalk (United States Department of Justice 2012), with an annual population growth rate estimate for California of 0.864% (United States Census Bureau 2016)[3]. With these data, I estimate incident counts per 100,000 individuals according to:

$$e_{ti}^{j} = 100{,}000 \cdot \left[\frac{\bar{e}_{it}^{j}}{\left(\frac{N_i}{1.00864^{(2012-t)}} \right)} \right].$$

e_{ti}^{j} denotes gun-related events per 100,000 individuals of type j, in year t, corresponding to law enforcement agency i. $\bar{e}$ denotes the total number events, and N_i is the year 2012 population estimate in locality i. This formula estimates events per 100,000 in a way that adjusts for

2 I omit reports from the California Highway Patrol, campus police agencies, the California Department of Parks and Recreation, hospital police, rail road and transit police, and other agencies with very specific jurisdictions that would not typically investigate shootings.

3 The Census Bureau reports a 5.4% population growth rate over 6.25 years in the state of California from April 1, 2010 to July 1, 2016. This equates to an average annual statewide population growth rate of 0.864%.

population growth over the 11 year time span of the data. This avoids systematic error in the violence measures in the earlier years of the study. Unfortunately, it does not account for heterogeneity in growth rates between California localities. I apply the state-level growth rate to all counties as a feasible alternative to using the true local growth rates, which are presently unavailable.

These data capture the variance in exposure across California localities, but cannot capture the variance in exposure within localities. Student subgroups from the same high school class will have identical exposure measures, but there is a likely systematic difference in the realized exposure levels of various student subgroups within a class. These differences are due in part to non-random sorting into neighborhoods, which systematically leaves certain student subgroups closer to violent occurrences. Sensitivity analysis will investigate the extent to which within locality variation in exposure contributes to differentials in estimates of group level effects.

2.2.3 American Community Survey Data

Control measures were added from the USA Integrated Public Use Micro Data Series (IPUMS). I employ data from the year 2000 5% national sample, as well as American Community Surveys (ACS) for years 2001 to 2013. The year 2000 data include individual-specific data for 434,963 Californians. The ACS data for years 2001 to 2013 contain person-level data for between 24,000 and 86,000 Californians in each ACS survey year. These data contain control measures of family structure, labor market outcomes, property values and rental rates, and household income.

These data include identifiers that facilitate meaningful links to CDE data. Person-level identifiers include race, whether any household members presently attend California public schools, and the Public Use Microdata Area (PUMA) in which the respondent resides. I constrain the data extract to respondents with students in California public schools, and calculate means over $race \times year \times PUMA$ specific respondent subgroups. These data have 474 California PUMAs, 11 data years, and enough information on respondent race to construct racial groups that are consistent with CDE racial classifications. The average $race \times year \times PUMA$ combination contains 493 respondent level observations ($\mu = 493, \sigma = 503$). Control measures were estimated by taking means over these groups. Cases with insufficient data to estimate the year specific mean were imputed to the $race \times PUMA$ level mean. Medians were calculated for the income measure.

2.2.4 Merging Data from Multiple Sources

Figure 2.1 illustrates the geographic scope of the data that produced the analytic sample. The figure shows that schools and crime agencies are well distributed across the state of California capturing urban centers and rural areas. The more populous areas near Los Angeles, San Diego, and San Francisco have more schools, and more law enforcement agencies, which will help detect variance in gun-violence exposure levels, and dropout rates.

Education data, crime data, and IPUMS control measures were combined based on geographic proximity using ArcMap Software. Schools were geocoded to latitude and longitude coordinates based on the school's physical address as listed in the CDE data. Crime agencies were matched to localities with the same name, and the geographic jurisdiction of the agency was operationalized as the geographic boundaries of the locality. All schools that lie within a law enforcement agency's jurisdiction are assigned the crime event densities recorded by that agency. Schools were matched to IPUMS control measures in a similar fashion, such that a school's geographic coordinates were matched to its corresponding PUMA. $\mathrm{School} \times \mathrm{race} \times \mathrm{year}$ specific observations in CDE data were matched to the $\mathrm{PUMA} \times \mathrm{race} \times \mathrm{year}$ specific set of corresponding control measures from IPUMs data.

See Figure 2.2 for a graphic example of the geospatial matching process. The map shows the locations of schools in San Luis Obispo County, California. The upper left portion of the graph shows the Morro Bay Police Department matched to the incorporated area of Morro Bay City. Del Mar Elementary and Morro Bay High School are located within the Morro Bay City boundaries, and are thus matched to the crime data of the Morro Bay Police Department. Also, these schools are matched to control data for PUMA 0603701. Baywood Elementary, Los Osos Middle, and Monarch Grove Elementary do not lie within the boundaries of incorporated places, and would instead be matched to crime data from the San Luis Obispo Sheriff's office. They would, however, be matched to PUMA 0603701, as was the previous set of schools.

The geospatial matching process that links education data to law enforcement agencies and control variables was fairly successful. I created an ArcMap geocoder using publicly available address feature files from the Bureau of the Census. This geocode successfully identified 88% of schools and 93% of law enforcement agencies. From here, I utilized a Texas A&M Geocoding service to geocode the remaining unmatched records. Among the focal student subgroups in this analysis (Black, White, Hispanic, and Asian), this process led to the successful match of 99 percent of CDE observations to crime data, and 60 percent of CDE data to $year \times race \times$

$PUMA$ specific IPUMS control variables. The remaining 40 percent were successfully imputed to $race \times PUMA$ specific control means.

2.2.5 Cross Sectional and Longitudinal Cohort Data Structures

These data were composed and analyzed in both a cross-sectional and longitudinal form. The cross-sectional representation was used to assess patterns in gun-violence exposure. The longitudinal transformation allows the estimation of gun-violence exposure effects on cohort-level dropout rates. See Chart 2.3 for a visual display of the longitudinal data transformation. The longitudinal transformation reshapes the data to place observations from grades 9, 10, 11, and 12 in successive years, into a single observation that follows a cohort over time. Cohort-level dropout rates were computed after this transformation, and thus, describe the eventual high school dropout rate of an entering high school cohort.

The cohort data were constructed with the imposition of two key assumptions.

(1) Low mobility between schools: Students tend to go to the same high school for the duration of their high school career. To control for variance in the accuracy of this assumption, I control for the proportion of the student body who attending the school for the first time in the present year.

(2) Regular promotion: Cohort construction assumes that students advance one grade every year. I control for variance in the accuracy of this assumption by controlling for school rank. Schools where students fail with higher frequencies should have a lower rank.

Chart 2.3 offers a visual display of cohort construction and lists key events over the course of the observation window for the education data.

Summary statistics for outcomes and mediators are presented in Tables 2.4. The table shows a mean dropout rate over the sample window of 10.54 percent. The average dropout rate for women was slightly lower for women (9.21 percent) and slightly higher for men (11.60) percent.

There are also noticeable differences in dropout rates conditional upon the level of gun-violence exposure students experience. The dropout rate among high exposure student subgroups is roughly 7.1 points higher. Again, the difference is again greater for male students (7.9) than for female students (6.4). The variance in dropout outcomes also appears to be higher in the high exposure subgroup.

Similar patterns are observable in the CAHSEE data. Across the observation period the pass rate for the English language arts and mathematics sections of CAHSEE lie around three-quarters. Pass rates are roughly ten points higher among low exposure student subgroups, and the variance in outcomes appears to be lower.

Table 2.5 offers descriptive statistics for control variables for the full sample, and by gun-violence exposure level. The table shows significant differences in the mean values of most control variables between the high and low exposure student subgroups. The differences indicate more advantage among the low exposure subgroup.

2.2.6 Gun-Violence Exposure Measurement and Observed Exposure Patterns

I study the effect of gun-violence exposure on school-level outcomes in a framework that uses per-capita crime rates to instrument for the dosage of violence exposure received by children. This approach is based in an underlying assumption concerning the visibility and pervasive presence of these events. Gun shots are loud, jarring, and self-publicizing. Acoustics research found that a range of handguns, including 0.357 Magnums, 0.38 Revolvers, and 9mm Pistols, generally fire at volumes between 150dB to 160dB (Beck et al. 2011). After sounds of this magnitude travel for a half-mile, they can still be as loud as 80dB[4]. This suggests that many people within a fairly large radius would be immediately aware that a shooting occurred.

Follow up events tend to offer additional publicity. This may include the sounds of police sirens and other emergency services personnel, as well as the images of police officers, squad cars, flashing blue and red lights, and yellow crime scene tape. In the worse cases, evidence of bloodshed and lost life may also be present. Media coverage of happenings often follows. Some variant of this sequence of events happens for every homicide, firearm related robbery, and firearm related assault in these data. When this happens frequently, it contributes to a neighborhood tone that affects businesses, residents, and children.

This work is focused on understanding the effects of three types of disturbances: (1) Firearm related robbery; (2) Firearm related assault, and (3) Homicide. The occurrence of these events is highly correlated ($\rho > .75$), and it appears that they may all contribute to a single shared effect on outcomes. Factor analysis supports this suspicion with evidence that all three measures heavily load on a single factor. Table 2.6 shows that all measures load on factor one with loadings that take values between 0.84 and 0.90. All factor one loadings exceed the threshold of 0.5 for "high" loadings, as described in Treiman (2009). Also, all factor two loadings fall below

4 Statement based on estimates from a sound and distance calculator provided by http://www.sengpielaudio.com/calculator-distance.htm . Estimate was uses an initial sound volume parameter of 150dB, and a distance from the source of 3000 feet. Estimates do not control for competing noise, obstructions, and other environmental factors.

this mark. These factor loadings offer objective evidence that the selected measures capture a single unified concept contributing to a common effect.

I construct a composite exposure measure by taking the mean of standardized measures for each event according to

$$g = \frac{1}{3}\left(\sum_{i \in V} Z(v_i)\right)$$

where

$$Z(v_i) = \frac{v_i - \overline{v_i}}{\sigma(v_i)}$$

$$V = \{Firearm\ Robbery, Firearm\ Assault, Homicide\}.$$

$$v_i = Number\ of\ type\ i\ events\ per\ 100{,}000\ persons$$

This simple construction standardizes all measures, and takes a mean over the resulting z-scores. This composite measure has an inter-item covariance of 0.77 and reliability estimate ($\alpha = 0.91$).

Figure 2.7 and Table 2.8 offers snapshots of composite exposure over time. The earliest panel shows relatively high exposure rates for all student subgroups. This is confirmed by the table of means, which shows that all groups experienced their highest exposure levels between 1985 and 1995. Over the thirty-year period from 1985 to 2015, all groups experience noticeable declines in composite exposure with Blacks experiencing the greatest total change. With these declines, a new pattern emerges in the graphs. From 1995 forward, Whites and Asians increasingly have a greater density at low exposure levels, while Blacks and Hispanics display no reciprocating trend. This is most visible in the latest panel where there plots for Whites and Asians have a noticeably high density in the region below negative one. This shows that demographic differences in exposure persist in California even after massive declines over all, and agrees with evidence that national crime declines still left crime concentrated in areas that were initially most troubled (Friedson and Sharkey 2015). Refer back to Table 2.4 and Table 2.5 to observe differences in mean values of study variables above and below the $g = -1$ switching point.

2.3 Trends in Gun-Violence Exposure and High School Cohort Dropout Rates

The analyses below explore trends in gun-violence exposure levels using the g measure defined above. This measure is a mean of three z-scores where each input component captures the variation in one of three types of gun-crimes used to construct the gun-violence exposure index (firearm assault, firearm robbery, and homicide). The g measure is not normalized in the same way as the $\dot{g}$ construct, meaning that a one-unit change has no clear interpretation in the context of group-level differences. g should be interpreted as a measure on a common z scale that is employed only as a way of displaying patterns in the data.

The figures below look at patterns of gun-violence exposure by two measures. The first measure considers grade eight exposure using the g metric discussed above. For that reason, denote the grade eight g measure as g_8. While this measure captures exposure at a single point in time, it is likely highly correlated with the gun-violence exposure levels students experienced at earlier and later ages. Because this measure is taken at a discreet point in time (grade eight), it has the strength of being a clear pre-treatment measure for all outcomes measured in grades nine through twelve. A grade eight exposure measure is later employed as the independent variable of choice for effect estimates largely for this reason.

The second measure is a cumulative exposure measure that is constructed to capture the variation in gun-violence exposure from grades eight through twelve. It is constructed as an equally weighted mean across g_i, $\forall i \in \{8,9,10,11,12\}$. Formally, define the cumulative exposure measure,

$$g_{cum} = \frac{1}{5} \cdot \sum_{i=8}^{12} g_i.$$

As a simplifying assumption, the formula equally weights exposure measures for all considered grades. It is likely the case that the age or grade at which someone is exposed carries some implication for the consequences of exposure. Even with this limitation, the measure is sufficient for its present purpose.

Figure 2.9 graphs trends in each component of the individual measures that contribute to the gun-violence exposure index. The index is based on rates of homicide, firearm related robbery, and firearm related assault. The figure clearly shows that these three types of crime co-move in the same way over time. Each measure rises and falls sharply between the 1994 and 2003 cohorts, and all measures show a modest slight downward trend after the class of 2003. These patterns are consistent with the known timing of declines in violent crime rates. This co-movement between crime types further suggests some similarity in the factors driving rates of gun-crimes independent of the particular type of gun-crime under consideration. This commonality offers further reason to focus on an index that captures the underlying rate of gun-crimes, instead of focusing solely on any particular crime type.

Figure 2.10 shows cohort dropout rates by race for the classes of 1994 to 2014 at California public high schools. For all groups, there is a u-shaped dip and rise in dropout rates from 1994 through 2008, followed by a steady decline afterwards. Even with this dip and decline across all groups, a ten percentage point difference in the black-white and Hispanic-white dropout differential persists for most of the data series. After the class of 2008 these differences narrow but do not close. The analytical sample employs the subset of these data spanning the classes of 2003 through 2014. The dropout rates in this observation window exhibit a hump-shaped pattern that affords sufficient variation for effect estimation. Efforts moving forward work to discern how gun-violence exposure affects dropout rates, and if gun-violence exposure affects some student subgroups more than others.

2.4 Statistical Model

This analysis aims to understand whether gun-violence exposure is significantly related to differences in the dropout rate between student cohorts of the same ethnicity at a given school. In other words, I wish to discern whether student cohorts of a fixed ethnicity who attend the same school at different points in time realize dropout rates that are significantly correlated with the levels of gun-violence exposure experienced through childhood. Assessing differences in outcomes within schools offers the advantage of holding certain components of the physical context constant, and considering how a change within this context affects high school dropout rates.

Relative to a cross-sectional approach, this analysis has the advantage of bypassing the between school covariance between gun-violence exposure and dropout rates. The between school covariance would likely overestimate the effect of interest by capturing the effects of factors that are correlated with gun-violence exposure and educational success, such as family structure, income levels, and parent's education. While factors such as these differ widely between schools and the neighborhoods where they reside, the profiles of these measures tend to change slowly within neighborhoods. Advantaged neighborhoods tend to remain advantaged, and disadvantaged neighborhoods tend to remain disadvantaged. The employed approach of examining effects within student subgroups at schools has the benefit of holding other school and neighborhood characteristics constant to assess gun-violence exposure effects.

This estimation employs a fixed effects model according to the following specification:

$$y_{irc} = \beta_0 + \beta_1 \cdot g_{irc} + \alpha_{ir} + \delta_c + \varepsilon_{irc}.$$

The subscripts $i, r,$ and c denote school, student racial subgroup, and graduating class, respectively. The fixed effects model considers the bivariate relationship between graduation rates (y_{irc}) and gun-violence exposure (g_{irc}). Fixed effects parameters are included at the school × student racial subgroup level as denoted by α_{ir}. I also include year specific fixed effects, δ_c, to account for changes over time that may lead to differences in cohort outcomes. Standard errors are clustered at the school level to account for the correlation in student outcomes between student cohorts from the same school.

I estimate this model on the full sample to characterize the overall relationship between the independent and dependent variable measures. Next, I check for differences in effects by student ethnicity by producing estimates that are conditioned on student race. Finally, I check for difference in effects between high and low exposure student subgroups.

2.5 The Bivariate Relationship between Gun-violence exposure and High School Dropout Rates

This analysis aims to characterize the bivariate relationship between gun-violence exposure and high school dropout rates. Future chapters introduce control variables and advanced techniques to produce more precise estimates. I focus on the bivariate relationship for several reasons. First, the bivariate analysis offers an initial examination of patterns in the data before the introduction of additional measures. This provides evidence that the techniques employed to merge, clean, and prepare the data led to an analytical file where the relationships of interest are detectable. Second, a bivariate analysis shows the patterns before control measures introduce the possibility of over controlling for some confounders, or inadequately controlling for others. Last, it affords the possibility of discerning whether bivariate and multivariate analyses lead to similar qualitative results.

The exposure measure employed in this chapter is an average of z-scores where each component z-score describes the variation in rates of a particular type of gun-crime. A one unit change in this measure roughly amounts to a one standard deviation shift in exposure, which is a very large change. The coefficient estimates describing average dropout effects will be relatively large for this reason. The arguments in this chapter will focus mostly on the relative magnitudes of estimated effects, instead of the pure point estimate.

See Table 2.11 for fixed effect estimates from the full model and by student racial subgroup. Sample wide, a one standard deviation increase in gun-violence exposure is associated with an increase in dropout rates of 13.6 percentage points among students of the same ethnicity who attend the same school at different points in time. The point estimate is highly significant ($p = 0.001$). This result indicates the existence of an overall positive effect of gun-violence exposure on dropout rates within school $\times$ student subgroups.

Next, I assess whether these effects differ in magnitude between student subgroup. The estimates show significant effects for all student subgroups. All groups register significant positive effects at no less than an $\alpha = 0.05$ level. The magnitude of the effects, however, differs substantially. Effect estimates for the white and Asian student subgroups range between 9 and 10 percent, while effect estimates for black and Hispanic students range between 16 and 17 percent. The magnitude of these estimates suggests that the dropout rates of black and Hispanic students are more affected by gun-violence exposure than the dropout rates of white and Asian students.

Last, I run conditional models to assess whether variance in high levels of exposure have a different effect compared to variance at low levels of exposure. The high exposure subsample returned an estimated effect of an 11 percent increase in the dropout rate, compared to a 14 percent increase in the dropout rate in the low exposure groups. A t-test suggests no significant difference in these effect estimates at standard confidence levels. Thus, the bivariate analysis offers no evidence of differential exposure effects across exposure levels.

2.6 Discussion

This chapter presents the data sources and construction that serve as the foundation for all results presented in this dissertation, as well as early results concerning the relationship between gun-violence exposure and high school dropout rates.

Several data sources contribute to the construction of the analytical data file employed in this chapter and the chapters that follow. Data on dropout rates and other educational measures were obtained from the California Department of Education. These data cover the outcomes of roughly 4.2 million ninth graders who attended California public high schools with the classes of 2003 through 2014. Data on gun crimes were obtained from the California office of the Attorney

General. These data include counts of specific types of reported gun crimes for over 200 police departments and sheriff's offices across California. Rates of firearm related robbery, firearm related assault, and homicides all contribute to a composite gun-violence index. I also introduce data from the American Community Survey, which contributes control measures in subsequent chapters.

This chapter addresses univariate patterns in the independent and dependent variables of interest (gun-violence exposure and high school dropout rates, respectively). Dropout rates have changed substantially over the sample window. The window captures periods where rates rise, and then decline. There are also persistent differences between the dropout rates of some student subgroups that become noticeably narrower during the sample window. The sample window also captures considerable variation in gun-violence rates. Earlier cohorts in the sample experienced the last portion of the decline in gun-violence that ended in the late 1990s. Later cohorts experienced less gun-violence, overall.

Results from a fixed effects model offer evidence of two important results. First, I find that cohorts who experience higher levels of gun-violence tend to have higher high school dropout rates. This result is based upon differences in outcomes among students of the same race/ethnicity category who attended the same school in the same neighborhood at different points in time. Year-level fixed effects were also included to account for variations in policy and other factors that affected the outcomes of all students.

Next, I consider whether effect estimates differ between student subgroups. Results clearly indicate larger effects for black and Hispanic student subgroups relative to white and Asian student subgroups. I explore this result further in subsequent chapters.

Last, I consider whether variation in exposure at higher exposure levels appears to have a different effect than variation in exposure at lower levels. Point estimates suggest greater effects at lower exposure levels. There was, however, no significant difference in the estimated effects between the two point estimates.

This chapter provides a foundation the dissertation by describing the construction of the analytical data file, and producing early evidence of important relationships between the independent and dependent variables. The interpretability of regression results is somewhat hampered by the unintuitive z-scale of the independent variable. Subsequent chapters introduce a transformation that makes regression coefficients more interpretable. Forthcoming analyses also introduce control measures to further refine effect estimates.

3. The Effects of Exposure to Community Gun-Violence on the High School Dropout Rates of California Public School Students*

Chapter 3 conducts an in-depth investigation of the relationship between gun-violence exposure and high school dropout rates in the state of California. The chapter aims to understand the extent to which gun-violence exposure effects dropout rates, under what conditions gun-violence exposure effects tend to be greatest, and whether gun-violence exposure affects some student subgroups more than others. The data employed in this section cover the full population of high school students in California public schools[5] from the class of 2003 through the class of 2014. This reflects the high school outcomes of roughly a half generation of California youth who will grow to become a relevant proportion of the state's working-age population. For this reason, significant effects in these data could have long-term implications for the state. This chapter's primary contribution is a characterization of the educational effects of youth exposure to gun-violence.

The chapter proceeds as follows. Section 1 offers an introduction and discusses the connection of this work to the present literature. Section 2 discusses a model and empirical approach for regression analysis. Section 3 presents results of the analysis. Section 4 offers a discussion of findings.

3.1. Introduction

Young African-American men, on average, face a very different set of average mortality risks than their peers in other racial groups. Whites, Asians, Hispanics, and Native American men all share the same leading cause of death between the ages of 1 and 34: accidental injury. African-American men are the only group for whom homicide eclipses all other causes of death (CDC

5 The California Department of Education estimates that private school K-12 enrollment ranged between 7.4 percent and 9.7 percent over the sample years. This implies that over 90 percent of California's school aged children attended public schools over the sample period.

2014B). Homicide is the most common cause of death for black males between the ages of 15 and 34, and accounts for almost 50 percent of deaths between ages 15 and 24 (CDC 2014B). Young African-American women face a similar pattern, where homicide is frequently the second or third leading cause of death, occupying the rank held by cancer and suicide for white, Hispanic, and Asian women (CDC 2014B). An estimated 68% of homicides in the United States involve the use of firearms, and the vast majority of these (69%) involve the use of handguns (Federal Bureau of Investigations Uniform Crime Report 2014). This suggests a clear link between firearms, and the mortality risks of young African-Americans.

Although the race-specific estimates referenced above apply to specific age-graded racial groups, the hazards described are not uniformly distributed across group members. Victimization is most likely to occur in adolescence (MacMillan 2001; Bowen and Bowen 1999). Violence is negatively correlated with socioeconomic status (Blau and Blau 1982), indicating that youth from less educated and lower income households are more likely to have encounters. Homicide rates tend to be higher for teens living in urban areas (Finkelhor and Ormrod 2001). For example, all 1997 youth homicides occurred in only 15 percent of US counties indicating a geographic and demographic concentration of crime and violence exposure (Finkelhor and Ormrod 2001).

The salience of homicide among the mortality risks of African-American youth indicates the volume of children and families who are affected by shootings. Firearm-related events resulting in homicide represent a small proportion of firearm-related incidents. Gun-violence effects on cause-of-death estimates are fully driven by fatal shootings. Beyond these fatal shootings, estimates suggest that there are 2.3[6] times more non-fatal shootings that resulted in injury, and an unknown number of firearm related incidents that did not result in bodily injury (Center for Disease Control 2005). While not all gun-related events are lethal, all gun-related crime and violence can be a threat to feelings of safety and security. Evidence below indicates that children can be affected by a range of violent experiences that may or may not involve loss of life. For this reason, this work operationalizes gun-violence exposure as a concept that reaches beyond firearm related homicide to other forms of gun-related crime and violence.

Violence exposure and victimization have well-documented psychological, physiological, and behavioral effects on children. Violence exposure is associated with the onset of post-traumatic stress disorder symptomology (PTSD) (Berman et al. 1996; Berton and Stabb 1996), depression (Moses 1999; Freeman, Mokros, and Poznanski 1993), and anxiety (Pynoos 1994; Hill et al. 1996)). There is evidence of nightmares and other anxiety-related sleep disturbances (Pynoos 1994). Children report feeling unsafe, "jumpy", and "scared" (Richters and Martinez 1993; Osofsky, Wewers, et al 1993). Young children are less likely to explore their environment (Osofsky and Fenechel 1994), and may have difficulty paying attention or concentrating due to intrusive thoughts (Pynoos 1994). Among young children, regression in developmental achievements such as toileting and language is common (Drell et al. 1993). There is also evidence of cumulative effects of trauma (Cummings et al. 1994; Cummings and Zahn-Waxler 1992), suggesting that traumatic events early in childhood may compound the negative effects of later life difficulty. In adolescence, violence exposure is associated with greater risks of running away from home, attempting suicide, and encountering the criminal justice system (Haynie 2009).

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6 Estimate based on counts of firearm related deaths, and firearm related non-fatal injury from years 2001 to 2014.

Violence also affects a parent's ability to protect their child. Parents who are living with violence frequently express feelings of helplessness and frustration due to an inability to safeguard their children (Osofsky 1995 ; Garbarino et al. 1992; Lorion and Saltzman 1993; Osofsky et al 1993; Richters and Martinez 1993). Parents experience further frustration when spaces, such as community centers, churches, and schools, are no longer viewed as safe places where their children are protected. This can leave parents feeling the need to be overprotective, and to challenge their child's autonomy due to an environment that does not safely admit exploration (Osofsky 1995).

All of these effects offer clear mechanisms and pathways that may mediate the estimated impact of exposure and victimization on the education, and adult outcomes, of children. There is evidence of short-term exposure effects that lower exam performance in the weeks that immediately follow an incident (Sharkey 2010), as well as cumulative effects of violence exposure due to learning losses over time (Burdick-Will 2016). A meta-analysis of 100 studies shows effects of violence exposure on educational outcomes including school dropout/graduation, school absence, academic achievement and other educational outcomes such as grade retention, learning outcomes and remedial classes, and standardized test scores (Fry et al. 2018).

Beyond test score effects, violence exposure and victimization can undermine one's fundamental need to feel safe, which must be met before prioritizing higher needs, such as education (Maslow 1954). In agreement, MacMillan and Hagan (2004) argue that, "… victimization diminishes educational self-efficacy, which subsequently undermines educational performance and attainment" (p. 127).

Evidence of negative causal effects of violence exposure on child outcomes is further supported by experimental evidence showing gains from moving to safer neighborhoods. Sharkey and Sampson (2010) found that Chicago residents who moved to safer neighborhoods beyond the city were less likely to become violent offenders. Positive effects were mediated by increased school quality, the change in neighborhood racial and economic makeup, and increased feelings of control over a new and safer environment. Also, evidence from a reanalysis of Moving to Opportunity (MTO) intervention data highlighted larger relocation effects for kids who moved in the study's most violent cities (Baltimore and Chicago). Data showed inverse correlations between beat-level crime, and reading and math test scores (Burdick-Will et al. 2011), as well as psychological benefits for a parents and children of living in safer neighborhoods (Katz et al. 2001; Goering and Feins 2003). For these reasons and others, violence exposure is viewed as a key causal pathway linking neighborhood context, and individual behavioral and health outcomes (Galster 2012).

This work also contributes to decades of work directed towards understanding dropout risk factors, trends, and differentials. See Rumberger et al. (2008), Kao and Thompson (2003), Heckman and LaFontaine (2010) for central results from this literature. This project models dropout rates over an eleven year period where the dropout rate moves non-monotonically, and dropout differentials between student subgroups show slight narrowing. This variation affords a means of assessing how gun-violence correlates with dropout rates over all, and how effects differ at the aggregate level by student subgroup.

While studies assessing violence exposure effects are generally designed to understand the effects of living in high crime neighborhoods, the question of exposure effects has become increasingly applicable to kids who live in communities where gun-violence is relatively infrequent. Since 1999, shootings have occurred with increasing regularity on school grounds in community contexts absent of typical high-crime correlates. Violence exposures from lone incidents tend to have different characteristics relative to violence exposure in high crime areas. School shootings tend to occur over a brief period of time, with clear time point delineating the initiation and termination of the threat. Also, one event is usually not indicative that more violence is likely. This differs from gun-violence in high crime areas where violent occurrences tend to represent one event in a seemingly infinite sequence, and the threat of additional violence never truly subsides. A portion of violence exposure effects is attributable to the threat of additional harm. Because the types of exposure mentioned above differ in their expectations of future occurrences, they likely differ in their long-term effects on children. The estimates that follow are most reflective of the effects associated with exposure in high crime areas.

The literature above offers clear evidence that children are affected by violence exposure and victimization. Violence exposure has physiological, psychological, and behavioral effects that interrupt the day-to-day lives of children, and may partly mediate poorer education outcomes. Coupling this with evidence of population-level heterogeneity in exposure levels suggests the possibility of measurable population-level effects. I investigate this possibility below.

This chapter has four key objectives. First, I offer evidence geared toward determining if and when gun-violence exposure levels affect high school dropout rates. Next, I build on the results to question one by further characterizing the intensity and extent of exposure effects. From here I assess whether gun-violence exposure effects differ across student race/ethnicity subgroups.

3.2. Data

See chapter 2 for a detailed description of the data and variable constructs employed in this chapter. This chapter employs the $\dot{g}$ measure of gun-violence exposure as the independent variable. See section 2.2.6 for a definition of $\dot{g}$**.** The $\dot{g}$ index is normalized such that a one unit change in $\dot{g}$ corresponds to a decrease in gun-violence exposure of an amount equivalent to the black-white differential in gun-violence exposure over the full sample window. This implies that regression results presented later in this chapter estimate the change in outcomes associated with closing the black-white exposure gap, or decreasing the Hispanic-white differential by an amount that is equivalent to the black-white differential.

The data employed in this chapter covers the high school outcomes of over four million California public school students, as well as the gun-related crimes of over three hundred California police and sheriff's offices. Refer back to chapter 2 for additional details on the data. Review Tables 2.4 and 2.5 for descriptive statistics of the data.

3.3. Model

Figure 3.1 depicts a static expression of the theoretical model that motivates this analysis. Both youth gun-violence exposure levels and high school dropout rates are heavily dependent upon parental characteristics and the community where one resides. Holding these constant, I hypothesize that gun-violence exposure levels beyond some threshold, g^*, leads to effects on youth that ultimately increase the likelihood of dropping out of high school.

The hypothesized critical threshold, g^*, is unobserved and unknown. The analysis begins by assuming $g^* = \underline{g}$ where $\underline{g}$ implies the lowest possible exposure level of zero exposure. This would imply that gun-violence exposure at all levels has some effect on dropout likelihoods. Results in the next section suggest that g^* equates to some interior exposure level such that $\underline{g} \leq g^* \leq \overline{g}$ where $\overline{g}$ is the highest gun-violence exposure level present in the data. This implies that high school dropout rates, and potentially educational attainment in general, are unaffected until exposure reaches some critical value. A separate set of analyses assess this possibility.

3.4. Effect Estimates

This work aims to understand how high school dropout rates respond to an aggregate measure of gun-violence exposure. I start by estimating effects under the model assumption that $g^* = \underline{g}$. This assumption implies the following linear model:

$$y_{irc} = X_{irc}\,\beta_0 + \sum_{r \in Race} \left[\beta_{1r}^{y} \cdot \mathbb{I}(Race = r)\right] + \gamma^{y} \cdot \dot{g}_{irc} + \epsilon_{irc}$$

$$\epsilon_{irt} \sim N(0, \Sigma_{\mathrm{i}})$$

In the expression above, X denotes a set of control measures, y is the outcome, and z is the composite gun-violence exposure index. The index variables $i, r,$ and $c,$ denote school, race, and class, respectively. I also run variants of this model that estimate $race \times exposure$ interaction effects. These regressions are estimated via maximum likelihood estimation to take advantage of the associated efficiency gains over least squares estimation. Standard errors are adjusted for clustering at the school level to adjust for school-specific variance components.

Results from these models suggest that dropout rates likely respond to gun-violence exposure non-linearly suggesting an alternative model where $\underline{g} \leq g^* \leq \overline{g}$. For this reason, I estimate regression discontinuity models that explore the existence of a critical exposure level, g^*, where significant measurable effects on dropout rates begin. The regression discontinuity model is formalized according to

$$\hat{y} = (\alpha_{low} + \beta_{low} \cdot g) \cdot 1(g < g^*) + \left(\alpha_{high} + \beta_{high} \cdot g\right) \cdot 1(g \geq g^*) + \gamma X.$$

This specification allows a separate y-intercept and slope for the exposure effect above and below g^*. Control variables are constrained to have a constant effect across exposure levels. I also estimate a variant of this model that accommodates quadratic exposure effects above g^*.

The regression discontinuity expression assumes a known value of g^*, however, g^* is unknown and must be identified through an of estimation process. For this reason, g^* is identified as the threshold that minimizes the sum of squared errors.

$$g^* = \underset{g}{argmin} \left\{ \underset{\alpha_{low}, \alpha_{high}, \beta_{low}, \beta_{high}, \gamma}{argmin} [y - \hat{y}]^2 \middle| g \right\}$$

This approach designates the threshold as the critical value that best fits the data.

Given the estimated threshold in the context of the specified regression discontinuity model, I summarize the effect of gun-violence exposure on dropout rates among students with exposure levels beyond g^* according to:

$$\delta_r = \int_{g \geq g^*} h_r(g) dF_r(g)$$

In the expression above, $h_r(g)$ is the group r effect of exposure level g, and $F_r(g)$ is the cumulative density function capturing the distribution of gun-violence exposure levels across students in group r. The expression shows that larger average group level effects can be driven both by differences in exposure levels, and difference in exposure effects.

The average treatment effect is calculated as

$$ATE = {p^r}_{g<g^*} \cdot \delta_r$$

Where ${p^r}_{g<g^*}$ is the proportion of students who experience exposure levels above the threshold according to ${p^r}_{g\geq g^*} = \int_{g\geq g^*} dF_{r(g)}$. The ATE will offer the best evidence concerning the extent to which gun-violence exposure has differential effects on dropout rates across student subgroups.

3.5. Results

3.5.1. Effect estimates for control variables in the linear model

See Table 3.2 for full sample and gender specific regression estimates. Control variables in early models included PUMA level control measures from IPUMS, school and student subgroup level control variables from the CDE, missing value flags for the afore mentioned variables, and dummy variables to control for ethnicity differences. Significance levels on missing value flags were not significant predictors of cohort level dropout rates, indicating that missing values were non-systematic. Missing value flags were, however, correlated with the CAHSEE policy variable. Missing value flags were omitted from the final model to improve CAHSEE policy effect estimates.

Parent's education and household structure have the expected effects on dropout rates. Increasingly higher levels of education lead to increasingly lower likelihoods of dropping out. Student subgroups with a high density of kids from homes with an absent father are much more likely to dropout. Among school characteristics, the largest effect is associated with classification as a school that is exclusively or primarily virtual[7]. According to present estimates, virtual schools[8] in California are associated with a 20 percent higher dropout rate than schools with primarily classroom-centered instruction. Other outcomes in this study also showed poorer outcomes at virtual schools. These estimates are consistent with evidence from, In the Public Interest (ITPI 2015), assessing the performance of California virtual schools. ITPI studies a particular vendor of virtual education services, and finds low graduation rates, negative academic growth, and consistently poor annual performance index rankings. ITPI attributes poor performance to a range of factors, including the financial model associated with California's virtual schools, low quality educational materials, and low pay for teachers and staff.

Estimates show no significant effects of CAHSEE legislation on cohort level dropout rates over the course of the sample window. Later estimates will restrict to the sample years immediately preceding and following the policy change to estimate a discrete positive discontinuity in the dropout rate associated with the new policy. Other control variables have the expected sign. The dropout rate decreases as parent's education increases. The dropout rate is increases slightly with the proportion of kids receiving free and reduced price lunch. It decreases with the proportion of kids in gifted and talented programs or migrant education programs. Teachers with full credentials are associated with lower dropout rates, while classification as a charter school or magnet school is associated with higher dropout rates. Schools that are better ranked produce fewer dropouts, and traditional schools (as opposed to

7 Exclusively virtual implies that the school has no physical building where students meet with each other or with teachers, and all instruction is virtual. Primarily Virtual implies that the school focuses on a systematic program of virtual instruction but includes some physical meetings among students or with teachers. Classification as exclusively or primarily virtual are CDE determined.

8 Virtual schools account for 0.13 percent of schools in these data.

Juvenile Court Schools, Special Education Schools, and other targeted types of instruction) have lower dropout rates. The dropout rate is increasing in the proportion of the local population who is out of the labor force, and in the proportion of households with no father present. The local log median income is also inversely associated with dropout rates. These estimates instill confidence that control measures are capturing relevant patterns in the data, facilitating cleaner estimates of the effect of gun-violence on dropout rates.

3.5.2. Gun-violence exposure effect estimates on cohort level dropout rates.

Table 3.2 presents estimates of gun-violence effects on high school cohort level dropout rates for the full sample, as well as by gender. The main effect of gun-violence exposure is associated with a 1.6 percent increase in the dropout rate for the full sample. The effect is slightly higher for men at 1.8 percent, compared to 1.3 percent for women. All estimates are highly significant. Recall that I normalized the gun-violence index such that a one unit change in the index corresponds to the difference between the average gun-violence exposure levels of African-American versus white students in these data. This yields the interpretation that decreasing population exposure by the black-white exposure differential could lower the statewide high school dropout rate by up to 1.6 percent.

Table 3.3 adds an interaction between gun-violence exposure and student race/ethnicity, and Table 3.4 shows the total effect estimates associated with these interactions. The total effects show that dropout rates for African-Americans and Hispanics are associated with gun-violence exposure at the highest significance level. Conversely, estimates for Whites and Asians are insignificant. I do not interpret this as evidence of a differential response to direct exposure.

between student subgroups. It is more likely the case that effect differences are driven by unobservable differences in the degree and intensity of exposure between student subgroups.

The magnitude of total effects for African-American and Hispanic males is strikingly large. A normalized index unit is associated with a 1.9 (2.5) percentage point differences in the African-American (Hispanic) male dropout rates, respectively. Estimates are slightly lower for the full sample. According to these estimates, decreasing gun-violence exposure rates by an amount equivalent to the Black-White (Hispanic-White) exposure differentials would be associated with decreasing the Black-White (Hispanic-White) dropout differential by 16 (19) percent.

Estimates suggest that gun-violence exposure only effects educational attainment when exposure exceeds a certain threshold. The total effects estimates above show no significant effects for the two student subgroups with the lowest exposure levels (Asians and Whites), and significant positive effects for the student subgroups with the highest exposure levels (Blacks and Hispanics). This suggests a non-linear exposure effect such that effects are indistinguishable from zero below a certain threshold, and positive above that threshold. The distribution of students in each subgroup relative to the threshold determines whether the subgroup, as a whole, is significantly affected by gun-violence exposure.

This argument is illustrated in Figure 3.5. The vertical axis of this heuristic shows the exposure effect while the horizontal axis indicates the exposure level. The density of student subgroups is depicted in the two regions of the graph by circles of various sizes and colors. A larger circle signifies a higher density of students in that exposure region, while the color and text label define the student subgroup. Figure 3.5 illustrates two of the paper's central results. First, that gun-violence exposure must exceed a certain threshold (denoted g^* in the figure) to have statistically detectable effects on dropout rates. Second, variance in the proportion of each student subgroup above the threshold contributes to differences in estimated subgroup level total effects of gun-violence exposure on dropout rates. In accord with argument two, the high density of Blacks and Hispanics in the high exposure region leads to significant subgroup-level effects, while effects are insignificant for white and Asian student subgroups. I explore both claims in the next set of analyses.

3.5.3. Estimation of the threshold model.

I re-estimate the effects of gun-violence exposure on high school dropout rates using a regression discontinuity model that allows separate effects for exposure levels above and below a defined threshold. I estimate this model in two steps. First, I discretize the gun-violence exposure index space into 60 points ranging in value from 0 to 6 and equally spaced in intervals of 0.1. Formally, $G = \{0.1, 0.2, 0.3, \dots, 5.9, 6.0\}$. Each of these 60 points represents a candidate value for the critical exposure threshold, g^*. I estimate the regression discontinuity model for all candidate values of g^* and record the resulting estimates and model fit parameters. Second, I designate G^* as the critical threshold corresponding to the model that best explains the observed variation in the outcome such that $R^2(g^*) \geq R^2(g), \forall\, g \in G$.

Recall that I estimate the following regression discontinuity model:

$$\hat{y} = (\alpha_{low} + \beta_{low} \cdot g\,) \cdot \mathbf{1}(g < g^*) + \left(\alpha_{high} + \beta_{high} \cdot g\right) \cdot 1(g \geq g^*) + \gamma X + \epsilon.$$

In this model, β_{low} captures the response to additional violence below the exposure threshold, g^*, while β_{high} captures the linear response above g^*. Figure 3.6 maps estimates of β_{low} across all candidate values for the critical threshold. The slope estimate at each point is based on data points at or below the corresponding violence exposure level, g.

I argue above that violence exposure has a statistically significant measurable effect on dropout rates only if exposure levels exceed a certain threshold. If this is the case, one would expect to see estimates of β_{low} near zero for low gun-violence exposure levels, and a positive trend as exposure levels increase. Figure 3.6 reflects this pattern by mapping estimates of β_{low} for the full analytic sample across a range of threshold values denoted as g. Whiskers in the figures below denote 95% confidence intervals. The figure displays the expected pattern. The effect of gun-violence exposure on dropout rates is initially statistically indistinguishable from zero. At $g \approx 1.5$, the estimated effect becomes strictly positive at confidence levels above 95%. The effect estimate peaks around 2.1 when $g \approx 2.6$ before decreasing modestly as at higher values of g.

Figure 3.7 shows the same plots by student subgroup. The graphs for Asian, black, and Hispanic students exhibit the same qualitative properties. Effects at low exposure levels are indistinguishable from zero. Effects become significant at $g \approx 1.5$ for black and Hispanic student subgroups, and slightly earlier for Asian students. Effect estimates peak at higher values for black and Hispanic students (3.2 and 2.2, respectively) relative to Asian students (1.7). All three groups show declines in effects beyond the peaks with the most noticeable declines being evident for black students. White students were the only group with insignificant effect estimates across all ranges of exposure.

Results of the full sample maximization procedure produce an optimal threshold value of $g^* = 1.4$. At this value the model explains 45% of the variation in dropout rates. Table 3.8 shows effect estimates from regression discontinuity models based on the threshold identified above. The linear model finds a 1.57 percentage point increase in dropout rates associated with decreasing violence exposure by the black-white differential. Model (2) incorporates the threshold identified above and estimates separate linear effects on each side of the threshold. For exposure levels below the threshold $(g < 1.4)$, there is no significant effect of exposure on dropout rates. Conversely, effects above the threshold are highly significant and positive at a coefficient estimate of 2.20. Model (3) adds a quadratic term above the threshold, which would be consistent with the peaks in Figures 3.6 and 3.7. The quadratic specification also finds insignificant effects below the threshold and significant effects above the threshold. Both the linear, and the quadratic terms are highly significant with the expected sign. Figure 3.9 maps the effects defined by these models.

3.5.4. *Interpreting the Threshold*

Translating the estimated threshold value into rates of specific types of violent crime offers a more intuitive understanding of the model's implications. The exposure threshold at which dropout effects become significant was estimated at a value of 1.4. This value corresponds to an average of 97 firearm related assaults ($\sigma = 39.8$), 171 firearm related robberies $(\sigma = 50.4)$, and 10 homicides$(\sigma = 4.4)$, all per 100,000 persons.

3.5.5. Implications for student subgroup dropout differentials

Table 3.10 shows the proportion of students in each student subgroup associated with a gun-violence measure above the identified threshold. White and Asian students have the lowest proportions at 10 percent and 23 percent, respectively. 23 percent of Hispanic students and 32 percent of black students lie above the threshold for significant effects on dropout rates.

Differential effects of violence exposure are influenced by two compositional components. First, differences in group level effects are driven in part by differences in the proportion of student subgroups who are exposed to violence levels beyond the threshold where significant effects begin. Twenty-two percent of students experience exposure levels beyond this threshold. Proportions are noticeably higher for the black and Hispanic student subgroups at 32% and 27%, respectively. Conversely, proportions are lower for the white and Asian student subgroups at 10% and 24%, respectively. Second, there are differences in the effects of exposure on dropout rates above this threshold. Differential effects are likely driven by unobserved differences in the intensity of exposure, as well as interactions between exposure levels and other factors that influence high school completion. Subgroup specific estimates of the quadratic regression discontinuity model suggest differences in effect estimates.

Figure 3.12 plots the quadratic regression discontinuity estimates presented in Table 3.11. The slope estimates below the threshold are insignificant for all groups except the Asian subgroup suggesting no significant effects on dropout rates at lower exposure levels. Quadratic effect estimates above the threshold are significant for all groups except the white student subgroup. The height of the curves suggests that effects are largest for black and Hispanic students. This is likely a result of unobserved heterogeneity in the intensity of exposure between student subgroups. Table 3.13 decomposes effects from the quadratic model to demonstrate the separate roles of differential effects and differential exposure intensity. Column *(a)* lists the proportion of each student subgroup that lies above the critical exposure level, g^*. 22.1% of students are above this threshold sample wide. Almost one-third of black students and over one-quarter of Hispanic students are above the threshold. Slightly less than one-quarter of Asian students are above the threshold. White students are least prevalent with roughly 1 in 10 registering exposure levels above the threshold.

In addition to differences in the proportion of student subgroups above the threshold, there are also differences of exposure among the subset of students above the threshold. Columns *(b)* and *(c)* show the mean and median exposure levels above the threshold. The distributions tend to be right skewed with high density at lower exposure levels, and several masses at higher exposure levels that pull the mean above the median. The white student subgroup is the only exception, suggesting fewer masses at extreme values.

Column (d) of Table 3.13 lists point estimates that quantify the quadratic effect estimates from Figure 3.12 under the assumption of uniform exposure across beyond the critical value, $g^* = 1.4$, up to the exposure level of $g = 5$[9]. Assuming uniform exposure facilitates the calculation of a summary statistic that excludes differences in exposure levels, which isolates differences in the intensity, as displayed in Figure 3.12 by curves of varying height. Average effects beyond the threshold for black and Hispanic students under this assumption sample wide and for black and Hispanic students are around 6 percentage points. Effects are lower for white and Asian students at 2.5 and 4.9 percentage points, respectively. Re-estimating effects employing the empirical exposure distribution leads to modest decreases in almost all estimates as listed in column (e). Hispanics were the only group with a larger effect, likely signifying a higher density at exposure levels near the crest of the effect.

9 While there are exposure measures with index levels beyond 5, this imposed upper bound includes over 99% of data points.

Finally, column *(f)* shows average group level gun-violence exposure effects from the quadratic threshold model. I find a sample wide effect estimate of 1.3. Effects are lower for white and Asian student subgroups at 0.2 and 1.0, respectively. Estimates are noticeably higher for Hispanic and black students at 1.7 and 2.0, respectively. For black and Hispanic students, these estimates account for 12 percent of their group level dropout rates. It also corresponds to 20% of the Hispanic-white dropout differential, and 18% of the black-white dropout differential.

3.6. Discussion and Conclusion

This chapter began with four primary objectives. The first objective was to understand if, and at what exposure levels, gun-violence affect high school dropout rates. The chapter starts with a linear regression model and employs a gun-violence exposure measure that is normalized such that a one-unit change corresponds to the average difference in gun-violence exposure between black and white students over the sample period. This normalization implies that regression estimates can be interpreted as the difference in dropout rates associated with the black-white differential in gun-violence exposure. This investigation began with a linear regression model that estimates significant full sample effects of gun-violence exposure on high school dropout rates. Interacting the gun-violence measure with race uncovered that the full sample estimates from the previous model were heavily concentrated among the black and Hispanic student subgroups.

From here, the chapter turns toward investigating the validity of assuming linear effects from gun-violence exposure. To do so, I specify a regression discontinuity model that estimates exposure effects both above and below a designated threshold. Results suggest the existence of a threshold where exposure levels below the threshold have no measurable effects on dropout rates, and exposure above the threshold is significantly related to higher dropout rates. An optimization procedure computationally identifies the threshold that best explains the relationship between gun-violence exposure and dropout rates. The procedure identifies a threshold value that corresponds to an average of 97 firearm related assaults ($\sigma = 39.8$), 171 firearm related robberies ($\sigma = 50.4$), and 10 homicides ($\sigma = 4.4$), all per 100,000 persons.

I compare the initial linear model to two regression discontinuity models with varied specifications and identify the discontinuous model with a quadratic term above the threshold as the preferred model. This model shows no significant effects below the threshold, and significant effects in the linear and quadratic terms above the threshold. This model shows no effects at low values of exposure, followed by effects that grow to some maximum value before declining. I also estimate this model for each student race/ethnicity subgroup.

I characterize the intensity and extent of exposure effects, and assess how effects differ across student subgroups. I characterize intensity effects by estimating the average affect among students who are experiencing gun-violence exposure levels above the critical threshold, and I characterize extent effects by considering what proportion of each student population experiences gun-violence exposure levels above the threshold value. Estimates show that Black and Hispanic students have the greatest representation above the threshold at about 32 and 27 percent respectively. White and Asian students are the least represented with densities of about 10 and 24 percent, respectively. Concerning the intensive margin, black students above the threshold are 2 percent more likely to dropout while Hispanic students above the threshold are slightly less likely to dropout. These effects account for 20 percent of the Hispanic-white dropout differential, and 18 percent of the black-white dropout differential.

This work was built on results from cross-sectional data that admits the possibility that confounders that are correlated with gun-violence levels may taint results. To address this issue, I ran fixed effects models to assess whether dropout rates at the same school over time were correlated with gun-violence exposure levels. Results indicate a strong relationship across student cohorts within the same school, suggesting that persistent differences that are correlated with spatial factors are not fully driving the results above.

The driving question of this work concerns the implications of youth gun-violence exposure levels for educational demographics. This chapter works with data from over 4 million grade 9 student-years covering over a decade of California's high school graduating classes to find that gun-violence exposure appears to have significant effects on educational attainment that are highly concentrated on specific populations. Estimates show that the black-white gun-violence exposure differential is associated with over 2 percent more black and Hispanic high school dropouts over the course of a decade. Together, black and Hispanic student comprise about 60% of these data. Conservatively, this yields an additional forty thousand black and Hispanic high school dropouts over the course of a decade.[10] This estimate suggests significant effects of gun-violence exposure on the state's educational demographics.

Thus far, the literature has focused primarily on understanding the effects of gun-violence exposure in specific environments where gun-violence exposure levels are elevated. My work looks beyond these high exposure subpopulations to assess the effects of gun-violence

10 I estimate an effect estimate of 1.7 percent against 60 percent of the data. There are over 4 million grade 9 student years in the data. $0.017 \times .6 \times 4{,}000{,}000 = 40{,}800$.

exposure on all students. I uncover dynamics suggesting that the educational outcomes of most students are unaffected by the levels gun-violence they experience. However, about 1 in 5 students experience gun-violence levels high enough to yield significant effects on schooling outcomes. Black and Hispanic students are over-represented in this high exposure subgroup, which explains these student subgroups register larger over-all effects of gun-violence exposure.

This work also yields an important policy result. Results suggest the possibility of eradicating gun-violence effects on population-level education outcomes without eradicating gun-violence. Because the dropout outcomes of 78 percent of students are unaffected by their present gun-violence exposure levels, these students require no corrective intervention. The last 22 percent, however, would benefit if gun-violence were reduced to the threshold level or lower. Thus, students can have a significantly better shot at success with a partial solution to local crime that reduces gun-violence exposure below threshold levels until a more comprehensive intervention can do more.

More work is needed to understand the mechanisms that mediate the relationship between gun-violence exposure and dropout rates. Literature above references a number of avenues that may mediate the relationship between the measures of interest. These include psychological and emotional effects of violence exposure (Berman et al. 1996; Berton and Stabb 1996), as well as the possibility of cumulative learning loss from prolonged (Burdick-Will 2016). The next chapter investigates mediating mechanism further.

4. Does learning loss mediate the elevated dropout rates of Black and Hispanic students who were exposed to higher rates of gun-violence?*

4.1. Introduction

The previous chapter offers evidence that gun-violence exposure affects educational attainment when exposure levels exceed a certain threshold. Across student subgroups, there are greater densities of black and Hispanic students experiencing exposure levels above the identified threshold, implying that these groups are disproportionately affected by gun-violence exposure. While these results offer helpful information concerning when and to what extent gun-violence exposure affects dropout rates, it says nothing about what factors mediate the relationship between gun-violence exposure and elevated dropout rates.

This work aims to discriminate between two classes of potential mediators referenced in the literature. Burdick-Will (2016) shows that prolonged gun-violence exposure leads to cumulative learning loss over the course of one's primary and secondary education. This could leave students slowly falling behind until they can no longer satisfy the requirements for advancing to the next grade level. Under this theory, students would dropout due to an eventual inability to satisfy a cognitive or evaluative requirement for advancement.

The second possibility argues that some out-of-school constraint contributes to the decision to leave school in the absence of any binding performance constraint that prevents academic advancement. This includes the possibility of avoiding school due to safety concerns on school grounds (Bowen and Bowen 1999), lowering one's educational objectives due to diminished self-efficacy (MacMillan and Hagan 2004), or leaving school to prioritize higher needs than education (Maslow 1954).

The distinction between these two mediating paths has important implications. If the first path is dominant and eventual constrains on academic performance are largely responsible for the identified dropout effects, then it might be helpful to structure interventions directed towards augmenting learning in high violence areas to offset learning loss effects. Conversely, if the second path is dominant, then interventions directed towards educating would not address the issues that motivate high dropout rates. There were would, instead, be a need to explore the factors beyond school that interact with gun-violence exposure to prevent obtaining a diploma that would otherwise be attainable.

This chapter has two main goals. First, I am to discern which of the mediating paths outlined above driving the dropout effects identified among the black and Hispanic student subgroups. I explore this issue by studying the effects of a statewide policy change that raised the cognitive requirements for high school completion. Second, the paper explores which student subgroups in high crime areas are most affected by the imposition of testing requirements. This paper uses California data with testing requirement imposed by CAHSEE legislation to explore this question. While the results are specific to California, the qualitative findings should be relevant to a number of other states with high school exit test requirements and areas with elevated levels of gun-violence.

4.2. Data

See chapter 2 for a detailed description of the data and variable constructs employed in this chapter. This chapter employs the $\dot{g}$ measure of gun-violence exposure as the independent variable. See section 2.2.6 for a definition of $\dot{g}$**.** The $\dot{g}$ index is normalized such that a one unit change in $\dot{g}$ corresponds to a decrease in gun-violence exposure of an amount equivalent to the black-white differential in gun-violence exposure over the full sample window. This implies that regression results presented later in this chapter estimate the change in outcomes associated with closing the black-white exposure gap, or decreasing the Hispanic-white differential by an amount that is equivalent to the black-white differential. Review Tables 2.4 and 2.5 for descriptive statistics of the data.

Much of the theoretical and empirical framework for this chapter exploits the onset of the California High School Exit Exam (CAHSEE). In 1999 the California state legislature voted to implement a statewide exam as a graduation requirement for all California public school students. This measure was a response to the realization that heterogeneity in graduation expectations across local education agencies sometimes left student earning a high school diploma without adequately developing the reading and math skills that are expected of high school graduates. CAHSEE policy was implemented with the objective of raising the academic standards for high school completion to leave students better prepared for post-secondary pursuits. Developmental versions of the CAHSEE exam were administered to the classes of 2003 through 2005, however, passing the exam was not yet required for graduation. The classes of 2006 through 2015 were required to pass reading and math sections of the CAHSEE exam to graduate high school. After the class of 2015, CAHSEE was (and remains to be) suspended as a state requirement for high school completion.

Unlike the previous chapter, chapter 4 analyses only employ the subset of the data that corresponds to the graduating classes of 2004 through 2007. Much of the theoretical and empirical framework for this chapter exploits the onset of the California High School Exit Exam (CAHSEE) as a graduation requirement beginning with the graduating class of 2006. Constraining to the classes of 2004 through 2007 facilitates estimating short term policy effects based on changes in the dropout rate between the two classes immediately before and after the onset of the CAHSEE requirement.

4.3. Theoretical and Empirical Model

4.3.1. Theoretical Model

The theoretical framework for this analysis follows the mathematical logic of a proof by contradiction. In a proof by contradiction, one starts with a declaration, derives implications of that declaration, and then shows that the declaration is false if the resulting implications are false. This chapter proceeds analogously by assuming that learning loss is the mediating link between gun-violence exposure and higher dropout rates of black and Hispanic students. I derive implications of this assumption, and test those implications empirically to infer the truth value of the initial assertion. The assertion of interest argues that elevated levels of gun-violence exposure cause cumulative learning loss, which leads to cognitive performance constraints that significantly decrease the likelihood of high school completion. I assume that this statement leads to the following two implications:

(1) Define J as the set of local education agencies in the state of California. For each local education agency, $j \in J$, there exists of some agency-specific cognitive performance threshold, h_j, where dropping out becomes significantly more likely for students who perform at a level of $\underline{h_j}$, and significantly less likely for student performing at level $\overline{h_j}$, where $\underline{h_j} \leq h_j \leq \overline{h_j}$.

(2) For some subset, S, of local education agencies in , $S \subseteq J$, there exists epsilon neighborhoods at h_j, defined as $N(h_j, \epsilon) = h_j \pm \epsilon$, for $\epsilon > 0$, where ϵ is *arbitrarily small*. Furthermore, there exists some density of students performing at levels

$\dot{h_u} \in \{N(h_j, \epsilon) \cap \overline{h_j}\}$ and $\dot{h_l} \in \{N(h_j, \epsilon) \cap \underline{h_j}\}$. [11]

Stated differently, let $f_j(h)$ be the probability density function governing the distribution of student cognitive performance in local education agency $\boldsymbol{j}$. Then the density of students immediately above or below the threshold weakly positive for all agencies such that $\int_{h_j}^{h_j+\epsilon} f_j(h)dh \geq 0$ and $\int_{h_{j-\epsilon}}^{h_j} f_j(h)dh \geq 0$. Furthermore, the inequality holds strictly for agencies in set S defined above such that $\int_{h_j}^{h_j+\epsilon} f_j(h)dh > 0$ and $\int_{h_{j-\epsilon}}^{h_j} f_j(h)dh > 0$.

Implication (1) argues that before the implementation of CAHSEE, every agency had some implicit unique one-dimensional threshold for cognitive performance such that performing below that threshold would challenge efforts at high school completion. This threshold can differ across local education agencies, but the statement implies that some minimum level of cognitive performance is required in order in order to satisfy the academic demands of high school.

Implication (2) assumes that there are students with cognitive performance levels in a small neighborhood ($N(h_j, \epsilon)$) around the threshold. Some students are just above the threshold (i.e. they lie within the intersection of the neighborhood and the set of points just above the threshold denoted, $\dot{h_u} \in \{N(h_j, \epsilon) \cap \overline{h_j}\}$). Conversely, others are just below the threshold and lie within the intersection of the neighborhood and the set of points just below the threshold denoted, $\dot{h_l} \in \{N(h_j, \epsilon) \cap \underline{h_j}\}$). The threshold is a binding constraint for students

[11] The u subscript denotes, “upper”, while the l subscript denotes, “lower”.

who are just below, while students are just above the threshold are doing just well enough to pass.

Define a local education agency specific density function, $f_j(h)$, as the density of students at a given cognitive performance level, h. By construction, $\int_h f_j(h)dh = 1$. This construction implies that the approximate proportion of students dropping out due to cognitive constraints before the CAHSEE implementation would be $\int_{h \le h_j} f_j(h)dh$. After CAHSEE, the cognitive requirements for graduation increased by ϵ_j, $\epsilon_j \ge 0$. Graduation requirements may have increased strictly for some students while other felt no change. This change increases the dropout rate from cognitive constraints to $\int_{h \le h_j + \epsilon_j} f_j(h)dh$. Statewide, this implies an average change in the dropout rate after the 2006 CAHSEE implementation of

$$\delta = E_j\left(\int_{h_j}^{h_j+\epsilon_j} f_j(h)dh\right) > 0$$

This implies that the proportion of dropouts due to cognitive performance limitations should increase after the implementation of the CAHSEE requirement.

According to this framework, the bump in dropout rates is a result of more students falling below the cognitive threshold for high school completion. This analysis is concerned with discerning whether the proportion of students who fall below the completion threshold is higher among populations who are exposed to higher levels of gun-violence. Formally, this implies empirically testing whether $E(\delta|\dot{g_L}) < E(\delta|\dot{g_H})$ where $\dot{g}_L < \dot{g}_H$. A significant difference in δ conditional on the gun-violence exposure level would offer evidence that cognitive limitations from learning loss likely contribute to elevated dropout rates in high crime areas. The next section formalizes an empirical test of these theoretical implications using regression analysis.

4.3.2. Empirical Approach

The analysis addresses a sequence of questions to understand CAHSEE effects and confirm assumptions on which the theoretical approach rests. First, I estimate the overall short-term change in dropout rates that accompanied the CAHSEE implantation. A significant positive effect would be consistent with claims that CAHSEE increased the cognitive requirements for graduation to a level that some would-be graduates were unable to satisfy.

I estimate the following model:

$$y_{irc} = X_{irc}\,\beta_0 + \gamma^y \cdot \dot{g_{irc}} + \delta_1^y \cdot \mathbb{I}(Exit\ Exam\ Policy) + \epsilon_{irc}$$

$$\epsilon_{irt} \sim N(0, \Sigma_\mathrm{i})$$

$$Race = \{Asian, black, Hispanic, white\}$$

The equation models dropout rates, y_{irc}, at the $school \times race \times class$ level of observation where subscript $i = school, r = race,$ and $c = class.$ The controls, X_{irc}, include controls for parent, school, and student level confounders. The error term is clustered at the school level to account for correlated outcomes among student subgroups from the same school. This first model is primarily interested in the coefficient estimate, δ_1^y, on the exit exam policy indicator. A significant positive estimate of δ_1^y would show that a significant short-term increase in dropout rates accompanied the onset of the California exit exam requirement.

Next the analysis checks for differences in the short-term CAHSEE effect across student subgroups. The updated model interacts race with the CAHSEE policy indicator according to the following specification.

$$y_{irc} = X_{irc}\,\beta_0 + \gamma^y \cdot \dot{g_{irc}} + \delta_1^y \cdot\ \mathbb{I}(Exit\ Exam\ Policy)$$

$$+\ \delta_{1,r}^y \cdot \sum_{r \in Race} \mathbb{I}(Exit\ Exam\ Policy) \cdot \mathbb{I}(Race = r) + \epsilon_{irc}$$

$$\epsilon_{irt} \sim N(0, \Sigma_\mathrm{i})$$

Interest is primarily in the race specific total effects (TE) the CAHSEE requirement,

$$TE_r =\ \delta_1^y + \delta_{1,r}^y, r \in Race$$

The race specific total effects offer evidence as whether different student subgroups were differentially affected by the onset of the exit exam requirement.

Finally, a third variation of the model explores whether within subgroup effects varied by gun-violence exposure levels.

$$y_{irc} = X_{irc}\,\beta_0 + \gamma^y \cdot \dot{g_{irc}} + \delta_1^y \cdot\ \mathbb{I}(Exit\ Exam\ Policy)$$

$$+\ \delta_{1,\dot{g}}^y \cdot \sum_{r \in Race} \mathbb{I}(Exit\ Exam\ Policy) \cdot \dot{g_{irc}}$$

$$+\ \delta_{1,r,\dot{g}}^y \sum_{r \in Race} \mathbb{I}(Exit\ Exam\ Policy) \cdot \mathbb{I}(Race = r) \cdot \dot{g_{irc}}\ + \epsilon_{irc}$$

$$\epsilon_{irt} \sim N(0, \Sigma_\mathrm{i})$$

Inference from this model is based on the interaction term , $\delta_{1,r,\dot{g}}^y$, as well as the total effect estimate constructed according to

$$TE_{r\dot{g}}\ =\ \delta_1^y\ + \delta_{1,\dot{g}}^y +\ \delta_{1,r,\dot{g}}^y\ , r \in Race$$

The race-specific component is omitted for full sample estimates. The empirical framework suggests that these total effects should be significant for black and Hispanic students if learning loss is limiting graduation rates.

4.4. Results

This section discusses the empirical results of the regression analysis, and relates findings to the theoretical model facilitating inference on the chapter's primary questions. The section starts by discussing the overall short-term change in the high school dropout rate that accompanied the 2006 implementation of the CAHSEE graduation requirement. From here I assess whether dropout affects differed among race/ethnicity specific student subgroups. Next, I assess whether students who were exposed to higher levels of gun-violence exposure experienced an additional bump in dropout rates, as theory implies. I end with follow-up analyses that enrich our understanding of results.

See Table 4.1 for regression estimates showing the short-term effects of CAHSEE implementation on dropout rates. Sample wide, the CAHSEE exam requirement led to a significant short-term increase in dropout rates of about 1.11 percent. The increase in the dropout rate was slightly higher for male students (1.13 percent), and slightly lower for female students (1.04 percent). The increase in dropout rates support the theoretical assertion that the CAHSEE exam requirement lead to a strict increase in the cognitive performance requirements for high school completion in a significant subset of local education agencies.

Figure 4.2 shows estimates of the CAHSEE effects by student subgroup. Looking at the effect estimates by student subgroups shows the effects were distributed across student subgroups non-uniformly. CAHSEE lead to a short-term increase in dropouts for all groups except for Hispanic students. See Effect estimates were significant at the highest levels ($\mathrm{p} \leq 0.001$) for the Asian and white student subgroups. Effect estimates for these groups ranged from 1.3 percent increase for the Asian student subgroup to a 1.5 percent increase for the white student subgroup. Effect Estimates for the black student subgroup were larger at 1.7 percent, but less significant ($p \leq 0.05$). The effect estimate for the Hispanic student subgroup takes a positive value of 0.7, but was not significantly different from zero.

Beyond estimating the change in the dropout rate that accompanied the onset of the CAHSEE requirement, these estimates also offer a means of approximating the proportion of California public high school students who were previously graduating with math and/or English language arts proficiency levels below the newly imposed CAHSEE state standards. This would be approximated by dividing the coefficient estimate by the graduation rate according to

$$\rho_r = \frac{TE_r}{E[y_{irc}|c \in \{2004,2005\}]}.$$

By this formulation, an estimated 1.3 percent of graduates from the classes of 2004 and 2005 received a diploma with English and/or math proficiency levels below the newly imposed state standards. This estimate is slightly higher for the black student subgroup (2.1 percent), and in the 1.4 to 1.6 percent range for the Asian and white student subgroups respectively. Because the total effects estimated for the Hispanic student subgroup above were not significantly different from zero, the projected proportion of Hispanic students graduating with skills below the new state mandates is necessarily zero. See Table 4.5 for estimates.

Table 4.5 shows race specific effects, and race specific effects interacted with the gun-violence exposure measure for comparison. Across the full sample, the CAHSEE × exposure interaction effect is insignificant from zero at traditional significance levels. This finding is supported by a total effect estimate of -0.02 and ninety-five percent confidence intervals that admit the possibility of zero effects. This estimate indicates an overall absence of additional dropout effects of the CAHSEE exam requirement for high school students in high exposure areas. The result of no additional effects in high gun-violence exposure populations was not maintained across all student subgroups. The black and Hispanic student subgroups both show no variation in effect magnitude conditional upon gun-violence exposure level. This important result indicates that there is no evidence that cumulative learning loss from long-term violence exposure lead to constrained cognitive performance that lowered the likelihood of high school completion. This result suggests that learning loss is likely not the mediator driving the elevated dropout rates of black and Hispanic students in areas that experience elevated rates of gun-violence exposure. While there is no evidence of differential effects in high versus low violence areas for black and Hispanic students, there is evidence of differential effects for the Asian and white student subgroups. Estimates for both groups produced evidence of a larger dropout penalty for students in high gun-violence exposure areas. Parameter estimates suggest a 1.7 percent increase for Asian students, and 1.4 percent increase in the dropout rate for white students.

The significant effects identified for white and Asian students suggests that learning loss may lead to binding cognitive performance constraints that can be limiting for these student subgroups. It appears to be the case that learning loss can be a limiting factor to the educational attainment of students who are not limited by other factors first. White and Asian students have higher graduation rates and seem to face fewer barriers to academic success than black and Hispanic students, on average. It appears that non-academic constraints interrupt the educational success of black and Hispanic students before cognitive performance limitations become binding obstacle to high school completion. Evidence of this argument is supported by Figure 4.6. The graphs plot mean high school dropout rates for each student subgroup among the subset of students in high crime areas with mean subgroup scores of 350 or less on the mathematics portion of the CAHSEE exam. A score of 350 or below fails to satisfy CAHSEE proficiency requirements. Thus, these estimates show dropout rates among students who would likely struggle to pass the CAHSEE exam, and who would thus struggle to meet the CAHSEE imposed cognitive performance requirements for high school graduation. The figures plot dropout rate densities for student subgroups who earned a score of 350 or less on the CAHSEE math exam. The $x-axis$ denotes the probability of dropping out of high school on a scale of zero to one hundred, while the $y-axis$ measures density of each subsample that exists at each dropout likelihood.

The plots indicate that low scoring black and Hispanic student dropout more regularly than low performing white and Asian students. Notice that the graphs for Asian and white students both start with high peaks at the lower dropout likelihoods. These peaks clustered near zero indicate high densities of Asian and white student subgroups that are unlikely to drop out of high school, regardless of their performance on cognitive assessments. The graphs for Hispanic and black students have a clear substantive difference. Initial peaks at lower dropout rates are either less pronounced, or completely absent. The graphs are also much longer with line segments that stretch toward dropout rates of 80 and 90 percent. These longer graphs indicate greater densities of students at higher dropout rates. Neither the white nor Asian graph reaches beyond the 50 percent.

Together, the evidence above suggests that learning loss is not driving the elevated dropout rates of black and Hispanic students. However, it may contribute to higher dropout rates among Asian and White students. These groups are more susceptible to learning loss effects because they have higher graduation rates and are more likely to stay in school long enough for cognitive performance to become a binding constraint on educational advancement. Black and Hispanic student who might eventually be limited by performance constraints appear to leave school before these constraints can become binding.

4.5. Discussion

Chapter 3 shows that higher levels of gun-violence exposure are significantly related to the group level dropout rates for black and Hispanic high school students in the state of CA. This paper studies the short-term effects of the implementation of the California High Exit Exam on dropout rates to help address two questions. First, I assess whether black and Hispanic students in high gun-violence exposure areas experienced a bump in dropout rates with the implementation of California's exit exam requirement in 2006. Second and more generally, I ask what can be learned about the mediating mechanisms that connect gun-violence exposure and elevated dropout rates. Specifically, I ask what can be learned about the role of learning loss from a policy change that increased the cognitive requirements for high school completion. Due to the structure of these data, this paper was only able to make inference about the role of learning loss as a mediating mechanism. Work is needed to understand what forces most heavily mediate gun-violence exposure effects on the students who are most exposed.

There was a 1.1 percent short-term increase in the dropout rate for the first two high school classes that were required to pass the CAHSEE exam. This bump was distributed across student subgroups non-uniformly. There was no significant change in the dropout rate for Hispanic students. There were however increases for all other student subgroups. The black student subgroup registered the largest absolute gain with an increase in dropout rates of 1.7 percent. The white and Asian student subgroups had the most significant effects with estimates ranging from 1.1 to 1.3 percent. These results show that there were students for whom the added requirement of CAHSEE testing appeared to be a barrier to high school completion.

Given that the exit had some short-term effect on dropout rates, one can consider whether the effects were larger in areas with higher levels of gun-violence. Results from the full sample offer no evidence that students in high crime areas were differentially affected. Analyses by student subgroup offer a slightly different story. No effects were identified for the student subgroup with the highest dropout rates (black and Hispanic students), but effects were identified for the student subgroups with the lowest dropout rates (white and Asian students).

This result uncovers an interesting dynamic concerning how gun-violence exposure affects dropout rates. The lack of significant effects for black and Hispanic students strongly suggests that there is no meaningful connection between dropout rates, the higher cognitive requirements of the CAHSEE implementation, and the effects of elevated levels of gun-violence exposure. Effects from cumulative learning loss, which is one of the known effects of gun-violence exposure, were thus not strong enough to lower graduation rates after an increase in the cognitive requirements of high school completion. Thus, learning loss is likely not responsible for binding learning limitations that constrain the educational attainment of black and Hispanic students. The same is likely not true for white and Asian students. Results show that exit exam implementation adversely affected the dropout rates of white and Asian students, suggesting that learning limitation correlated with gun-violence exposure was sufficient for limiting the educational attainment of students in these subgroups.

These opposing results between black and Hispanic versus white and Asian students are not due to differential responses to the same violence exposure experience. Instead it appears to be the result of differences in other external factors that affect educational success. Black and Hispanic students are less advantaged, on average. Evidence presented above shows that among students in the same class of cognitive ability, white and Asian students are much less likely to dropout relative to black and Hispanic students. This suggests that other factors interrupt the success of black and Hispanic students before performance limitations can become a binding constraint. White and Asian students, however, face less disadvantage as a group and are more likely to survive high school until a cognitive constraint is the only barrier to a high school diploma.

5. Conclusions and Future Work

This research constructs a unique dataset that facilitates a population-level investigation of the relationship between gun-violence exposure levels and high school dropout rates across all California public high schools for the graduating classes of 2003 through 2014. I geospatially merge data from three separate sources to build a dataset with detailed education and crime data, as well as additional control measures from the American Community Survey.

My initial exploration of the relationship between gun-violence exposure and high school dropout rates employs a bivariate fixed effects model to understand whether the outcomes of student cohorts at the same school are significantly related to the differences in gun-violence exposure experienced by cohorts. Estimates suggest significant effects sample wide, and larger effects among the black and Hispanic student subgroups. These dynamics, which are central to later analyses, are already evident in simple bivariate models fixed effects models that only control for class year.

Chapter three turns to investigating the functional form governing the response of dropout rates to elevated rates of gun-violence exposure, as well as obtaining a nuanced understanding of the differential effects across student subgroups. I find that gun-violence exposure has measurable effects on high school dropout rates only when violence levels exceed a certain threshold. Black and Hispanic students are more likely to attend schools that register gun-violence levels above this threshold than their white and Asian peers. Among black and Hispanic students who experience gun-violence levels above the identified threshold, it is estimated that decreasing their gun-violence exposure levels by the black-white exposure differential over the sample period would be associated with a roughly 1.7 (2.0) percent decrease in the dropout rates for Hispanics (blacks). Out of over four million 9th graders described by these data, this represents at least 40,000 more black and Hispanic high school dropouts over the decade period spanning the data. This result suggests that gun-violence exposure effects can influence the educational demographics of a population.

The evidence above shows that there are significant gun-violence exposure effects concentrated on specific subsets of the student population. However, we presently know relatively little about what mediates the link between gun-violence exposure and elevated dropout rates. Literature details a number of physiological, psychological, and behavioral side effects that likely influence educational success (see section 1.1). Evidence from Burdick-Will (2016) also discusses learning loss as a potential link. Her work shows that prolonged violence exposure can erode learning and lead to cumulatively less learning over time. It is presently unclear whether learning losses from gun-violence exposure are playing a dominant role in mediating dropout effects.

I address this question by exploiting a statewide policy change to assess whether learning loss is contributing significantly to the elevated dropout rates of black and Hispanic students in high gun-violence exposure areas. Under some assumptions, I derive an implication of the policy change that must hold if learning loss is leading to cognitive performance constraints that impede high school completion. From there, I empirically test the implication, which facilitates inference on the theoretical question of interest.

My theoretical model (section 4.3.1) implies that the short-term change in dropout rates associated with the 2006 implementation of the California High School Exit Exam (CAHSEE), should differ depending on the level of gun-violence exposure experienced by students. Regression results show no evidence this for black and Hispanic students. In both groups, the short-term effect of the policy was the same regardless of the level of gun-violence exposure in the experienced. This suggests that cognitive performance constraints from learning loss are not the binding constraint limiting the high school completion rates of black and Hispanic students in high exposure areas.

While there was no gun-violence gradient for CAHSEE policy effects among black and Hispanic students, there were significant effects among both white and Asian students. An investigation of this result lead to evidence that low performing white and Asian students were less likely to drop out of school than low performing black and Hispanic students. Thus, white and Asian students were still in school by the time their cognitive performance became a limiting constraint. Conversely, black and Hispanic students were more likely to leave before performance became limiting.

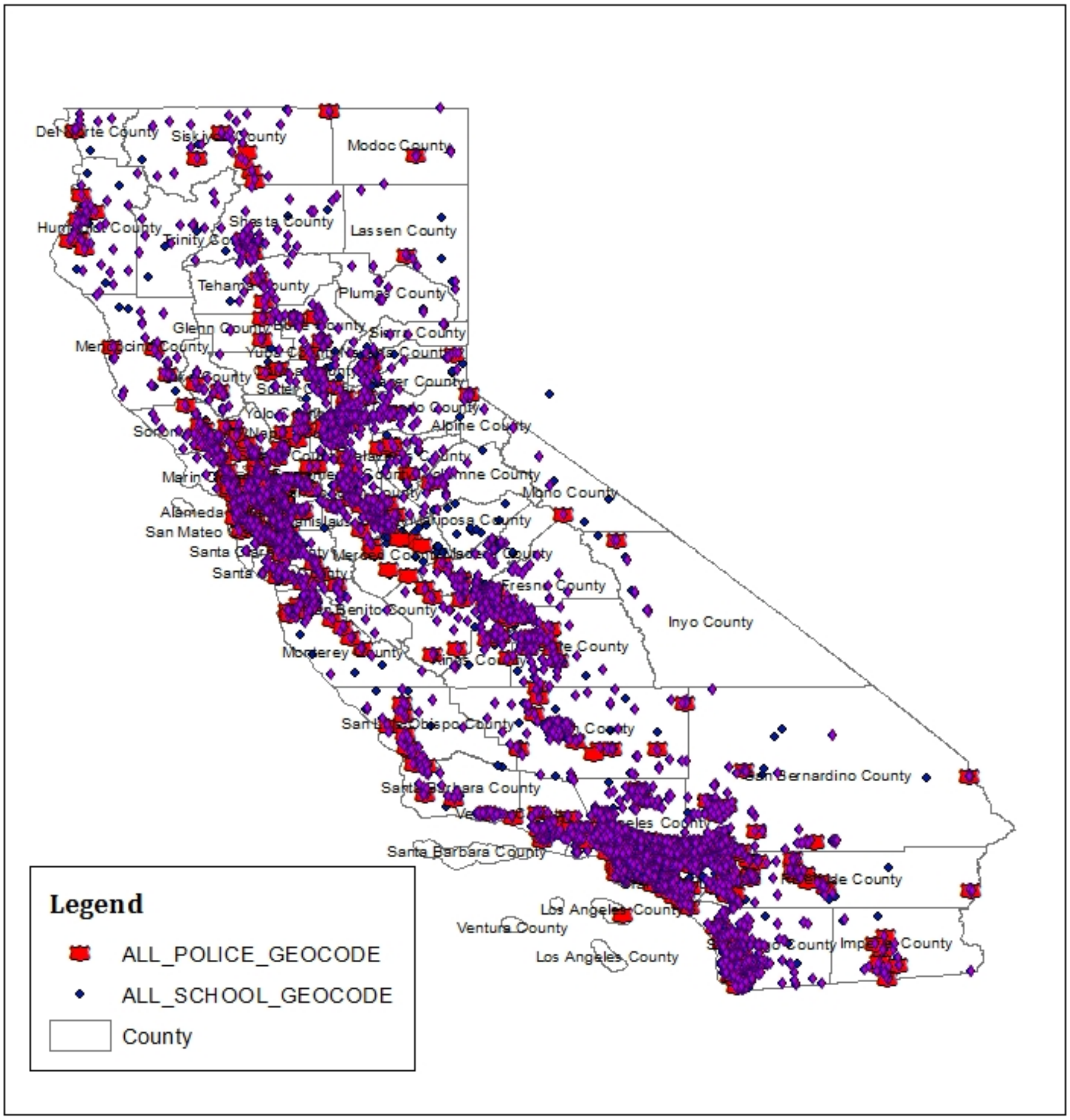
As this work progresses, I would like to do more with the cohort version of these data. I aim to move beyond the present results to learn more about how the timing of gun-violence exposure effects the outcomes. I also aim to further discern how the trajectory of a high school cohort is affected by exposure to violence.

These data are exciting, in part, because of potential links to other rich datasets. I have plans to link the Los Angeles county observations from these data to incident-level crime data from the Los Angeles County Police Department and the Los Angeles County Sheriff's Department. This may facilitate a project that offers cleaner estimates of causal effects, as well as another setting for assessing the threshold hypothesis. I am also considering the feasibility of linking this high school data set to the middle schools that serve as feeders. Finally, I have taken steps to lay the foundation for linking these data to death records that offer a more accurate measure of the mortality risk faced by kids in high violence areas.

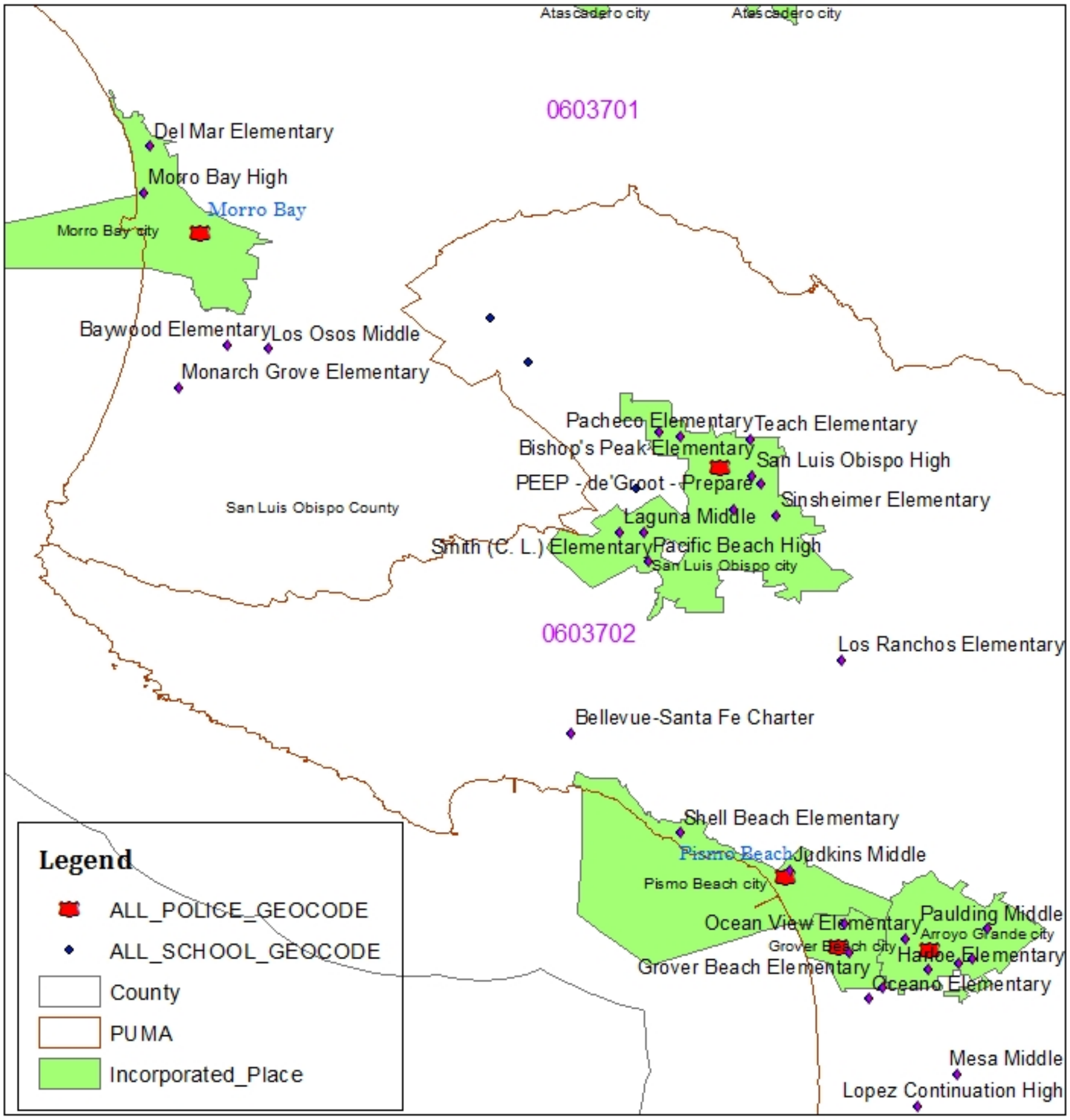
These projects will further strengthen the literature on gun-violence exposure effects, and add depth to our understanding of the associated population-level effects of exposure.

6. Appendix of Tables and Figures

2.1 Figure: Geographic Scope of California Statewide Education and Crime Data



2.2 Figure: Education, Crime, and IPUMS Data Match Example



2.3 Chart: Cohort Data Construction and CAHSEE Policy Timeline

	Data year															
Graduating Class Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
2003	8	9	10	11	12											
2004		8	9	10	11	12										
2005			8	9	10	11	12									
2006				8	9	10	11	12								
2007					8	9	10	11	12							
2008						8	9	10	11	12						
2009							8	9	10	11	12					
2010								8	9	10	11	12				
2011									8	9	10	11	12			
2012										8	9	10	11	12		
2013											8	9	10	11	12	
2014												8	9	10	11	12

Year	Timeline of Significant Events
1999	Law passed imposing classes 2006+ to pass CAHSEE to earn diploma
2003	CAHSEE content standards adopted; State dropout definition modified
2005	Last class to take CAHSEE without consequence
2006	First class required to pass CAHSEE
2015	CAHSEE graduation requirement suspended

Chart Key	
	CAHSEE Test opportunity for classes required to pass for graduation
	CAHSEE Test opportunity for classes NOT required to pass for graduation
	2003 CAHSEE Content Standards imposed
	Treatment measured for cohort analysis
	Control variables measured

2.4 Table: Mean Values and Sample Sizes of Outcomes and Mediators for Full Sample and By Gun-Violence Exposure Level

Outcomes and CAHSEE Mediators	Full Sample				Violence Exposure Level				
					Low (g<-1)		High (g>=-1)		
	Mean	Std. Dev.	Student Subgroups	Grade 9 Student Years	Mean	Std. Dev.	Mean	Std. Dev.	High-Low Sig Diff.
Dropout Rates									
All (0/100)	10.54	12.62	39,719	4,164,371	5.39	8.74	12.56	13.35	***
Males (0/100)	11.60	13.46	37,585	4,156,547	5.93	9.35	13.83	14.22	***
Females (0/100)	9.21	11.93	36,182	4,146,144	4.64	8.27	11.00	12.66	***
CAHSEE Performance									
ELA Percent Passed (0/100)	77.15	16.53	28,338	3,772,193	85.68	13.84	73.70	16.19	***
Math Percent Passed (0/100)	75.15	20.43	28,395	3,777,069	84.53	16.92	71.14	20.50	***
ELA Mean Standard Score (0/100)	58.80	11.62	28,667	3,774,554	65.59	11.08	56.00	10.51	***
Math Mean Standard Score (0/100)	57.76	13.97	28,810	3,780,466	65.00	13.46	54.59	12.86	***

† p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table presents mean values weighted by grade nine enrollment counts. T-tests of significance are based simple regressions with grade nine enrolment weights. Standard errors are adjusted with clusters at the school level.

2.5 Table : Descriptive Values of Control Variables for Full-Sample and by Gun-Violence Exposure Level

	Full Sample		Violence Exposure Level				
			Low (g<-1)		High (g>=-1)		High-Low Sig Diff.
Control Measure	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
Student Characteristics							
Asian(0/1)	0.09	0.29	0.11	0.31	0.07	0.26	***
Hispanic (0/1)	0.52	0.50	0.33	0.47	0.59	0.49	***
African-American (0/1)	0.09	0.28	0.04	0.19	0.11	0.31	***
Pct. Receiving Free/Reduced Price Lunch (0/100)	44.16	26.58	24.24	20.67	52.78	24.10	***
Pct. Migrant Ed. Programs (0/100)	1.84	4.75	2.08	5.49	1.75	4.48	
Pct. In Gifted and Talented Program (0/100)	11.98	9.91	13.58	9.76	11.47	9.95	***
Pct. New students (0/100)	13.12	13.82	10.84	12.43	14.19	14.27	***
Parents Education							
Pct. Graduate Education (0/100)	10.65	11.41	17.40	14.36	7.89	8.41	***
Pct. College Graduates (0/100)	19.83	11.21	26.32	11.94	17.34	9.79	***
Pct. High School Graduates (0/100)	23.97	10.03	17.36	10.63	26.25	8.02	***
School Qualities							
Virtual School (0/1)	0.00	0.04	0.00	0.03	0.00	0.04	
Charter School (0/1)	0.06	0.23	0.01	0.12	0.08	0.26	***
Magnet School (0/1)	0.19	0.39	0.07	0.25	0.24	0.43	***
CAHSE Policy (0/1)	0.76	0.43	0.77	0.42	0.75	0.43	**
Traditional School (0/1)	0.88	0.33	0.85	0.36	0.88	0.32	
School Rank (1/10)	5.52	2.48	6.03	2.42	5.29	2.45	***
Pct. Teachers with Full Credentials (0/100)	90.24	9.42	93.95	5.94	88.79	10.01	***
Community Demographics							
Pct. Advanced Degree (0/1)	1.21	1.95	1.49	1.85	1.05	1.83	***
Pct. High School Graduates (0/1)	5.06	2.76	5.07	2.91	5.00	2.62	
Pct. Out of the labor market (0/1)	47.62	7.57	45.56	7.97	48.53	7.28	***
Pct. Employed or in Military(0/1)	44.47	8.20	47.45	8.42	43.10	7.82	***
Pct. Fatherless Households	22.22	10.85	17.75	6.64	24.27	11.66	***
Log Median Income (9.6/12.0)	10.89	0.39	11.17	0.37	10.77	0.34	***

† $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

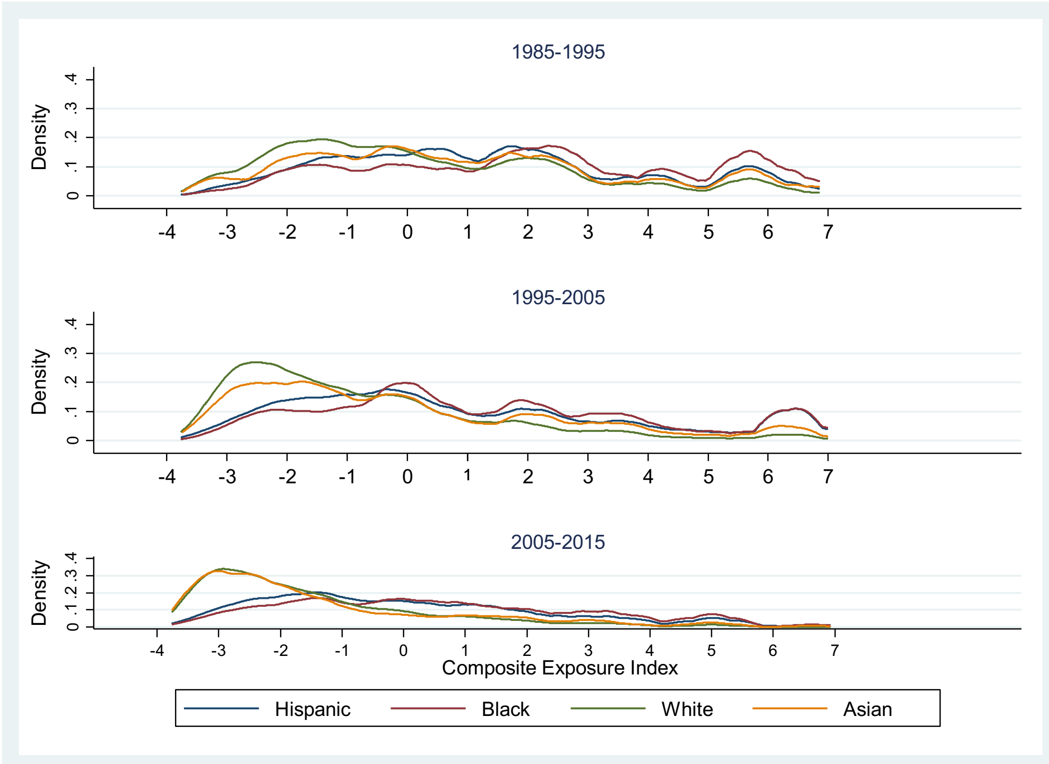
Table presents mean values weighted by grade nine enrollment counts. T-tests of significance are based simple regressions with grade nine enrollment weights. Standard errors are adjusted with clusters at the school level. Percentages for community demographics are multiplied by one hundred to achieve a (0/100) scale. Regression estimates use these variables the (0/1) scale.

2.6 Table Factor Loadings for Firearm Related Disturbances

Disturbance*	Factor 1	Factor 2
Homicide	0.837	0.043
Firearm Robbery	0.894	-0.024
Firearm Assault	0.901	-0.016

*All disturbances are measured per 100,000 individuals in a population. Loadings were estimated in STATA using a sample of 593,047 observations.

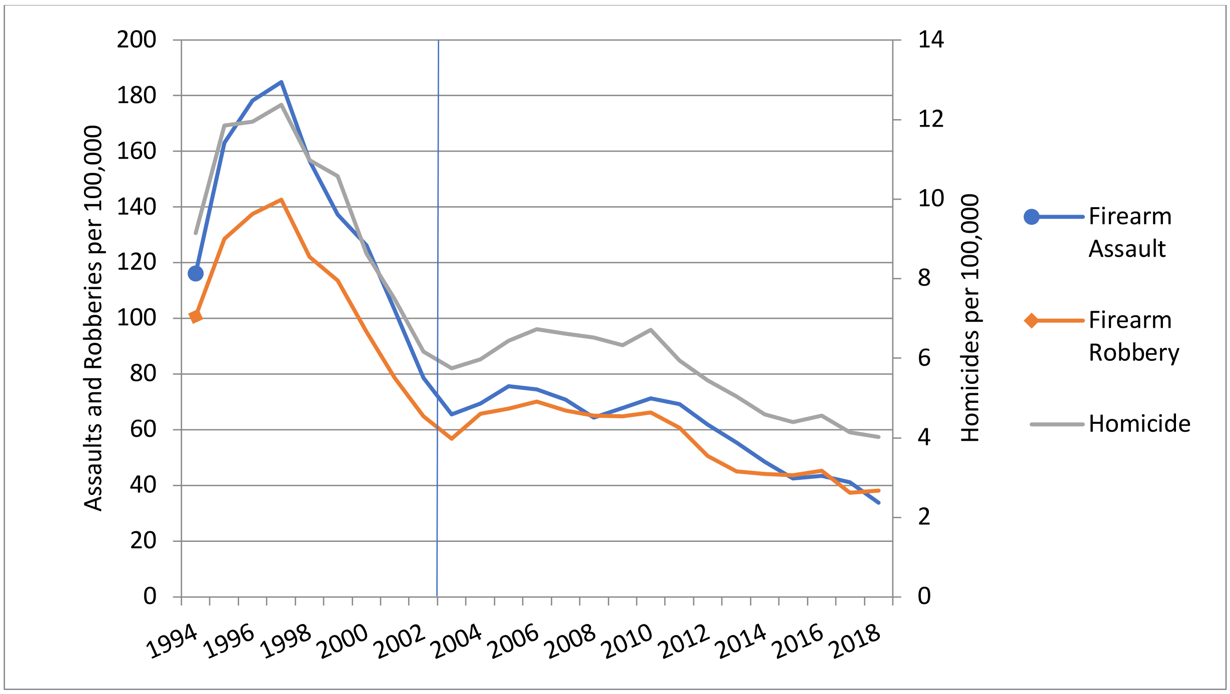
2.7 Figure: Composite Gun-violence Exposure over time by student racial group



2.8 Table: Composite Gun-violence Exposure over time by student racial group

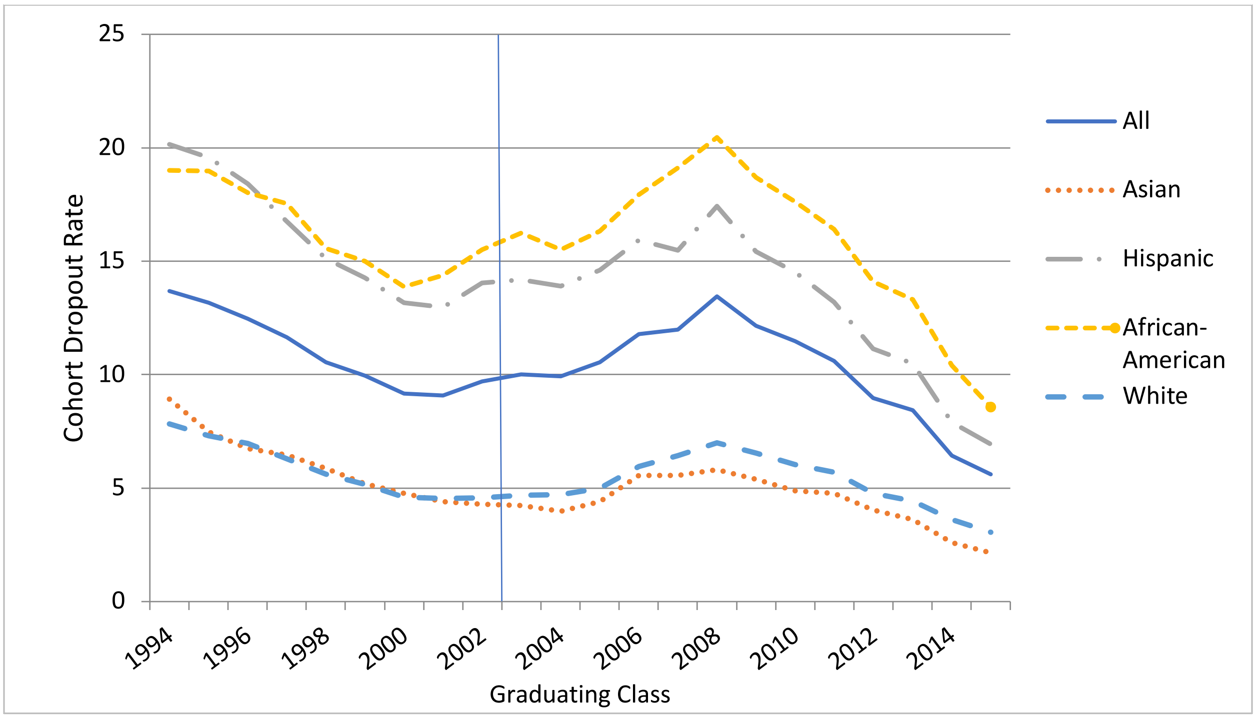
Period	$\mu_{Group}(Composite\ Exposure)$				$\Delta = \mu_{group} - \mu_{White}$		
	Asian	Black	Hispanic	White	Asian	Black	Hispanic
1985-1995	5.45	10.40	7.67	2.13	3.33	8.27	5.54
1995-2005	1.18	3.68	2.79	-0.26	-0.95	3.94	3.06
2005-2015	-0.73	1.53	0.27	-1.31	-2.86	2.84	1.58
2015	-1.32	0.67	-0.33	-1.60	**-3.44**	**2.27**	**1.27**
Total Change	6.77	9.73	8.00	3.73	-	-	-

2.9 Figure: Gun-Crime Rates Per 100,000 During Student's Grade 8 Academic Year for California High School Graduating Classes of 1994 through 2018.



2.10 Cohort Level Dropout Rates Over Time and By Race for California Public High School Students

(Class of 1994-High School Class of 2014)

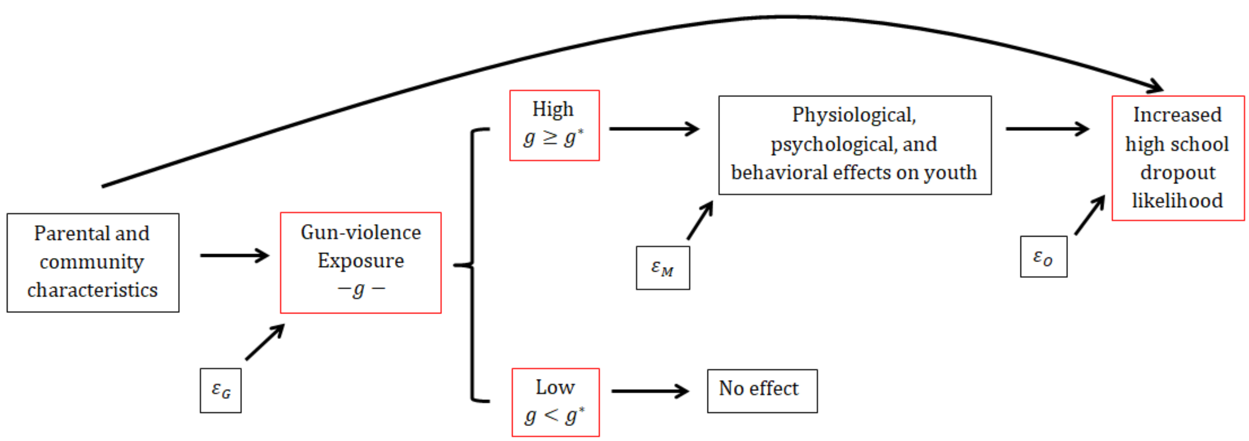


The veritical line denotes the beginning of the analysis sample with the class of 2003.

2.11 Table: Bivariate Fixed Effects Estimates: Gun-Violence Exposure on Dropout Rates

	Full Sample		Asian		Hispanic		Black		White		High Exposure		Low Exposure	
Gun-Violence Exposure	13.60	***	9.14	*	16.17	***	16.26	**	9.85	*	13.54	**	10.78	**
	(4.07)		(4.46)		(4.61)		(5.29)		(4.21)		(4.29)		(3.48)	
N	40,797		7,813		12,356		9,341		11,287		30,375		18,085	
N Groups	5,083		921		1,552		1,188		1,422		2,325		3,632	
N Clusters	1,641		921		1,552		1,188		1,422		746		1,177	

3.1 Path Model: Effect of Gun-violence Exposure on Youth Education Outcomes



3.2 Table: Cross-Sectional Regression Effects of Violence Exposure on Cohort-Level High School Dropout Rates for the Full Sample and by Gender

Covariates	Full Sample b/se		Male b/se		Female b/se	
Gun-Violence Exposure (-1/6.1)	1.568	***	1.817	***	1.294	***
	(0.345)		(0.382)		(0.311)	
Asian(0/1)	-1.949	**	-2.378	**	-1.636	**
	(0.689)		(0.762)		(0.628)	
Hispanic (0/1)	1.541	***	1.646	***	1.483	***
	(0.423)		(0.463)		(0.391)	
African-American (0/1)	-0.564		-0.500		-0.903	
	(1.480)		(1.586)		(1.383)	
Pct. Receiving Free/Reduced Price Lunch (0/100)	0.027	†	0.034	*	0.019	
	(0.014)		(0.016)		(0.013)	
Pct. Migrant Ed. Programs (0/100)	-0.093	*	-0.125	**	-0.061	†
	(0.037)		(0.040)		(0.034)	
Pct. In Gifted and Talented Program (0/100)	-0.112	***	-0.121	***	-0.101	***
	(0.022)		(0.024)		(0.020)	
Pct. New students (0/100)	0.179	***	0.186	***	0.169	***
	(0.040)		(0.042)		(0.038)	
Parent: Graduate Education (0/100)	-0.030		-0.033		-0.028	
	(0.019)		(0.020)		(0.017)	
Parent: High School Graduates (0/100)	-0.062	†	-0.070	*	-0.053	†
	(0.033)		(0.035)		(0.030)	
Parent: College Graduates (0/100)	-0.047	*	-0.045	*	-0.046	*
	(0.020)		(0.022)		(0.018)	
Community: High School Graduates (0/1)	0.502		-0.160		0.614	
	(3.251)		(3.542)		(3.052)	
Pct. Teachers with Full Credentials (0/100)	-0.087	**	-0.085	*	-0.092	**
	(0.034)		(0.037)		(0.031)	
Virtual School (0/1)	19.701	***	21.554	***	18.462	***
	(3.286)		(3.562)		(3.082)	
Charter School (0/1)	4.370	*	4.901	*	3.949	*
	(2.016)		(2.154)		(1.906)	
Magnet School (0/1)	2.484	**	3.120	***	1.915	**
	(0.785)		(0.863)		(0.708)	
CAHSEE Policy (0/1)	-0.190		-0.306		-0.163	
	(0.324)		(0.357)		(0.298)	
Traditional School (0/1)	-0.717		-0.774		-0.595	
	(0.522)		(0.573)		(0.466)	
School Rank (1/10)	-0.554	***	-0.596	***	-0.492	***
	(0.082)		(0.088)		(0.077)	

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Covariates		Full Sample b/se		Male b/se		Female b/se	
	Community: Advanced Degree (0/1)	4.504		3.712		4.837	
		(5.153)		(5.772)		(4.729)	
	Pct. Out of the labor market (0/1)	24.871	*	25.123	*	24.810	*
		(10.499)		(11.428)		(9.781)	
	Pct. Employed or in Military(0/1)	16.365	†	16.172		16.242	†
		(9.603)		(10.345)		(9.033)	
	Pct. Fatherless Households	15.094	**	14.941	**	15.384	***
		(4.680)		(5.054)		(4.335)	
	Log Median Income (9.6/12.0)	-2.623	***	-3.033	***	-2.134	**
		(0.787)		(0.878)		(0.702)	
	Constant	26.751	*	32.281	**	20.403	*
		(11.084)		(12.146)		(10.147)	
N	Schools	756		755		755	
	Student Subgroups	30,079		29,045		28,984	
	Student-years	3,877,529		3,873,005		3,871,343	
	p	0.000		0.000		0.000	

† $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

3.3 Table: Cross-Sectional Regression Effects of Violence Exposure on Cohort-Level High School Dropout Rate with Race x Exposure Interactions, Full Sample and by Gender

Covariates	Full Cohort b/se		Male b/se		Female b/se	
Gun-Violence Exposure (-1/6.1)	0.576		0.621		0.450	
	(0.353)		(0.387)		(0.322)	
Asian x Gun-Violence	-0.543	*	-0.546	†	-0.526	*
	(0.265)		(0.313)		(0.233)	
Hispanic x Gun-Violence	1.533	***	1.854	***	1.273	***
	(0.344)		(0.376)		(0.317)	
African-American x Gun-Violence	1.189	**	1.325	**	1.176	**
	(0.404)		(0.442)		(0.380)	
Asian(0/1)	-1.589	*	-1.904	*	-1.385	*
	(0.737)		(0.806)		(0.679)	
Hispanic (0/1)	1.668	***	1.812	***	1.584	***
	(0.423)		(0.462)		(0.393)	
African-American (0/1)	-0.159		-0.029		-0.543	
	(1.427)		(1.523)		(1.337)	
Pct. Receiving Free/Reduced Price Lunch (0/100)	0.025	†	0.032	*	0.018	
	(0.014)		(0.015)		(0.013)	
Pct. Migrant Ed. Programs (0/100)	-0.077	*	-0.104	**	-0.048	
	(0.036)		(0.040)		(0.034)	
Pct. In Gifted and Talented Program (0/100)	-0.110	***	-0.118	***	-0.099	***
	(0.021)		(0.023)		(0.020)	
Pct. New students (0/100)	0.179	***	0.186	***	0.169	***
	(0.040)		(0.042)		(0.038)	
Parent: Graduate Education (0/100)	-0.031	†	-0.034	†	-0.028	†
	(0.018)		(0.020)		(0.017)	
Parent: High School Graduates (0/100)	-0.050		-0.056	†	-0.043	
	(0.032)		(0.034)		(0.029)	
Parent: College Graduates (0/100)	-0.044	*	-0.041	†	-0.044	*
	(0.020)		(0.021)		(0.018)	
Community: High School Graduates (0/1)	1.300		0.760		1.335	
	(3.169)		(3.441)		(2.990)	
Pct. Teachers with Full Credentials (0/100)	-0.081	*	-0.078	*	-0.087	**
	(0.033)		(0.036)		(0.031)	
Virtual School (0/1)	19.473	***	21.273	***	18.278	***
	(3.270)		(3.542)		(3.070)	
Charter School (0/1)	4.624	*	5.202	*	4.173	*
	(2.006)		(2.139)		(1.900)	

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Covariates		Full Sample b/se		Male b/se		Female b/se	
	Magnet School (0/1)	2.362	**	2.968	***	1.825	*
		(0.784)		(0.857)		(0.712)	
	CAHSEE Policy (0/1)	-0.156		-0.264		-0.138	
		(0.319)		(0.350)		(0.293)	
	Traditional School (0/1)	-0.754		-0.819		-0.620	
		(0.520)		(0.572)		(0.464)	
	School Rank (1/10)	-0.551	***	-0.593	***	-0.490	***
		(0.081)		(0.086)		(0.076)	
	Community: Advanced Degree (0/1)	8.041		7.951		7.902	†
		(4.915)		(5.508)		(4.518)	
	Pct. Out of the labor market (0/1)	21.040	*	20.569	†	21.508	*
		(10.357)		(11.236)		(9.680)	
	Pct. Employed or in Military(0/1)	14.397		13.829		14.499	
		(9.433)		(10.145)		(8.883)	
	Pct. Fatherless Households	13.927	**	13.913	*	13.873	**
		(5.091)		(5.464)		(4.719)	
	Log Median Income (9.6/12.0)	-3.035	***	-3.473	***	-2.546	***
		(0.790)		(0.877)		(0.708)	
	Constant	32.900	**	38.955	**	26.461	**
		(10.987)		(12.008)		(10.081)	
N	Schools	756		755		755	
	Student Subgroups	30,079		29,045		28,984	
	Student-years	3,877,529		3,873,005		3,871,343	
	p	0.000		0.000		0.000	

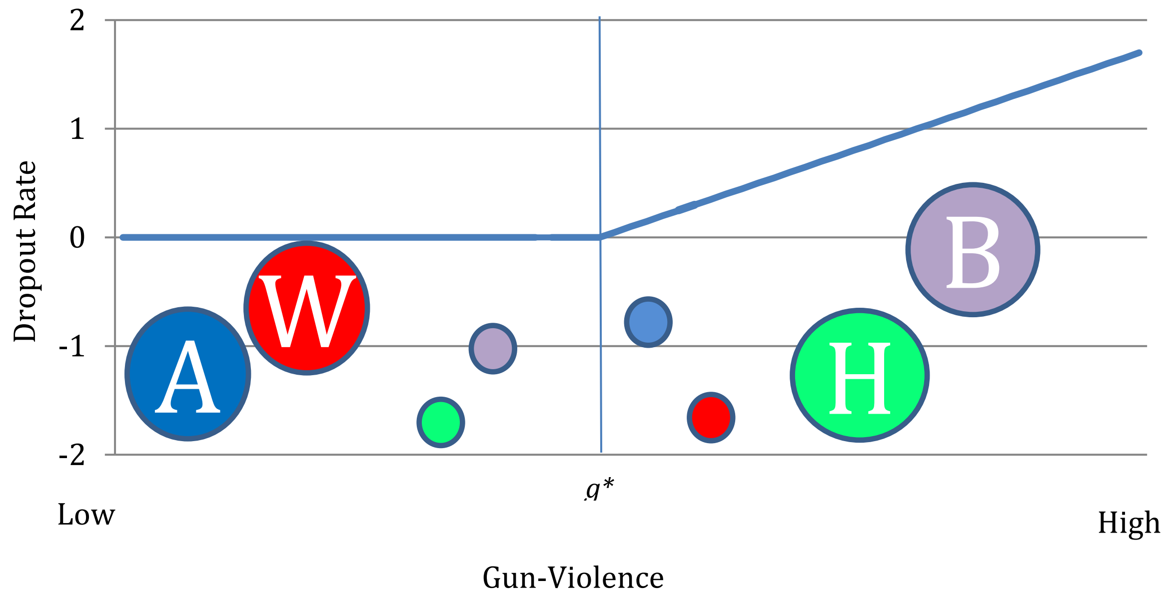
† p<0.10, * p<0.05, ** p<0.01, *** p<0.001

3.4 Table: Total Effect Estimates of Gun-Violence Exposure on High School Dropout Rates for the Full Sample and by Gender

	Full Sample		Male		Female	
	b/se		b/se		b/se	
African-American	1.765	***	1.946	***	1.626	***
	(0.432)		(0.477)		(0.397)	
Asian	0.032		0.075		-0.076	
	(0.342)		(0.389)		(0.304)	
Hispanic	2.108	***	2.475	***	1.723	***
	(0.413)		(0.454)		(0.373)	
White	0.576		0.621		0.450	
	(0.353)		(0.387)		(0.322)	

† p<0.10, * p<0.05, ** p<0.01, *** p<0.001

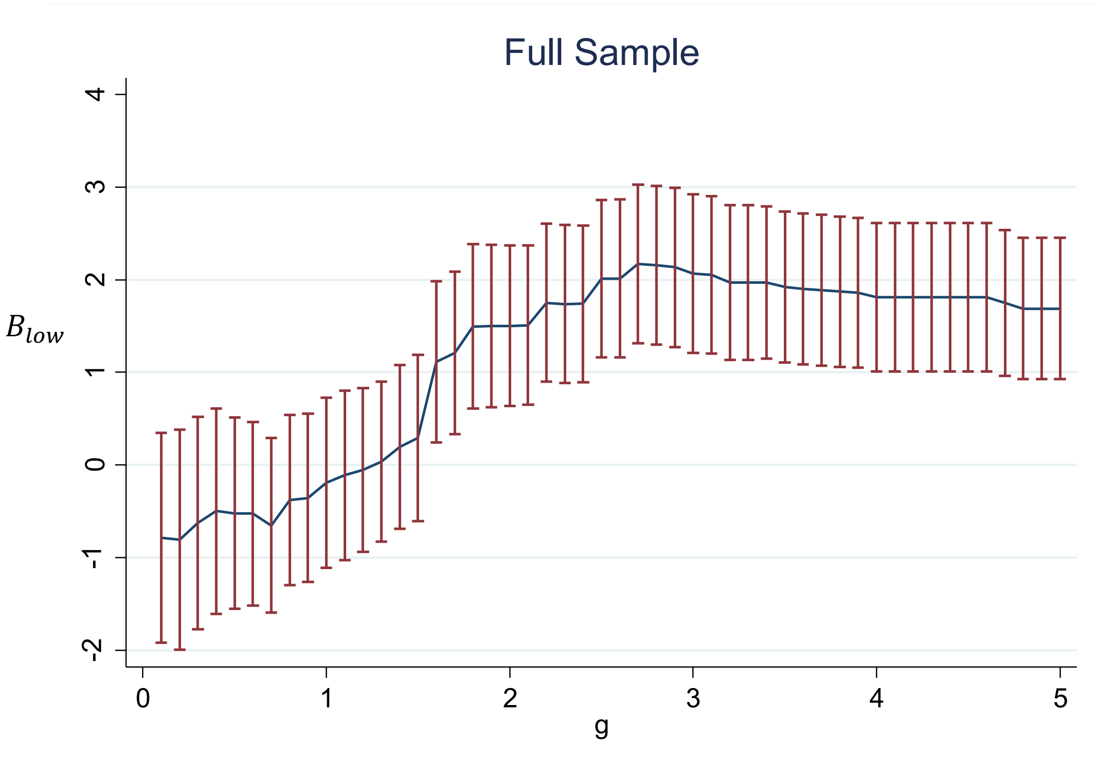
3.5 Gun-Violence Exposure Threshold Effect



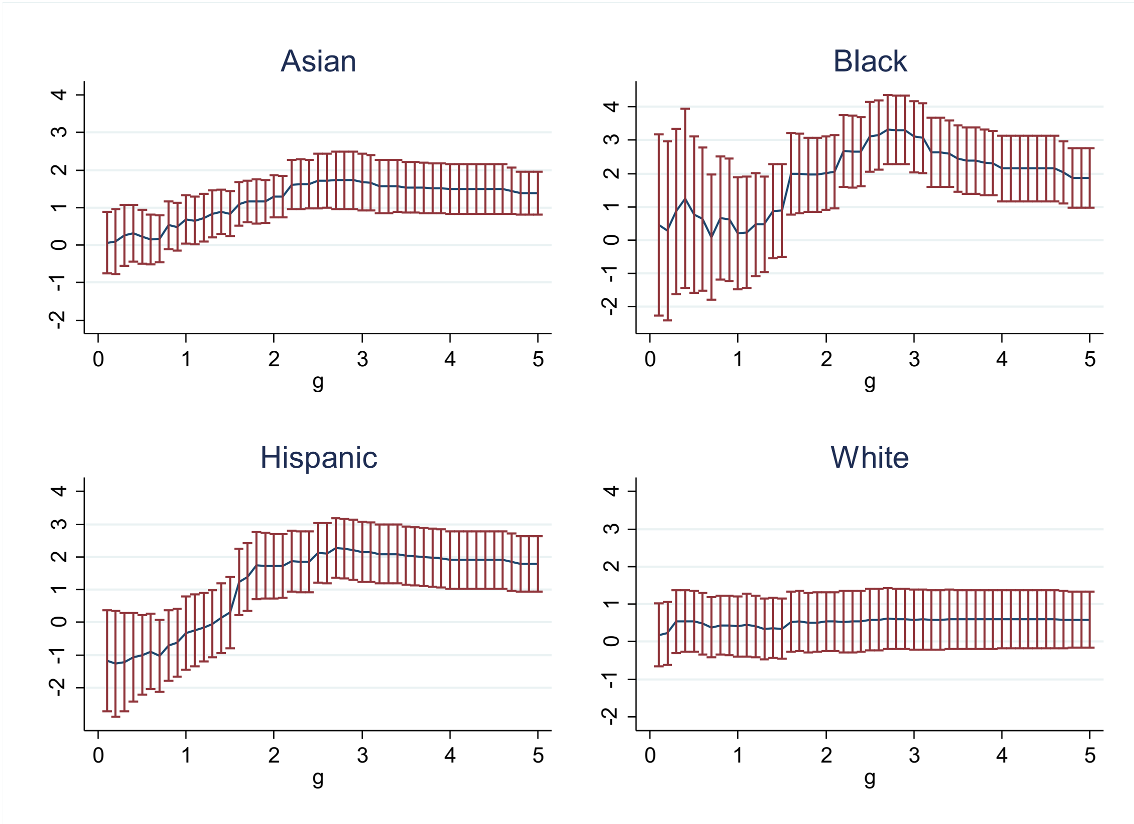
Note: A=Asian, W=White, H=Hispanic, B=Black. Graph is heuristic. The size of each circle represents the relative density of students in

3.6 Figure: Regression Discontinuity Model: Effect Estimates (β_{low}) Below the Discontinuity Threshold

(g)



3.7 Figure: Regression Discontinuity Model: Mapping of β_{low} Slope Estimates by Student Subgroup

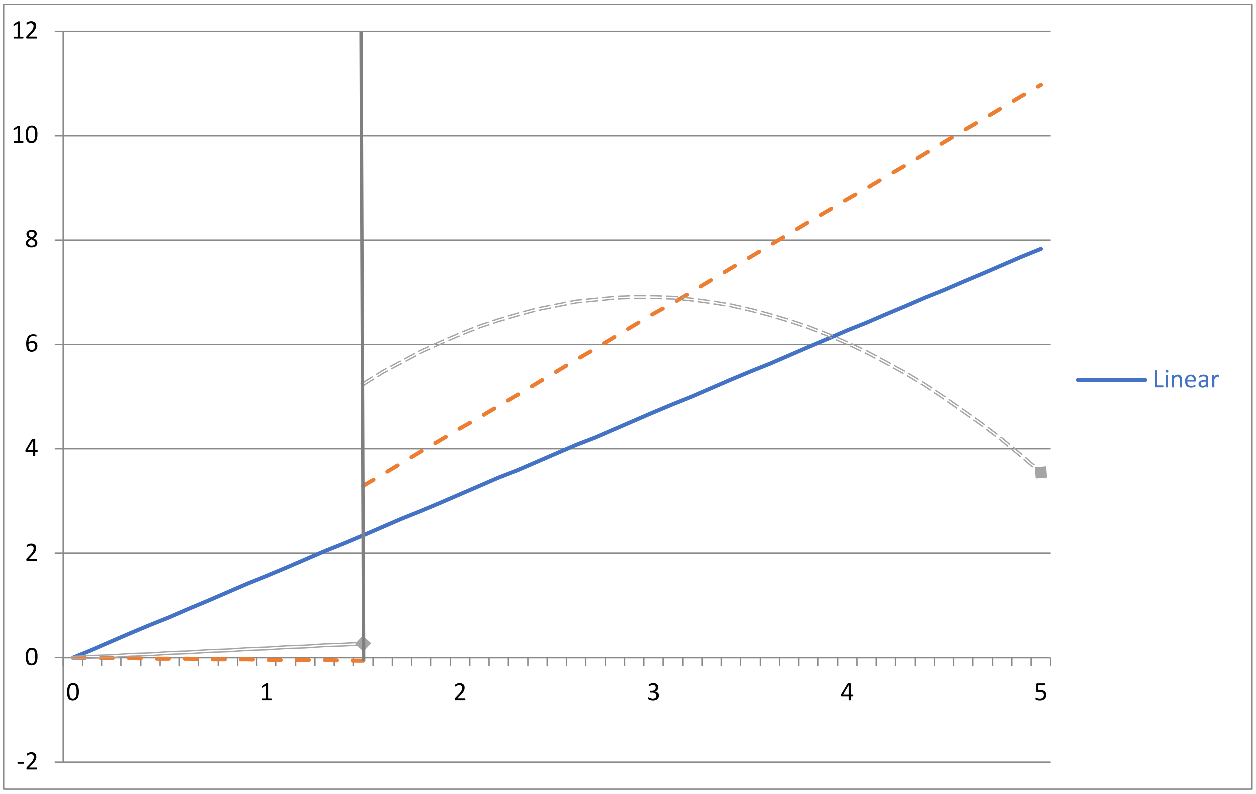


3.8 Table: Cross Sectional Effect Estimates from threshold models.

	Linear Model		Regression Discontinuity Models: Linear/ Linear		Regression Discontinuity Models: Linear/ Quadratic	
Gun-Violence	1.57	***				
	(0.346)					
Gun-Violence (g<1.4)			-0.04		0.18	
			(0.434)		(0.449)	
Gun-Violence (g>=1.4)			2.20	***	4.69	***
			(0.407)		(0.810)	
Gun-Violence^2 (g>=1.4)					-0.80	***
					(0.160)	
R^2	0.45		0.45		0.46	

† p<0.10, * p<0.05, ** p<0.01, *** p<0.001

3.9 Figure: Threshold Model Graphical Representation



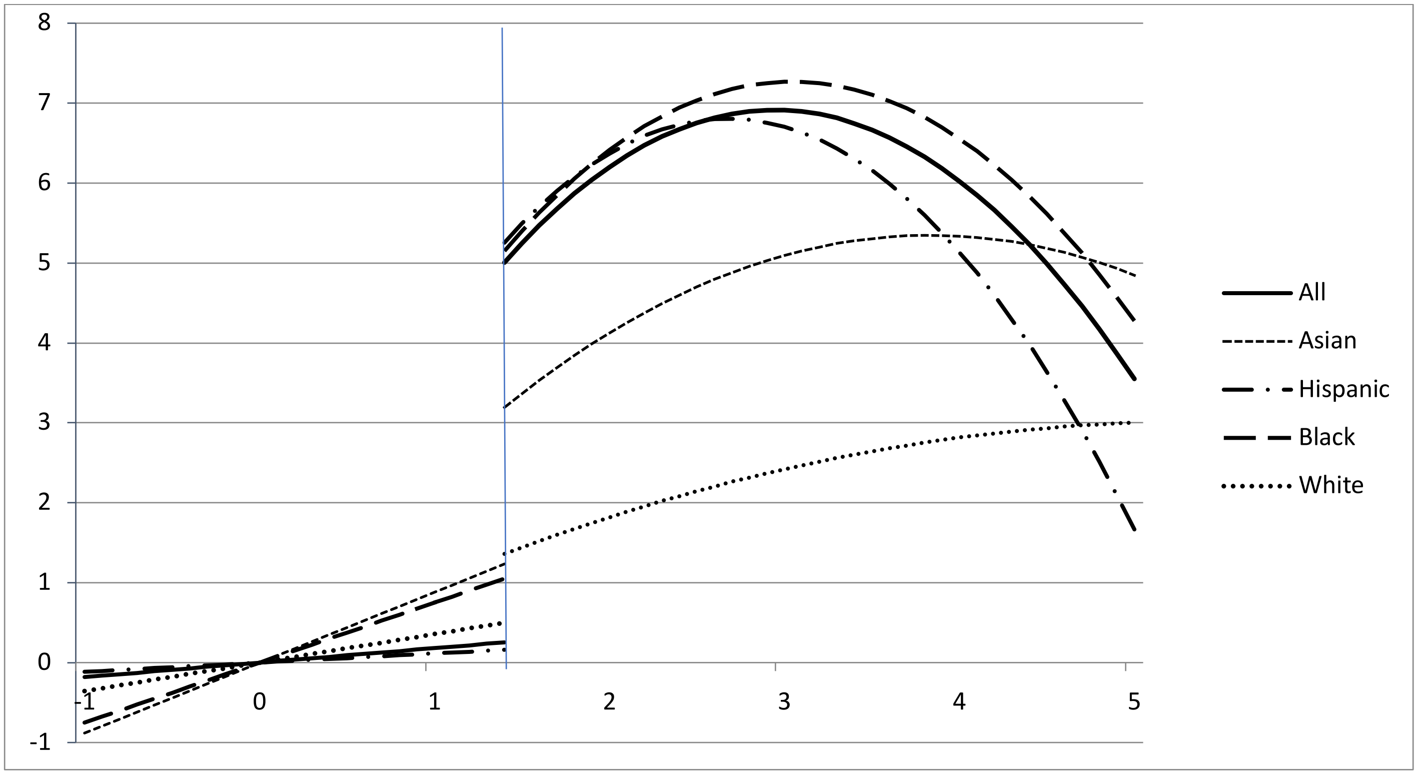
3.10 Table: Proportion of Student Population/subpopulation Above Threshold

All	22.1%
Asian	23.9%
Hispanic	27.4%
Black	32.2%
White	9.9%

3.11 Table: Regression Discontinuity Estimates for Linear and Quadratic Models by Student Subgroup

Regression Discontinuity Model		All		Asian		Hispanic		Black		White	
Linear/ Quadratic											
	Gun-Violence (g<1.4)	0.18		0.88	**	0.11		0.75		0.36	
		(0.449)		(0.300)		(0.545)		(0.714)		(0.410)	
	Gun-Violence (g>=1.4)	4.69	***	2.79	***	5.09	***	4.77	***	1.12	
		(0.810)		(0.817)		(0.831)		(0.889)		(0.947)	
	Gun-Violence^2 (g>=1.4)	-0.80	***	-0.36	*	-0.95	***	-0.78	***	-0.10	
		(0.160)		(0.145)		(0.192)		(0.162)		(0.184)	
	R^2	0.46		0.30		0.42		0.36		0.36	
	RMSE	7.27		4.92		7.72		10.23		5.27	
Linear/Linear											
	Gun-Violence (g<1.4)	-0.04		0.74	*	-0.12		0.14		0.35	
		(0.434)		(0.305)		(0.529)		(0.709)		(0.405)	
	Gun-Violence (g>=1.4)	2.20	***	1.37	***	2.38	***	1.73	***	0.82	+
		(0.407)		(0.309)		(0.462)		(0.427)		(0.462)	
	R^2	0.45		0.30		0.41		0.35		0.36	
	RMSE	7.32		4.94		7.77		10.32		5.27	

3.12 Figure: Quadratic Regression Discontinuity Gun-violence Exposure Effects on Dropout Rates



3.13 Table: Average Quadratic Treatment Effect Decomposition

	Proportion Above Threshold	Exposure Level Above Threshold		Average Effect Above Threshold Assuming Uniform Exposure for All groups with Subgroup Specific Parameter Estimates	Mean Effect Assuming Empirical Exposure Distribution for all groups	Average Exposure Effect
	p	Mean $\bar{g}_{g \geq g^*}$	Median $g_{g \geq g^*}^{50pct}$	$ATE_{g \geq g^*} \mid F_{Uniform}$	$ATE_{g \geq g^*} \mid F_{Empirical}$	$p \cdot ATE_{g \geq g^*} \mid F_{Empirical}$
	(a)	*(b)*	*(c)*	*(d)*	*(e)*	*(f)*
All	22.1%	2.15	1.99	5.95	5.92	1.31
Asian	23.9%	2.41	2.13	4.85	4.18	1.00
Hispanic	27.4%	2.07	1.87	5.53	6.04	1.65
Black	32.2%	2.43	2.14	6.43	6.09	1.96
White	9.9%	2.12	2.13	2.45	1.85	0.18

3.14 Table: Average Effects as a Proportion of Dropout Rates and Differentials

	Dropout Rates	Average Exposure Effect/Dropout Rate	Subgroup vs. White Differential	Proportion of Difference Attributable to Gun-violence Exposure
All	10.54	12.42%	-	-
Asian	4.59	21.82%	-0.86	-
Hispanic	13.64	12.11%	8.19	20.17%
Black	16.60	11.81%	11.15	17.59%
White	5.45	3.35%	-	-

4.1 CAHSEE Policy Effects on High School Graduating Classes of 2004-2007

	Full Cohort		Male		Female	
Covariates	b/se		b/se		b/se	
Gun-Violence Exposure (-1/6.1)	1.6284	***	1.8528	***	1.4005	***
	0.447		0.499		0.399	
Pct. UCCSU (0/1)	0.528		0.834		0.346	
	1.043		1.228		0.937	
Asian(0/1)	-1.420		-1.859	†	-1.079	
	(0.883)		(0.969)		(0.831)	
Hispanic (0/1)	2.050	***	2.059	***	2.061	***
	(0.532)		(0.593)		(0.489)	
African-American (0/1)	-0.211		-0.174		-0.463	
	(1.990)		(2.127)		(1.893)	
Pct. Receiving Free/Reduced Price Lunch (0/100)	0.064	**	0.075	**	0.052	**
	(0.021)		(0.023)		(0.019)	
Pct. Migrant Ed. Programs (0/100)	-0.227	***	-0.272	***	-0.180	***
	(0.059)		(0.066)		(0.053)	
Pct. In Gifted and Talented Program (0/100)	-0.103	***	-0.114	***	-0.088	***
	(0.029)		(0.032)		(0.026)	
Pct. New students (0/100)	0.079	***	0.082	***	0.074	***
	(0.022)		(0.023)		(0.020)	
Parent: Graduate Education (0/100)	-0.026		-0.019		-0.033	
	(0.027)		(0.030)		(0.025)	
Parent: High School Graduates (0/100)	-0.125	*	-0.126	*	-0.123	*
	(0.052)		(0.057)		(0.049)	
Parent: College Graduates (0/100)	-0.065	*	-0.057		-0.073	*
	(0.033)		(0.036)		(0.030)	
Pct. Teachers with Full Credentials (0/100)	-0.012		0.000		-0.027	
	(0.034)		(0.037)		(0.031)	
Virtual School (0/1)	13.965	***	15.432	***	12.040	***
	(1.379)		(3.556)		(1.300)	
Charter School (0/1)	3.463		3.877		3.220	
	(2.210)		(2.415)		(2.053)	
Magnet School (0/1)	2.456	*	3.047		1.902	†
	(1.110)		(1.194)		(1.030)	

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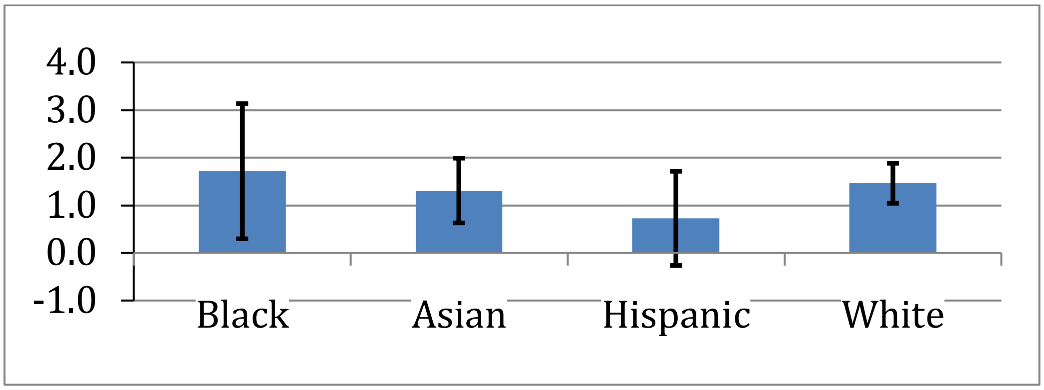
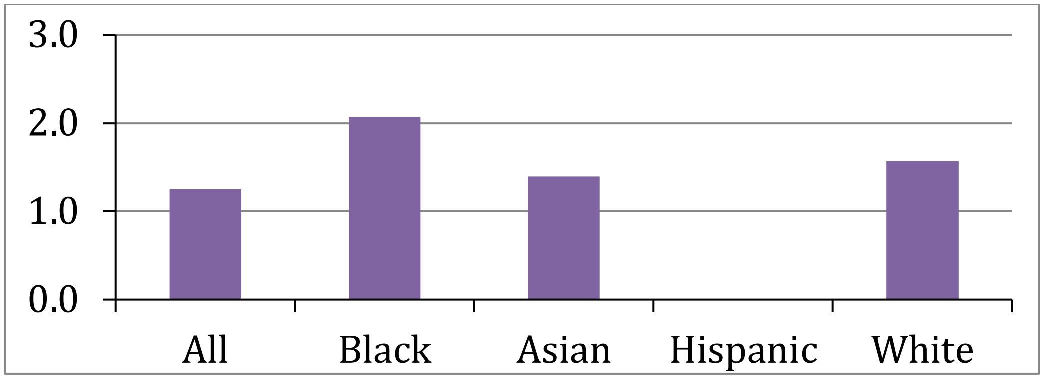
Covariates							
	CAHSEE Policy (0/1)	1.112	**	1.138	**	1.041	***
		(0.339)		(0.376)		(0.312)	
	Traditional School (0/1)	-0.440		-0.353		-0.536	
		(0.605)		(0.665)		(0.555)	
	School Rank (1/10)	-0.687	***	-0.751	***	-0.611	***
		(0.097)		(0.108)		(0.088)	
	Community: Advanced Degree (0/1)	29.506	†	26.895		30.644	*
		(15.700)		(17.509)		(14.065)	
	Community: High School Graduates (0/1)	-51.008	**	-54.433	**	-51.296	***
		(16.833)		(18.863)		(15.318)	
	Pct. Out of the labor market (0/1)	19.426		17.482		23.432	*
		(12.255)		(13.524)		(11.385)	
	Pct. Employed or in Military(0/1)	12.498		10.661		15.961	
		(10.665)		(11.798)		(9.940)	
	Pct. Fatherless Households	16.478	**	16.709	*	16.828	**
		(6.280)		(6.774)		(5.918)	
	Log Median Income (9.6/12.0)	-3.722	***	-4.298	***	-3.118	***
		(0.987)		(1.100)		(0.892)	
	Constant	39.262	**	47.061	**	29.713	*
		(13.509)		(14.863)		(12.374)	
N	Schools	704		704		704	
	R^2	0.51		0.50		0.48	
	Student-years	1,335,935		1,334,289		1,334,551	
	RMSE	6.99		7.95		6.71	
	p	0.00		0.00		0.00	

† p<0.10, * p<0.05, ** p<0.01, *** p<0.001

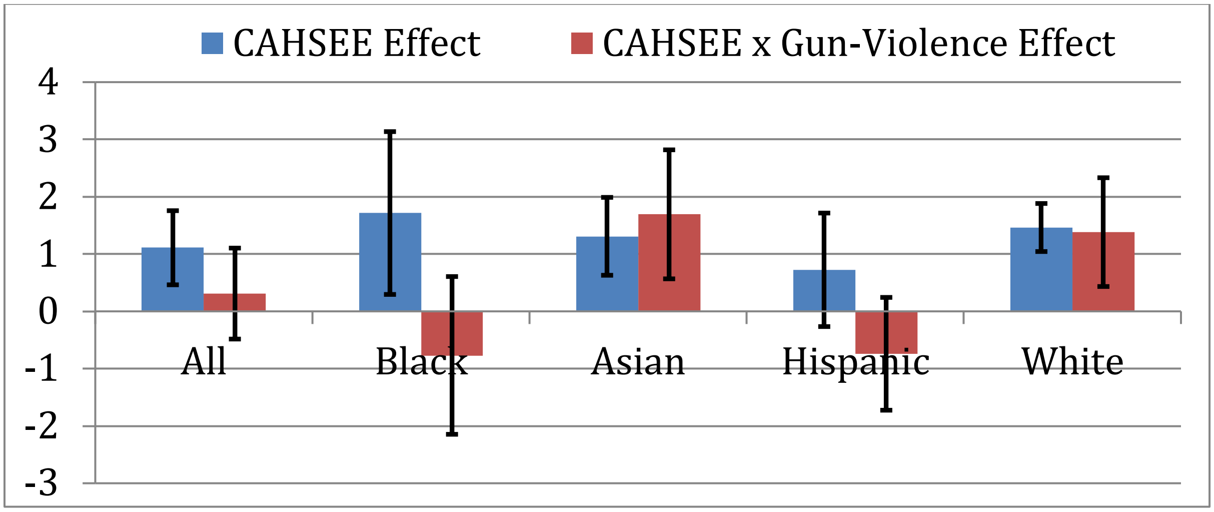
4.2 Figure: Percent Short-term Increase in dropout rates associated with CAHSEE by Student Subgroup



4.3 *Figure:* Estimated Proportion of 2004, 2005 graduates with proficiency levels below 2006 CA standards



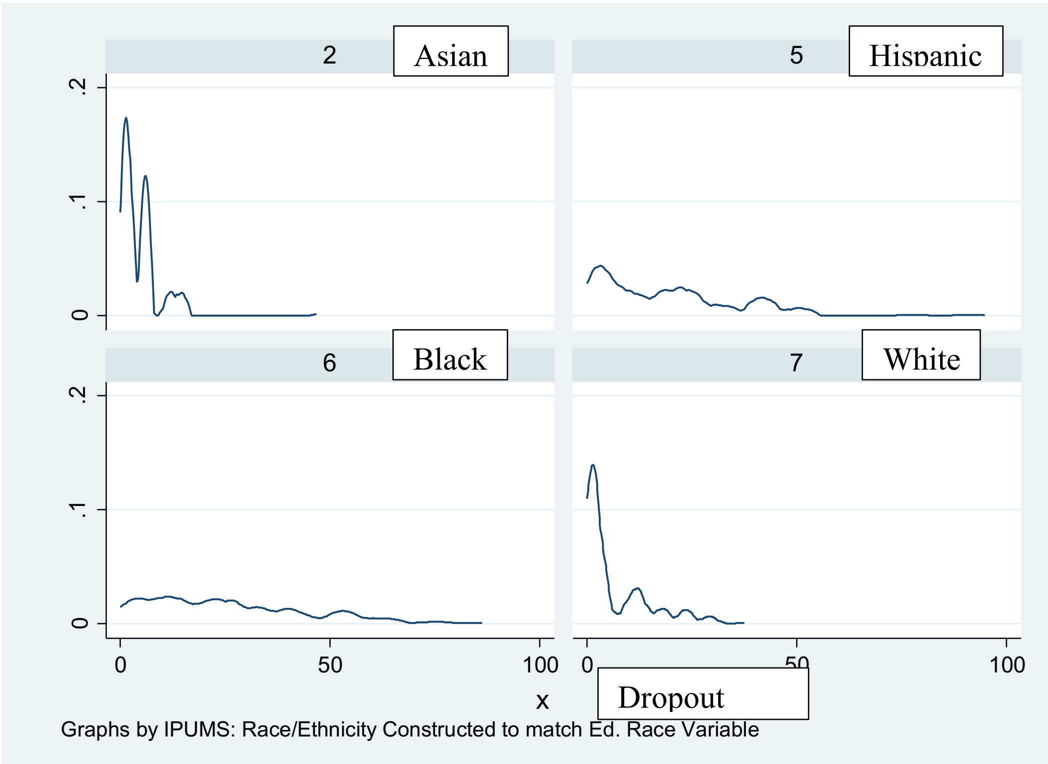
4.4 *Figure*: CAHSEE and CAHSEE × Gun-Violence Exposure Total Effect Estimates on Dropout Rate by Student Race/Ethnicity



4.5 *CAHSEE* Policy Interaction Total Effects and Proportion of Students Graduating Below State Standards

	All		African-American		Asian		Hispanic		White	
	Policy total Effect	Below State Standard	Policy total Effect	Below State Standard	Policy total Effect	Below State Standard	Policy total Effect	Below State Standard	Policy total Effect	Below State Standard
	B/SE	Est	B/SE	Est	B/SE	Est	B/SE	Est	B/SE	Est
CAHSEE	1.112 **	1.250	1.716 *	2.069	1.309 ***	1.396	0.725	-	1.463 ***	1.568
	(0.339)		(0.725)		(0.347)		(0.505)		(0.214)	
CAHSEE x Exposure	-0.020	-	0.119	-	2.048 ***	2.200	-0.314	-	1.913 ***	2.060
	(0.534)		(0.709)		(0.593)		(0.529)		(0.471)	

4.6 *Figure*: Dropout densities by student subgroups for kids in high crime areas with mean subgroup scores of 350 or less in math.



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