COMPULSORY SCHOOLING LAWS AND IN-SCHOOL CRIME: ARE DELINQUENTS INCAPACITATED?

by

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ABSTRACT

Minimum dropout age (MDA) laws have been touted as effective policies to bring delinquents off streets and into classrooms. These laws work mainly through incapacitating delinquents by decreasing the number of unsupervised hours available to commit crime. Given that these laws constrain delinquent juveniles, one question to better understand the costs and benefits of these laws is: to what extent do MDA laws displace crime from streets to schools? Answering this question may be valuable given that in-school crime affects education production through creating a negative and unsafe learning environment, which may lead to decreases in student achievement. This research extends the sparse research on in-school crime by studying how MDA laws affect crimes committed in U.S. public high schools. The analysis is conducted using a difference-in-difference estimator exploiting variation between state-level MDA laws over time. The results indicate that a MDA of 18 significantly increases in-school crime. Specifically, attacks without a weapon, threats without a weapon, and drug incidences. A MDA of 17 is found to have no effect on in-school crime.

OVERVIEW

Crime is prevalent in all societies and generally results in societal and individual costs. Juvenile crime and crimes against juveniles are of particular concern because of the compounding affect over the delinquent's life and the lives of their victims (Cohen (1998)). Minimum Dropout Age (MDA) laws have been touted as effective public policies to bring delinquents off the streets and into classrooms. MDA laws have been shown to lower dropout rates, increase educational attainment, and reduce the rates of juvenile street crime. These results are discussed in Lleras-Muney (2002), Goldin and Katz (2003), Oreopoulos (2009), and Anderson (2011). MDA laws also incapacitate delinquents by decreasing the number of unsupervised hours available to commit crime (Jacob and Lefgren (2003) and Luallen (2006)).

While the literature shows that MDA laws have positive effects, there is still need for concern. Anderson (2011) shows that females in states with a MDA of 18 are more likely to report missing school for fear of safety than those attending schools in states with MDA laws of 16 or 17. This result has major implications because attending school is a necessary factor in academic achievement. Walker and McGarvey (2010) investigate in-school crime and its effect on student achievement in Georgia. Their preliminary results show that in-school crime is associated with lower pass rates. Studying why teachers exit the teaching profession, Gilpin (2011) finds that new teachers threatened by a student increases their probability of exiting the teaching profession by 8 percentage points. The work environment of teachers is somewhat unique in the sense that teachers have to face delinquent students that pose the threat of attacks and other violent crimes. Lastly, school resources may be allocated differently with additional more costly students in schools. Resources might be reallocated from student resources such as larger classrooms or additional desks to additional in-school crime prevention.

Research has shown that higher MDA laws decrease juvenile street crime, but research is sparse on in-school crime despite its numerous economic and policy implications. This thesis will explore the effects of MDA laws on in-school crime. Using rates of in-school crime reported to school administrators. A difference-in-difference (DD) estimator uncovers the effect of state-level changes in MDA laws. The effect is further studied across demographic groups. An overview of the results are as follows. First, results for the effects of MDA laws on student school attendance show that a change in MDA from 16 to 17 or 18 has no effect on average daily attendance (ADA), increases student suspensions, and decreases student expulsions. A change in MDA of 16 to 18 significantly increases in-school crime, specifically, attacks without a weapon, threats without a weapon, and drug incidences. A MDA of 17 does not to have any effect on in-school crime. Robustness tests of results address potential endogeneity between crime and crime fighting resources. The use of alternative control groups and the effect of MDA laws on in-school crime across demographics are also explored.

The thesis is organized as follows. Chapter 2 reviews the previous literature on MDA laws, juvenile crime, and in-school crime. Chapter 3 introduces the data and describes variables used in the study. Chapter 4 describes the empirical strategy and results from the implications of MDA laws on ADA. Chapter 5 presents the main specification of the effect of MDA laws on in-school crime. Chapter 6 analyzes robustness of results across demographics. Chapter 7 concludes by summarizing this thesis.

REVIEW OF THE LITERATURE

This thesis is at the crossroads of juvenile crime and MDA laws. As such, a review of both literatures is conducted.

Compulsory Schooling Laws and Minimum Dropout Ages

MDA laws are set at the state level and cover a variety of aspects of education. For example, there are legal provisions specifying the maximum age at which a child is legally compelled to begin school, the minimum age at which a child may leave school, the average length of the school term (in days), and the circumstances under which a child is exempt from attending school. In addition, state level child labor legislation may influence school enrollment and attendance of teenagers by setting a floor on the age they are legally employable (Edwards (1978)).

MDA laws are effective at raising student educational attainment. Lleras-Muney (2002) provides comprehensive background information on compulsory schooling laws (CSLs) and, in particular, MDA laws. The growth in secondary school attendance played a pivotal role in American economic growth during 1915-1939. Lleras-Muney (2002) shows that two types of laws contributed to the increase in educational attainment, laws specifying the ages a child must attend school and laws specifying the age in which a child could legally obtain a work permit. Interestingly, she also finds that the laws changed the distribution of education, with decreases in educational inequality. This decrease is attributed to educational attainment gain for those in the lowest percentiles.

Increased MDA laws have had cascading effects on secondary school enrollment and the growth of the U.S. economy. Research by Denison (1985) finds that improvements in human capital explain 28 percent of the per capita growth residual between 1925 and 1982.

The bulk of this increase in human capital was due to the growth of high school attendance. Schmidt (1996) and Goldin and Katz (2003) analyze the efficacy of MDA laws on the growth of high school attendance for the early 20th century. They both find that requiring students to attend an additional year of school increases overall educational attainment by approximately 5 percent.

Juvenile Crime

The economic literature on juvenile crime concentrates on the individual costs, the societal costs, and the determinants of juvenile crime. Minimum wage laws, wage differentials, age, sex, family background, intelligence, biomedical factors, community conditions, race, crime control strategies and economic factors have all been cited as determinants of juvenile crime (Hashimoto (1987), Freeman (1996), Grogger (1998)). Haveman and Wolfe (1995) suggest that any study dealing with juvenile behavior should consider three different sets of variables: behavioral and attitudinal attributes of parents (such as drug and alcohol abuse and religious commitment), behavior and educational attainments of siblings, and characteristics and qualities of the schools they are attending.

Levitt (1998) also studies the determinants of juvenile crime. He investigates why juvenile violent crime has risen almost twice as quickly over the last twenty years as that of adults. For example, between 1978 and 1993, juvenile murder arrest rates rose 177 percent compared to the adult murder arrest rates (which actually fell by 7 percent). Levitt shows that changes in punishments account for 60 percent of the differential between juvenile and adult arrest rates. Grogger (1998) examines the effect of wages on youth crime and finds that youth behavior is responsive to wage incentives, i.e., the fall in youth wages may have contributed to rising youth crime during the 1970s and 1980s.

Reducing the rates of juvenile crime can have compounding effects. Cohen (1998) estimates the potential benefits of saving high-risk youths based on the lifetime costs associated with the typical career criminal, drug abuser, and high-school dropout. Using a 2 percent discount rate, external costs of a typical career criminal are estimated to be \$1.8 - \$2.0 million, a heavy drug user to be \$500,000 - \$1.3 million, and a high school dropout to be \$330,000 - \$530,000. Disregarding individuals who are both heavy drug users and career criminals, the monetary value of saving a high-risk youth is \$2.3 to \$3.2 million.[1] Lochner (2010) finds that preschool and school-age programs have substantially reduced juvenile and adult crime for some disadvantaged high-risk populations. He also finds it difficult to draw strong conclusions about the relative benefits of trying to target children at very young ages versus intervening at later ages to keep adolescents from dropping out of high school.

Crime and Schooling

Incapacitation suggests that keeping children in school will keep them out of trouble. This increased concentration of youth at school increases the potential interactions that may lead to delinquency and physical altercations. School-based peer effects, concentration, and juvenile behavior are investigated in Gaviria and Raphael (2001). They use a sample of tenth-graders to test for peer-group influences on the propensity to engage in five activities: drug use, alcohol drinking, cigarette smoking, church going, and the likelihood of dropping out of high school. The authors find strong evidence of peer-group effects at the school-level for all five activities. Their results are congruent with previous literature focusing on neighborhood level effects.

[1] Costs are inflated to today's dollars.

The literature on juvenile crime suggests that school attendance reduces certain juvenile crimes, such as property crimes, and increases other juvenile crimes, such as violent crimes (Jacob and Lefgren (2003), Luallen (2006), and Anderson (2011)). The changes in crime are attributed to either an incapacitation effect, or a geographic concentration effect. The literature utilizes juvenile crime statistics that include in-school and out-of-school crime reported to law enforcement. Jacob and Lefgren (2003) and Luallen (2006) both use out-of-school crime rates and are unable to the measure the net effect of schooling on juvenile crime. The net effect is the difference between the change in in-school and out-of-school crime due to a change in the requirements for school attendance. Since their papers exploit teacher in-service days and teacher strike days, the net change in in-school and out-of-school crime is not captured. Thus, crime may have simply moved from schools to streets. Anderson (2011) uses youth juvenile crime reported to law enforcement which includes both in-school and out-of-school crimes, and finds similar changes in juvenile crime. His estimates suggest that increases in MDA decrease certain juvenile crime rates.

As mentioned by Anderson (2011), a large proportion of in-school crimes do not get reported to law enforcement by school administrators. Overall, 41.3% of crimes are not reported and there is substantial variation by the type of crimes being committed (author's calculations). For example, 32.1% of in-school drug crimes, including distribution, possession, and usage, are not reported to law enforcement while 40.1% of in-school violent crimes go unreported to law enforcement. This underreporting is due to school administrators choosing to not involve law enforcement when a crime is committed and not because the crime goes unnoticed by school administrators. This suggests that juvenile crime rates using youth arrest rates contain substantial measurement error when measuring total crime. Thus, the effects identified in the literature may be due to school administrators choosing to not report crimes to law enforcement.

The purpose of this thesis is to extend the juvenile crime literature by studying how MDA laws affect in-school crime. This paper uses total crime incidents reported to school administrators. This measure of crime mitigates issues regarding underreporting of crime. While the issue of why school administrators do not fully report all in-school crimes to authorities is important, it is beyond the scope of this paper.

The literature on in-school crime is recent and has made a few important contributions. Deming (2009) estimates the longer-term effect on adult crime of winning an admissions lottery to attend a better middle school or high school. He finds that attending a better school reduces arrest rates amongst the highest risk youth, 0.76 felony arrests for lottery losers, and 0.41 for lottery winners. These findings suggest that schools may be a particularly important setting for the prevention of future crime. Walker and McGarvey (2010) aim to quantify the link between violent in-school crime and academic progress. Their preliminary results find crime has negative correlation to academic achievement and has positive correlation to dropout rates, especially among racial minority students. Anderson (2011) estimates that females in states with a MDA of 18 are 4.6 percentage points more likely to report missing school for fear of their safety relative to females in states with MDA laws of 16 and 17.

Further literature focusing on in-school crime comes from criminology. Garofalo, Siegel and Laub (1987) investigate school-related victimization among adolescents. They find that school-related victimization appears to consist primarily of bullying, injured pride, and misguided mischief, as opposed to predatory or calculated attempts to harm. Parker et al. (1991), explores trends in victimization of juveniles in three settings: schools, homes, and streets/parks. Their results indicate that overall in-school victimization rates remain relatively stable during the period studied. Furthermore, the victimization rates of juveniles in other settings had significant effects on in-school victimizations. These results suggest that the underlying causes of victimization are important determinants of in-school victimization. Dusenbury et al. (1997) uses literature review and telephone interviews to identify promising school-based violence prevention measures.

Individual and Societal Returns From Changes in MDA Laws

The juvenile crime literature has not studied the impact of MDA laws on in-school crime. Several studies use changes in MDA laws over time as a natural experiment to generate causal estimates of the returns to education. In general, all the studies investigating the returns to education point to significant individual and social gains from compulsory attendance. Social gains are positive externalities from additional schooling, such as increased education of one individual raising the productivity and earnings of other individuals, or reduction of crime due to MDA laws. Papers that investigate the individual returns are Lang and Kropp (1986), Angrist and Krueger (1991), Lleras-Muney (2005), Oreopoulos (2006*a*), Oreopoulos (2006*b*), Oreopoulos (2007), Black, Devereux and Salvanes (2008), and Oreopoulos (2009). Research studying the social returns from CSLs are Acemoglu and Angrist (2000), Lochner and Moretti (2004), and Anderson (2011).

Oreopoulos (2007) estimates average lifetime wealth increases by 15 percent for an additional year of schooling caused by MDA laws. He also finds that students who are forced into additional schooling are less likely to report poor health, being depressed, looking for work, being in a low-skilled manual occupation, and being unemployed. Monetary returns are not the only private benefits of MDA laws. Black, Devereux and Salvanes (2008) show a significant negative effect on the probability of having a child as a teenager as a result of additional schooling due to MDA laws. These results suggest that students who dropout may be myopic - immediate costs of attending school are larger than the benefit for adolescents that tend to focus on the present. Forgoing substantial gains from additional schooling is more consistent with a model where adolescents ignore or heavily discount consequences of their decisions.

Similar to the individual returns to compulsory schooling, the social returns range as well. Acemoglu and Angrist (2000) use MDA laws to estimate human-capital externalities from additional education and find a 1-2 percent increase in average wages, over and above the roughly equal private returns found in Angrist and Krueger (1991). Along with estimating private returns, there may be other benefits of compulsory education such as crime reduction. Lochner and Moretti (2004) estimate that one additional year of schooling results in a 0.37 percentage point reduction in the probability of incarceration for Blacks, and a 0.10 percentage point reduction for Whites. They estimate that a 1-percent increase in the high school completion rate of all men ages 20-60 would save the United States as much as \$1.4 billion per year in reduced cost from crime incurred by victims and society, or $\$1,170-\$2,100$ per additional high school graduate. Similar results are provided in Buonanno and Leonida (2009) using evidence from Italian data. Anderson (2011) uses FBI uniform crime reports to analyze the contemporaneous relationship between school attendance and juvenile street crime. His results find that a change in the MDA from 16 to 18 decreases arrest rates among 16 to 18 year-olds by approximately 17 percent. This incapacitation effect holds for property, violent, and drug crime arrests.

DATA

To examine the effect of MDA laws on in-school crime, school-level data is used as well as detailed data on state-level MDA laws. This section introduces the school data and the MDA law data, and then describes the control variables used in the analysis. The in-school crime data will be fully described in Chapter 5.

The school characteristics and crime data are provided by the restricted-access versions (2003-04, 2005-06, 2007-08, and 2009-10) of the School Survey on Crime and Safety (SSOCS). The SSOCS is a school-level, bi-annual survey regarding school violence and pays particular attention to the frequency of varying types of in-school crime and delinquency. The final data set consists of roughly 3,130 school-level observations from U.S. public high schools.[1] The data set includes in-school violence and crime indicators as well as school and student body characteristics such as total enrollment, percent of student body that is male, and the number of security guards and police officers present in schools.

The repeated cross-sectional data set is weighted with replication weights provided with the survey to construct a representation of U.S. high schools. Since the schools were selected with unequal probabilities, sampling weights are required for analysis to inflate the survey responses to population levels. The full sample weights provided with the restricted use data files take into account three components. First, a “base weight,” which is defined to be the reciprocal of the probability of selecting a school for the sample. Second, the weight includes a correction for unit non-response. Finally, a post-stratification adjustment based on the Public School Universe File of the 1998-1999 Common Core of Data.

The state-level MDA data comes from the National Center for Educational Statistics’ *Digest of Education Statistics*, as well as various reports and policy briefs. The NCES provides yearly MDA laws for all 50 states. However, comparing the NCES MDA data

[1] The number of observations are rounded to the nearest 10’s place per restricted-use data license.

with individual state-level legislation identified some discrepancies. Where discrepancies occurred, the MDA mandate by state legislation is used. For instance, the NCES reports Minnesota having a MDA of 18 for 2003, 2004, 2005, and a decrease to 16 in 2006. However, Minnesota had a MDA of 16 for the entire period. Another instance is Rhode Island. NCES reports that Rhode Island increased their MDA from 16 to 18 in 2005, then decreased it to 16 in 2006. However, Rhode Island had a MDA of 16 for the entire period. The MDA data in this thesis has been verified for every state for the entire sampling period.

Table 3.1 reports the MDA laws for states in each year of the sample. In the period examined, there are 5 states that change their MDA: Colorado, Illinois, Indiana, Nebraska, and Nevada. No state in the sample decreases their MDA. Illinois and Colorado increase their MDA from 16 to 17. Indiana and Nebraska increase their MDA from 16 to 18, and Nevada increases its MDA from 17 to 18 (Table 3.1). Table 3.3 shows that a MDA of 16 is most prevalent in the sample period (41% of the schools), followed by MDA of 18 (39% of all schools), and MDA of 17 (20% of all schools). A MDA of 16 becomes less prevalent throughout the sample, which indicates that the national MDA average is increasing.

Since the beginning of the 20$^{\text{th}}$ century, MDA laws have been steadily increasing. Figure 3.1 summarizes dropout rates over the past century along with the average MDA for the United States. As illustrated in Figure 3.1, over the past half century, overall dropout rates have fallen from approximately 29 percent to 6 percent. Furthermore, the average MDA has increased from 16 to almost 17 years of age, with half of this increase occurring after 1990. This figure shows a positive correlation between CSLs and school attendance.

The empirical specifications in this thesis uses control variables to account for school-level demographics and adult street crime. Bi-annual descriptive statistics for the control variables are listed in Table 3.3 for the entire sample period. The "Change" column in Table 3.3 is the difference between the two year averages of 2003 & 2005 and 2007 & 2009.

The SSOCS data provide a rich set of school level control variables. Despite minor fluctuations, the mean enrollment is 1,072 students and remains stable across the sample. The most populated school in the sample contains 5,090 students and the lowest populated school contains 100 students.[2] The mean student-to-teacher ratio is 13.9 students per teacher. The maximum is 39 students per teacher, and the minimum is 4 students per teacher.

The SSOCS data also contains several in-school crime prevention resources (ICPRs) i.e., random dog sniffs, random sweeps, mandatory uniforms, and whether security cameras are present.[3] ICPRs available to the schools are an important consideration when analyzing in-school crime. First, ICPRs increase the probability of being caught, which increases the cost of committing crimes. Second, measured crime rates may increase because searches may reveal criminal behavior that might not have otherwise been found. On average, 63% of schools practice random dog sniffs, and 27% of schools practice random sweeps. The average number of schools that have random sweeps decreases over the sample. Only 0.5% of schools require students to wear uniforms. The low number of schools with uniforms is likely because the sample is only public high schools.

The numbers of in-school officers and security guards are also included. Security guards are the most prevalent in high schools with an average of 0.83 guards per 1,000 students. In-school police officers are the least prevalent law enforcement in schools with a mean rate of 0.11 officers per 1,000 students compared to 0.6 resource officers per 1,000 students.[4]

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[2] An enrollment floor of 100 students per school is implemented.

[3] Random dog sniffs are used to check for drugs. Random sweeps are used to check for contraband including drugs and weapons.

[4] Resource officers include all career law enforcement officers with arrest authority who have specialized training and are assigned to work in collaboration with school organizations.

The percent of student body that is eligible for free lunch provides a control for the affluence of the school. Schools located in high income neighborhoods have relatively fewer students eligible for free lunch, and schools located in low income neighborhoods have considerably more students eligible for free lunch. The mean percentage of students eligible for free lunch across the sample is 37.8%. In the sample, 41 schools or 1.3% of the sample have 100% of students eligible for free lunch, and 19 schools or 0.6% of the sample have 0% eligible.

Other student body demographic variables that are included are, the percent of student body that is male, the percent of student body that is below the 15th percentile on standardized tests, the percent of student body of a minority race.[5] The average percent of student body that is male is 49.1%, and as expected, does not change across the sample. The mean percentage of students below the 15th percentile on standardized tests is 13.9%. The maximum percentage of students below the 15th percentile on standardized tests is 99%. The percent of students below the 15th percentile on standardized tests also has a slight decreasing trend between 2003 and 2009. The mean percent of student body that is of a minority race is 27% and decreases by 10% across the sample period.

The adult street crime variable is reported at the county level in the FBI's Uniform Crime Reports. This variable is linked to the SSOCS data by county-level identifiers. The variable controls for adult street crime in the county where the school is located, and not necessarily where students live. The sample mean for adult street crime is .06 arrests per 1,000 persons per year.

The study also controls for urbanization by using indicator variables for whether the school is located in a city, rural or, urban area. Nineteen percent of schools in the sample

[5] The percent of student body of a minority race is calculated as: 1 - percent of student body that is of the majority race.

are located in cities, 32% are located in urban areas, and 49% are located in rural areas or towns.

Tables and Figures

Table 3.1: Minimum Dropout Ages by State and Year

State[a]	2002	2003	2004	2005	2006	2007	2008	State	2002	2003	2004	2005	2006	2007	2008
Alabama	16	16	16	16	16	16	16	Montana	16	16	16	16	16	16	16
Alaska	16	16	16	16	16	16	16	**Nebraska**	**16**	**16**	**16**	**18**	**18**	**18**	**18**
Arizona	16	16	16	16	16	16	16	**Nevada**	**17**	**17**	**17**	**17**	**17**	**18**	**18**
Arkansas	17	17	17	17	17	17	17	New Hampshire	16	16	16	16	16	16	16
California	18	18	18	18	18	18	18	New Jersey	16	16	16	16	16	16	16
Colorado	**16**	**16**	**16**	**16**	**17**	**17**	**17**	New Mexico	18	18	18	18	18	18	18
Connecticut	18	18	18	18	18	18	18	New York[b]	17	17	17	17	17	17	17
District of Columbia	18	18	18	18	18	18	18	New York[c]	16	16	16	16	16	16	16
Delaware	16	16	16	16	16	16	16	North Carolina	16	16	16	16	16	16	16
Florida	16	16	16	16	16	16	16	North Dakota	16	16	16	16	16	16	16
Georgia	16	16	16	16	16	16	16	Ohio	18	18	18	18	18	18	18
Hawaii	18	18	18	18	18	18	18	Oklahoma	18	18	18	18	18	18	18
Idaho	16	16	16	16	16	16	16	Oregon	18	18	18	18	18	18	18
Illinois	**16**	**16**	**17**	**17**	**17**	**17**	**17**	Pennsylvania	17	17	17	17	17	17	17
Indiana	**16**	**16**	**16**	**18**	**18**	**18**	**18**	Rhode Island	16	16	16	16	16	16	16
Iowa	16	16	16	16	16	16	16	South Carolina	17	17	17	17	17	17	17
Kansas	18	18	18	18	18	18	18	South Dakota	16	16	16	16	16	16	16
Kentucky	16	16	16	16	16	16	16	Tennessee	17	17	17	17	17	17	17
Louisiana	18	18	18	18	18	18	18	Texas	18	18	18	18	18	18	18
Maine	17	17	17	17	17	17	17	Utah	18	18	18	18	18	18	18
Maryland	16	16	16	16	16	16	16	Vermont	16	16	16	16	16	16	16
Massachusetts	16	16	16	16	16	16	16	Virginia	18	18	18	18	18	18	18
Michigan	16	16	16	16	16	16	16	Washington	18	18	18	18	18	18	18
Minnesota	16	16	16	16	16	16	16	West Virginia	16	16	16	16	16	16	16
Mississippi	17	17	17	17	17	17	17	Wisconsin	18	18	18	18	18	18	18
Missouri	16	16	16	16	16	16	16	Wyoming	16	16	16	16	16	16	16

[a] States that change their MDA during the sample period are boldface.
[b] Cities in the state of New York with a population greater than 4,500.
[c] Cities in the state of New York with a population less than 4,500.

Table 3.2: Definitions of the Variables Used

Variables	Description/ Definition	Source
Dependent Variables		
Average Daily Attendance	The average percent of students present throughout the school year	SSOCS
Suspensions[a]	The number of out-of-school suspensions lasting 5 or more days, but less than the remainder of the school year	SSOCS
Expulsions[a]	The number of student removals with no continuing school services for at least the remainder of the school year	SSOCS
Transfers[a]	The number of student transfers to specialized schools for disciplinary reasons[a]	SSOCS
In-School Crime[a,b]	The number of attacks without a weapon, threats without a weapon, drug crimes, property crimes, and violent crimes	SSOCS
Attacks w/o Weapon[a,b,c]	An actual and intentional touching or striking of another person against his or her will, or the intentional causing of bodily harm to an individual. Without the use of a weapon	SSOCS
Threats w/o Weapon[a,b,c]	The threat of an actual and intentional touching or striking of another person against his or her will, or the intentional causing of bodily harm to an individual. Without the use of a weapon	SSOCS
Drug crimes[a,b]	Distribution, possession, or use of illegal drugs	SSOCS
Property Crimes[a,b]	Aggregate of thefts and vandalisms. Theft/larceny - taking things worth over $10 without personal confrontation. Vandalism - the willful damage or destruction of school property including bombing, arson, graffiti, and other acts that cause property damage.	SSOCS
Violent Crimes[a,b]	Aggregate of rapes, sexual batteries, attacks with a weapon, threats with a weapon, possessions of a firearm, robberies, robberies with a weapon, and possessions of a knife.	SSOCS
Natural Disasters	= 1 if school has a written plan that describes procedures to be performed during a natural disaster	SSOCS
Compulsory Schooling Laws		
Minimum Dropout Age of 16	= 1 if a state has a MDA of 16	NCES and state-level legislative policy briefs
Minimum Dropout Age of 17	= 1 if a state has a MDA of 17	NCES and state-level legislative policy briefs
Minimum Dropout Age of 18	= 1 if a state has a MDA of 18	NCES and state-level legislative policy briefs
Community Characteristics		
Adult Street Crime	County-level street crime per 1,000 persons over 18 years of age	UCR
City	= 1 if school is located in a city	SSOCS
Urban	= 1 if school is located in an urban area	SSOCS
School Characteristics		
Enrollment	Total student enrollment (in thousands)	SSOCS
Student to Teacher Ratio	Students per full-time-equivalent teacher	SSOCS
Random Dog Sniffs	= 1 if school practices random dog sniffs for drugs	SSOCS
Random Sweeps	= 1 if school practices random sweeps for contraband not including dog sniffs	SSOCS
Uniform	= 1 of school requires students to wear uniforms	SSOCS
Security Cameras	= 1 if security camera(s) monitor the school	SSOCS
Number of Security Guards[a]	The number of full-time security guards	SSOCS
Number of Resource Officers[a]	The number of full-time school resource officers (SROs)	SSOCS
Number of Officers[a]	The number of full-time sworn law enforcement officers—not SROs	SSOCS
Student Body Characterisics		
Percent Eligible for Free Lunch	Percent of student body that is eligible for free or reduced-price lunch	SSOCS
Percent Male	Percent of student body that is male	SSOCS
Percent Below 15^{th} % on Std. Tests	Percent of student body below 15th percentile on standardized tests	SSOCS
Percent Minority	Percent of student body that is of minority race	SSOCS

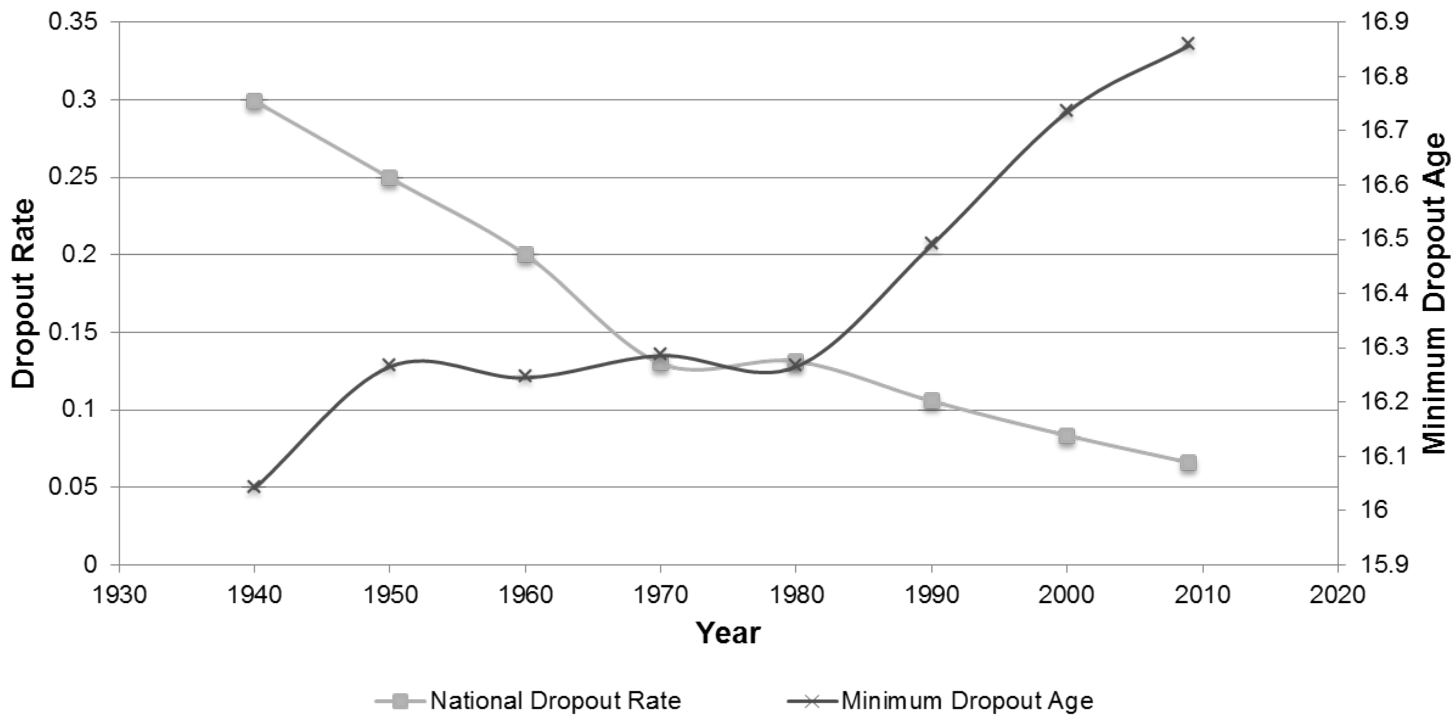
[a] Per 1,000 students.
[b] Specialized school - a school that is specifically designed for students who were referred for disciplinary reasons.
[c] Total number of crime incidents brought to the attention of school administrators.
[d] Weapon - any instrument or object used with the intent to threaten, injure, or kill. This includes look-alikes if they are used to threaten others.

Table 3.3: Descriptive Statistics

Variables	2003[a]	2005[a]	2007[a]	2009[a]	All-Years[a]	Change[b]
Compulsory Schooling Laws						
Minimum Dropout Age of 16	0.46	0.43	0.36	0.38	0.41	-17%
	(0.50)	(0.50)	(0.48)	(0.48)	(0.49)	
Minimum Dropout Age of 17	0.15	0.20	0.25	0.20	0.20	30%
	(0.35)	(0.40)	(0.43)	(0.40)	(0.40)	
Minimum Dropout Age of 18	0.39	0.37	0.39	0.42	0.39	7%
	(0.49)	(0.48)	(0.49)	(0.49)	(0.49)	
Neighborhood Characteristics						
Adult Street Crime	0.05	0.05	0.05	0.07	0.06	14%
	(0.03)	(0.03)	(0.03)	(0.29)	(0.15)	
City	0.19	0.18	0.19	0.19	0.19	3%
	(0.39)	(0.38)	(0.39)	(0.39)	(0.39)	
Urban	0.34	0.33	0.33	0.26	0.32	-12%
	(0.47)	(0.47)	(0.47)	(0.44)	(0.46)	
School Characteristics						
Enrollment	1089	1076	1100	1025	1072	-2%
	(755)	(772)	(735)	(725)	(747)	
Student-to-Teacher Ratio	13.30	12.99	13.23	16.09	13.93	11%
	(3.64)	(3.79)	(3.78)	(4.40)	(4.13)	
Random Dog Sniffs	0.62	0.64	0.62	0.65	0.63	0%
	(0.49)	(0.48)	(0.49)	(0.48)	(0.48)	
Random Sweeps	0.27	0.29	0.25	0.28	0.27	-6%
	(0.44)	(0.45)	(0.43)	(0.45)	(0.44)	
Uniform	0.04	0.04	0.05	0.08	0.05	65%
	(0.19)	(0.20)	(0.22)	(0.27)	(0.22)	
Security Cameras	0.61	0.72	0.80	0.86	0.75	24%
	(0.49)	(0.45)	(0.40)	(0.35)	(0.43)	
Number of Security Guards	0.76	0.77	0.92	0.88	0.83	18%
	(1.36)	(1.39)	(1.54)	(1.63)	(1.49)	
Number of Resource Officers	0.60	0.64	0.60	0.57	0.60	-5%
	(0.92)	(1.00)	(0.92)	(0.91)	(0.94)	
Number of Officers	0.09	0.14	0.12	0.07	0.11	-15%
	(0.41)	(0.58)	(0.62)	(0.41)	(0.51)	
Student Body Characterisics						
Percent Eligible for Free Lunch	34.99	35.88	37.05	43.16	37.88	13%
	(24.27)	(24.14)	(24.13)	(24.06)	(24.35)	
Percent Male	49.50	49.36	49.16	48.43	49.10	-1%
	(7.30)	(8.62)	(9.55)	(10.80)	(9.20)	
Percent Below 15^{th} % on Std. Tests	14.49	14.20	14.10	13.14	13.97	-5%
	(14.31)	(14.73)	(15.37)	(13.57)	(14.50)	
Percent Minority	28.91	28.15	29.47	21.90	27.02	-10%
	(30.04)	(29.65)	(29.64)	(17.95)	(27.33)	

[a] Means with standard deviations in parentheses.
[b] Percent change between the averages of 2003-2005 and 2007-2009. Two year averages are used to account for unanticipated or large deviations.

Figure 3.1: Average Dropout Rate Among 14 to 18 Year Olds and Minimum Dropout Age



Author's calculations.

THE EFFECT OF MDA LAWS ON AVERAGE DAILY ATTENDANCE

The first empirical focus of this thesis will estimate the impact of MDA laws on keeping juveniles in school. This estimation will use average daily attendance (ADA) reported in the SSOCS as the dependent variable.[1] This section introduces why this estimation is necessary, describes the dependent variable, presents the empirical model, and discusses the results.

Impact of MDA Laws on Average Daily Attendance

Identification is secured through MDA laws being effective at retaining potential dropouts in school. If these laws do not keep delinquents in school, then the identification will be quite weak. The literature has shown that MDA laws are effective at increasing high school attendance. This thesis will examine if ADA is affected by MDA laws and will also investigate whether MDA laws have an effect on students suspensions, student expulsions, and student transfers. This section empirically measures the effect of MDA laws on who is attending school when and how the punishments change as a result.

The existing literature provides evidence that MDA laws increase student school attendance. Angrist and Krueger (1991) find that roughly 25 percent of potential dropouts remain in school as a result of compulsory schooling laws. The authors use a difference-in-difference (DD) model with data from the 1960, 1970, and 1980 Censuses. The authors provide two main enforcement mechanisms for compulsory schooling laws. First, the Fair Labor Standards Act prohibits the employment of children under 14. Second, child labor laws reinforce the compulsory schooling laws because they restrict children of compulsory

[1] A school's average daily attendance is defined as the average percent of students present throughout the school year.

schooling age from participating in the work force, entering the workforce being the principal alternative to attending school. These laws are also enforced through truant officers that are employed to administer these laws. Truant officers generally have the power to take children into custody without a warrant, and a delinquent student's parents can face criminal penalties, such as misdemeanor-level fines and/or imprisonment, if they fail to send their child to school. Oreopoulos (2009) explores the efficacy of these laws using Current Population Survey (CPS) data between 1979 and 2005 along with American Community Surveys (ACS) data between 2000 and 2005. To narrow the effect to recent laws, Oreopoulos (2009) limits the sample to individuals aged 20 to 29. His results suggest that an MDA above 16 increases an individual's years of schooling by about 0.13 years. He also finds that a higher MDA leads to a higher rate of four-year college/university attendance.

Data and Descriptive Statistics

Average daily attendance is reported in the SSOCS by the survey respondent. Summary statistics are provided in Table 4.1. Average daily attendance has a slightly decreasing trend from 2003 to 2009. The decreasing trend is based on the percent change between the two year average of 2003 & 2005 and the two year average of 2007 & 2009. Despite minor fluctuations, the average daily attendance for US schools is approximately 93%. For the implication test, it is important to control for in-school demographics because the student composition in a school is likely to have important effects on how many students attend.

The effect of MDA laws on student suspensions, student expulsions, and student transfers is also estimated in this section. Table 4.1 show descriptive statistics for these three student punishments. The average number of student suspensions is 17.6 per 1,000 students per year, the average number of expulsions is 2.5 per 1,000 students per year, and the average number of student transfers is 10.3 per 1,000 students per year. Student suspensions, expulsions, and transfers all have decreasing trends over the sample period.

Empirical Specification

Using school-level average daily attendance (ADA) (in percent), the effectiveness of MDA laws can be tested. The empirical model exploits the exogenous variation created from state-level changes in MDA laws. The empirical model is a difference-in-difference (DD) estimator and the specification is

$$ADA_{ist} = \alpha + \beta_1 MDA17_{st} + \beta_2 MDA18_{st} + \beta_3 \boldsymbol{X}_{ist} + \beta_4 \boldsymbol{S}_s + \beta_5 \boldsymbol{T}_t + \varepsilon_{ist} \tag{4.1}$$

where ADA_{ist} is average daily attendance for school i, in state s, at time t, $MDA17_{st}$ and $MDA18_{st}$ are indicators for the state-level MDA laws in state s at time t. $\boldsymbol{X}_{ist}$ is a vector of school characteristics, $\boldsymbol{S}_s$ are state fixed effects, $\boldsymbol{T}_t$ are time fixed effects, and ε_{ist} is a random error term.

The control group is students in states with a MDA of 16 and the treatment group is students in states with a MDA greater than 16. The variables of interest are β_1 and β_2. These coefficients are expected to be significantly positive if higher MDA laws are effective at keeping would be dropouts in school. The model is also estimated to measure the effect of MDA laws on suspensions, expulsions, and transfers. Suspension and expulsions also provide insight to whether or not more students are attending school as a result of these laws.

When interpreting the signs of β_1 and β_2, there are two direct effects of MDA laws. First, a positive effect occurs if constrained delinquents are forced to attend school. Second, a negative effect occurs if attending delinquents are misbehaving and getting suspended, thus lowering average daily attendance or, the presence of these delinquents are influencing other students to not attend school. Only the net effect is observed using aggregate school-level data.

Results

The results of the effect of MDA laws on ADA, suspensions, expulsions, and transfers are presented in Table 4.2. The coefficients on the MDA variables are not significantly different from zero for ADA. These coefficients measure the net effect of the impact, and as a result the sign and significance are ambiguous. The expectation is that MDA laws should have positive effects on average daily attendance. However, negative effects on average daily attendance occur when delinquents attend school and are suspended for bad behavior in school. As evident from the suspension regression (Table 4.2) a MDA of 18 significantly increases suspensions. A negative effect also occurs in the ADA regression if students avoid school for fear of safety as a result of the constrained delinquents attending school. The conflicting effects result in ambiguous signs and significance for the MDA coefficients.[2] Anderson (2011) provides evidence that a MDA of 18 increases the likelihood of females not attending school for fear of safety.

Interestingly, the results indicate that MDA of 18 increases suspensions and decreases expulsions. This finding suggests that an increase in a state's MDA puts more students into school and the schools suspend more students but expel less. Therefore, additional delinquent students attend school, misbehave and are more likely to be suspended but less likely to be expelled, on average.

Even though the model does not provide positive estimates of MDA laws on ADA, there is substantial literature already showing that MDA laws are effective tools for making students attend school. As mentioned above, Angrist and Krueger (1991) and Oreopoulos (2009) identify strong effects on educational attainment as a result of higher MDA laws. Moreover, Goldin and Katz (2003) and Lleras-Muney (2002) analyze MDA laws at the beginning of the 20th century and find that MDA increase overall educational attainment.

[2] Robustness checks were estimated for the effect of the MDA laws on ADA across income levels, enrollment levels, and street crime levels, no significant results were found.

The coefficients on the control variables are consistent with economic theory and previous literature. If a school is located in the inner city, the average daily attendance is lower. Greater percentages of students eligible for free lunch, placing below the 15th percentile on standardized test, and minorities all have negative effects on average daily attendance. The number of resource and police officers have positive effects on average daily attendance.

Tables

Table 4.1: Summary Statistics for Dependent Variables Across Time

Variables	2003[a]	2005[a]	2007[a]	2009[a]	All-Years[a]	Changes[b]
Attendance						
Average Daily Attendance	93.3	93.2	92.7	93.0	93.1	-0.4%
	(4.0)	(3.8)	(4.8)	(4.4)	(4.3)	
Suspensions	21.4	18.3	15.6	15.5	17.6	-21.8%
	(35.8)	(25.5)	(20.5)	(23.6)	(26.9)	
Expulsions	2.8	2.5	2.1	2.6	2.5	-11.1%
	(7.8)	(6.0)	(5.5)	(7.8)	(6.9)	
Transfers	11.6	11.4	10.7	7.7	10.3	-20.0%
	(21.0)	(20.3)	(22.6)	(16.2)	(20.2)	
Crime Rates						
In-School Crime	52.2	56.9	46.9	48.3	51.0	-12.7%
	(47.2)	(48.4)	(32.5)	(44.5)	(43.8)	
Attacks w/o Weapon	20.9	19.2	19.1	17.5	19.1	-8.8%
	(27.5)	(20.0)	(35.6)	(25.5)	(27.7)	
Threats w/o Weapon	15.8	14.4	12.7	12.7	13.9	-15.6%
	(32.3)	(25.2)	(29.0)	(25.1)	(28.0)	
Drug Crimes	2.6	8.0	6.7	7.4	6.2	33.7%
	(7.9)	(11.2)	(7.3)	(10.0)	(9.5)	
Property Crimes	18.2	19.7	20.8	18.3	19.3	3.3%
	(20.1)	(20.4)	(21.1)	(20.7)	(20.6)	
Violent Crimes	3.0	5.3	4.2	4.8	4.3	7.8%
	(7.0)	(8.3)	(5.8)	(11.2)	(8.4)	
Observations						
Observations[c]	840	760	750	780	3,130	
Weighted Observations[c]	8,840	9,410	9,270	9,770	37,300	

[a] Means with standard deviations in parentheses.
[b] Percent change between the averages of 2003-2005 and 2007-2009. Two year averages are used to account for unanticipated or large deviations.
[c] The number of observations are rounded to the nearest 10s place as per restricted-use data license.

Table 4.2: Estimation Results: The Average Marginal Effects on School Attendance Variables

	Average Daily Attendance		Suspensions		Expulsions		Transfers	
Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Minimum Dropout Age of 17	0.237	0.55	-4.633***	-2.96	-1.525***	-2.78	1.021	0.48
Minimum Dropout Age of 18	-0.390	-0.34	4.865***	3.87	-1.935***	-3.28	0.951	0.56
City	-1.293***	-3.84	1.733	0.99	-0.463	-0.86	-1.930	-1.63
Urban	0.181	0.98	0.063	0.04	-0.231	-0.54	-1.020	-0.87
Enrollment	-0.239*	-1.89	1.515	1.62	-0.011	-0.05	0.426	0.72
Student-to-Teacher Ratio	-0.015	-0.50	0.192	1.19	0.123*	1.72	0.200*	2.00
Adult Street Crime	0.368*	1.79	2.089*	2.01	0.028	0.09	1.486**	2.36
Percent Eligible for Free Lunch	-0.027***	-4.07	0.115***	3.10	0.016	1.61	0.090***	3.44
Percent Male	0.001	0.05	-0.077	-1.43	-0.006	-1.95	0.011	0.23
Percent Below 15^{th} % on Std. Tests	-0.045***	-5.76	0.180***	2.78	0.027	1.42	0.036	1.30
Percent Minority	-0.019***	-3.03	0.047	1.03	0.006	0.62	0.065*	1.69
Number of Security Guards	-0.229**	-2.06	0.307	0.49	0.090	0.69	0.009	0.04
Number of Resource Officers	0.204*	1.71	0.082	0.14	0.040	0.19	0.396	0.59
Number of Officers	0.289*	1.94	-0.867	-0.72	0.013	0.08	0.441	0.30
Time Fixed Effects	Yes		Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes		Yes	
In-School Security	Yes		Yes		Yes		Yes	
School Controls	Yes		Yes		Yes		Yes	
Resource Controls	Yes		Yes		Yes		Yes	
R-Squared	0.253		0.149		0.127		0.240	

Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

THE EFFECT OF MDA LAWS ON IN-SCHOOL CRIME

The main interest is whether changes in MDA laws have an effect on in-school crime. The literature has shown that MDA laws are effective policies to keep juveniles in school. Anderson (2011) shows that juvenile crime is reduced as a result of a change in MDA from 16 to 18. In this section, I estimate whether in-school crime increases as a result of additional delinquents attending school. This section introduces the crime indicators, describes the empirical specification, presents the results, and concludes with robustness checks.

Main Test

Given that MDA laws incapacitate delinquent students to remain in school, it is expected that juvenile crimes may be displaced from streets to schools. This effect is studied using a DD model. The DD estimation measures the difference in in-school crime between public high school students in states with a MDA of 16 to high school students in states with a MDA of 17 or 18, and the difference between the two over time.

The DD model exploits exogenous variation created from state-level changes in MDA laws. One weakness of the DD model is the potential for the standard errors to be biased due to serial correlation of the policy variables over time within a state. To account for this, the standard errors are clustered at the state level (Bertrand, Duflo and Mullainathan (2004)). A robustness check is conducted using multiple control groups. There are also two potential endogeneity problems that arise from including police officers, resource officers and security guards as controls. First, a possible simultaneity issue arises where increases in MDA laws causes both, more crime and schools to allocate additional resources to crime prevention. Second, a possible reverse causality may occur where additional officers are found in high crime schools.

Data and Descriptive Statistics

Descriptive statistics for all the crime indicators used for this study are presented in Table 4.1. In-school crime rates are normalized per 1,000 students. First survey respondents report numbers of incidents to the SSOCS. Then, incident reports are transformed into rates by dividing by total enrollment over 1000 (in-school crime/(total enrollment/1000)). There are six crime rates examined, total in-school crime, attacks without a weapon, threats without a weapon, drug incidences, property crimes, and violent crimes. Drug incidences include usage, distribution, and possession. Property crime is an aggregate of thefts and vandalisms. The violent crime variable is an aggregate of rapes, sexual batteries, attacks with a weapon, threats with a weapon, possessions of a firearm, robberies, robberies with a weapon, and possessions of a knife. On average, 51 crimes per 1,000 students occur within school each year. The two most prevalent in-school crimes are attacks without a weapon, and property crime. These crimes occur on average 19 times per 1,000 students per year. The average rate of threats without a weapon is 13.9 per 1,000 students per school year, and drug and violent crimes are least prevalent in school, with 6.2 and 4.3 incidences per 1,000 students per year, respectively. The "Changes" column in Table 4.1 presents how in-school crime rates change over the sample. This column is the difference in the two year averages of 2003 & 2005 and 2007 & 2009. Downward trends are evident for in-school attacks and threats without weapons. In contrast, there are relatively large upward trends in the number of in-school drug, property, and violent related crimes.

To descriptively examine the impact of state-level MDA laws on in-school crime, Table 5.1 explores the differences in mean crime rates for states that changed their MDA and states that did not. This table presents a simple comparison for both groups before and after law changes. Attacks and threats without weapons decrease in both sets of states over time. The decrease is larger in states that change their MDA. Drug rates increased more over the sample in states that did not change their MDA relative to states that did change their MDA. Property crime increases in states that did not change their MDA and decreases in states that did change their MDA. Violent crime increases over time in both groups, with a larger increase in states that do change their MDA. The above is a simple descriptive statistic and does not control for any influences on in-school crime.

Empirical Specification

The distribution of in-school crime has a heavy right skew with large outliers and many schools reporting zero crimes. Preliminary regressions show that using crime rates as the dependent variable violated the normality assumption. The normality assumption is a *classical linear model assumption*, and states: "The population error ε is independent of the explanatory variables $x_1, x_2, ...x_n$ and is normally distributed with zero mean and variance σ^2 : ε ~Normal $(0,\sigma^2)$" (Wooldridge (2006) pg. 104). This violation is illustrated in the Q-normal plot located in Appendix A. Q-normal plots show a normal distribution if the plotted residuals follow the line from the origin. The residuals from the regression using the in-school crime rate is plotted in Figure A.1 located in Appendix A. These figures illustrate that the normality assumption is not satisfied. When the error term is not normally distributed, the t distributions can be a poor approximation of the distribution of the t statistic, causing biased t-tests. The normality assumption holds in the limit, if and only if there is no heteroskedasticity present in the model. A Breusch-Pagan test for heteroskedasticity rejects the null hypothesis of homoskedasticity for all crime rates.

A transformation of the crime rates is one way to resolve these issues. The dependent variables are transformed using a Box-Cox transformation. The Box-Cox transformed variables satisfy the normality assumption. The Q-normal plot for the Box-Cox regression using in-school crime is presented in Appendix A. As illustrated in Figure A.2 the residuals follow the line from the origin closely. This implies a normal distribution of the error term. Transforming the crime variables also alleviates heteroskedasticity, as tested using Breusch-Pagan tests. The Box-Cox transformation is:

$$\widetilde{Crime}^{j}_{ist} = \frac{((Crime^{j}_{ist} + C^{j})^{\lambda^{j}} - 1)}{\lambda^{j}} \tag{5.1}$$

where $\widetilde{Crime}^{j}_{ist}$ is the Box-Cox transformed crime rate for school i, in state s, at time t, $Crime^{j}_{ist}$ is the crime rate being transformed, C^{j} is a scale shift parameter, and λ^{j} is the power shift parameter for the j^{th} crime rate. A benefit of the Box-Cox transformation with a scale shift is that it accounts for zero value observations, whereas a log transformation does not. One notable difference between the Box-Cox transformed crime rates and the non-transformed crime rates is the average crime rates are significantly lower.

The DD specification estimating the effect of MDA laws on in-school crime is:

$$\widetilde{Crime}^{j}_{ist} = \alpha + \beta_1 MDA17_{st} + \beta_2 MDA18_{st} + \beta_3 \boldsymbol{X}_{ist} + \beta_4 \boldsymbol{S}_s + \beta_5 \boldsymbol{T}_t + \varepsilon_{ist} \tag{5.2}$$

Control: High school students in states with a MDA = 16

Treatment: High school students in states with a MDA $>$ 16

Sample: All public high schools surveyed in the SSOCS

where $\widetilde{Crime}^{j}_{ist}$ is the j^{th} Box-Cox transformed crime rate, for school i, in state s, at time t. $MDA17_{st}$ and $MDA18_{st}$ are indicators for the state-level MDA laws, $\boldsymbol{X}_{ist}$ is a vector of school characteristics discussed in Chapter 3 (Table 3.3), $\boldsymbol{S_s}$ are state fixed effects, $\boldsymbol{T_t}$ are time fixed effects, and ε_{ist} is a random error term.

The coefficients of interest are β_1 and β_2 that represent the marginal effect on students in states with MDA laws of 17 or 18, relative to students in states with a MDA law of

16. The coefficients β_1 and β_2 are expected to be positive and significant if constrained delinquents increase in-school crime.

The treatment group consists of the schools in states that change their MDA. The treatment schools from the five states that change total 330 school-level observations.[1] This makes the treatment group approximately 10.4% of the total sample.

Results

To understand the effect of changes in MDA laws on in-school crime, the model is built-up using four regressions with increasing controls. The results of these four estimations are presented in Table 5.3. The first estimation controls for state and time fixed effects, the second adds time invariant controls, and the third adds controls for school characteristics. The last controls for state fixed effects, time fixed effects, school characteristics, and crime prevention resources. The coefficients on MDA of 18 are positive and significant for all four estimations presented in Table 5.3. The full specification, including crime prevention resources, show that in-school crime increases by 0.435 in-school crime incidences per 1,000 students per year (0.85% increase in the average rate of in-school crime).[2]

Estimated coefficients associated with demographic and adult street crime variables indicate relationships consistent with economic intuition. Additional officers reduce the amount of attacks without a weapon and threats without a weapon. Security cameras have a positive relationship with attacks without a weapon, threats without a weapon, and drug incidences. This suggests that the presence of security cameras facilitates the capture of culprits or that they are installed in high crime schools. The positive and significant coefficient on drug sweeps imply that schools with high drug crime implement these programs and that the drug sweeps are successful at finding drugs.

[1] The number of observations are rounded to the nearest 10's place per restricted-use data license.
[2] The coefficient estimates are a lower bound. Thus, crime increases by at least the coefficient amount.

It is also useful to investigate how different in-school crimes are effected by MDA laws. Table 5.4 looks at the effect of MDA laws on attacks without a weapon, threats without a weapon, drug incidences, property crimes, and violent crimes. Theses models are estimated using a DD model with state and time fixed effects, in which we control for student body demographics, school resources, and community characteristics. The controls also include the number of in-school law enforcement officers per 1,000 students, and school-level crime prevention resources (Table 3.3). The magnitude of the MDA coefficients are reported in Table 5.4. The coefficients on MDA of 18 indicate that attacks without a weapon increase by 0.625 per 1,000 students per year (3.3% increase in the average rate of attacks without a weapon), threats without a weapon increase by 0.592 per 1,000 students per year (4.6% increase in the average rate of threats without a weapon), and drug incidences increase by 0.439 per 1,000 students per year (7.1% increase in the average rate of drug crimes). MDA laws of 17 or 18 do not have significant effects on property crime. This suggests that delinquents who attend school as a result of MDA laws are not focused on crimes such as theft or vandalism. MDA laws of 17 or 18 do not have significant effects on violent crime.[3] The positive relationship between a MDA of 18 and in-school crime suggests that constrained marginal individuals increase crime in U.S. public high schools.

These results can be compared to the previous literature to provide evidence of the incapacitation and concentration effects. Jacob and Lefgren (2003) and Luallen (2006) show that property crimes decrease when youth are incapacitated to schools. The empirical results of this thesis indicate that changes in MDA laws do not increase in-school property crime. Thus, combining results indicate that youth are incapacitated with respect to property crimes, i.e., the net effect of incapacitation on juvenile property crime is negative.

[3] A placebo effect is also estimated with an indicator for whether or not the school has a written plan for natural disasters to test whether MDA laws can have an effect when one should not exist. The results are presented in Table B.1 of Appendix B. The coefficients on MDA 17 and 18, respectively, are insignificant.

Jacob and Lefgren (2003) and Luallen (2006) also show that juvenile violent crime rates increase when youth are incapacitated to schools. However, given that 59.1% of attacks without a weapon occurring in-school are not reported to law enforcement, and 40.1% of violent crimes occurring in-school are not reported to law enforcement, measurement error is susceptible. The empirical results of this thesis indicate that in-school violent crime rates do not change from changes in MDA laws. Therefore, the results of this thesis do not provide empirical evidence to support the geographic concentration effect of youth for violent crime. The empirical results of this thesis indicate that attacks without a weapon and threats without a weapon increase when the MDA is increased. This provides empirical support to the concentration effect for attacks and threats without a weapon.

Robustness of Results to Potential Endogeneity

There are two potential endogenity issues in the crime estimations. The first is the potential simultaneity issue: increases in MDA cause both, more crime, and schools to allocate additional resources to crime prevention (e.g. more police officers, security cameras, or additional drug sniffs). To study this issue, school resource regressions are estimated with an identical specification as the crime regressions. The second potential issue is reverse causality. Reverse causality is between law enforcement officers and in-school crime i.e., more officers may be observed in schools with higher crime. To study this issue, schools with non-zero amounts of security guards, police officers, or resource officers are excluded from the sample and then the empirical analysis of changes in MDA laws on crime is conducted.

Potential Simultaneity

The simultaneity issue exists if schools in states that increase their MDA to 18 foresee crime increasing in their schools and compensate by allocating additional resources to crime prevention. If increases in MDA cause both more crime and increases in the amount of crime prevention then the expected value of the error term in the crime regression is not zero, i.e., If $E[\varepsilon|X_1...X_n] \neq 0$, then OLS estimates are biased and inconsistent.

School resource regressions are estimated to empirically test whether or not simultaneity is an issue potentially biasing the results. The results of this estimation are presented in Tables 5.5 & 5.6. The results show that a MDA of 18 compared to a MDA of 16 does not increase any of the crime prevention resources. In fact, the results indicate that a MDA of 18 actually reduces the number of resource officers per 1,000 students. These results imply that changes in MDA laws do not systematically increase ICPRs.

Potential Reverse Causality

The crime literature points out a significant reverse causality when including police officers in crime equations because police officers persistently have a positive effect on crime. Levitt (1997) uses the timing of mayoral and gubernatorial elections as instrumental variables to identify causal effects of police on crime. This thesis identifies and solves the potential endogeneity problem of officers in the in-school crime equation by analyzing the large population of schools without law enforcement present.

Reverse causality is a concern because the resulting endogeneity would cause the expected value of the error term to be non-zero ($E[\varepsilon|X_1...X_n] \neq 0$), making OLS biased and inconsistent. The scatter plot between the number of resource officers and rate of in-school crime is presented in Figure 5.1. This scatter plot shows evidence that reverse causality is not a concern in this estimation. If there were a strong positive relationship between in-school crime and the number of resource officers, then the number of officers would increase as crime goes up. As evidenced in the scatter plots, the number of in-school officers does not increase with crime. The challenge of increasing the number of officers in a school is that, on average, each school only has 1 or fewer officers. Furthermore, low-income schools are the most resource constrained and may find an additional officer to be cost prohibitive.

To empirically test for reverse causality, schools with non-zero amounts of security guards, police officers, or resource officers are excluded from the sample then the DD model is estimated to measure the effect of MDA laws on in-school crime. Descriptive statistics of the crime rates for schools without law enforcement officers are presented in Table 5.7. The average rate of crime in this group is slightly less compared to the total sample, 49.6 per 1,000 students compared to 51.0 per 1,000 students, respectively. If reverse causality is not an issue, the results from this estimation will be similar to those of the main regressions. Approximately 28% (860 schools) of the sample do not have any law enforcement officers or security guards.[4] The results to this estimation are presented in Table 5.8. The results show that a MDA of 18 increases the rate of in-school crime. This estimation shows a larger coefficient for a MDA of 18 compared to the main estimation, 0.853 opposed to 0.435. Since the results are similar when police officers, security guards and resource officers are excluded and included, evidence is provided that the regressions are not affected by endogeneity.

Robustness of Results to Alternative Control Groups

This section explores how sensitive the results are to alternative control groups. First, I exclude certain states from the regressions: states with low sampling (Delaware, North

[4] The number of observations are rounded to the nearest 10's place per restricted-use data license.

Dakota, Vermont), states typically excluded in the MDA literature (Alaska, Hawaii, Mississippi, and Washington D.C.), and states with multiple MDA laws (New York). Separate regressions are conducted for each excluded group, and then a regression with all of them excluded is conducted. Second, I exclude certain states dependent on their MDA laws, e.g, excluding all schools in states with a MDA of 17.

Excluding Certain States

There are four different estimations that will exclude states. The first robustness check will be to exclude low sample states. There are three states in the sample that have less than ten school-level observations. The low observation states are Delaware, North Dakota, and Vermont. The second check excludes states that are typically excluded in the MDA literature. These are: Alaska, Hawaii, Mississippi, and Washington D.C.. The third check will exclude states with multiple MDA laws. This includes New York.[5] The fourth check excludes all the low sampled states, the typically excluded states, and the states with multiple MDA laws.

The results from these robustness checks are displayed in Table 5.9. "Control Group A" shows the results excluding the low sample states, "Control Group B" shows the results from the exclusion of the typically excluded states, "Control Group C" show the results from excluding New York, and "Control Group D" presents the results from excluding all of the relevantly excluded states. The coefficients on the MDA variables have similar coefficients to the baseline regressions.

[5] A city in New York state with a population less than 4,500 has a MDA of 16 and New York cities with populations greater than 4,500 have a MDA of 17.

Excluding Certain MDA Laws

There are three changes in MDA laws that occur during the sample: increases from 16 to 18, from 16 to 17, and from 17 to 18. It is useful to examine if individual changes to MDA laws have comparable results. To examine these changes, states that do not have the MDA being examined are dropped. For example, to measure the effect of a change from 16 to 18, any states that have or had a MDA of 17 during the sample are excluded.

Table 5.9 shows the results from the three alternate specifications. The estimation results from dropping schools in states with a MDA of 16 are reported in Table 5.9, column "Drop MDA 16." Likewise, estimation results from dropping schools in states with a MDA of 17 and 18 are reported in columns "Drop MDA 17" and "Drop MDA 18."The results are similar to the main results for the effect of MDA laws of 17 and 18 on in-school crime.

Tables and Figures

Table 5.1: Difference-in-Difference of Means Across Crimes

Variables	2003	2009	Difference[a]
No MDA Change States			
In-School Crime	51.88	47.22	-4.66
Attacks w/o Weapon	19.83	17.01	-2.82
Threats w/o Weapon	14.87	12.80	-2.08
Drug Crimes	2.23	7.38	5.15
Property Crimes	17.66	17.89	0.23
Violent Crimes	2.94	4.51	1.57
MDA Change States			
In-School Crime	55.53	56.57	1.03
Attacks w/o Weapon	31.63	21.19	-10.45
Threats w/o Weapon	24.44	12.17	-12.27
Drug Crimes	5.74	7.15	1.41
Property Crimes	23.47	21.38	-2.09
Violent Crimes	3.36	7.19	3.83

[a] Simple difference, 2009 less 2003.

Table 5.2: Box-Cox Transformation Parameters for In-School Crime Rates

Variable	C (Scale Shift)[a]	λ (Power Shift)[a]
In-School Crime	1.731	0.264
Attacks w/o Weapon	0.027	0.271
Threats w/o Weapon	0.038	0.084
Drug Crimes	0.006	0.335
Property Crimes	0.001	0.213
Violent Crimes	0.004	0.168

[a] See equation 5.1 for further details.

Table 5.3: Estimation Results: The Average Marginal Effects on In-School Crime Rates

Variables	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Minimum Dropout Age of 17	0.447***	4.93	0.425***	5.22	-0.096	-0.50	0.030	0.23
Minimum Dropout Age of 18	0.713***	6.09	0.730***	6.66	0.488***	4.15	0.435***	3.64
City			0.220	1.53	-0.031	-0.20	-0.049	-0.35
Urban			-0.240***	-2.85	-0.097	-1.00	-0.119	-1.22
Enrollment					-0.010	-0.10	-0.008	-0.10
Student-to-Teacher Ratio					0.025	1.59	0.024	1.41
Adult Street Crime					0.405***	7.35	0.404***	6.87
Percent Eligible for Free Lunch					0.016***	5.31	0.015***	4.89
Percent Male					0.000	0.09	0.002	0.44
Percent Below 15^{th} % on Std. Tests					0.005	1.00	0.004	1.02
Percent Minority					0.001	0.38	0.002	0.64
Number of Security Guards							-0.522*	-1.70
Number of Resource Officers							-0.009	-0.06
Number of Officers							0.063	1.25
Uniform							0.080	0.84
Security Cameras							-0.208	-1.41
Time Fixed Effects	Yes		Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes		Yes	
School Controls	No		No		Yes		Yes	
In-School Security	No		No		No		Yes	
Resource Controls	No		No		No		Yes	
Drug Prevention	No		No		No		No	
R-Squared	0.082		0.088		0.122		0.126	

Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Table 5.4: Estimation Results: The Average Marginal Effects on Various In-School Crime Rates

	Attacks w/o Weapon		Threats w/o Weapon		Drug Crimes		Property Crimes[a]		Violent Crimes[a]	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Minimum Dropout Age of 17	-0.358*	-1.74	-0.471	-0.91	0.381	0.57	0.375	0.83	-0.364	-1.48
Minimum Dropout Age of 18	0.625***	2.76	0.592**	2.46	0.439**	2.33	-0.056	-0.11	-0.109	-0.44
City	-0.342*	-1.87	-0.052	-0.22	0.103	0.66	0.197	0.88	0.243	1.54
Urban	-0.334**	-2.13	0.153	0.84	-0.192*	-1.75	0.390***	2.75	-0.164	-1.53
Enrollment	0.103	0.91	0.698***	3.87	0.999***	7.73	-0.052	-0.56	0.528***	3.82
Student-to-Teacher Ratio	0.031	1.38	0.013	0.52	0.035*	1.72	0.032	1.54	0.007	0.41
Adult Street Crime	0.127	1.23	0.854***	6.70	-0.112	-1.30	-0.048	-0.38	-0.354***	-3.63
Percent Eligible for Free Lunch	0.024***	5.10	0.026***	4.61	0.002	0.50	0.003	0.85	0.009**	2.28
Percent Male	-0.003	-0.49	0.002	0.16	0.005	0.71	0.004	0.55	0.005	0.91
Percent Below 15^{th} % on Std. Tests	0.010*	1.96	0.001	0.17	0.005	0.93	-0.004	-0.86	0.003	0.72
Percent Minority	0.009**	2.20	-0.008	-1.49	0.001	0.19	0.001	0.24	0.001	0.20
Number of Security Guards	-1.092**	-2.68	-0.919**	-2.37	-0.343	-0.95	-0.207	-0.56	0.186	0.65
Number of Resource Officers	0.321*	1.82	0.341*	1.74	0.537***	3.16	-0.170	-1.00	0.268**	2.13
Number of Officers	0.027	0.37	0.083	1.12	0.033	0.55	0.024	0.49	0.084*	1.85
Uniform	-0.063	-0.56	0.174	1.56	0.247***	2.98	0.154	1.65	0.035	0.42
Security Cameras	-0.198*	-1.75	-0.175	-1.33	0.198	0.92	-0.095	-0.56	-0.173	-1.25
Random Dog Sniffs					0.397***	3.02				
Random Sweeps					0.124	0.94				
Time Fixed Effects	Yes		Yes		Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes		Yes		Yes	
School Controls	Yes		Yes		Yes		Yes		Yes	
In-School Security	Yes		Yes		Yes		Yes		Yes	
Resource Controls	Yes		Yes		Yes		Yes		Yes	
Drug Prevention	No		No		Yes		No		No	
R-Squared	0.137		0.086		0.287		0.103		0.085	

[a] Crime aggregates are addressed in Table 3.3.
Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Table 5.5: Estimation Results: The Average Marginal Effects on In-School Law Enforcement Officer Rates

	Security Guards		Resource Officers		Officers	
Variables	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Minimum Dropout Age of 17	0.358***	2.90	-0.061	-0.32	-0.073	-0.23
Minimum Dropout Age of 18	-0.561	-1.27	-0.311**	-2.55	0.025	0.42
City	0.763***	4.95	0.112	1.37	0.007	0.15
Urban	0.377***	3.51	0.031	0.56	-0.022	-1.04
Enrollment	0.091	1.18	-0.106**	-2.27	-0.010	-0.60
Student-to-Teacher Ratio	-0.003	-0.16	-0.007	-0.59	-0.006	-0.92
Adult Street Crime	0.044	0.81	-0.045	-0.78	0.021	1.23
Percent Eligible for Free Lunch	0.005	1.67	0.004**	2.07	0.000	0.04
Percent Male	-0.003	-0.79	-0.004	-1.21	0.001	0.58
Percent Below 15^{th} % on Std. Tests	0.011**	2.43	0.007**	2.12	0.003	1.50
Percent Minority	0.010**	2.51	-0.002	-1.08	0.002**	2.06
Time Fixed Effects	Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes	
School Controls	Yes		Yes		Yes	
In-School Security	No		No		No	
Resource Controls	No		No		No	
Drug Prevention	No		No		No	
R-Squared	0.293		0.136		0.081	

Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Table 5.6: Estimation Results: The Average Marginal Effect on In-School Crime Prevention Resources

	Drug Sniff[a]		Random Sweep[a]		Sec. Camera[a]	
Variables	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Minimum Dropout Age of 17	-0.019	-0.19	-0.475**	-2.45	0.638**	2.09
Minimum Dropout Age of 18	-0.164	-1.29	-0.100	-0.20	0.334	1.00
City	-0.801***	-6.38	0.100	0.96	0.039	0.32
Urban	-0.329***	-2.83	-0.055	-0.77	0.095	0.89
Enrollment	0.113*	1.70	0.087	1.47	0.287**	2.49
Student-to-Teacher Ratio	0.007	0.83	-0.013	-1.39	0.006	0.42
Adult Street Crime	2.850**	2.03	0.212***	3.72	0.529	0.71
Percent Eligible for Free Lunch	0.002	0.69	0.020***	5.35	0.005**	1.99
Percent Male	-0.003	-0.74	-0.003	-0.90	-0.004	-0.70
Percent Below 15^{th} % on Std. Tests	-0.000	-0.16	0.001	0.34	0.008***	2.92
Percent Minority	-0.007**	-2.50	0.002	1.64	-0.003	-1.17
Time Fixed Effects	Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes	
School Controls	Yes		Yes		Yes	
In-School Security	No		No		No	
Resource Controls	No		No		No	
Drug Prevention	No		No		No	
R-Squared	0.219		0.100		0.150	

[a] Coefficients estimated using a probit limited probability model.
Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Table 5.7: Descriptive Statistics for Schools Without Law Enforcement Officers

Variables	Mean	Std. Dev.
Dependent Variable		
In-School Crime	49.6	44.1
Compulsory Schooling Laws		
Minimum Dropout Age of 16	0.39	0.49
Minimum Dropout Age of 17	0.19	0.39
Minimum Dropout Age of 18	0.42	0.49
Neighborhood Characteristics		
Adult Street Crime	0.05	0.03
City	0.04	0.19
Urban	0.21	0.41
School Characteristics		
Enrollment	566	397
Student-to-Teacher Ratio	13.0	4.2
Percent Eligible for Free Lunch	35.4	21.9
Percent Male	49.4	8.9
Percent Below 15^{th} % on Std. Tests	10.9	10.0
Percent Minority	15.3	19.4
Observations		
Observations[a]	860	
Weighted Observations[a]	13,530	

[a] The number of observations are rounded to the nearest 10s place per restricted-use data license.

Table 5.8: Estimation Results: The Average Marginal Effects on In-School Crime for Schools Without Law Enforcement Officers

	Coeff.	t-stat
Minimum Dropout Age of 17	0.924	1.54
Minimum Dropout Age of 18	0.853***	4.32
City	-0.691**	-2.12
Urban	-0.129	-0.70
Enrollment	0.097	0.38
Student-to-Teacher Ratio	0.031	0.75
Adult Street Crime	0.263	0.06
Percent Eligible for Free Lunch	0.020***	3.34
Percent Male	-0.002	-0.16
Percent Below 15^{th} % on Std. Tests	-0.008	-0.93
Percent Minority	-0.005	-0.90
Time Fixed Effects	Yes	
States Fixed Effects	Yes	
School Controls	Yes	
In-School Security	No	
Resource Controls	No	
Drug Prevention	No	
R-Squared	0.194	

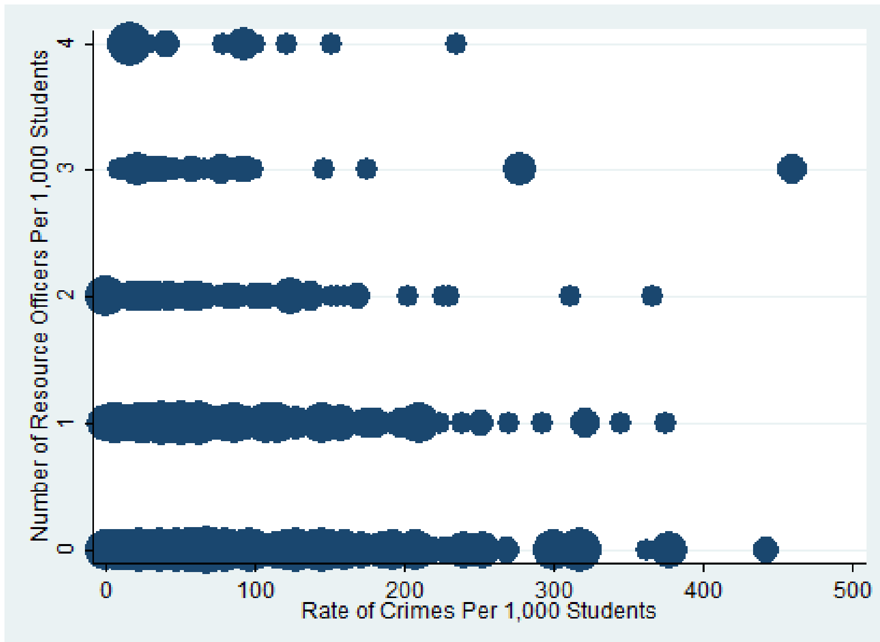
Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Table 5.9: Estimation Results: The Average Marginal Effects on In-School Crime Rates for Different Control Groups

	Control Group A		Control Group B		Control Group C		Control Group D		Drop MDA 16		Drop MDA 17		Drop MDA 18	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
MDA 17	0.0389	0.31	0.042	0.34	0.0323	0.25	0.0558	0.44					0.0347	0.24
MDA 18	0.445***	3.73	0.452***	3.81	0.426***	3.4	0.454***	3.65	-0.0544	-0.25	0.511***	6.05		
Time Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
School Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
In-School Security	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Resource Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Drug Prevention	No		No		No		No		No		No		No	
R-Squared	0.126		0.126		0.125		0.126		0.143		0.122		0.135	

Control Group A: Excludes low sample states (VT, ND, DE)
Control Group B: Excludes states that generally excluded from MDA models (AK, DC, HI, MS)
Control Group C: Excludes states with Multiple MDA laws (NY)
Control Group D: Excludes all excludable states (VT, ND, DE, AK, DC, HI, MS, NY)
Drop MDA 16: Excludes states that have a MDA of 16 at any time in the sample period
Drop MDA 17: Excludes states that have a MDA of 17 at any time in the sample period
Drop MDA 18: Excludes states that have a MDA of 18 at any time in the sample period
Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Figure 5.1: Scatter Plot: In-School Crime Rate and the Number of Resource Officers



ROBUSTNESS OF RESULTS ACROSS DEMOGRAPHICS

The results presented in the previous section provide inferences for the average marginal effect of MDA laws on in-school crime for public high schools across the country. These effects may be heterogeneous across demographics. Thus, it is useful to estimate the effects of MDA laws across demographics. This section explains the usefulness of this robustness check, introduces the empirical specification, and discusses the results.

Robustness of Results Across Demographics

Further public policy implications can be obtained by focusing on how rates of in-school crime are affected by MDA laws across different income levels, enrollment levels, and adult street crime levels. Understanding the relationship between in-school crime and MDA laws across demographics provide additional insight for evaluating the effectiveness of future changes in MDA.

Empirical Specification

Robustness checks will be conducted to understand how the laws affect different demographic and socio-economic subgroups. To do this, the DD model will be extended with interaction terms for quartiles of a particular subgroup. The general specifications is as follows:

$$
\begin{aligned}
\widetilde{Crime}^{j}_{ist} \quad = \quad & \alpha + \beta_1 MDA17_{st} + \beta_2 MDA18_{st} + \beta_3 Subgroup \\
& + \beta_4 (MDA17_{st} * S_1) + \beta_5 (MDA18_{st} * S_1) \\
& + \beta_6 (MDA17_{st} * S_2) + \beta_7 (MDA18_{st} * S_2) \\
& + \beta_8 (MDA17_{st} * S_3) + \beta_9 (MDA18_{st} * S_3) \\
& + \beta_{10} \boldsymbol{X}_{ist} + \beta_{11} \boldsymbol{S}_s + \beta_{12} \boldsymbol{T}_t + \varepsilon_{ist}
\end{aligned}
\tag{6.1}
$$

Control: High School students in states with a MDA of 16 not in the subgroup quartile

Treatment: High School students in states with a MDA of 17 or 18 in the subgroup quartile

Sample: All public high schools surveyed in the SSOCS

Subgroups: Percent eligible for free lunch, enrollment size, street crime (adult)

the specification is extended to include the subgroup variable of interest and a set of interaction variables between the indicator for the quartile in the subgroup, S_k for $k = \{1, 2, 3\}$, and the MDA laws.

The coefficients of interest are β_1, β_2, and β_4 through β_9. These capture the effect of the treatment on the treated. The interaction terms measure the marginal effect of the MDA laws of 17 and 18 on the specific quartile of the subgroup, relative to the control group. The coefficients of interest are expected to be either positive or negative and significant if MDA laws affect the relevant subgroups differently.

Income Levels

The literature suggests characteristics of parents and schools need to be considered in any study on juvenile and in-school crime (Haveman and Wolfe (1995)). Analysis of the effect of MDA laws on in-school crime across income distributions incorporates a few important features. Table 6.1 provides descriptive statistics for in-school crime across the four income quartiles. The percent of students eligible for free lunch provides the income index for the school. "1" represents schools with the lowest percentage of students eligible for free lunch (high income). Likewise, "4" represents the upper quartile of the schools with the most students eligible for free lunch (low income). The table makes evident that as the percentage of low-income students increase, crime rates increase. This relationship is observed in states that changed their MDA during the sample and in states that do not change their MDA during the sample.

I test whether there are differences across income groups for in-school crime using a DD model (Equation 6.1). Table 6.2 presents the estimated results which indicate that a MDA of 18 significantly increases in-school crime in all four income quartiles. Comparing magnitudes of the effect across income quartiles, in-school crime increases most in the second and third income quartiles. This finding may indicate unobserved attention is given to the lowest income schools.

Enrollment Levels

School enrollment is an important consideration when analyzing in-school crime for a few reasons. First, more students increase the likelihood of interactions that lead to conflict. Second, schools with high enrollments may be harder to monitor. Third, high enrollments lead to more opportunities for delinquents to negatively influence "good" students. Finally, high enrollments are generally associated with higher diversity among students and staff.

Enrollment quartiles are constructed to estimate the effects of MDA laws on in-school crime across school size. Table 6.1 presents descriptive statistics for states across the four enrollment quartiles. Surprisingly, descriptive statistics show that in-school crime rates tend to decrease as school enrollment increases. This relationship occurs in states that do not change their MDA and states that do change their MDA. This relationship is counter-intuitive, however these are descriptive statistics that only control for enrollment.

Enrollment quartiles are interacted with the MDA law variables then the fully specified DD model is estimated. The results to this specification are presented in Table 6.2. They show that a MDA of 18 significantly increases in-school crime. Significant positive effects of a MDA of 18 on in-school crime are found in the second, third, and fourth quartiles of enrollment. There is no significant effect of a MDA of 18 on the first enrollment quartile schools (smallest 25% of schools).

The descriptive statistics show downward trends in crime with increasing enrollment. The DD model controls for school demographics, street crime, and crime prevention resources. With additional controls, crime is increasing with higher enrollment levels. This is what economic intuition and previous literature suggest. As enrollment increases there are more interaction between students, the increase in interaction increases the likelihood that delinquent behavior will occur (Gaviria and Raphael (2001)).

Adult Street Crime

The last specification seeks to determine whether changes in MDA laws are heterogeneous based on the rate of street crime surrounding the school. Street crime is of interest because neighborhood effects have been cited in the literature as major factors influencing juvenile crime (Parker et al. (1991), Gaviria and Raphael (2001), Jacob and Lefgren (2003), and Luallen (2006)). Table 6.1 shows descriptive statistics for in-school crime across street crime quartiles. The table illustrates small changes for in-school crime rates across street crime levels.

The quartiles of street crime are interacted with MDA law variables to estimate the effect of changes in MDA laws. The results to this specification are presented in Table 6.2. The results indicate that a MDA of 18 significantly increases in-school crime in counties in the first, second, and fourth street crime quartiles. These results are consistent with the literature suggesting neighborhood street crime significantly effects in-school crime.

Tables and Figures

Table 6.1: Means of In-School Crime Rates Across Income, Enrollment, and Street Crime Quartiles

Demographics	Quartiles	No Change States	Change States	All States
Income[a]	1	35.9	44.5	37.2
	2	49.0	56.9	50.3
	3	53.8	62.2	54.6
	4	58.3	92.9	61.4
Enrollment	1	52.0	69.0	54.7
	2	51.3	53.8	51.6
	3	49.2	64.2	51.0
	4	46.1	52.1	46.8
Street Crime	1	47.9	64.5	50.3
	2	47.6	64.6	49.3
	3	48.7	59.3	49.5
	4	52.4	57.8	53.3

[a] The lowest percentages of students eligible for free lunch are in quartile 1.

Table 6.2: Estimation Results: The Average Marginal Effects on In-School Crime Across Percent Eligible for Free Lunch, Enrollment, and Street Crime Quartiles

	Income[a]		Enrollment[a]		Street Crime[a]	
Variable	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Minimum Dropout Age of 17	0.188	0.75	0.425***	2.78	-0.430	-1.10
Minimum Dropout Age of 18	0.433*	1.76	0.545***	4.08	0.486**	2.30
Percent Eligible for Free Lunch	0.012**	2.52	0.016***	5.04	0.014***	4.76
Enrollment	0.011	0.15	-0.148	-1.63	-0.007	-0.09
Adult Street Crime	0.372***	9.76	0.429***	8.42	0.412***	7.08
MDA17*Free Lunch$_1$	-0.326	-1.10				
MDA17*Free Lunch$_2$	0.243	0.96				
MDA17*Free Lunch$_3$	-0.043	-0.15				
MDA18*Free Lunch$_1$	-0.415	-1.48				
MDA18*Free Lunch$_2$	0.202	0.87				
MDA18*Free Lunch$_3$	0.094	0.41				
MDA17*Enrollment$_1$			-1.133**	-2.53		
MDA17*Enrollment$_2$			-0.271	-1.30		
MDA17*Enrollment$_3$			-0.074	-0.42		
MDA18*Enrollment$_1$			-0.557**	-2.60		
MDA18*Enrollment$_2$			0.036	0.19		
MDA18*Enrollment$_3$			-0.043	-0.35		
MDA17*Street Crime$_1$					0.650	1.32
MDA17*Street Crime$_2$					0.621	1.32
MDA17*Street Crime$_3$					0.679	1.42
MDA18*Street Crime$_1$					-0.269	-1.08
MDA18*Street Crime$_2$					-0.028	-0.10
MDA18*Street Crime$_3$					-0.455*	-2.01
Time Fixed Effects	Yes		Yes		Yes	
States Fixed Effects	Yes		Yes		Yes	
School Controls	Yes		Yes		Yes	
In-School Security	Yes		Yes		Yes	
Resource Controls	Yes		Yes		Yes	
Drug Prevention	No		No		No	
R-Squared	0.135		0.089		0.291	

Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

CONCLUSION

This thesis investigates the implications of changes in state-level MDA laws on school attendance and in-school crime rates. The first investigation estimating the effect of changes in MDA laws on average daily attendance (ADA) are inconclusive. The two opposing effects cancel each other out. First, a negative effect on ADA from increases in suspensions and students not attending for fear of safety. Second, the positive effect on ADA from decreases in expulsions. The MDA literature confirms that MDA laws are effective at bringing delinquent students off the streets and into schools. The second investigation estimates the effect of MDA laws on rates of in-school crime. The results conclude that a change in MDA of 16 to 18 increases in-school crime by 0.85%. Specifically, attacks without a weapon, threats without a weapon, and drug incidences are significantly increased by a change in MDA of 16 to 18. These results are robust across alternative control groups.

The results estimated in this thesis add valuable information to the debate about the effect of school on juvenile crime. The previous literature on this subject has not accounted for measurement error in in-school crime. The measurement error being an underreporting of in-school crimes from school administrators to law enforcement. This thesis incorporates the measurement error and suggests that the effects from the current literature on school and juvenile crime may have underestimated the net effect.

The increase in in-school crime as a result of changes in MDA laws has significant negative effects because in-school crime enters the education production function in numerous ways. Increases in in-school crime can decrease student attendance through a fear of safety, decrease student achievement, and increase teacher attrition. However, MDA laws have also been shown to also increase lifetime earnings, increase overall productivity of the work force, and reduce juvenile street crime. When analyzing a policy change towards a higher MDA, state policymakers need to consider both the positive and negative effects involved with the change.

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APPENDICES

APPENDIX A

Q-NORMAL PLOTS

Figure A.1: Q-Normal Plot for the In-School Crime Rate

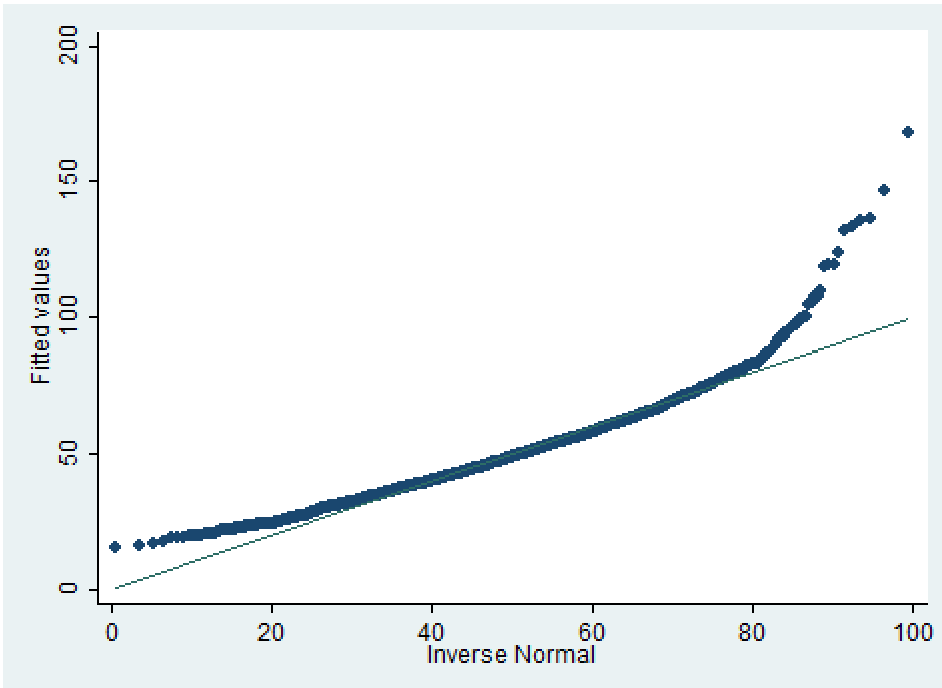
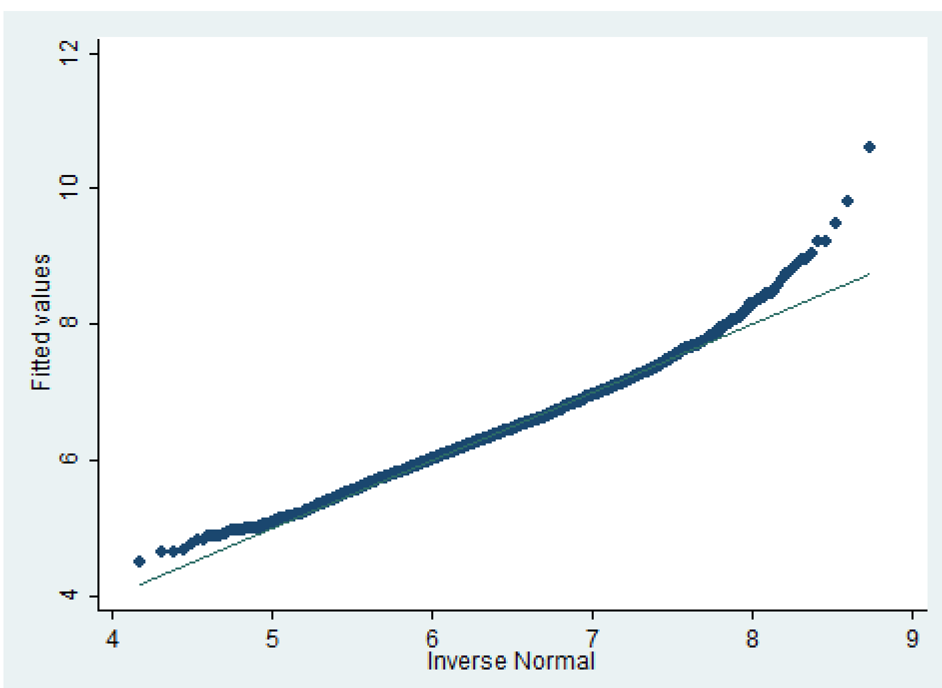


Figure A.2: Q-Normal Plot for the Box-Cox Tranformed In-School Crime Rate



APPENDIX B

PLACEBO ROBUSTNESS CHECK

Table B.1: Estimation Results: The Average Marginal Effects on Whether the School Has a Written Plan for Natural Disasters

	Natural Disaster	
Variable	Coeff.	*t-stat*
Minimum Dropout Age of 17	0.012	0.44
Minimum Dropout Age of 18	0.032	1.39
City	-0.024*	-1.81
Urban	-0.013	-1.22
Enrollment	0.009	1.38
Student-to-Teacher Ratio	0.003*	1.90
Adult Street Crime	-0.007	-0.83
Percent Eligible for Free Lunch	0.000	0.14
Percent Male	0.001	1.38
Percent Below 15^{th} % on Std. Tests	0.000	0.45
Percent Minority	0.000	0.30
Random Dog Sniffs	-0.007	-0.51
Random Sweeps	0.011	1.02
Number of Security Guards	-0.006	-1.12
Number of Resource Officers	-0.001	-0.13
Number of Officers	-0.020	-0.81
Time Fixed Effects	Yes	
States Fixed Effects	Yes	
In-School Security	Yes	
School Controls	Yes	
Resource Controls	Yes	
Drug Prevention	No	
R-Squared	0.134	

Asterisks *, **, *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.