In School and Out of Trouble? The Minimum Dropout Age and Juvenile Crime*

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Abstract

Does increasing the minimum dropout age reduce juvenile crime rates? Despite popular accounts that link school attendance to keeping youth out of trouble, little systematic research has analyzed the contemporaneous relationship between schooling and juvenile crime. This paper examines the connection between the minimum age at which youth can legally dropout of high school and juvenile arrest rates by exploiting state-level variation in the minimum dropout age. Using county-level arrest data for the United States between 1980 and 2006, a difference-in-difference-in-difference-type empirical strategy compares the arrest behavior over time of various age groups within counties that differ by their state's minimum dropout age. The evidence suggests that minimum dropout age requirements have a significant and negative effect on property and violent crime arrest rates for individuals aged 16 to 18 years-old, and these estimates are robust to a range of specification checks. The results are consistent with an incapacitation effect; school attendance decreases the time available for criminal activity. A separate analysis of a nationally representative survey of high school students, however, illustrates that crime is potentially displaced from the streets to schools when the minimum dropout age is higher.

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"Dropout prevention is crime prevention."
Los Angeles County Sheriff Lee Baca

I. Introduction

Does increasing the minimum age at which youth are legally permitted to leave school keep them off the streets and away from crime? Previous research illustrates a correlation between youth dropouts and juvenile criminal behavior (see, e.g., Thornberry et al. 1985; Fagan and Pabon 1990). Dropouts are estimated to be responsible for 1.1 billion dollars in annual juvenile crime costs in the state of California.[1] Because of crime's deleterious consequences, it is important to understand whether or not being in school has a causal influence on juvenile offending; evidence suggests that involvement in juvenile crime adversely impacts economic outcomes later in life. Incarceration is associated with lower educational attainment and decreased future earnings (Hjalmarsson 2008; Waldfogel 1994a; Waldfogel 1994b; Western 2002). Juvenile crime not only has an immediate impact on the delinquent and their victim(s), but can impose negative externalities on those not directly involved with criminal acts (see, e.g., Grogger 1997).

Previous studies have focused on a wide array of determinants of juvenile crime. In general, much of the literature has concentrated on deterrence and punishment as crime-reducing mechanisms.[2] Research has also documented the impact of wages (Hashimoto 1987; Grogger 1998), high school experience (Arum and Beattie 1999), youth employment (Apel et al. 2008), underage drinking (French and Maclean 2006), and curfew ordinances (Kline 2009) to name a few.

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[1] This number reflects an estimate that includes criminal justice expenditures, incarceration costs, school disruption costs and victim costs (Belfield and Levin 2009).
[2] See, e.g., Becker (1968), Corman and Mocan (2000), Di Tella and Schargrodsky (2004), Freeman (1996), Friedman (1999), and Levitt (1997, 1998).

This paper joins the sparse, yet growing, literature on the effects of education on crime by investigating the relationship between the minimum dropout age (MDA) and juvenile arrest rates.[3] In general, the literature can be divided into two categories: the longer-run relationship between education and crime and the contemporaneous relationship between education and crime. Research on the longer-run relationship has focused on the impact of educational attainment on subsequent criminal behavior. More specifically, these studies are interested in whether the accumulation of education as a youth has an impact on adult criminal activity. Empirical research in this area, however, is not decisive. Tauchen et al. (1994) and Witte and Tauchen (1994) find that having a parochial school education is significantly associated with lower criminal behavior, but a high school degree has no significant effect. Grogger's (1998) results indicate that wages have a negative effect on crime, but having additional years of education or a high school diploma do not influence criminal activity. However, these findings do not rule out education having an indirect impact on crime through the labor market. On the other hand, Lochner (2004) estimates a negative effect of education on property and violent crimes using self-reported data from the NLSY. Lochner and Moretti (2004) find that schooling significantly decreases the probability of incarceration and arrest. Lastly, Buonanno and Leonida (2009) show education to have a negative effect on crime using a panel of 20 Italian regions over the period 1980 to 1995.

To date, significantly fewer studies have investigated the contemporaneous relationship between schooling and crime. This paper fits within this area of research on the connection between time spent at school and criminal activity. Farrington et al. (1986), Gottfredson (1985), and Witte and Tauchen (1994) find that time spent at school is associated with lower levels of

[3] For a more comprehensive review of the literature, see the excellent discussion by Lochner (2010).

criminal behavior. These studies do not control, however, for the potential endogeneity of schooling. Two recent papers have explicitly studied the incapacitation and concentration effects of school attendance.[4] An incapacitation effect of school is that it keeps juveniles occupied, leaving less time and opportunity to commit crimes. In contrast, keeping children in school increases the number of potential interactions that facilitate delinquency. Jacob and Lefgren (2003) examine the impact of school attendance on crime by exploiting variation in teacher in-service days. Luallen (2006) uses teacher strikes as a source of variation in student attendance. Both papers find that property crimes committed by juveniles decrease significantly when school is in session, but violent juvenile crime rates increase on these days.

Using a difference-in-difference-in-difference-type (DDD) estimation strategy, this paper exploits the variation in minimum dropout age laws, across states over time, to find strong evidence that increases in the minimum dropout age reduce rates of property and violent crime among high school-aged individuals. The magnitude of the negative effect is greater when the sample is restricted to counties with large black populations. These findings suggest that policy interventions to keep kids in school may be successful at decreasing delinquent behavior.

This paper is the first to systematically analyze the effect of minimum dropout age laws on juvenile crime. Beyond this, at least three other important contributions are made to the literature. First, besides being one of the few papers to explore the contemporaneous link between schooling and crime, this paper distinguishes itself from previous research by attempting to understand the underlying factors that drive this relationship. Jacob and Lefgren (2003) and Luallen (2006) are only able to test for the existence of extremely short-run incapacitation/concentration effects. This paper tries to disentangle competing mechanisms and

[4] The incapacitation function of criminal sanctions is to prevent individuals from doing harm to society by removing them from the population (Shavell 1987).

demonstrate which is most important to explaining the contemporaneous education and crime relationship. Several possible mechanisms are considered. To the extent being in school reduces the time available for delinquent activity, then we might expect an increase in the minimum dropout age to negatively influence criminal behavior. Following the literature, this phenomenon is termed the incapacitation effect. Also, those compelled by law to remain in school longer may build important human capital that decreases their relative returns to crime. Lastly, spillover effects and "voluntary incapacitation" may influence individuals slightly above the minimum dropout age. These mechanisms are discussed in further detail in Section VI. Relative to other factors, the results suggest incapacitation effects are important and large.

Second, by explicitly examining changes in MDA laws, this paper's focus is on the marginal juvenile who is legally obligated to stay in school longer. While Jacob and Lefgren (2003) and Luallen (2006) analyze mechanisms that release entire student bodies from school, this paper concentrates on a policy that affects a small portion of the high school-aged population. Arguably, students on the margin of dropping out are of the utmost importance from a policy and social perspective because they represent a group of high risk offenders.

Lastly, after establishing a strong and negative relationship between the MDA and juvenile crime, this paper briefly addresses whether increases in the MDA displaces delinquency from the streets to schools. Using Youth Risk Behavior Survey data, results show that females in high MDA states are more likely to report being offered drugs on school property and report missing days of school because they fear for their safety. Self-reported rates of in-school theft are also greater for younger high school students in high MDA states. These estimates highlight a potential unintended consequence of increases in the MDA and a vital component that must be included in a policy-maker's cost-benefit analysis.

The remainder of the paper is organized as follows: Section II discusses the background of dropout laws, relevant literature, and empirical evidence concerning the relationship between compulsory schooling and attendance; Section III describes the data; Section IV lays out the empirical strategy; Section V discusses the results; Section VI attempts to understand the causal relationship between schooling and crime; Section VII addresses the displacement of delinquency from the streets to schools; Section VIII concludes.

II. Minimum Dropout Age Laws

Background of Laws

In 1852, Massachusetts was the first state to enact a compulsory schooling law. By 1918, all states had a law in place (Lleras-Muney 2002). In general, these laws specify a minimum and maximum age for which attendance is required. Historically, compulsory schooling laws have changed frequently across states. Table 1 illustrates there has been a strong movement towards increasing the minimum dropout age in recent years.[5]

Not surprisingly, compulsory schooling legislation is more complex than simply specifying a minimum dropout age. Some states allow exemptions if the child is working or has obtained parental consent. States also vary in their degrees of punishing truancy. Additionally, it is not uncommon for a state to punish the parents of a truant child. See Oreopoulos (2008) for a more complete discussion of state-by-state legislation.[6]

Relevant Literature

[5] For example, Illinois and Indiana have recently increased their minimum dropout age from 16 to 17 and 18, respectively. Other states, however, have maintained a constant minimum dropout age over the past 50 years. Iowa, Michigan, and Montana have had a dropout age of 16 during this period, while Ohio, Oklahoma, and Utah have maintained an age of 18. In addition, several states have raised and lowered their minimum dropout age across the period.

[6] In particular, Table 1 in Oreopoulos (2008) lists examples of exemptions and punishments for states with a minimum dropout age greater than 16.

Previous research has focused on compulsory schooling legislation to estimate the returns to education. Acemoglu and Angrist (2001) instrument educational attainment with compulsory schooling laws to find that the individual returns to compulsory schooling are approximately 8 percent. Oreopoulos (2006) uses a regression discontinuity design and compares local average treatment effects estimates for North America to the U.K. His conclusion is that the gains from compulsory attendance are substantial whether the laws impact a majority or minority of the school-aged population. For Canada, Oreopoulos (2006) finds that an extra year of mandated education is associated with an increase in average annual income by about 12 percent.

Mentioned above, Lochner and Moretti (2004) estimate the effect of educational attainment on criminal activity later in life using the variation in state compulsory schooling laws to instrument endogenous schooling decisions. It is important to note, their study focuses on the number of years of mandatory schooling as opposed to the minimum dropout age. Though positively correlated, a higher minimum dropout age does not necessarily mean more years of compulsory schooling because states also differ in their mandatory starting age.[7] Because this paper's attention is on the contemporaneous relationship between being in school and crime, the minimum dropout age is the variable of interest. Other applications of compulsory schooling include mortality and teenage childbearing (Black et al. 2008; Lleras-Muney 2005).

The Minimum Dropout Age and Attendance: Empirical Evidence

This study is concerned with the reduced form relationship between the minimum dropout age and juvenile crime. Implicit to this relationship is that these laws are effective at impacting attendance rates. Previous research is in accordance with this assumption. Angrist and Krueger (1991) find that approximately 25% of potential dropouts in the United States

[7] For example, Oregon and Maryland both require 12 years of compulsory schooling; yet, the minimum dropout ages for Oregon and Maryland are 18 and 16, respectively.

remain in school because of compulsory schooling laws. Wenger (2002) illustrates that increasing a state's dropout age is consistently predicted to decrease the probability that an individual will drop out of high school. More specifically, she finds the change in probability is equivalent to a decrease in the dropout rate of roughly sixteen percent. The results in Oreopoulos (2008) also suggest that more restrictive compulsory schooling laws have reduced dropout rates. Using less recent data, Lleras-Muney (2002) provides strong evidence that compulsory schooling laws were responsible for increased attendance from 1915 to 1939.

As pointed out by Angrist and Krueger (1991), the efficacy of compulsory schooling legislation is likely due to two enforcement mechanisms. In a majority of states, children are not permitted to work during school hours unless they are of an age at or beyond their state's compulsory schooling requirement. Additionally, young workers are required to obtain work permits that are often granted by school administrators. This, to an extent, allows schools to monitor the behavior of youth who are below the minimum dropout age. It is possible the fraction of dropouts who seek employment are less likely to commit crimes than the youth who dropout and have no interest in working. For the latter individuals, direct enforcement and policing may be more effective means of mandating attendance. More specifically, state legislation provides truancy officers to enforce the law; officers are given the authority to arrest truant youth without a warrant. Truancy regulations are also enforced by school officials and, as mentioned, are often implemented under the context of parental responsibility.

III. Data for County-level Panel Regressions

Dependent Variables

The juvenile arrest data come from the FBI's Uniform Crime Reports (UCR).[8] These data are aggregated by the age of the offender at the county-level for the period 1980-2006.[9] Arrest rates are arrests per 1,000 people of the specified age group.[10] Arrests are reported for violent crimes (aggravated assault and robbery), property crimes (auto theft, larceny, and burglary) and drug related crimes (selling and possession). The violent, property, and drug crime indices represent unweighted aggregations of their respective individual components. The decision to exclude rape and murder from the violent crime index was made because these crimes account for a very small fraction of juvenile violent crime.[11] This paper analyzes male arrest rates.

Collection of the arrest data was completed through a cooperative effort of self-reporting by more than 16,000 city, county, and state law enforcement agencies. Of course, with a project of this magnitude, there are reasons to be cautious of the self-reported data. Gould et al. (2002) point out that arrest rates understate the true level of crime because not every crime committed is reported to the police. Additionally, under-reporting can vary by crime type or county of jurisdiction. Data collection and reporting methods may vary by jurisdiction as well. Fortunately, county-fixed effects eliminate the impact of time-invariant, cross-county differences in data collection and reporting techniques.

[8] U.S. Department of Justice, FBI, *Uniform Crime Reports: Arrests by Age, Sex, and Race*. Washington, DC: U.S. Department of Justice, FBI; Ann Arbor, MI: Inter-university Consortium for Political and Social Research (ICPSR, distributor).
[9] Data for the year 1984 were unavailable.
[10] These rates were calculated using the National Cancer Institute, Surveillance Epidemiology and End Results, U.S. Population Data.
[11] It should be noted, the results presented below are robust to including rape and murder in the violent crime index.

The primary reason for using arrest rates is that detailed age data are not available in the UCR offense reports.[12] Although arrests are not a perfect measure of youth criminal behavior and understate the true level of crime, other research indicates that arrest data serve as an accurate representation of underlying criminal activity.[13] Furthermore, this type of measurement error is unlikely correlated with the minimum dropout age. Using the UCR data, Lochner and Moretti (2004) report the correlation between arrests and crimes committed to be very high.[14]

Following Gould et al. (2002), this paper restricts the sample to all counties with an average population exceeding 25,000 between 1980 and 2006. This selection criterion is intended to capture a representative population and eliminate counties where arrest reports are more likely to be inaccurate. In addition, counties with less than 13 out of 26 complete years of data are omitted from the sample. Alaskan and Hawaiian counties are also excluded because of their significantly different demographics and economies. Finally, in the results reported below, counties in Mississippi are dropped because Mississippi was the only state during the sample time frame to have a minimum dropout age less than 16. The decision to drop Mississippi was made because the control group, described in detail below, consists of youth below the age of 16. The results, however, change little when Mississippi counties are included in the analysis.

Independent Variables

Annual county-level demographic variables come from the U.S. Census Bureau. The regressions control for the county population density, the percentage black, the percentage male, and the percentages in the age ranges 10-19, 20-29, 30-39, 40-49, 50-64, and 65 plus. Data on real per capita personal income and the average annual wage of jobs covered by unemployment

[12] It would not be possible to include complete age data in the UCR offense reports because the ages of criminals who are not caught remain unknown.
[13] See, e.g., Hindelang (1978, 1981).
[14] 0.96 for rape and robbery, 0.94 for murder, assault, and burglary, and 0.93 for auto theft.

insurance come from the Bureau of Economic Analysis. The per capita income and wage variables are deflated by the Consumer Price Index to convert to 2000 dollars. Variables indicating each state's minimum legal drinking age across each year of the period under study were provided by Dee (2001).[15] The state minimum dropout ages come from Oreopoulos (2008) and the National Center for Education Statistics' *Digest of Education Statistics.*

Table 2 presents descriptive statistics for all counties in the sample. Table 3 provides a breakdown of the mean arrest rates for 16, 17, and 18 year-olds by their county's prevailing dropout age law. For property and violent crimes, the highest total crime arrest rates are shown for counties with a minimum dropout age of 16. Across age groups, property crime arrest rates appear lowest for 16 year-olds, while 17 and 18 year-olds appear to commit property crimes at comparable rates. Violent crime arrest rates increase with age. The highest rate of property crime arrests can be attributed to 17 year-olds in counties with a minimum dropout age of 16; and, the highest rate of violent crime arrests occur for 18 year-olds in counties with a dropout age of 16. Drug sale arrests are most prevalent among 18 year-olds in counties with a dropout age of 16, while drug possession arrests are greatest for 18 year-olds in counties with a dropout age of 18.

Figures 1 and 2 illustrate the relationship between the average minimum dropout age for states in the sample and the rates of property crime and violent crime among 16, 17, and 18 year-olds, respectively. Figure 1 shows a substantial fall in the rates of property crime arrests after the early '90s. During this same period, the average minimum dropout age was steadily increasing. In the early '80s, there was a substantial increase in the average minimum dropout age and a contemporaneous decrease in arrest rates. Both series remained quite constant for the rest of the

[15] Minimum legal drinking age data from Dee (2001) do not cover the latter portion of the sample time frame under consideration. This is not problematic because all states had a minimum legal drinking age of 21 by 1990.

decade. Figure 2, on the other hand, provides less evidence that the minimum dropout age has possibly had an impact on violent crime. As with property crime, violent crime arrest rates decreased from the early ‘90s onward when the average minimum dropout age was increasing. Unlike property crimes, violent crime arrests increased drastically from the late ‘80s until about 1992. Because these crime trends were experienced by most regions in the United States, it is more nearly appropriate to compare the magnitude of the changes between counties with differing minimum dropout ages. In addition, these data also suggest that it is important to control for preexisting trends. These concerns are dealt with in the analysis that follows.

IV. Empirical Strategy

As mentioned, this study aims to evaluate the impact of the minimum dropout age on juvenile arrest rates by exploiting variation in state-level compulsory schooling laws. One expects to observe a higher percentage of 16 and 17 year-olds attending school in states with minimum dropout ages of 18 when compared to states with a dropout age of 16 or 17. The question that follows: Are students that would have otherwise dropped out less likely to commit crimes when forced to stay in school?

To empirically estimate the impact of the minimum dropout age on the rates of juvenile arrest, this paper uses a difference-in-difference-in-difference-type (DDD) estimation strategy.[16] This approach relies on state-wide variation in compulsory schooling laws and on arrest data among age groups that are plausibly unaffected by the minimum dropout age as controls for unobserved state- and year-specific juvenile arrest shocks. The control group consists of

[16] For other applications of the DDD approach to policy analysis, see, e.g., Beegle and Stock (2003) on the labor market effects of disability discrimination laws; Dee (2001) on the effects of the minimum legal drinking age on teen childbearing; Dee et al. (2005) on graduated driver licensing and teen traffic fatalities; Genadek et al. (2007) on divorce laws and female labor supply; Kellog and Wolff (2008) on daylight savings time and energy; Ludwig (1998) on concealed-gun-carrying laws and violent crime.

individuals that are always below the minimum dropout age. Because all states have a minimum dropout age of at least 16, the control group is comprised of 13, 14, and 15 year-olds. The treatment group consists of youth who are subject to changes in the law (i.e. 16, 17, and 18 year-olds).

The empirical framework presented here relies on the assumption that criminal behavior among youth below the minimum dropout age tracks the trend of those individuals aged 16-18 except that they are not subject to more or less restrictive dropout laws. By utilizing the control group, common confounding factors are subtracted out from the estimates and the effects of the policy are more precisely measured. The reference counties chosen for analysis are all counties in states with a minimum dropout age equal to 16. In sum, this strategy compares the outcomes for youth that are affected by the minimum dropout age to the outcomes for youth that are not affected by the minimum dropout age (one "difference") in states with a minimum dropout age of 16 versus states with dropout ages of 17 or 18 (a second "difference") over time (the third "difference"). This paper estimates the following equation:

$$\begin{aligned}\text{ArrestRate}_{ijst} = {} & \alpha + \beta_1\text{MDA17}_{st} + \beta_2\text{MDA18}_{st} + \beta_3\text{age16}_i + \beta_4\text{age17}_i + \beta_5\text{age18}_i \\ & + \beta_6(\text{MDA17}_{st} * \text{age16}_i) + \beta_7(\text{MDA17}_{st} * \text{age17}_i) + \beta_8(\text{MDA17}_{st} * \text{age18}_i) \\ & + \beta_9(\text{MDA18}_{st} * \text{age16}_i) + \beta_{10}(\text{MDA18}_{st} * \text{age17}_i) + \beta_{11}(\text{MDA18}_{st} * \text{age18}_i) \\ & + \mathbf{X}_{\mathbf{jst}}\boldsymbol{\beta}_{\mathbf{12}} + \mathbf{C}_{\mathbf{j}}\boldsymbol{\beta}_{\mathbf{13}} + \mathbf{T}_{\mathbf{t}}\boldsymbol{\beta}_{\mathbf{14}} + \mathbf{Trend}_{\mathbf{s}}\boldsymbol{\beta}_{\mathbf{15}} + \varepsilon_{ijst}\end{aligned} \tag{1}$$

where i indexes the age group, j indexes the county, s indexes the state, and t indexes the year.

In equation (1), the dependent variable ArrestRate denotes the arrest rate per 1,000 of age group i in county j and state s at time t. On the right-hand side, MDA17 and MDA18 are equal to one if the state has a minimum dropout age of 17 or 18, respectively, and equal to zero otherwise. The variables age16, age17, and age18 are dummy variables that control for differences in age groups that are common across years. **X** is a vector of the county- and state-level controls as described above. **C** represents county fixed effects and **T** represents time fixed effects. The county fixed effects control for differences in counties that are common across years, while the time fixed effects control for differences across time that are common to individuals of all ages and all counties. Lastly, **Trend** represents linear state-specific time trends that account for time-series variations within each state.

The coefficients of interest are β_6, β_7, β_8, β_9, β_{10}, and β_{11}. These interaction term coefficients represent the estimates of the effects of minimum dropout ages on juvenile arrest rates. More specifically, these coefficients measure the differential impacts of MDA legislation on youth 16, 17, and 18 years of age. If increases in the minimum dropout age decreases crime among juveniles 16 to 18 years of age, then we expect the coefficients β_6 through β_{11} to be negative. If increasing the dropout age only impacts individuals of ages where the law binds, then we expect only β_6, β_9, and β_{10} to be negative. In describing the incapacitation effect, Section VI discusses why we might expect only β_6, β_9, and β_{10} to be negative.

This estimation approach addresses at least three important endogeneity problems. First, there is a strong association between age and crime rates. As a result, comparing the criminal behavior of 16-18 year-olds to 13-15 year-olds raises some concerns. This method, however, alleviates this issue because it also compares arrest rates of 16-18 year-olds in states with a minimum dropout age of 17 or 18 to arrest rates of 16-18 year-olds in states with a dropout age of 16. Second, expectations of when a student will be able to dropout may influence current criminal behavior. For example, a 16 year-old in a state with a minimum dropout age of 17 may behave differently than a 16 year-old in a state with a minimum dropout age of 18 because the former anticipates being able to dropout sooner. Again, this approach mitigates these concerns because it compares youth of different ages within states that have similar minimum dropout ages. Lastly, this technique controls for the potential endogeneity of the minimum dropout age laws. This is accomplished by differencing over time. That is, changes in arrest rates are examined as opposed to differences in levels. As a result, permanent differences in the characteristics of states are taken into account.

All models are estimated with weighted least squares where mean county populations are used as weights. Following Bertrand et al. (2004), standard errors are clustered at the state-level. This procedure accounts for the possibility that standard errors may be biased due to serial correlations of the policy variables over time within a state.

A caveat to mention is the classification of states with respect to MDA laws is basic. The approach merely relies on the presence of a law in a state during a particular year and does not control for particular nuances in the laws. As noted previously, state laws vary along several dimensions, but a practical, parsimonious way to empirically consider all the differences is not clear. Besides an attempt made below to address major exemptions to the laws, the estimation strategy used simply estimates the average effects of these laws and the differences in outcomes across states by the general classification of each state's dropout age.

V. Results

Before proceeding to the DDD regression results, Table 4 summarizes the mean differences of arrest rates by minimum dropout age laws and age group. Table 4 restricts focus to arrest rates for MDA = 16 and MDA = 18 counties. For a comparison of MDA = 16 to MDA = 17 counties and MDA = 17 to MDA = 18 counties, see Tables A1 and A2, respectively, in the Appendix. For the treatment group, that is, youth who are 16 to 18 years of age, the mean total crime arrest rate is approximately 6.2 arrests lower per 1,000 of the age group population in MDA = 18 counties as opposed to MDA = 16 counties. For property and violent crimes, the arrest rates are roughly 3.8 and 2.5 arrests per 1,000 lower, respectively, in MDA = 18 counties. These are statistically significant changes. The control group shows that 13 to 15 year-olds actually have a higher mean property crime arrest rate in MDA = 18 counties. Violent crime arrest rates for the control group are essentially the same across county-type. Subtracting the MDA = 16 and MDA = 18 difference in the control group from the MDA = 16 and MDA = 18 difference in the treatment group shows property crimes are lower by approximately 7.7 arrests per 1,000 and violent crimes are lower by roughly 2.4 arrests per 1,000.

Total Crime Arrest Rates

Table 5 presents the DDD estimates from equation (1). Each column of Table 5 represents separate regression results where the total crime arrest rate is the dependent variable (i.e. property crimes plus violent crimes). The estimates in Column 1 compare arrest rates for counties in states with a minimum dropout age of 16 to all other counties. The approach taken in Column 2, and throughout the remainder of the paper, allows for differences between counties in MDA = 17 and MDA = 18 states. This latter specification is preferred because one expects dropout ages of 16 and 17 to impact juveniles differently.

Controlling for other factors, the total crime arrest rates for all age groups are not statistically different for counties in states with an MDA = 16 as opposed to counties in states with higher dropout ages (MDA16 in Column 1; MDA17 and MDA18 in Column 2). Column 1 indicates that being in a state with a minimum dropout age of 16 is associated with statistically significant and higher arrest rates for 16 and 17 year-olds. For 16 year-olds, the coefficient estimate indicates a higher rate of crime by approximately 5 incidences per 1,000 of the age group population. This estimate increases to nearly 6.6 more incidences per 1,000 for 17 year-olds. In Column 2, exposure to dropout ages of 17 and 18 is associated with decreases in the arrest rate. All coefficient estimates are negative with results for 17 year-olds in MDA = 17 states and 16 and 17 year-olds in MDA = 18 states being statistically significant at the 5% level. For example, exposure to a dropout age of 18 reduces total crime arrest rates for 16 and 17 year-olds by roughly 5.8 and 7.4 incidences per 1,000 of the age group population, respectively.

To put these estimates into further perspective, this represents a 9.7% decrease from the mean rate of total crime arrests for 16 year-olds in MDA = 16 states and an 11.5% decrease from the mean for 17 year-olds in MDA = 16 states. Because this paper's focus is on the differential arrest rates of individuals by age, only the coefficients on the interaction terms are reported in the results that follow.

Arrest Rates by Types of Offenses

Table 6 breaks down total crime into property and violent crimes and their respective components. In addition, drug crime arrests are reported and separated into arrests associated with the selling of drugs and arrests associated with the possession of drugs.

The estimates in Table 6 suggest that increasing the minimum dropout age has a negative impact on property and violent crime. The results in Column 1 indicate that a minimum dropout age of 18 reduces property crime arrests by approximately 3.5 and 4.6 incidences per 1,000 of the age group population for 16 and 17 year-olds, respectively. These numbers represent a 6.9% reduction from the mean rate of property crime for 16 year-olds in MDA = 16 states and an 8.7% reduction from the mean for 17 year-olds in these same states. In Column 1, all coefficients are negative in sign, while results for 16 and 17 year-olds in MDA = 18 states are significant. The coefficient estimates for 16 and 17 year-olds in MDA = 17 states are not significant at conventional levels.

For the individual property crime offenses, all coefficient estimates are negative with the exception of the auto theft and larceny estimates for 18 year-olds in MDA = 17 states. For larceny and burglary, an MDA of 18 appears to be important for juvenile offending. In Column 3, exposure to a minimum dropout age of 18 reduces larceny arrests among 17 year-olds by approximately 2.6 incidences per 1,000 of the age group population. This represents approximately an 8.3% reduction from the mean rate of larceny for 17 year-olds in MDA = 16 states. For burglary, an MDA of 18 is associated with a reduction in arrests from the mean by approximately 11% and 10% for 16 and 17 year-olds, respectively. The result for 17 year-olds, however, is only weakly significant at the 10% level. The statistically insignificant effects of exposure to a minimum dropout age of 17 are not completely surprising because the sample variation in an MDA of 17 was limited relative to an MDA of 18.

Similar to property crime, all of the interaction term coefficient estimates are negative in the violent crime regression. For 17 year-olds, an MDA = 17 is associated with a reduction of violent crime arrests by 2.3 incidences per 1,000; an MDA = 18 reduces violent crime arrests among this age group by 2.7 incidences per 1,000. These figures represent reductions of approximately 21% and 25%, respectively, from the mean rates for 17 year-olds in MDA = 16 states. Coefficient estimates for 16 year-olds are negative and large in magnitude, but not significant at conventional levels. Interestingly, results for 18 year-olds are significant, albeit at the 10% level. One would initially not expect a minimum dropout age of 17 to impact an 18 year-old differently than a minimum dropout age of 16 if incapacitation is the predominate mechanism driving the schooling and crime relationship. In each case, an 18 year-old is free to dropout if he so chooses. Perhaps the most reasonable explanation is that forcing a student to attend school one more year increases the likelihood the student will finish high school. This suggestion is supported by the aforementioned literature on the effects of compulsory schooling. As a result, these students may be less likely to get into trouble. Additionally, it could be that forcing students to stay in school longer increases the costs of committing crime a year or two later because an accumulation of human capital increases expected future income. Arguments similar to those presented here can be made for 17 year-olds in MDA = 17 states and 18 year-olds in MDA = 18 states. For these two cases, however, significant results may also be reflecting a lag in the dropout process. Individuals that turn 17 in MDA = 17 states or 18 in MDA = 18 states may not dropout immediately. Some may be compelled to finish out the year or time might be required to obtain parental consent.[17] These issues will be re-visited in a more rigorous fashion in Section VI.

For individual violent crimes, all coefficient estimates are negative. The minimum dropout age appears to be an important factor for decreasing assaults. For example, an MDA of 18 is associated with a 14% and 23% reduction from the mean rates of arrest in MDA = 16 states for youth 16 and 17 years of age, respectively. One potential explanation is estimates for assault may be picking up the fact that physical altercations within schools are broken up before they escalate into more serious conflicts. For robbery, results are significant for 18 year-olds in MDA = 18 states.

In addition to property and violent crime arrests, Table 6 also presents results for arrests concerning the selling and possession of drugs. Though all coefficient estimates are negative in sign, the only individually significant result is in Column 9 for 17 year-olds exposed to an MDA of 18; this coefficient is weakly significant at the 10% level. It is important to note, however, the

[17] In Arkansas, individuals are legally obligated to finish the school year in which they turn 17, the state's prevailing minimum dropout age.

coefficient estimates are jointly significant at the 1% level for arrests related to the selling of drugs.

Arrest Rates for Subsamples of Population

When considering a policy change, it is vital to know whether or not the change in law has a homogeneous influence across all population types. In general, this information is important to policy makers whose goal is to impact specific populations or areas where the policy may be most effective. Table 7 reports estimates for property and violent crimes for subsamples of the original population. Columns 1 and 3 of Table 7 report coefficient estimates for more "urban" counties. Here, the sample is restricted to counties whose population density is in the top 50th percentile. The coefficient estimates are very similar to the baseline estimates reported in Columns 1 and 4 of Table 6.

Columns 2 and 4 of Table 7 illustrate results for counties whose black population is at least 15% of the total county population.[18] Ideally, one would want to estimate equation (1) for only black youth to observe if any differential impacts of the minimum dropout age across race exist. Unfortunately, it is not possible to observe race for the age-specific UCR data. Historically, dropout and arrest rates have been much higher among blacks than whites. As a result, to the extent that increasing the minimum dropout age decreases delinquency, we might expect compulsory schooling legislation to have a more profound influence on the population of black youth. Columns 2 and 4 of Table 7 suggest this is the case. For property crimes, the magnitudes of the coefficient estimates are much larger for 16 and 17 year-olds who are exposed to an MDA of 18 when compared to the baseline estimates reported in Table 6. Estimates from the violent crime equation suggest a similar phenomenon. Taken together, these estimates imply

[18] Admittedly, 15% was chosen rather arbitrarily. Results remain similar for the range of values between 10% and 20%. The sample size is diminished greatly for values much higher than 20%.

a decrease in total crime arrest rates of 21.6% for 16 year-olds and 19.8% for 17 year-olds who are exposed to an MDA of 18. These reductions are roughly double in magnitude of those reported for the baseline sample.

Alternative Control Group Specifications

Table 8 presents results for property and violent crime using three different control group specifications. Columns 1 and 4 illustrate the baseline estimates where 13-15 year-olds comprise the control group. A concern is that minimum dropout age laws could impact youth below the minimum dropout age if peer effects matter. For example, if increasing the MDA decreases delinquency among 16-18 year-olds, and these youth are peers with 13-15 year-olds, then we might expect to observe decreases in delinquency among 13-15 year-olds as well.[19] Additionally, lower crime rates among 16-18 year-olds, due to more restrictive dropout laws, may allow for more resources to be used towards policing crime among younger age groups. Fortunately, both of these potential issues would cause coefficient estimates to understate, rather than overstate, the true impact of the MDA on 16-18 year-olds.

As a robustness check, Columns 2 and 5 present results where 19 year-olds are considered as controls. Regardless of the state, 19 year-olds are not legally obligated to attend school. One might argue that 19 year-olds serve as a better control group because they are more similar to 16-18 year-olds than are 13-15 year-olds. A potential issue with this specification, however, is that 19 year-olds in high MDA states were themselves less likely to have committed crime when younger and, as a result, may be less likely to commit crime at 19. Yet, if this is the case, the impact of MDA laws on 16-18 year-olds would be understated. For both property and violent crime, all coefficient estimates are negative in sign. While only 2 of the 12 coefficients

[19] See Gaviria and Raphael (2001) for a discussion of school-based peer effects and juvenile behavior.

are individually significant, it should be noted that the estimates are jointly significant at the 5% level for both regressions.

Columns 3 and 6 illustrate results where 13-15 year-olds and 19 year-olds are used together as the control group. These estimates are very similar to the baseline. In sum, Table 8 provides further support for the negative relationship between the minimum dropout age and juvenile arrest rates.

Sensitivity of Results to Alternative Specifications

Table 9 investigates the sensitivity of the results to a range of alternative specifications. Columns 1 and 2 illustrate results where counties in states that have an MDA > 16 and **do not** offer dropout exemptions are excluded from the sample.[20] This exercise is performed because it is important to know from a policy perspective if the results are driven primarily by states with the least flexible legislation. Results for this specification are comparable to the baseline estimates in Table 6 with the exception of the smaller in magnitude and less precise coefficients in the violent crime equation for youth in MDA = 17 states.[21]

Columns 3 and 4 of Table 9 restrict attention to arrest rates for youths in states that ever changed their MDA during the sample time frame. The impact of an MDA = 18 remains strong for property crimes committed by 16 year-olds. In general, the violent crime coefficients are estimated less precisely than the baseline estimates. The coefficients are jointly significant at the 1% and 5% levels for the property crime and violent crime regressions, respectively. This helps

[20] As an example, individuals in New Mexico can dropout one year before reaching their state's MDA of 18 if they have obtained a work permit. In Arkansas, youths can dropout a year early if they attend an adult education program at least 10 hours per week.

[21] The less precise violent crime results for youth in MDA = 17 states could simply be due to the fact that there is substantially less sample variation among these types of states under this sample selection criteria.

to confirm the results are not primarily driven by offsetting changes in behavior in control states coincident with changes in MDA legislation.

Columns 5 and 6 of Table 9 restrict the original sample selection criteria to include only counties with at least 20 years of complete data. The results remain closely the same to those of the baseline for these regressions.

Lastly, because the regressions are population weighted, the sensitivity of the results to states with large populations is examined in Columns 7 and 8. Each California and New York increased their MDA over the sample time period and together contribute approximately 10,000 observations to the full sample. When counties from these states are dropped the main finding holds; increases in the MDA reduces arrest rates among 16-18 year-olds.

MDA Laws and Measures of Police Enforcement

Another concern is that increases in the minimum dropout age are made alongside increases in policing efforts. If police officers exert more effort towards reducing juvenile crime when MDA laws become more restrictive, then one might incorrectly attribute decreases in crime rates to the dropout age policy. To examine this further, Table 10 considers models where observable measures of police enforcement are regressed on the MDA law indicators.[22] The dependent variables are police expenditures per capita and the number of sworn officers per capita. Data come from the Bureau of Justice Statistics and were available for the period 1982-2005.

If the MDA effects are spurious due to increased policing, then the measures of police enforcement should be positively associated with more restrictive MDA legislation. Table 10

[22] The measures of police enforcement are observed annually at the state-level. Both regression models control for the fraction of the population aged 15-19, the fraction of the population that is black, the minimum legal drinking age, state fixed effects, year fixed effects, and state-specific time trends. The models are estimated with weighted least squares where state populations are used as weights.

provides no evidence that higher MDA laws coincide with increases in policing effort.[23] Estimates in Column 2 actually suggest that police expenditures per capita are lower in MDA = 18 states. As pointed out by Lochner and Moretti (2004), this is consistent with trade-offs related to strict state-level budget constraints. Overall, the results in Table 10 support the notion that observed decreases in juvenile arrest rates can be attributed to the MDA laws and not stricter police enforcement.

VI. Why Does the Minimum Dropout Age Decrease Juvenile Crime?

The previous results provide strong evidence that increases in the minimum dropout age cause decreases in juvenile arrest rates. This section discusses and attempts to reveal the underlying mechanisms that drive this relationship. Incapacitation and human capital effects are the first two mechanisms considered. Possible spillover and "voluntary incapacitation" effects are also discussed.

An exogenous increase in the minimum dropout age may have an incapacitation effect on youth. As mentioned previously, the incapacitation effect means that juveniles have less time and opportunity to commit crime while in school. Additionally, while in school, youth are more likely to be monitored. An incapacitation effect implies one of two things for future offending. What one might call a "shifting" effect results in a postponement of criminal behavior. In this scenario, increasing the dropout age simply shifts the age-crime profile of youth out a few years. That is, criminal behavior is merely pent up and the result is an observation of increased arrest rates when individuals leave school at a later date. Alternatively, increasing the minimum dropout age may serve to keep potential delinquents out of trouble during the years of their life

[23] Carpenter (2007) finds similar results for zero-tolerance drunk-driving laws and police enforcement. Using data for earlier years, Lochner and Moretti (2004) show results similar to those presented here for the relationship between compulsory schooling laws and police expenditures and employment.

when they are most likely to commit crime, but have no impact on subsequent offending. Upon leaving school, it is possible that youth have "grown up" and return to their original age-crime profile. In the latter case, an increase in the minimum dropout age unambiguously decreases crime. To differentiate, in what follows, the former effect is referred to as the "shifting" effect, while the latter is simply termed the incapacitation effect.

In addition, an increase in the minimum dropout age can decrease crime through the human capital channel. In regards to future crime, more schooling increases the wage rate; hence, increasing the opportunity cost of crime. Furthermore, in addition to the fact that expectations of future income are changed, youth may learn important values in school that alter their taste for crime and influences their current criminal behavior. For example, schooling may decrease crime by affecting the psychic costs of breaking the law (Arrow 1997).

Lastly, effects may exist where changes in the minimum dropout age impact youth of ages slightly above which the law binds. First, consider "voluntary incapacitation" effects. Beyond a general lag in the dropout process, individuals required to go to school longer because of a higher minimum dropout age may also be more likely to graduate, since time to complete high school declines once they can legally leave school. If this results in a decreased perceived cost of graduating, students who would have left school under more lenient laws may choose to stay enrolled (Oreopoulos 2006). Also, youth may choose to delay dropping out after an increase in the dropout age in order to signal to employers they are better potential workers than those who elect to drop out as soon as the law permits (Lang and Kropp 1986). Second, spillover effects may exist due to the labor market. We might expect an increase in wages for those just above the minimum dropout age when an increase in the dropout age decreases the supply of teenage workers. It is possible that an observed decrease in, say, the crime rates of 18 year-olds is caused by an increased opportunity cost of time.

If increasing the minimum dropout age only has an incapacitating effect on youth, then these laws should have no impact on youth of ages ***above*** which the law binds. If individuals actually dropout on their birthday, then the laws should have no impact on juveniles of ages ***at*** which the law binds as well. Some of the results above indicate that 17 year-olds in MDA = 17 states and 18 year-olds in MDA = 17 states and MDA = 18 states are influenced by changes in the dropout age. To investigate this further, Table 11 includes 19 to 21 year-olds in the sample. The regression model follows the baseline specification with the exception of including the arrest rates of the older individuals. To ensure examination of only 19 to 21 year-olds that went to high school entirely under one MDA regime, state-year observations that correspond to law changes when these individuals were 16 or 17 years-olds are excluded from the analysis.[24]

Given the discussion above, it is apparent that identifying the underlying causal mechanism is more difficult when the MDA influences individuals of an age at or above which the law binds. However, if the incapacitation effect dominates, then impacts of changes in the law should be relatively large at ages where the law binds than at ages above the minimum dropout age.[25] Table 11 illustrates that none of the results for 19 to 21 year-olds for the property crime and violent crime equations are individually statistically significant.[26, 27] The violent

[24] Here, the goal is to match 19 to 21 year-olds up with the minimum dropout age that was in place when they were in high school. The results change little when the state-year observations that correspond to law changes are included in the sample.

[25] Another point worth mentioning is that dropout age laws may also impact the supply of victims. This may be most important for violent crimes. To the extent that increasing the dropout age keeps potential victims in school longer, then we might expect to observe a decrease in crimes such as rape.

[26] The coefficients for the property crime equations for older age groups in MDA = 17 states are actually large and positive; however, these results are nowhere near significant. Positive and large coefficients favor the “shifting” hypothesis, but because of the large standard errors this hypothesis is rejected.

crime coefficients, however, are jointly significant at the 1% level. Though this suggests the MDA may be important for violent criminal behavior after high school, the magnitudes of the coefficients are much smaller than those for 16 to 18 year-olds.[28]

Results from Table 11 provide strong support for the incapacitation effect as an important underlying mechanism to the observed MDA and juvenile crime relationship. Despite this, in some model specifications presented above, youth of ages at or one year above which the law binds also appear to be influenced by changes in the minimum dropout age. To address the possibility of spillovers existing due to the labor market, Table 12 focuses on the timing of the MDA laws. If increasing the MDA decreases the supply of teenage workers, then we might expect the opportunity cost of crime to increase for those workers aged slightly above the MDA as a result of increased wages.

Table 12 presents results where the age and MDA interactions are replaced by interaction terms between the age dummies for the 19-21 year-olds and dummies that indicate the state and year (or a one year lag) that a law was enacted to raise the minimum dropout age.[29] Overall, the estimates in Table 12 provide little support for spillovers existing due to the labor market for the 19-21 year-old age groups.[30] Though evidence of labor market spillovers is weak, it is not possible to rule out other possible factors such as the "voluntary incapacitation" effects discussed

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[27] It is important to mention that in Lochner and Moretti's (2004) analysis of state-level data their full 2SLS models for total arrest rates return estimates that are not statistically significant at conventional levels. This result is consistent with the findings here that incapacitation effects are stronger than human capital effects for high school-aged youths.

[28] When considering the components of the violent crime index separately, coefficient estimates for the robbery equation were not jointly significant. Estimates for the assault equation were jointly significant at the 1% level. This result is consistent with Lochner and Moretti's (2004) specifications that show state-level measures of average education and high school graduation rates to matter for assault rates, but not robbery rates, among adult males aged 20-59. In their presentation of arrest rates by individual type of crime, however, they only report OLS estimates that do not explicitly consider the potential endogeneity of schooling.

[29] These indicators consider all possible increases in the MDA (i.e. 16 to 17, 17 to 18, and 16 to 18).

[30] The results are robust when 16 to 18 year-olds are included in the control group.

above. Unfortunately, due to limitations of the data, further interpretation of the results should be done with caution.

VII. Do MDA Laws Displace Crime to Schools?

The above results provide strong evidence that increasing the minimum dropout age has a significant and negative effect on juvenile arrest rates. Yet, it is important to bear in mind these estimates do not fully consider the potential displacement of delinquency from the streets to schools. If youth commit a crime within school that is punished by arrest, then this is reflected in the results above. Nevertheless, these results do not account for possible increases of within-school delinquency that do not end in arrest. It is possible that by increasing the minimum dropout age more delinquents are kept in school and, as a result, other students suffer costs due to their presence. Such consequences could be increased bullying, threats, gang activity or simply a general decrease in the perception of school safety. Evidence suggests that students who fear victimization at school are more likely to stay at home (Pearson and Toby 1992).

To investigate this issue further, this paper employs restricted use state-identified versions of the 1993-2007 national Youth Risk Behavior Surveys (YRBS).[31] The YRBS data have been used by economists to study a wide range of topics concerning policy evaluations and youth behavior.[32] Table 13 provides descriptive statistics of the variables used in this analysis. Table 14 presents descriptive statistics that are broken down by age, sex, and the state law for all

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[31] There are 11 states in the data that are observed before and after making an MDA law change during this time period.

[32] For other studies that use the YRBS data, see, e.g., Anderson (2010) on the effect of an anti-methamphetamine campaign on teen meth use; Carpenter and Cook (2008) on the effect of cigarette taxes on youth smoking; Carpenter and Stehr (2008) on the effects of mandatory seatbelt laws on seatbelt use, motor vehicle fatalities, and crash-related injuries; Chatterji et al. (2004) on alcohol abuse and suicide attempts; Cawley et al. (2007) on the impact of state physical education requirements on youth physical activity and overweight; Grossman and Markowitz (2005) on risky sexual behavior and substance use; Gruber and Zinman (2001) on trends in youth smoking; Katzman et al. (2007) on the social market for cigarettes; Tauras et al. (2007) on the demand for smokeless tobacco among male high school students.

dependent variables. After taking missing values into account, there is complete information on slightly over 104,000 individuals in the national YRBS. The national surveys are conducted every other year by the Centers for Disease Control and Prevention and provide a nationally representative sample of U.S. high school students.[33] The primary purpose of the YRBS is to gather information on youth activities that influence health. In addition to containing information on risky behaviors and standard demographic characteristics, the YRBS asks students questions pertaining to in-school victimization, safety, and drug availability. In this paper, the dependent variables of interest are binary indicators for whether or not the respondent has missed school in the past month for fear of safety in school or on the way to or from school, has been threatened or injured in the past month with a weapon on school property, has had property stolen or damaged at school in the past year, and has been offered, sold, or given an illegal drug at school in the past year.

To estimate the effect of the MDA on in-school delinquency, this paper uses a standard two-way fixed effects model that amounts to estimating the following equation:

$$Y_{ist} = \alpha + \beta_1 \mathrm{MDA17}_{st} + \beta_2 \mathrm{MDA18}_{st} + \mathbf{X}_{\mathbf{ist}}\boldsymbol{\beta}_{\mathbf{3}} + \mathbf{Z}_{\mathbf{st}}\boldsymbol{\beta}_{\mathbf{4}} + \mathbf{S}_{\mathbf{s}}\boldsymbol{\beta}_{\mathbf{5}} + \mathbf{T}_{\mathbf{t}}\boldsymbol{\beta}_{\mathbf{6}} + \mathbf{Trend}_{\mathbf{s}}\boldsymbol{\beta}_{\mathbf{7}} + \varepsilon_{ist} \qquad (2)$$

where i indexes the individual, s indexes the state, and t indexes the year.

In equation (2), the dependent variable Y denotes the outcomes of interest. On the right-hand side, MDA17 and MDA18 are the same as described above. **X** is a vector of individual-level controls and **Z** is a vector of time-varying state-level characteristics. **S** and **T** represent state and time fixed effects, respectively. Lastly, **Trend** is a vector of linear state-specific time trends. All regressions are estimated with probit models and are weighted by the sample weights

[33] Though intended to be nationally representative, not all 50 states are represented in any given year the survey has been conducted.

provided with the YRBS data.[34] As in equation (1), standard errors are clustered at the state-level (Bertrand et al. 2004). Clustering at the state-level is conservative because it takes into account any dependence of errors within and across schools in the same state.

Equation (2) relies on an identification strategy that removes unobserved and potentially confounding cross-sectional heterogeneity by relying on within-state changes in MDA laws over time. The coefficients of interest, β_1 and β_2, capture the relative effects of MDA = 17 and MDA = 18 laws on youth outcomes within states and over time relative to the associated outcomes for individuals in MDA = 16 states. If delinquency is displaced to schools under higher MDA laws, then we expect β_1 and β_2 to be negative for individuals who would never dropout regardless of the law. It is not clear, however, the direction of the effect for those who are forced to stay in school because of MDA laws. Due to this, results are also presented for the subsample of respondents who are under the age of 16 (i.e. those individuals who are legally obligated to attend school regardless of their state of residence).[35]

A limitation of the YRBS is that school-level identifiers are not available. As a result, the estimation strategy relies on the state-level unemployment rate, per capita real state income, the state's average student/teacher ratio, state expenditures per student, and the arrest rate of individuals under the age of 20 as proxies for neighborhood- and school-level conditions.[36] Another limitation is the inability to observe whether a respondent attends a private or public school. However, because MDA laws are less likely to impact private school students and

[34] Results are robust to estimation of linear probability models.

[35] For the YRBS analysis, it is not appropriate to implement the DDD design used above. This is because youths under the age of 16 may be impacted by those individuals who are kept in school due to the MDA.

[36] It is important to mention the results remain similar when omitting these state-level covariates. This fact helps to reinforce the two-way fixed effects research design.

models are estimated with a pooled sample of public and private students, regression estimates would underestimate the true impact of the MDA on in-school outcomes for this reason.

Table 15 reports marginal effects of the probit models where each cell represents a separate regression. As above, the estimates for the MDA17 coefficients should be viewed more cautiously than the MDA18 results because of the relatively limited sample variation for MDA = 17 states. For the full sample, individuals in MDA = 17 and MDA = 18 states do not report statistically significantly different rates of being threatened or injured with a weapon on school property or being victims of in-school theft than individuals from MDA = 16 states. The results do show, however, that an MDA = 18 is associated with an increase in the rate at which females missed school because they felt unsafe by 3.8 percentage points.[37] Given that the mean rate of missing school due to feeling unsafe is 6.2 percent for females in MDA = 16 states, this represents about a 61% increase relative to the mean. Additionally, females exposed to an MDA = 17 and MDA = 18 were 14.2 and 15 percentage points more likely to report being offered, sold, or given an illegal drug on school property, respectively. These point estimates represent increases of approximately 69% and 72% for females in MDA = 17 and MDA = 18 states, respectively, relative to females in MDA = 16 states.

Columns 3 through 6 present results from regressions that consider only students under the age of 16. Since the direction of the effect is not clear for individuals who are forced to stay in school because of the law, these results provide a cleaner test of the displacement hypothesis. For the "safety" regressions, females in MDA = 18 states no longer report statistically significantly different rates of missing school for fear of safety. It is possible the significant result from the full sample is due to the inclusion of females who are directly influenced by

[37] Admittedly, the measure for school safety is not perfect because it also includes the fear for safety when travelling to and from school. Ideally, one would only want to observe fear for safety when on school property.

MDA laws. Females who are more likely to be fearful of their classmates may also be more likely to drop out of school entirely. There is some evidence weapon threats/injuries are more prevalent in MDA = 18 states, but this result is only weakly significant at the 10% level. Unlike the results from the full sample, students under the age of 16 and who are exposed to an MDA = 18 are more likely to report in-school theft. The point estimate of 18.3 percentage points reflects an approximate 55% increase in the mean rate of theft relative to individuals in MDA = 16 states. This result is stronger in magnitude and more precisely estimated for male students. Lastly, the estimates from the "drug" equation are similar to those presented for the full sample.

These results highlight an important potential consequence of increases in the minimum dropout age. Nevertheless, the issue of displaced delinquency deserves further attention. The approach taken above is limited because neighborhood- and school-level conditions are unobserved in the data. Admittedly, state-level characteristics used to proxy for potentially vital variables at a lower level of aggregation are far from ideal. Due to negative peer effects that displaced delinquents might generate, future research will also want to consider the impact increases in the MDA might have on the academic outcomes of students who stay in school regardless of the dropout age. This could be important for the short- and long-run outcomes of these individuals.

VIII. Conclusion

Juvenile crime in the United States is widespread and a major concern for policy-makers. To date, much attention has been paid to identifying key determinants of juvenile crime. Little is known, however, about the contemporaneous link between schooling and delinquent behavior. This paper examines the effect of the legal minimum dropout age on juvenile arrest rates and attempts to shed some light on the underlying mechanisms that drive this relationship.

Using a difference-in-difference-in-difference-type empirical strategy and U.S. county arrest data, this paper finds that minimum dropout age requirements have a significant and negative effect on juvenile arrest rates. Results from the preferred specification suggest that a minimum dropout age of 18 decreases arrest rates among 16 and 17 year-olds by approximately 9.7% and 11.5%, respectively. The negative effect holds for both property and violent crimes. The magnitude of the effect is greater for counties with large black populations. Furthermore, it appears the incapacitation effect is an important mechanism underlying the link between schooling and delinquency. Keeping juveniles in school decreases the time and opportunity available to commit crimes. Despite this, several specifications indicate that arrest rates for individuals of ages at or one year above which the law binds are affected. Spillover effects due to the labor market do not appear as a likely cause, suggesting "voluntary incapacitation" effects may be driving this observation. Youth required to attend school longer because of a higher minimum dropout age may also be more likely to graduate, since time to complete high school decreases once they can legally dropout. If this is the case, then we might expect to observe a decrease in the arrest rates for those students who would have left school under more lenient laws. Lastly, possible human capital effects cannot be ruled out for violent crimes.

Not only do these findings provide support for the efficacy of programs intended to keep juveniles in school and out of trouble, but they also identify a potential benefit of minimum dropout age laws. Back-of-the-envelope calculations imply that nearly $120 million dollars could be saved annually on the nation's direct cost of property crime if all states were to set an MDA = 18.[38, 39] This estimate, however, likely pales in comparison to potential benefits reaped

[38] From this paper's analysis, an MDA = 18 is associated with an approximate 8% decrease in arrests for 16 and 17 year-olds. According to the UCR data, 16 and 17 year-olds are responsible for 47.2% of property crime arrests for the population under the age of 18. The percent of all male property crimes that can be attributed to males under the

from more difficult-to-measure variables associated with keeping kids in school. Cohen (1998) estimates that a high school dropout causes roughly $300,000 in external costs during their lifetime. To put this number into further perspective, consider that the average public expenditures per pupil enrolled in elementary and secondary schools is approximately $10,000 (National Center for Education Statistics 2008). The cost of high school graduation incentive programs have been estimated to be around $12,000 per student (Greenwood et al. 1996). In 2007, over 1.2 million individuals dropped out of high school (Alliance for Excellent Education 2007).

Despite the benefits discussed, it is important to bear in mind these estimates do not fully consider the potential displacement of delinquency from the streets to schools. It is possible other students bear costs when an increase in the dropout age forces more delinquents to remain in school. Results presented above from the Youth Risk Behavior Survey data suggest females in high MDA states are more likely to report being offered drugs on school property and report missing days of school because they fear for their safety. Rates of in-school theft are also greater for younger high school students in high MDA states. It is imperative that policy-makers take these potential consequences into consideration when weighing the costs and benefits associated with an increase in the minimum dropout age. Future research will also want to consider negative peer effects that displaced delinquents might generate in the classroom. Specifically, it would be desirable to research whether an increase in the minimum dropout age has an adverse impact on the academic outcomes of students who stay in school regardless of their state's law.

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age of 18 is 25.7%. Taken together, these estimates imply that if all states had an MDA = 18, then property crime arrests for the entire male population would be decreased by roughly 1%. Given that the Federal Bureau of Investigation estimates the nation's cost of lost physical property due to property crimes committed by males to be $11.97 billion, this implies an annual cost savings of $119.7 million. This calculation is based off of estimates for 2006.

[39] Interestingly, this estimate is very similar to the cost savings associated with introducing zero-tolerance drunk-driving laws (see Carpenter 2007).

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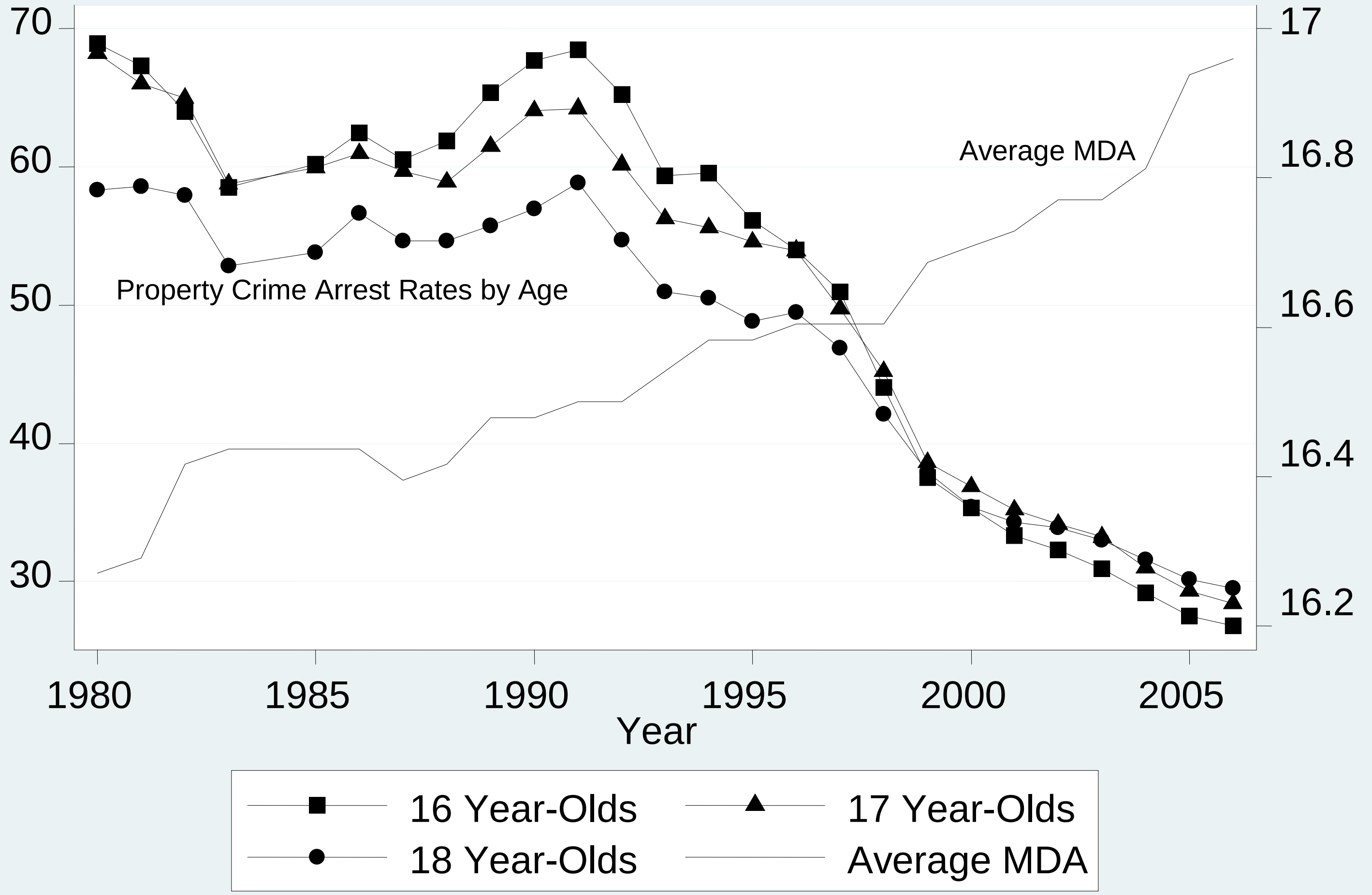
Figure 1

County Sample Property Crime Arrest Rates vs. Average MDA (1980-2006)



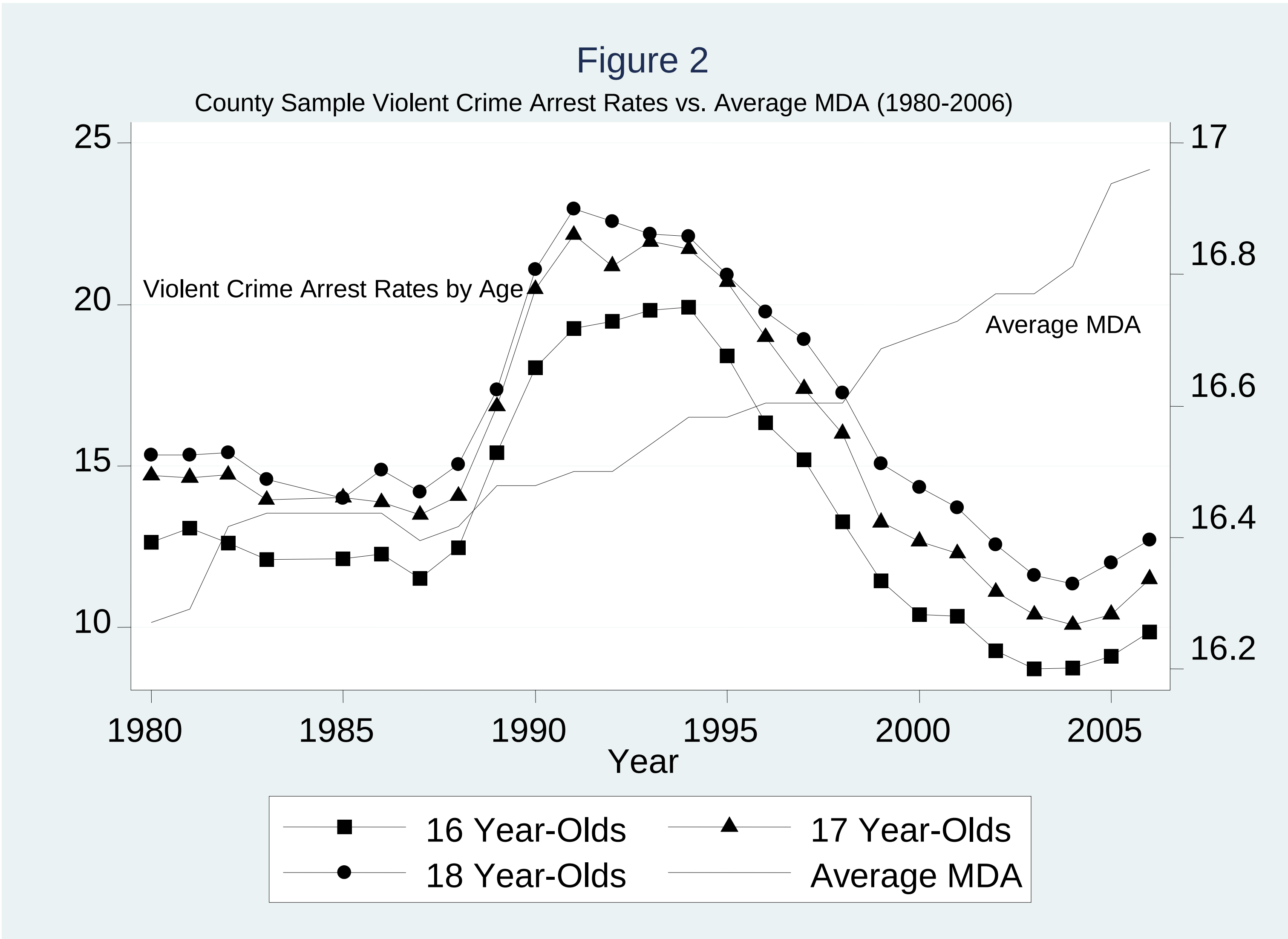


Figure 2
County Sample Violent Crime Arrest Rates vs. Average MDA (1980-2006)
Violent Crime Arrest Rates by Age
Average MDA
25
20
15
10
17
16.8
16.6
16.4
16.2
1980
1985
1990
1995
2000
2005
Year
16 Year-Olds
17 Year-Olds
18 Year-Olds
Average MDA

Table 1. Number of States by Mandatory Minimum Dropout Age, 1950-2005

	1950	1960	1970	1980	1990	2000	2005
MDA ≤ 16	40	41	39	38	31	27	21
MDA = 17	5	4	6	6	10	8	9
MDA = 18	4	4	4	5	8	14	19

Notes: (1) Alaska and Hawaii are not included. (2) Washington D.C. is included.

Table 2. Descriptive Statistics for County Panel Data, 1980-2006

Variable	Mean	Std. Dev.
Property crime arrest rate, ages 13-15	36.79	29.00
Property crime arrest rate, ages 16-18	50.17	31.06
Violent crime arrest rate, ages 13-15	4.57	9.45
Violent crime arrest rate, ages 16-18	9.73	14.08
Minimum dropout age = 16	0.54	0.50
Minimum dropout age = 17	0.22	0.41
Minimum dropout age = 18	0.24	0.43
Minimum legal drinking age = 18	0.07	0.26
Minimum legal drinking age = 19	0.08	0.27
Minimum legal drinking age = 20	0.01	0.11
Minimum legal drinking age = 21	0.84	0.37
Real income per capita (2000 dollars)	23529.71	6278.71
Average annual wage (2000 dollars)	23154.53	8154.36
Population density (thousands)	0.62	2.63
Percent male	0.49	0.14
Percent black	0.13	0.13
Percent aged under 9	0.15	0.02
Percent aged 10 to 19	0.15	0.02
Percent aged 20 to 29	0.15	0.04
Percent aged 30 to 39	0.15	0.02
Percent aged 40 to 49	0.13	0.02
Percent aged 50 to 64	0.14	0.02
Percent aged 65 and over	0.12	0.03

Notes: (1) N = 53,338 for 16 to 18 year-olds. N = 35,592 for 13 to 15 year-olds. (2) The sample is based on the selection criteria described in the text. (3) Arrest rates are annual incidents per 1,000 of the age group population.

Table 3. Descriptive Statistics: Dependent Variables

	MDA = 16 counties			***MDA = 17 counties***			***MDA = 18 counties***		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N
16 year-olds									
Property crime arrest rate	50.74	34.03	9615	46.16	30.24	3922	50.74	34.14	4243
Auto theft arrest rate	5.25	8.29	9615	5.36	7.87	3922	6.23	7.40	4243
Larceny arrest rate	30.07	21.07	9615	27.14	19.11	3922	32.05	23.76	4243
Burglary arrest rate	15.42	13.41	9615	13.66	11.49	3922	12.45	10.01	4243
Violent crime arrest rate	8.76	17.79	9615	7.48	8.99	3922	7.15	6.34	4243
Aggravated assault arrest rate	5.54	7.12	9615	4.86	5.35	3922	4.73	4.44	4243
Robbery arrest rate	3.22	12.29	9615	2.63	5.09	3922	2.41	3.24	4243
Total crime arrest rate	59.50	45.14	9615	53.65	35.87	3922	57.88	36.49	4243
Drug sale arrest rate	2.89	10.13	9615	2.39	6.47	3922	2.25	3.80	4243
Drug possession arrest rate	11.49	14.39	9615	9.81	12.58	3922	13.00	9.97	4243
Total drug crime arrest rate	14.37	21.65	9615	12.19	16.66	3922	15.25	11.25	4243
17 year-olds									
Property crime arrest rate	53.35	32.43	9615	46.61	27.16	3922	48.42	31.64	4243
Auto theft arrest rate	4.89	7.31	9615	4.86	6.69	3922	5.40	6.21	4243
Larceny arrest rate	31.62	20.77	9615	27.34	17.63	3922	30.68	22.31	4243
Burglary arrest rate	16.84	13.21	9615	14.41	11.47	3922	12.34	9.70	4243
Violent crime arrest rate	10.92	17.87	9615	8.74	9.78	3922	8.11	6.73	4243
Aggravated assault arrest rate	7.04	8.35	9615	5.58	5.64	3922	5.36	4.80	4243
Robbery arrest rate	3.87	11.39	9615	3.16	5.60	3922	2.75	3.40	4243
Total crime arrest rate	64.27	43.49	9615	55.35	32.10	3922	56.53	34.14	4243
Drug sale arrest rate	4.45	12.09	9615	3.80	8.65	3922	3.08	4.96	4243
Drug possession arrest rate	17.29	21.70	9615	15.16	18.69	3922	17.27	13.28	4243
Total drug crime arrest rate	21.74	29.67	9615	18.96	24.01	3922	20.35	14.98	4243
18 year-olds									
Property crime arrest rate	52.20	29.95	9615	47.41	24.70	3922	47.80	27.53	4243
Auto theft arrest rate	4.18	5.99	9615	3.99	5.42	3922	4.48	4.84	4243
Larceny arrest rate	30.97	19.50	9615	28.32	16.22	3922	30.05	20.01	4243
Burglary arrest rate	17.05	12.89	9615	15.10	11.39	3922	13.27	9.87	4243
Violent crime arrest rate	12.43	16.46	9615	10.61	10.23	3922	9.55	7.52	4243
Aggravated assault arrest rate	8.22	9.00	9615	7.06	7.07	3922	6.32	5.65	4243
Robbery arrest rate	4.21	9.56	9615	3.55	5.07	3922	3.23	3.65	4243
Total crime arrest rate	64.63	39.97	9615	58.02	29.83	3922	57.35	29.65	4243
Drug sale arrest rate	6.04	12.72	9615	5.79	9.63	3922	4.97	7.08	4243
Drug possession arrest rate	23.78	29.92	9615	2138	22.75	3922	25.40	18.45	4243
Total drug crime arrest rate	29.82	37.29	9615	27.17	28.40	3922	30.37	20.86	4243

Notes: (1) The sample is based on the selection criteria described in the text. (2) Arrest rates are annual incidents per 1,000 of the age group population.

Table 4. Mean Differences of Arrest Behavior, MDA = 16 and MDA = 18 Counties

	Total Crime	Property Crime	Violent Crime
16 and over (16 – 18 yr. olds)			
MDA = 16			
Mean	62.800	52.098	11.713
Std. Error	0.253	0.190	0.108
N	28845	28845	28845
MDA = 18			
Mean	56.551	48.333	9.172
Std. Error	0.292	0.271	0.067
N	13299	13299	13299
Difference 1	-6.249	-3.765	-2.541
Std. Error	0.387	0.331	0.127
16 and under (13 – 15 yr. olds)			
MDA = 16			
Mean	40.561	35.875	5.088
Std. Error	0.261	0.211	0.088
N	19230	19230	19230
MDA = 18			
Mean	44.226	39.790	4.928
Std. Error	0.340	0.319	0.052
N	8866	8866	8866
Difference 2	3.665	3.915	-0.160
Std. Error	0.429	0.382	0.103
Difference 1 – Difference 2	-9.914	-7.680	-2.381
Std. Error	0.577	0.506	0.163

Notes: Arrest rates are annual incidents per 1,000 of the age group population.

Table 5: Teen Arrest Rates and the Minimum Dropout Age, 1980-2006

	Total Crime	
	I	II
MDA16	-1.020	…
	(1.664)	
MDA17	…	-0.039
		(1.519)
MDA18	…	1.860
		(2.559)
MDA16*age16	4.910*	...
	(2.453)	
MDA16*age17	6.584**	...
	(2.620)	
MDA16*age18	4.935	...
	(3.068)	
MDA17*age16	...	-3.564
		(2.680)
MDA17*age17	...	-5.392**
		(2.638)
MDA17*age18	...	-1.998
		(2.941)
MDA18*age16	...	-5.782**
		(2.598)
MDA18*age17	...	-7.369**
		(3.032)
MDA18*age18	...	-6.839*
		(3.896)
N	88935	88935
R^2	0.811	0.811
F-stat	2.28	1.55
	[0.092]	[0.183]
Age Group FE	YES	YES
County FE	YES	YES
Year FE	YES	YES
State Trend	YES	YES

Notes: (1) Each column is a separate regression. (2) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (3) Control group consists of individuals 13 to 15 years of age. (4) All regression models control for county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, and state-specific time trends. (5) F-statistics test the joint significance of the interaction terms. P-values are in brackets. (6) County mean populations are used as weights. (7) Standard errors are clustered at the state-level. (8) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 6: Teen Arrest Rates by Crime Type, 1980-2006

	Property Crime				Violent Crime			Drug Crime		
	Property Crime	Auto Theft	Larceny	Burglary	Violent Crime	Agg. Assault	Robbery	Drug Crime	Selling	Possession
MDA17*age16	-2.063	-0.147	-0.731	-1.185	-1.502	-0.797*	-0.705	-1.712	-0.816	-0.896
	(1.861)	(0.662)	(1.129)	(0.732)	(1.117)	(0.441)	(0.758)	(1.587)	(1.004)	(1.619)
MDA17*age17	-3.124	-0.151	-1.645	-1.329	-2.268***	-1.609***	-0.660	-1.803	-0.833	-0.971
	(2.197)	(0.599)	(1.411)	(0.820)	(0.816)	(0.395)	(0.495)	(2.872)	(1.293)	(3.119)
MDA17*age18	-0.508	0.070	0.032	-0.611	-1.490*	-1.279*	-0.211	-2.871	-0.808	-2.063
	(2.444)	(0.531)	(1.559)	(0.888)	(0.866)	(0.644)	(0.412)	(3.433)	(1.595)	(3.977)
MDA18*age16	-3.518**	-0.494	-1.351	-1.673**	-2.263	-1.058*	-1.206	-3.489	-1.858	-1.631
	(1.656)	(0.538)	(0.984)	(0.655)	(1.505)	(0.614)	(0.939)	(2.695)	(1.200)	(1.551)
MDA18*age17	-4.645**	-0.369	-2.614**	-1.662*	-2.723*	-1.565*	-1.158	-6.188	-2.878*	-3.309
	(1.971)	(0.565)	(1.106)	(0.861)	(1.432)	(0.788)	(0.692)	(3.826)	(1.527)	(2.502)
MDA18*age18	-4.630	-0.297	-2.899*	-1.434	-2.209*	-1.495	-0.714**	-4.870	-2.540	-2.330
	(2.895)	(0.885)	(1.657)	(0.920)	(1.285)	(1.055)	(0.326)	(4.661)	(1.701)	(3.200)
N	88935	88935	88935	88935	88935	88935	88935	88935	88935	88935
R^2	0.726	0.637	0.702	0.620	0.864	0.750	0.872	0.664	0.659	0.600
F-stat	2.58	0.26	1.75	1.51	1.95	3.44	0.94	2.01	3.44	1.51
	[0.031]	[0.954]	[0.131]	[0.196]	[0.094]	[0.007]	[0.475]	[0.084]	[0.007]	[0.197]
Age Group FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State Trend	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: (1) Each column is a separate regression. (2) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (3) Control group consists of individuals 13 to 15 years of age. (4) All regression models also control for the minimum dropout age, county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, and state-specific time trends. (5) F-statistics test the joint significance of the interaction terms. P-values are in brackets. (6) County mean populations are used as weights. (7) Standard errors are clustered at the state-level. (8) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 7: Teen Arrest Rates for Subsamples of Population, 1980-2006

	Property Crime		Violent Crime	
	I	II	I	II
MDA17*age16	-1.979	-3.628	-1.491	-2.920
	(1.899)	(3.582)	(1.242)	(3.826)
MDA17*age17	-3.096	-6.970*	-2.303**	-3.879
	(2.014)	(3.731)	(0.899)	(3.431)
MDA17*age18	-0.460	-2.365	-1.580*	-1.427
	(2.327)	(3.927)	(0.909)	(2.814)
MDA18*age16	-3.476**	-6.976*	-2.417	-6.293
	(1.639)	(3.545)	(1.647)	(4.338)
MDA18*age17	-4.490**	-7.147*	-2.875*	-6.600*
	(1.863)	(3.954)	(1.523)	(3.809)
MDA18*age18	-4.312	-7.213	-2.282*	-5.428**
	(2.903)	(4.942)	(1.307)	(2.640)
N	55535	28855	55535	28855
R^2	0.744	0.787	0.869	0.885
F-stat	2.46	3.31	1.71	2.35
	[0.039]	[0.015]	[0.141]	[0.060]
Age Group FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
State Trend	YES	YES	YES	YES

Notes: (1) Column I: Counties with population density in top 50th percentile; Column II: Counties with percent black > 15%. (2) Each column is a separate regression. (3) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (4) Control group consists of individuals 13 to 15 years of age. (5) All regression models also control for the minimum dropout age, county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, and state-specific time trends. (6) F-statistics test the joint significance of the interaction terms. P-values are in brackets. (7) County mean populations are used as weights. (8) Standard errors are clustered at the state-level. (9) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 8: Teen Arrest Rates and Alternative Control Groups, 1980-2006

	Property Crime			Violent Crime		
	I	II	III	I	II	III
MDA17*age16	-2.063	-4.099	-2.741	-1.502	-0.659	-1.279
	(1.861)	(4.054)	(2.331)	(1.117)	(1.449)	(1.221)
MDA17*age17	-3.124	-5.161**	-3.803**	-2.268***	-1.563	-2.182***
	(2.197)	(2.219)	(1.582)	(0.816)	(0.996)	(0.812)
MDA17*age18	-0.508	-2.545	-1.187	-1.490*	-0.739	-1.358*
	(2.444)	(1.748)	(1.626)	(0.866)	(0.688)	(0.792)
MDA18*age16	-3.518**	-1.410	-2.815	-2.263	-1.367	-2.080
	(1.656)	(4.310)	(2.184)	(1.505)	(1.507)	(1.416)
MDA18*age17	-4.645**	-2.537	-3.943***	-2.723*	-1.918	-2.631**
	(1.971)	(2.708)	(1.336)	(1.432)	(1.195)	(1.272)
MDA18*age18	-4.630	-2.521	-3.927**	-2.209*	-1.463**	-2.176**
	(2.895)	(1.651)	(1.802)	(1.285)	(0.671)	(1.028)
N	88935	71148	106722	88935	71148	106722
R^2	0.726	0.726	0.706	0.86	0.900	0.855
F-stat	2.58	2.72	2.42	1.95	2.95	2.31
	[0.031]	[0.024]	[0.041]	[0.094]	[0.016]	[0.050]
Age Group FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State Trend	YES	YES	YES	YES	YES	YES
Control group:						
13-15 year-olds	X		X	X		X
19 year-olds		X	X		X	X

Notes: (1) Each column is a separate regression. (2) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (3) All regression models also control for the minimum dropout age, county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, and state-specific time trends. (4) F-statistics test the joint significance of the interaction terms. P-values are in brackets. (5) County mean populations are used as weights. (6) Standard errors are clustered at the state-level. (7) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 9: Sensitivity of Results to Alternative Specifications, 1980-2006

	Exclude counties in states without dropout exemptions		Only states that increase their MDA		Exclude counties with less than 20 years of complete data		Exclude CA & NY	
	Prop. Crime	Viol. Crime	Prop. Crime	Viol. Crime	Prop. Crime	Viol. Crime	Prop. Crime	Viol. Crime
MDA17*age16	-2.549	-1.279	-2.365	-2.815	-1.881	-1.695	-1.446	-0.183
	(1.823)	(0.933)	(1.939)	(2.217)	(1.992)	(1.317)	(2.123)	(0.524)
MDA17*age17	-2.727	-1.398*	-2.030	-3.045*	-3.097	-2.480***	-4.158*	-1.421**
	(3.410)	(0.770)	(2.307)	(1.644)	(2.332)	(0.921)	(2.364)	(0.666)
MDA17*age18	-0.778	-0.742	3.264	-1.549	-1.601	-1.946**	-1.376	-0.534
	(2.927)	(1.385)	(2.658)	(1.508)	(2.635)	(0.882)	(2.861)	(0.786)
MDA18*age16	-3.259*	-2.390	-5.015***	-3.120	-3.188*	-2.428	-2.300	-1.639***
	(1.874)	(1.754)	(1.354)	(2.735)	(1.798)	(1.727)	(2.077)	(0.462)
MDA18*age17	-4.891**	-2.820*	-2.687	-2.494	-4.530**	-3.004*	-5.152**	-2.625***
	(2.253)	(1.647)	(2.329)	(2.503)	(2.189)	(1.594)	(2.225)	(0.652)
MDA18*age18	-5.730*	-2.316	-0.026	-1.020	-5.521*	-2.600*	-6.143*	-2.846***
	(3.267)	(1.506)	(2.212)	(1.552)	(3.229)	(1.384)	(3.545)	(0.803)
N	64465	64465	42510	42510	66640	66640	78715	78715
R^2	0.751	0.870	0.761	0.881	0.745	0.869	0.652	0.667
F-stat	2.16	0.93	7.11	3.57	2.17	3.29	1.74	6.21
	[0.072]	[0.487]	[0.000]	[0.015]	[0.066]	[0.010]	[0.134]	[0.000]
Age Group FE	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
State Trend	YES	YES	YES	YES	YES	YES	YES	YES

Notes: (1) Each column is a separate regression. (2) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (3) All regression models also control for the minimum dropout age, county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, and state-specific time trends. (4) F-statistics test the joint significance of the interaction terms. P-values are in brackets. (5) County mean populations are used as weights. (6) Standard errors are clustered at the state-level. (7) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 10: MDA Laws and Measures of Police Enforcement, 1982-2005

	Police Officers Per Capita	Police Expenditures Per Capita
MDA17	0.073	-0.299
	(0.061)	(1.816)
MDA18	-0.014	-10.400***
	(0.048)	(2.151)
N	1152	1058
R^2	0.971	0.981
State FE	YES	YES
Year FE	YES	YES
State Trend	YES	YES

Note: (1) Each column is a separate regression. (2) The dependent variable in the first column is the number of sworn police officers per capita. The dependent variable in the second column is police protection expenditures per capita in 2000 dollars. (3) All regression models control for the fraction of the population aged 15-19, the fraction of the population that is black, the minimum legal drinking age, state fixed effects, year fixed effects, and state-specific time trends. (4) State populations are used as weights. (5) Standard errors are clustered at the state-level. (6) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 11: Including 19-21 year-old Arrest Rates, 1980-2006

	Property Crime	Violent Crime
MDA17*age19	2.612	-0.521
	(2.940)	(0.794)
MDA17*age20	2.737	-0.515
	(3.339)	(0.825)
MDA17*age21	2.588	-0.616
	(3.397)	(0.970)
MDA18*age19	-2.488	-1.282
	(4.128)	(1.058)
MDA18*age20	-1.999	-0.685
	(4.860)	(1.110)
MDA18*age21	-2.056	-0.382
	(5.236)	(1.233)
N	133008	133008
R^2	0.698	0.851
F-stat	0.87	3.80
	[0.521]	[0.004]
Age Group FE	YES	YES
County FE	YES	YES
Year FE	YES	YES
State Trend	YES	YES

Notes: (1) Each column is a separate regression. (2) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (3) Control group consists of individuals 13 to 15 years of age. (4) All regression models also control for the minimum dropout age, county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, state-specific time trends, and interactions between the minimum dropout age indicators and the age dummies for 16 to 18 year olds. (5) F-statistics test the joint significance of the interaction terms. P-values are in brackets. (6) County mean populations are used as weights. (7) Standard errors are clustered at the state-level. (8) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 12: Timing of Laws and Possible Labor Market Spillovers, 1980-2006

	Property Crime	Violent Crime
Time0*age19	-1.234	0.212
	(2.151)	(1.252)
Time0*age20	-1.687	-0.036
	(2.231)	(0.951)
Time0*age21	1.057	0.002
	(2.444)	(0.935)
Lag1*age19	-0.203	-0.214
	(1.445)	(0.689)
Lag1*age20	0.032	-0.803
	(1.422)	(0.684)
Lag1*age21	0.540	-0.129
	(1.509)	(0.642)
N	88935	88935
R^2	0.647	0.851
Age Group FE	YES	YES
County FE	YES	YES
Year FE	YES	YES
State Trend	YES	YES

Notes: (1) Each column is a separate regression. (2) The dependent variable in each column is the arrest rate per 1,000 of the age group population. (3) Control group consists of individuals 13 to 15 years of age. (4) All regression models control for the current minimum dropout age, time = 0 and time = -1 dummies, county demographic variables, income per capita, the average annual wage, the minimum legal drinking age, age fixed effects, county fixed effects, year fixed effects, and state-specific time trends. (5) County mean populations are used as weights. (6) Standard errors are clustered at the state-level. (7) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 13. Descriptive Statistics for YRBS Data, 1993-2007

Variable	Mean	Std. Dev.
Dependent Variables		
In last 30 days, missed school because felt unsafe at school or on way to or from school.	0.066	0.249
In last 12 months, threatened or injured with weapon at school.	0.082	0.274
In last 12 months, property stolen or damaged at school.	0.311	0.463
In last 12 months, been offered, sold, or given an illegal drug at school.	0.277	0.448
Individual-level Independent Variables		
Male	0.491	0.500
Age under 15	0.093	0.290
Age 15	0.220	0.414
Age 16	0.256	0.436
Age 17	0.264	0.441
Age 18	0.168	0.373
Grade 9	0.239	0.427
Grade 10	0.244	0.430
Grade 11	0.254	0.435
Grade 12	0.260	0.439
Ungraded	0.003	0.052
White	0.410	0.492
Black	0.247	0.432
Hispanic	0.228	0.420
Asian/Pacific Islander	0.031	0.174
American Indian/Alaska Native	0.012	0.108
Other race	0.072	0.258
State-level Independent Variables		
MDA 16	0.426	0.494
MDA 17	0.194	0.395
MDA 18	0.377	0.485
State income per capita (2000 dollars)	28149.49	4318.07
State unemployment rate	5.443	1.282
State student/teacher ratio	16.777	2.732
State expenditures per student (2000 dollars)	7753.47	1644.54
State arrest rate for under 20 age group (per 100,000)	4789.87	1521.16

Notes: (1) N = 78,764 for theft variable. N = 104,108 for all other variables. The sample size is smaller for the theft variable because the theft question was not asked in all years of the survey.

Table 14. Descriptive Statistics: YRBS Dependent Variables

	MDA = 16		MDA = 17		MDA = 18	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Both sexes						
Felt unsafe	0.061	0.240	0.063	0.243	0.074	0.261
Weapon threats/injuries	0.080	0.272	0.082	0.274	0.083	0.276
Theft	0.303	0.460	0.321	0.467	0.315	0.465
Drugs	0.262	0.440	0.260	0.438	0.305	0.460
Males						
Felt unsafe	0.060	0.237	0.060	0.238	0.072	0.259
Weapon threats/injuries	0.106	0.308	0.106	0.307	0.112	0.315
Theft	0.342	0.474	0.360	0.480	0.348	0.476
Drugs	0.321	0.467	0.318	0.466	0.356	0.479
Females						
Felt unsafe	0.062	0.242	0.065	0.247	0.075	0.264
Weapon threats/injuries	0.056	0.230	0.058	0.234	0.055	0.229
Theft	0.266	0.442	0.284	0.451	0.283	0.451
Drugs	0.207	0.405	0.201	0.401	0.254	0.436
Both sexes under age 16						
Felt unsafe	0.065	0.246	0.064	0.245	0.085	0.278
Weapon threats/injuries	0.089	0.285	0.087	0.283	0.097	0.296
Theft	0.333	0.471	0.353	0.478	0.351	0.477
Drugs	0.255	0.436	0.248	0.432	0.299	0.458
Males under age 16						
Felt unsafe	0.062	0.241	0.061	0.240	0.081	0.273
Weapon threats/injuries	0.116	0.320	0.108	0.310	0.125	0.331
Theft	0.363	0.481	0.387	0.487	0.381	0.486
Drugs	0.299	0.458	0.294	0.456	0.332	0.471
Females under age 16						
Felt unsafe	0.067	0.251	0.067	0.250	0.088	0.283
Weapon threats/injuries	0.066	0.248	0.069	0.254	0.072	0.258
Theft	0.306	0.461	0.324	0.468	0.324	0.468
Drugs	0.217	0.412	0.208	0.406	0.270	0.444

Table 15: Do MDA Laws Displace Crime to Schools? Evidence from YRBS Data

	All Ages			Under 16		
	Everyone	Males	Females	Everyone	Males	Females
Felt unsafe						
MDA17	-0.008	-0.015	-0.000	-0.009	-0.016	0.000
	(0.008)	(0.014)	(0.009)	(0.013)	(0.012)	(0.019)
MDA18	0.018	-0.001	0.038***	0.008	-0.006	0.018
	(0.019)	(0.026)	(0.015)	(0.030)	(0.029)	(0.030)
Weapon threats/injuries						
MDA17	0.001	-0.022	0.021	-0.003	-0.039	0.034
	(0.020)	(0.025)	(0.021)	(0.033)	(0.035)	(0.047)
MDA18	0.002	-0.020	0.019	0.065*	0.066	0.051
	(0.018)	(0.025)	(0.019)	(0.040)	(0.068)	(0.042)
Theft						
MDA17	-0.005	-0.034	0.020	-0.009	-0.000	-0.017
	(0.022)	(0.028)	(0.029)	(0.028)	(0.042)	(0.033)
MDA18	0.061	0.057	0.051	0.183***	0.258**	0.099*
	(0.045)	(0.064)	(0.078)	(0.061)	(0.116)	(0.058)
Drugs						
MDA17	0.079***	0.008	0.142***	0.056*	-0.034	0.124***
	(0.020)	(0.032)	(0.022)	(0.032)	(0.041)	(0.037)
MDA18	0.084	0.006	0.150***	0.067	-0.017	0.124**
	(0.053)	(0.056)	(0.054)	(0.063)	(0.080)	(0.055)

Notes: (1) Sample is 1993-2007 National Youth Risk Behavior Surveys. N = 78,764 for full sample theft regression. N = 104,108 for full sample school safety, weapon threats/injuries, and drug regressions. N = 24,718 for under 16 sample theft regression. N = 32,525 for under 16 sample school safety, weapon threats/injuries and drug regressions. (2) Each cell is a separate probit regression. Marginal effects are reported. (3) At the individual-level, all regression models control for age, grade, and race. At the state-level, all regression models control for log(income per capita), the unemployment rate, the average student-to-teacher ratio, log(expenditures per student), and log(under 20 arrest rate). All regression models also include state fixed effects, year fixed effects, and state-specific time trends. (4) Standard errors are clustered at the state-level. (5) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Appendix

Table A1. Mean Differences of Arrest Behavior, MDA = 16 and MDA = 17 Counties

	Total Crime	Property Crime	Violent Crime
16 and over (16 – 18 yr. olds)			
MDA = 16			
Mean	62.800	52.098	11.713
Std. Error	0.253	0.190	0.108
N	28845	28845	28845
MDA = 17			
Mean	55.689	46.855	9.902
Std. Error	0.298	0.253	0.095
N	12159	12159	12159
Diff. 1	-7.111	-5.243	-1.811
Std. Error	0.391	0.316	0.144
16 and under (13 – 15 yr. olds)			
MDA = 16			
Mean	40.561	35.875	5.088
Std. Error	0.261	0.211	0.088
N	19230	19230	19230
MDA = 17			
Mean	39.354	35.092	4.761
Std. Error	0.337	0.301	0.074
N	8106	8106	8106
Diff. 2	-1.207	-0.783	-0.326
Std. Error	0.426	0.368	0.116
Diff. 1 – Diff. 2	-5.904	-4.460	-1.485
Std. Error	0.578	0.485	0.184

Note: Arrest rates are annual incidences per 1,000 of the age group population.

Table A2. Mean Differences of Arrest Behavior, MDA = 17 and MDA = 18 Counties

	Total Crime	Property Crime	Violent Crime
16 and over (16 – 18 yr. olds)			
MDA = 17			
Mean	55.689	46.855	9.902
Std. Error	0.298	0.253	0.095
N	12159	12159	12159
MDA = 18			
Mean	56.551	48.333	9.172
Std. Error	0.292	0.271	0.067
N	13299	13299	13299
Diff. 1	0.862	1.478	-0.730
Std. Error	0.417	0.371	0.116
16 and under (13 – 15 yr. olds)			
MDA = 17			
Mean	39.354	35.092	4.761
Std. Error	0.337	0.301	0.074
N	8106	8106	8106
MDA = 18			
Mean	44.226	39.790	4.928
Std. Error	0.340	0.319	0.052
N	8866	8866	8866
Diff. 2	4.872	4.698	0.167
Std. Error	0.478	0.439	0.091
Diff. 1 – Diff. 2	-4.010	-3.220	-0.897
Std. Error	0.403	0.574	0.147

Note: Arrest rates are annual incidences per 1,000 of the age group population.