# 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 U.S. between 1980 and 2006, a difference-in-difference-in-difference 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 youth aged 16 to 18 years-old, and these estimates are robust to a range of specification checks. Furthermore, the results are consistent with an incapacitation effect; school attendance decreases the time available for criminal activity. Not only do these findings provide support for the efficacy of programs intended to keep youth in school and out of delinquency, but this information is likely to be of value to policy-makers deciding on whether or not to increase their state's minimum dropout age.

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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 suggests a correlation between youth dropouts and juvenile criminal behavior (see, e.g., Thornberry et al. 1985; Fagan and Pabon 1990). In California, it has been estimated that dropouts are responsible for 1.1 billion dollars in annual juvenile crime costs (Belfield and Levin 2009). 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 proposes 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.[1] 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] 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. Little research has been devoted to studying the contemporaneous relationship between schooling and crime. Most of the previous work has focused on proxies for educational attainment and subsequent criminal behavior. 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 that a high school degree has no significant effect. Grogger's (1998) results indicate that having additional years of education or a high school diploma do not have a significant effect on criminal activity. On the other hand, Lochner (2004) and Lochner and Moretti (2004) estimate a negative effect of education on property and violent crimes.

More closely related to this paper, other research has studied 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 criminal behavior. However, these studies do not control for the potential endogeneity of schooling. Two recent papers have explicitly studied the incapacitation and concentration effects of school attendance.[2] An incapacitation effect of school is that it keeps juveniles occupied, leaving less time and opportunity to commit crimes. However, forcing children to stay in school increases the concentration of juveniles and, thus, the number of 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

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

significantly when school is in session, but violent juvenile crime rates increase on these days. In related research, Aizer (2004) finds that children with adult supervision are less likely to participate in delinquent behavior. Her results suggest that after-school programs geared to engage school-age children may decrease delinquency and have important implications for their development of human capital and future earnings.

Using a difference-in-difference-in-difference (DDD) estimation strategy, this paper exploits the variation in compulsory schooling laws, across states over time, to find strong evidence that increases in the minimum dropout age reduce incidences of property and violent crime arrests among high school-aged youth. The magnitude of the negative effect is greater when the sample is restricted to “black” counties. Robustness checks help to confirm the results are not driven by omitted state-specific characteristics. These findings suggest that policy interventions to keep kids in school may be successful at decreasing juvenile crime.

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. Several possible mechanisms are discussed. First, the incapacitation effect is considered. To the extent that being in school reduces the time available for delinquent activity, we might expect an increase in the minimum dropout age to negatively influence criminal behavior. Second, those compelled by law to remain in school longer may build important human capital that decreases their relative returns to crime. Lastly, spillover effects that influence youth slightly above the minimum dropout age may also impact delinquency. These mechanisms are discussed in further detail in Section VI. The results favor an incapacitation effect, but possible spillovers also appear important.

The remainder of the paper is organized as follows: Section II discusses the background of compulsory schooling 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 identification strategy; Section V discusses the results; Section VI attempts to understand the causal relationship between schooling and crime; Section VII concludes.

## II. Compulsory Schooling Laws

### *Background of Compulsory Schooling 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. For example, Illinois and Indiana have recently increased their minimum dropout age from 16 to 17 and 18, respectively. However, there are also states that have maintained a constant minimum dropout age for over the past 50 years. Iowa, Michigan, and Montana have had a leaving 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.

Not surprisingly, compulsory schooling legislation is more complex than simply specifying a mandatory leaving 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.[3]

***Relevant Literature***

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 and school entry 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. In a theoretical treatment, Eckstein and Zilcha (1994) present an overlapping generations model where parents under invest in their children's education because they do not consider the external effect on the aggregate production function. They show that in the long run the majority of the population can be made better off when compulsory attendance is implemented.

In other applications of compulsory attendance, Black et al. (2008) examine whether increasing mandatory schooling causes females to postpone having children. They find that minimum school requirements have a significant and negative effect on the probability of having a child as a teenager. Lleras-Muney (2005) uses compulsory schooling laws as an instrumental variable to show that education has a negative effect on mortality. Closely related to this study, Lochner and Moretti (2004) estimate the effect of educational attainment on criminal activity

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

later in life using the variation in state compulsory schooling laws to instrument endogenous schooling decisions. It is important to note, these studies focus 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. 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. 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.

***Compulsory Schooling and Attendance: Empirical Evidence***

This study is concerned with the reduced form relationship between compulsory schooling laws and juvenile crime. Implicit to this relationship is that compulsory schooling 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 U.S. 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 school leaving 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 the state's compulsory schooling age. 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. Consider, 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

The juvenile arrest data come from the FBI's Uniform Crime Reports (UCR).[4] These data are aggregated by the age of the offender at the county-level for the period 1980-2006.[5] Arrest rates are arrests per 1,000 people of the specified age group.[6] 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

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[4] 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).

[5] Data for the year 1984 were unavailable from the ICPSR.

[6] These rates were calculated using the National Cancer Institute, Surveillance Epidemiology and End Results, U.S. Population Data.

crimes account for a very small fraction of juvenile violent crime. 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 measurement error in the arrest rates can exist 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.

It is important to note that arrests, as opposed to the actual number of offenses committed, are used as the measure of criminal activity. The primary reason for using arrest rates is that detailed age data are not available in the UCR offense reports. Although arrests are not a perfect measure of youth criminal behavior and likely understate the true level of crime, other research indicates that arrest data serve as an accurate representation of underlying criminal activity.[7] 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.[8]

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

[7] See, e.g., Hindelang (1978, 1981).
[8] 0.96 for rape and robbery, 0.94 for murder, assault, and burglary, and 0.93 for auto theft.

data are omitted from the sample. Alaskan and Hawaiian counties are also excluded because of their significantly different demographics and economies. Finally, all 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.

County-level demographic variables come from the U.S. Census Bureau. The regressions control for the county population density, the percentage of the county population that was black, the percentage that was 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 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). The state-by-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 minimum dropout law. For property and violent crimes, the highest arrest rates are shown for counties with a minimum dropout age of 16. Across age cohorts, 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 and violent crime arrests can be attributed to 17 year-olds in counties with a minimum dropout age of 16 and 18 year-olds in counties with a minimum dropout age of 16, respectively. Drug sale arrests are most prevalent among 18 year-olds in counties with a leaving age of 16, while drug possession arrests are greatest for 18 year-olds in counties with a leaving 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 mid '80s, when the average minimum dropout age was fairly constant, the property crime rates showed little change. Figure 2, on the other hand, provides less confirmation that the mandatory leaving age has 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 U.S., 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 Identification

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 leaving 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.[9] 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 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). Identification in this DDD framework 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 compulsory schooling 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, the DDD framework 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 mandatory leaving age of 16 versus states with leaving ages of 17 or 18 (a second "difference") over time (the third "difference"). This paper estimates the following equation:

[9] 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.

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\begin{aligned}
Y_{ijst} &= \alpha + \beta_1 \mathrm{MDA17_{st}} + \beta_2 \mathrm{MDA18_{st}} + \beta_3 \mathrm{age16_i} + \beta_4 \mathrm{age17_i} + \beta_5 \mathrm{age18_i} \\
&+ \beta_6 (\mathrm{MDA17_{st}} \times \mathrm{age16_i}) + \beta_7 (\mathrm{MDA17_{st}} \times \mathrm{age17_i}) + \beta_8 (\mathrm{MDA17_{st}} \times \mathrm{age18_i}) \\
&+ \beta_9 (\mathrm{MDA18_{st}} \times \mathrm{age16_i}) + \beta_{10} (\mathrm{MDA18_{st}} \times \mathrm{age17_i}) + \beta_{11} (\mathrm{MDA18_{st}} \times \mathrm{age18_i}) \\
&+ \mathbf{X_{jst}} \boldsymbol{\beta}_{12} + \mathbf{C_j} \boldsymbol{\beta}_{13} + \mathbf{T_t} \boldsymbol{\beta}_{14} + \mathbf{Trend} \boldsymbol{\beta}_{15} + \varepsilon_{ijst}
\end{aligned}
\qquad (1)
$$

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

In equation (1), 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 interaction term coefficients, $\beta_6$, $\beta_7$, $\beta_8$, $\beta_9$, $\beta_{10}$, $\beta_{11}$, represent the difference-in-difference-in-difference-type estimates of the effects of minimum dropout ages on juvenile arrest rates. More specifically, these coefficients measure the differential impacts of compulsory schooling legislation on youth 16, 17, and 18 years of age. If increases in compulsory schooling decreases crime among youth 16 to 18 years of age, then we expect the coefficients $\beta_6$ through $\beta_{11}$ to be negative. If increasing the dropout age only impacts youth of ages where the law binds, then we expect only $\beta_6$, $\beta_9$, and $\beta_{10}$ to be negative. In describing the incapacitation effect, Section VI discusses why we might expect only $\beta_6$, $\beta_9$, and $\beta_{10}$ to be negative.

The DDD 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. However, the DDD estimator alleviates this issue because it also compares arrest rates of 16-18 year-olds in states with a mandatory leaving age of 17 or 18 to arrest rates of 16-18 year-olds in states with a leaving 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, the DDD estimator mitigates these concerns because it compares youth of different ages within states that have similar mandatory leaving ages. Lastly, the DDD technique controls for the potential endogeneity of the compulsory schooling laws. This is accomplished by differencing over time. That is, the DDD estimator examines changes in arrest rates, as opposed to differences in levels. As a result, permanent differences in the characteristics of states are taken into account.[10]

All DDD 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.

[10] Another concern is that the minimum dropout age is associated with police enforcement. However, Lochner and Moretti (2004) find little evidence that compulsory schooling legislation is correlated with police expenditures or the number of policemen.

## 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 cohort 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.

Figure 3 illustrates the relationship between increases in compulsory schooling and arrest rates over time. The plotted points represent the estimated coefficients on lead and lag indicators for whether total crime arrest rates of 16 to 18 year-olds decrease after an increase in the MDA in a regression that controls for age, county, and year effects.[11] Time zero stands for the year the laws were reformed. This figure demonstrates a relatively discrete change in arrest behavior around the changes in the minimum dropout age and suggests that increasing the minimum dropout age is associated with lower arrest rates for 16 to 18 year-olds.

[11] This figure only documents counties in states that changed from an MDA = 16 to an MDA = 18.

***Total Crime Arrest Rates***

Table 5 presents the DDD estimates from equation (1). The coefficients illustrated are those of the interaction terms between the minimum dropout age indicators and the age cohort dummies. 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 leaving ages of 16 and 17 to impact youth differently. Column 1 indicates that being in a state with a mandatory leaving 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 cohort population. This estimate increases to nearly 6.6 more incidences per 1,000 for 17 year-olds. In Column 2, movement away from a minimum dropout age of 16 to leaving ages of 17 and 18 is associated with decreases in the arrest rate. Here, 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, movement to a mandatory leaving 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 cohort 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.

***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. For example, the results in Column 1 indicate that the movement to a minimum dropout age of 18 reduces property crime arrests by approximately 3.5 and 4.6 incidences per 1,000 of the age cohort population for 16 and 17 year-olds, respectively. These numbers represent roughly a 6.9% reduction from the mean rate of property crime for 16 year-olds in MDA = 16 states and about 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 slightly smaller in magnitude than the estimates for similar aged youth in MDA = 18 states, however, these estimates are not significant at conventional levels.

For the individual property crime offenses, all coefficient estimates suggest a negative relationship between the minimum dropout age and the rate of juvenile arrest with the exception of the auto theft and larceny estimates for 18 year-olds in MDA = 17 states. Here, the point estimates are positive, but small in magnitude suggesting little difference in the impact of a leaving age of 16 or 17 for an 18 year-old. This is unsurprising given that the choice to dropout for an 18 year-old is equally unconstrained in either type of state. In Column 3, movement 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 cohort population. This represents roughly an 8.3% reduction from the mean rate of larceny for 17 year-olds in MDA = 16 states. For burglary, a leaving age 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, movement to an MDA = 17 reduces violent crime arrests by approximately 2.3 incidences per 1,000; an MDA = 18 reduces violent crime arrests among this age group by approximately 2.7 incidences per 1,000. These figures represent reductions of roughly 21% and 25%, respectively, from the mean rates of 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. 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 decreases their aptitude for committing crime a year or two later. 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. However, for these two cases, significant results may 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. 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, increasing the leaving age to 18 is associated with a 14% and 23% reduction from the mean 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 related to the selling and possession of drugs. Though all coefficient estimates are negative in sign, only the result for 17 year-olds in MDA = 18 states is significant; this coefficient is weakly significant at the 10% level.

***Arrest Rates for Subsamples of Population***

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 $50^{th}$ percentile. The coefficient estimates are very similar to those 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. 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. Although some of the coefficient estimates are not as precise as those reported in Table 6, the magnitudes of the estimates are roughly double in size.

***Robustness Check: Alternative Control Group Specifications***

Table 8 presents results for property and violent crime using three different control group specifications. Columns 1 and 4 represent the baseline model where 13-14 year-olds and 15 year-olds comprise the control group. When only 13-14 year-olds are used as controls the magnitude of the coefficient estimates increases slightly for both property and violent crimes. Property crime estimates are, in general, slightly more precise than the baseline estimates. Violent crime estimates are slightly less precise. Restricting the control group to only 13 and 14 year-olds potentially resolves issues associated with peer effects. A concern is that compulsory schooling laws could impact youth below the mandatory leaving age if these youth are friends with those who are directly influenced by the law. For example, if increasing the MDA decreases delinquency among 16-18 year-olds, and these youth are friends with 15 year-olds, then we might expect to observe decreases in delinquency among 15 year-olds as well. If this is the case, then including 15 year-olds as controls would cause coefficient estimates to understate the true impact of the MDA on 16-18 year-olds. Not only are youth more likely to associate with individuals closer to their own age, but most 13 and 14 year-olds are enrolled in middle or junior high school. As a result, they are less likely to be peers with 16-18 year-olds than are 15 year-olds.[12]

Columns 3 and 6 of Table 8 present results when only 15 year-olds are considered as controls. One might argue that 15 year-olds serve as a better control group because they are more similar to 16-18 year-olds than are 13-14 year-olds. For both property and violent crime, the magnitudes of the coefficient estimates are slightly smaller than baseline. Although none of the property crime estimates are significant at conventional levels, the results still suggest a negative relationship between property crime and the minimum dropout age. The precision of the violent crime estimates is similar to that of the baseline specification in Table 6. In sum, Table 8 provides further support for the negative relationship between the minimum dropout age and juvenile arrest rates.

***Robustness Check: Sensitivity of DDD Coefficients to Alternative Specifications***

Table 9 investigates the sensitivity of the DDD coefficients to a range of alternative specifications. Columns 1 and 2 present "long difference" results using only the endpoints of the sample. This approach stresses the low-frequency/long-term relationship between the minimum dropout age and juvenile arrest rates. The coefficient estimates that are significant for the property crime regression are negative and larger in magnitude than those from the baseline specification in Column 1 of Table 6. The coefficients for the violent crime equation are similar in magnitude to those presented in Column 5 of Table 6; however, some precision is gained in the "long difference" estimates.

Columns 3 and 4 of Table 9 illustrate results where counties in states that have an MDA > 16 and do not offer dropout exemptions are excluded from the sample. Results for this

[12] 13 and 14 year-old arrest rates are not examined separately because the UCR group these two ages together into one statistic.

specification are comparable to the baseline results in Table 6 with the exception of the smaller and less significant coefficients in the violent crime equation for youth in MDA = 17 states.

Columns 5 and 6 of Table 9 show that unweighted regressions for property crime yield coefficients greater in magnitude than the Table 6 baseline estimates. Coefficients for the unweighted violent crime regression are very similar to the baseline.

In Columns 7 and 8 of Table 9, counties with less than 20 of 26 years of complete data are dropped from the sample. The results remain closely the same to those of the baseline for these regressions.

Lastly, the sensitivity of the results to largely populated states is examined.[13] When California and New York counties are removed the estimates for the property crime equation remain fairly similar to those in Table 6. For violent crime, the coefficients on the MDA = 18 interaction terms change little in magnitude, but become much more significant.

***Robustness Check: The Effect of the Current Minimum Dropout Age on Older Men***

Outside of some possible spillover effects of compulsory schooling legislation, one would not expect to observe large effects of changes in the current minimum dropout age on arrest rates of much older individuals. As a robustness check, Table 10 reports results where individuals aged 25 to 29 are used as the treatment group. The reported standard errors are very large and none of the coefficient estimates are anywhere near significant. These findings strengthen the notion that the main results are not being driven by omitted state-specific variables and provide strong support for the legitimacy of the DDD estimates for 16-18 year-olds.

[13] This is done because the regressions are population weighted.

## 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 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 youth dropout at a later date. Alternatively, increasing the minimum leaving age may serve to keep potential delinquents out of trouble during the years of their life when they are most apt 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, increases in compulsory schooling unambiguously decrease 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. Additionally, besides 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, spillover effects may exist where changes in the minimum dropout age impact youth of ages slightly above which the law binds. Youth 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, then students who would have left school under more lenient laws may choose to stay enrolled in school (Oreopoulos 2006). Also, youth may choose to delay dropping out after an increase in the leaving 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) find evidence in support of this "sorting" hypothesis. Finally, we might expect an increase in wages for those just above the minimum dropout age when an increase in the leaving 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 compulsory schooling 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 youth 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. Columns 1 and 2 follow the baseline specification with the exception of including the arrest rates for the older individuals. Columns 3 and 4 exclude state-year observations that correspond to law changes when 19 to 21 year-olds were 16 or 17 years-old. This ensures observation of only 19 to 21 year-olds that went to high school entirely under one minimum dropout age regime.[14]

Given the discussion above, it is apparent that identifying the underlying causal mechanism is more difficult when spillover effects exist. 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.[15] Table 11 illustrates that none of the results for 19 to 21 year-olds are statistically significant. Moreover, the magnitudes of the negative coefficients for older individuals in MDA = 18 states are smaller than those for 16 to 18 year-olds in these states. The same observation holds for the violent crime equations for individuals in MDA = 17 states. The coefficients for the property crime equations for older age cohorts in MDA = 17 states are actually large and positive; however, these results are nowhere near significant.[16]

Because of the insignificant results for 19 to 21 year-olds, evidence for incapacitation effects over human capital effects is supported in this analysis. However, in some of the model specifications, youth of ages at or one year above which the law binds also appear to be influenced by changes in the minimum dropout age. As a result, it is not possible to rule out spillover effects such as those discussed above. Unfortunately, due to limitations of the data, further interpretation of the results should be done with caution.

[14] Columns 3 and 4 are the preferred specifications because 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.

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

[16] Positive and large coefficients favor the "shifting" hypothesis, but because of the large standard errors this hypothesis is rejected.

## VII. Conclusion

Juvenile crime in the United States is widespread and a major concern for policy-makers. Much attention has been paid to identifying key determinants of juvenile crime. Presently, little is known about the contemporaneous link between schooling and delinquent behavior. This paper examines the effect of the mandatory 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 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 movement to a minimum dropout age of 18 decreases arrest rates among 16 and 17 year-olds by approximately 9.7% and 11.5%, respectively, from the mean arrest rates of similar aged youth in states with a minimum dropout age of 16. The negative effect holds for both property and violent crimes. The magnitude of the effect is greater for "black" counties. Furthermore, it appears the incapacitation effect is an important mechanism underlying the link between schooling and crime, but spillover effects also influence youth of ages at and slightly above which the law binds.

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 potentially beneficial consequence of compulsory schooling laws. State-level policy-makers deciding on whether or not to increase the minimum dropout age will want to consider these potential benefits.

Finally, it is important to bear in mind these estimates do not fully consider the potential displacement of delinquency from the streets to school. If youth commit a crime within school that is punishable by arrest, then this is reflected within the results presented above. However, these results do not account for possible increases of within-school delinquency that do not end in arrest. It is entirely 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 has shown, students who fear victimization at school are more likely to stay at home (Pearson and Toby 1992). It would be desirable to study this issue further to better understand the overall effects of the minimum dropout age on in-school delinquent behavior.

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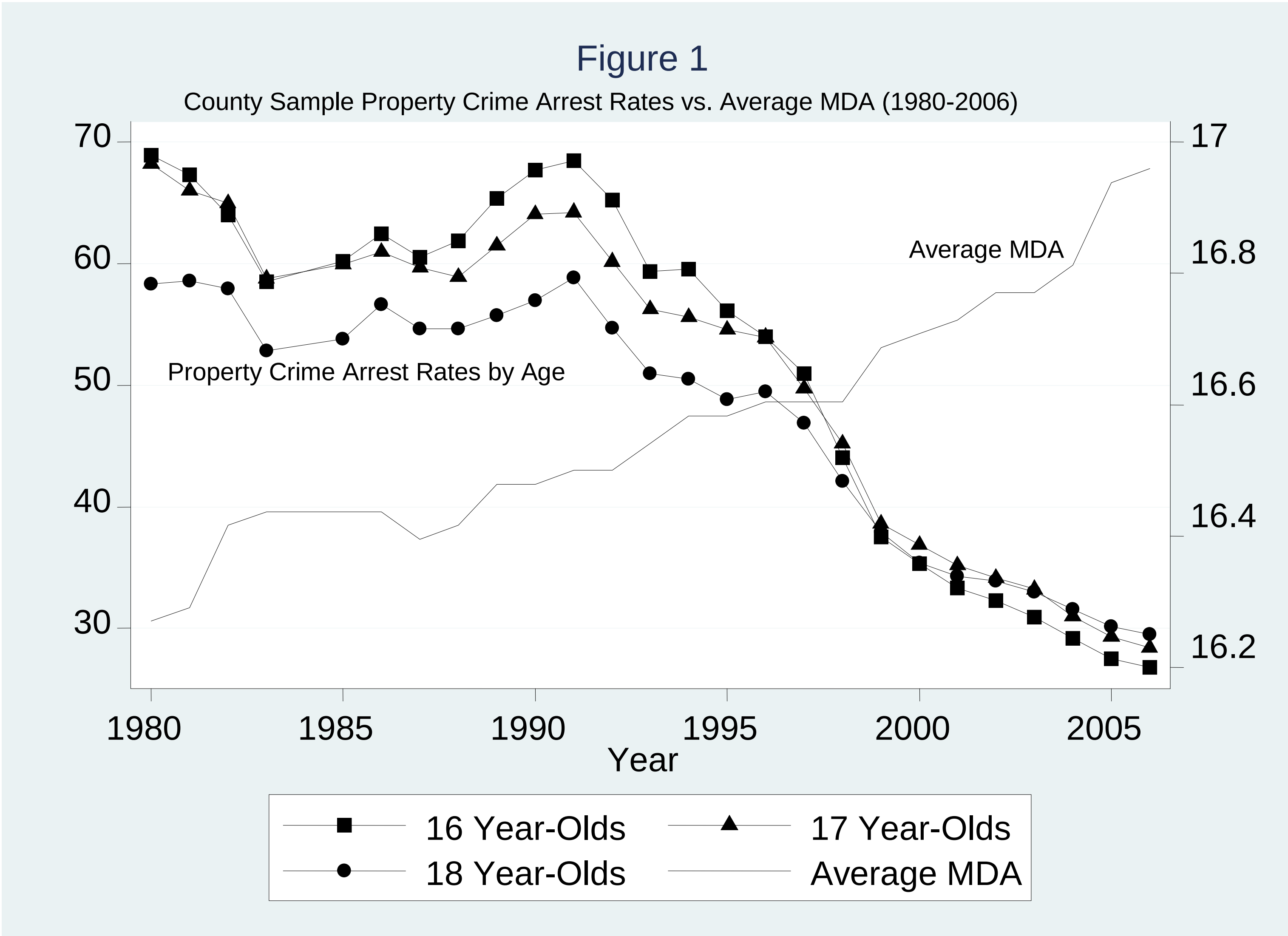
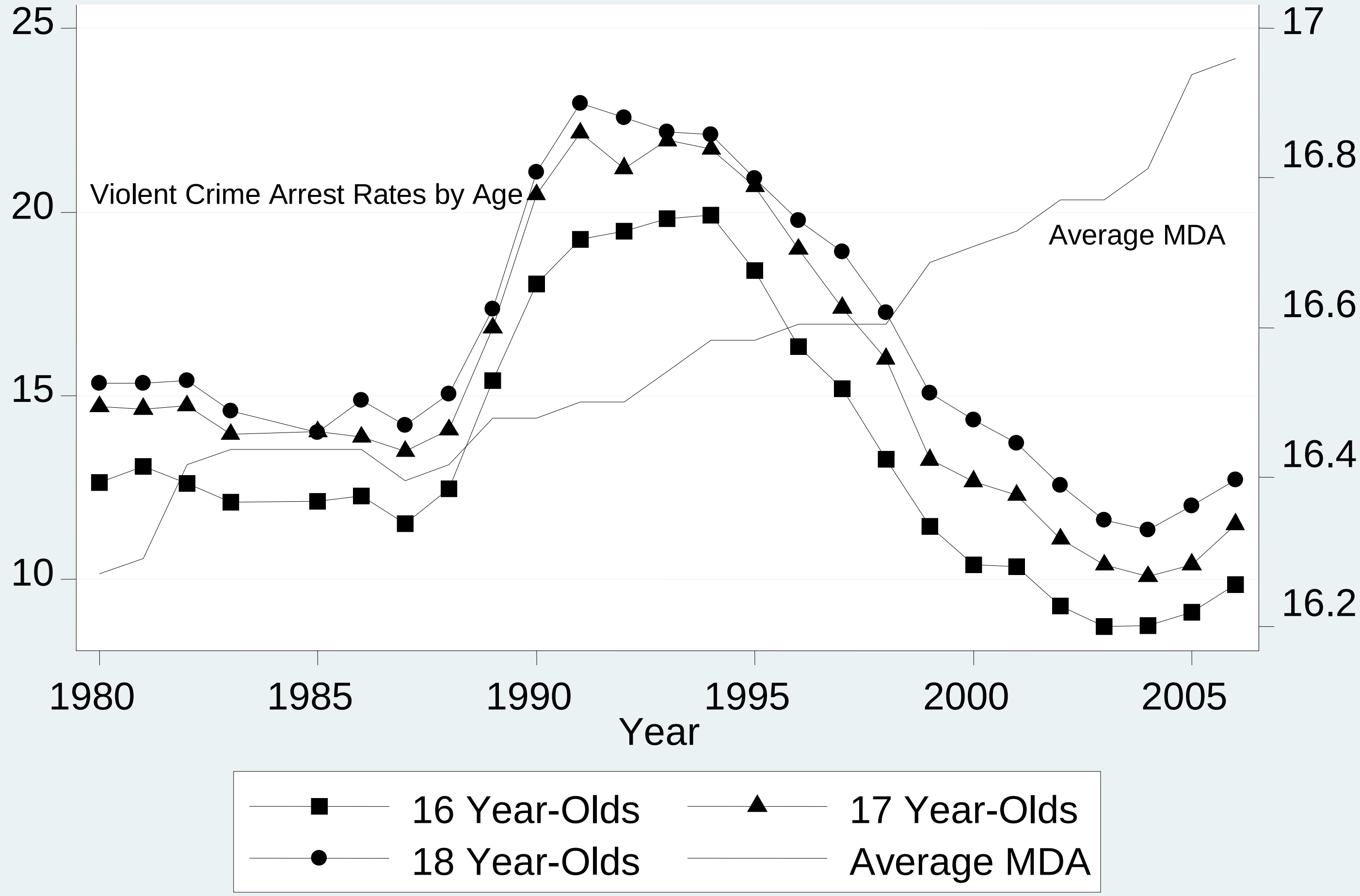


Figure 1
County Sample Property Crime Arrest Rates vs. Average MDA (1980-2006)
70
60
50
40
30
17
16.8
16.6
16.4
16.2
Average MDA
Property Crime Arrest Rates by Age
1980
1985
1990
1995
2000
2005
Year
16 Year-Olds
17 Year-Olds
18 Year-Olds
Average MDA

Figure 2

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



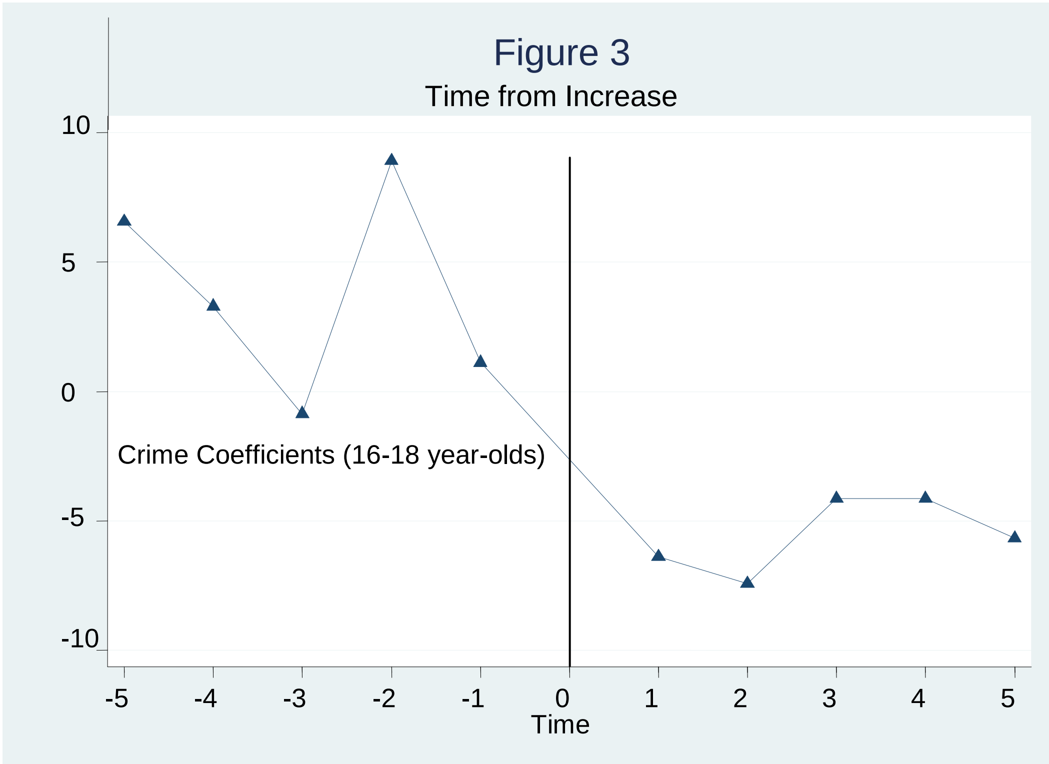


Figure 3
Time from Increase
10
5
0
-5
-10
Crime Coefficients (16-18 year-olds)
-5
-4
-3
-2
-1
0
1
2
3
4
5
Time

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 |

Note: (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 |

Note: (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 incidences per 1,000 of the age cohort 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 |

Note: (1) The sample is based on the selection criteria described in the text. (2) Arrest rates are annual incidences per 1,000 of the age cohort 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 |
| Diff. 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 |
| Diff. 2 | 3.665 | 3.915 | -0.160 |
| Std. Error | 0.429 | 0.382 | 0.103 |
| Diff. 1 – Diff. 2 | -9.914 | -7.680 | -2.381 |
| Std. Error | 0.577 | 0.506 | 0.163 |

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

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

| | Total Crime | |
|---|---|---|
| | I | II |
| 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 |
| Age Cohort FE | YES | YES |
| County FE | YES | YES |
| Year FE | YES | YES |
| State Trend | YES | YES |

Note: (1) Each column is a separate regression. (2) Control group consists of individuals 13 to 15 years of age. (3) 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. (4) County mean 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 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 |
| Age Cohort 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 |

Note: (1) Each column is a separate regression. (2) Control group consists of individuals 13 to 15 years of age. (3) 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. (4) County mean 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 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 |
| Age Cohort FE | YES | YES | YES | YES |
| County FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| State Trend | YES | YES | YES | YES |

Note: (1) Column I: Counties with population density in top $50^{th}$ percentile; Column II: Counties with percent black > 15%. (2) Each column is a separate regression. (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) 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 8: Teen Arrest Rates and Alternative Control Group Specifications, 1980-2006

| | Property Crime | | | Violent Crime | | |
|---|---|---|---|---|---|---|
| | I | II | III | I | II | III |
| MDA17*age16 | -2.063 | -3.050 | -1.075 | -1.502 | -2.101 | -0.903 |
| | (1.861) | (2.634) | (1.534) | (1.117) | (1.687) | (0.589) |
| MDA17*age17 | -3.124 | -4.112** | -2.137 | -2.268*** | -2.867** | -1.670*** |
| | (2.197) | (2.028) | (2.811) | (0.816) | (1.313) | (0.553) |
| MDA17*age18 | -0.508 | -1.495 | 0.479 | -1.490* | -2.089 | -0.891 |
| | (2.444) | (2.135) | (3.122) | (0.866) | (1.270) | (0.764) |
| MDA18*age16 | -3.518** | -4.685* | -2.351 | -2.263 | -3.186 | -1.341* |
| | (1.656) | (2.341) | (1.453) | (1.505) | (2.264) | (0.776) |
| MDA18*age17 | -4.645** | -5.812*** | -3.479 | -2.723* | -3.646* | -1.800** |
| | (1.971) | (1.842) | (2.546) | (1.432) | (2.156) | (0.805) |
| MDA18*age18 | -4.630 | -5.796** | -3.463 | -2.209* | -3.132 | -1.286 |
| | (2.895) | (2.481) | (3.566) | (1.285) | (1.908) | (0.927) |
| N | 88935 | 71148 | 71148 | 88935 | 71148 | 71148 |
| $R^2$ | 0.726 | 0.745 | 0.750 | 0.864 | 0.856 | 0.913 |
| Age Cohort 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: | | | | | | |
| 13-14 year-olds | X | X | | X | X | |
| 15 year-olds | X | | X | X | | X |

Note: (1) Each column is a separate regression. (2) 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. (3) County mean populations are used as weights. (4) Standard errors are clustered at the state level. (5) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

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

| | Long difference estimates using only data from 1980 and 2006 | | Exclude counties in states without dropout exemptions | | Unweighted | | 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 | Prop. Crime | Viol. Crime |
| MDA17*age16 | -4.680** | -1.206 | -2.549 | -1.279 | -3.715 | -0.918 | -1.881 | -1.695 | -1.446 | -0.183 |
| | (1.875) | (0.785) | (1.823) | (0.933) | (3.043) | (0.728) | (1.992) | (1.317) | (2.123) | (0.524) |
| MDA17*age17 | -3.739 | -1.659* | -2.727 | -1.398* | -5.884 | -1.821** | -3.097 | -2.480*** | -4.158* | -1.421** |
| | (2.587) | (0.837) | (3.410) | (0.770) | (3.577) | (0.872) | (2.332) | (0.921) | (2.364) | (0.666) |
| MDA17*age18 | 2.564 | -1.363 | -0.778 | -0.742 | -3.918 | -1.463 | -1.601 | -1.946** | -1.376 | -0.534 |
| | (3.194) | (0.902) | (2.927) | (1.385) | (3.982) | (1.284) | (2.635) | (0.882) | (2.861) | (0.786) |
| MDA18*age16 | -6.892*** | -2.049** | -3.259* | -2.390 | -4.690 | -1.440* | -3.188* | -2.428 | -2.300 | -1.639*** |
| | (1.653) | (0.846) | (1.874) | (1.754) | (3.054) | (0.720) | (1.798) | (1.727) | (2.077) | (0.462) |
| MDA18*age17 | -5.488** | -2.513*** | -4.891** | -2.820* | -9.621*** | -2.633*** | -4.530** | -3.004* | -5.152** | -2.625*** |
| | (2.070) | (0.760) | (2.253) | (1.647) | (3.204) | (0.837) | (2.189) | (1.594) | (2.225) | (0.652) |
| MDA18*age18 | 1.571 | -1.651** | -5.730* | -2.316 | -9.080** | -2.712** | -5.521* | -2.600* | -6.143* | -2.846*** |
| | (3.085) | (0.676) | (3.267) | (1.506) | (4.026) | (1.178) | (3.229) | (1.384) | (3.545) | (0.803) |
| N | 6830 | 6830 | 64465 | 64465 | 88935 | 88935 | 66640 | 66640 | 78715 | 78715 |
| $R^2$ | 0.854 | 0.907 | 0.751 | 0.870 | 0.589 | 0.745 | 0.745 | 0.869 | 0.652 | 0.667 |
| Age Cohort 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 |

Note: (1) Each column is a separate regression. (2) 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. (3) County mean populations are used as weights. (4) Standard errors are clustered at the state level. (5) *, significant at 10% level; **, significant at 5% level; ***, significant at 1% level.

Table 10: Impact of Current Law on 25 to 29 year-old Arrest Rates, 1980-2006

| | Property Crime | Violent Crime |
|---|---|---|
| MDA17*age25-29 | 4.255 | 0.331 |
| | (4.633) | (1.479) |
| MDA18*age25-29 | -0.219 | 1.750 |
| | (5.868) | (1.780) |
| N | 53361 | 53361 |
| $R^2$ | 0.663 | 0.706 |
| Age Cohort FE | YES | YES |
| County FE | YES | YES |
| Year FE | YES | YES |
| State Trend | YES | YES |

Note: (1) Each column is a separate regression. (2) Control group consists of individuals 13 to 15 years of age. (3) 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. (4) County mean 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 I | Violent Crime I | Property Crime II | Violent Crime II |
|---|---|---|---|---|
| MDA17*age16 | -2.063 | -1.502 | -2.330 | -1.655 |
| | (1.861) | (1.117) | (1.794) | (1.066) |
| MDA17*age17 | -3.124 | -2.268*** | -2.933 | -2.199*** |
| | (2.196) | (0.816) | (2.136) | (0.804) |
| MDA17*age18 | -0.508 | -1.490* | -0.025 | -1.286 |
| | (2.443) | (0.866) | (2.417) | (0.892) |
| MDA17*age19 | 2.037 | -0.772 | 2.612 | -0.521 |
| | (3.255) | (0.801) | (2.940) | (0.794) |
| MDA17*age20 | 2.177 | -0.744 | 2.737 | -0.515 |
| | (3.703) | (0.844) | (3.339) | (0.825) |
| MDA17*age21 | 2.191 | -0.832 | 2.588 | -0.616 |
| | (3.796) | (1.008) | (3.397) | (0.970) |
| MDA18*age16 | -3.518** | -2.263 | -3.662** | -2.589* |
| | (1.656) | (1.505) | (1.740) | (1.436) |
| MDA18*age17 | -4.645** | -2.723* | -4.748** | -3.161** |
| | (1.971) | (1.431) | (1.914) | (1.299) |
| MDA18*age18 | -4.630 | -2.209* | -5.181* | -2.858** |
| | (2.894) | (1.285) | (2.971) | (1.104) |
| MDA18*age19 | -2.108 | -0.797 | -2.488 | -1.282 |
| | (3.822) | (1.218) | (4.128) | (1.058) |
| MDA18*age20 | -1.751 | -0.270 | -1.999 | -0.685 |
| | (4.472) | (1.233) | (4.860) | (1.110) |
| MDA18*age21 | -1.774 | 0.040 | -2.056 | -0.382 |
| | (4.796) | (1.350) | (5.236) | (1.233) |
| N | 142296 | 142296 | 133008 | 133008 |
| $R^2$ | 0.693 | 0.849 | 0.698 | 0.851 |
| Age Cohort FE | YES | YES | YES | YES |
| County FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| State Trend | YES | YES | YES | YES |
| Exclusion of state-year observations that correspond to law changes when 19 to 21 year-old cohorts were 16 or 17 years-old. | NO | NO | YES | YES |

Note: (1) Each column is a separate regression. (2) Control group consists of individuals 13 to 15 years of age. (3) All regression models control for the current 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) County mean 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.

## 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 cohort 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 cohort population.