IN SCHOOL AND OUT OF TROUBLE? THE MINIMUM DROPOUT AGE AND JUVENILE CRIME

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Abstract—This paper examines the relationship between the minimum high school dropout age and juvenile arrest rates by exploiting state-level variation in dropout age laws. County-level arrest data for the period 1980 to 2008 and difference-in-difference-in-difference-type empirical strategy are used to compare the arrest rates 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 16 to 18 years old. The results are consistent with an incapacitation effect of schooling.

> *Dropout prevention is crime prevention.*
> —Lee Baca, Los Angeles County sheriff

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 (Thornberry, Moore, & Christenson, 1985; Fagan & Pabon, 1990). In the state of California alone, dropouts are estimated to be responsible for $1.1 billion in annual juvenile crime costs.[1] Because of crime's deleterious consequences, it is important to understand whether being in school has a causal influence on juvenile offending; evidence suggests that involvement in juvenile crime has an adverse impact on economic outcomes later in life. Incarceration during adolescence is associated with lower educational attainment and decreased future earnings (Waldfogel, 1994a, 1994b; Hjalmarsson, 2008). Furthermore, juvenile crime not only has an immediate impact on delinquents and their victims, but can impose negative externalities on those not directly involved with criminal acts (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 (Grogger, 1998), high school experience (Arum & Beattie, 1999), youth employment (Apel et al., 2008), underage drinking (French & Maclean, 2006), and curfew ordinances (Kline, 2012), to name a few.

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 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 criminality. Empirical research in this area is not decisive. Tauchen, Witte, and Griesinger (1994) and Witte and Tauchen (1994) find that having a parochial school education is associated with lower criminal behavior, but a high school diploma has no 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 does not influence criminal activity. However, Grogger's (1998) findings do not rule out education as having an indirect impact on crime through the labor market. On the other hand, Lochner (2004), Lochner and Moretti (2004), and Buonanno and Leonida (2009) illustrate that education is negatively related to adult crime. In a similar vein, Deming's (2011) results suggest that school quality predicts subsequent criminal behavior.

To date, considerably fewer studies have investigated the contemporaneous relationship between schooling and crime. This paper fits within this area of research. Gottfredson (1985), Farrington et al. (1986), and Witte and Tauchen (1994) find that time spent at school is associated with lower levels of criminal behavior. These studies do not control, however, for the potential endogeneity of schooling. Jacob and Lefgren (2003) and Luallen (2006) estimate the impact of school attendance on crime by exploiting variation in teacher in-service days and teacher strike days, respectively. Both papers show that property crimes committed by juveniles decrease when school is in session, but violent juvenile crime rates increase on these days. The authors suggest that incapacitation effects likely explain the property crime results, while concentration effects may underlie the violent crime findings. An incapacitation effect of school is that it

[1] This number reflects an estimate that includes criminal justice expenditures, incarceration costs, school disruption costs, and victim costs (Belfield & Levin, 2009).

[2] See, for example, Becker (1968), Freeman (1996), Levitt (1998), and Corman and Mocan (2000).

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

TABLE 1.—NUMBER OF STATES BY MANDATORY MINIMUM DROPOUT AGE (MDA), 1950–2008

	1950	1960	1970	1980	1990	2000	2008
MDA ≤ 16	42	43	40	39	33	30	25
MDA = 17	5	4	6	6	10	8	8
MDA = 18	4	4	5	6	8	13	18

Washington, DC, is included.

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, especially physical altercations.

This paper exploits the spatial and temporal variation in minimum dropout age laws to find strong evidence that increases in the minimum dropout age reduce rates of property and violent crime among high school–aged individuals. Estimates for drug-related crimes are large in magnitude and negative in sign but are generally not statistically significant. Though this paper presents robust evidence on the effect of MDA laws on property and violent crime arrest rates, it is not possible to precisely pin down the channels through which education affects crime. Nevertheless, by studying effects across age groups and types of crimes, it is possible to provide suggestive evidence on the mechanisms that are relatively important. Specifically, the results are consistent with an incapacitation effect; however, it should be noted that other mechanisms cannot necessarily be ruled out (for example, human capital effects). These findings suggest that policies designed to keep kids in school may be successful at decreasing delinquent behavior.

This paper makes at least four important contributions to the literature. First, previous research has not systematically analyzed the effects of minimum dropout age laws on juvenile crime. Second, Jacob and Lefgren (2003) and Luallen (2006) are able to test only for the existence of extremely short-run effects of school attendance. An increase in the minimum dropout age can result in students staying in school for up to two additional years. In-service and strike days consist of much shorter lengths of time. Consequently, the school attendance and crime dynamic is likely to differ considerably between these policies.

Third, 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.

Finally, after establishing a strong and negative relationship between the MDA and juvenile crime, this paper discusses the potential for delinquency and other risky behaviors to be displaced from the streets to schools when the MDA is higher. Using the national Youth Risk Behavior Survey data, a brief analysis highlights that this is a potentially important

issue that policymakers should consider when deciding whether to increase their state's minimum dropout age.

II. Background and Relevant Literature

In 1852, Massachusetts was the first state to enact a compulsory schooling law. By 1918, all states had some form of a compulsory schooling 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. Table 1 illustrates there has been a strong movement toward increasing the minimum dropout age in recent years.[4]

Not surprisingly, the 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 by their punishment of truancy; it is not unusual for a state to punish the parents of a truant child.[5]

Previous work has generally focused on compulsory schooling laws to estimate the returns to education.[6] Lochner and Moretti (2004) estimate the effect of educational attainment on adult criminal activity using variation in state compulsory schooling laws to instrument endogenous schooling decisions.[7] Other applications of compulsory schooling include mortality and teenage childbearing (Lleras-Muney 2005; Black, Devereux, & Kjell, 2008).

This study is concerned with the reduced-form relationship between the minimum dropout age and juvenile crime. Implicit in this relationship is that these laws increase school attendance rates. Angrist and Krueger (1991) find

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

[5] Oreopoulos (2009) offers a more complete discussion of the legislation. In particular, table 1 in Oreopoulos (2009) lists examples of exemptions and punishments for states with a minimum dropout age greater than 16.

[6] See, for example, Acemoglu and Angrist (2001) and Oreopoulos (2006a, 2006b).

[7] It is important to note that Lochner and Moretti (2004) 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 twelve 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.

that approximately 25% of potential dropouts in the United States remain in school because of compulsory schooling laws. Results from other research on the effectiveness of compulsory schooling are consistent with the conclusions drawn from Angrist and Krueger (1991).[8] Despite the existing evidence, this paper presents results on the relationship between the minimum dropout age and dropout status. (These results, based on U.S. Census data, are discussed in the online appendix and are presented in table A1.) In short, the results confirm that increases in the MDA significantly decrease the likelihood of dropping out.

As Angrist and Krueger (1991) pointed out, 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 above 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 that dropouts who seek employment are less likely to commit crimes than those who leave school 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 often implemented under the context of parental responsibility.

III. Data for County-Level Panel Regressions

A. Dependent Variables

The juvenile arrest data come from the FBI's Uniform Crime Reports (UCR).[9] These data are aggregated by the age of the offender at the county level for the period 1980 to 2008. Arrest rates are arrests per 1,000 of the specified age group population.[10] Arrests are reported for violent crimes (murder, rape, robbery, aggravated assault, and sim-

ple assault), property crimes (larceny, burglary, motor vehicle theft, and arson), and drug-related crimes (selling and possession).[11] The violent, property, and drug crime indices represent unweighted aggregations of their respective individual components. While this paper analyzes arrest rates for both sexes, the majority of the results focus on males because the male arrest rate is roughly four times higher than the female arrest rate.

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, Weinberg, and Mustard (2002) point out that arrest rates understate the true level of crime because not every crime committed is reported to the police. Moreover, underreporting 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.

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.[14] Using the UCR data, Lochner and Moretti (2004) report that the correlations between arrests and crimes committed is very high.[15]

In choosing the appropriate sample, I excluded counties with ten or fewer years of arrest data reported from the analysis. In addition, age-specific county-year arrest counts that are greater than 2 standard deviations from the mean for the 29-year period are dropped from the sample. This is done because each county arrest count is an aggregation of police agency reports and not all agencies report every year. To further guard against this issue, this paper controls for the

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[8] Li (2006) uses data from the High School and Beyond Survey to show that increasing the dropout age to 18 increases the probability of completing high school. Moreover, he shows the effects are much more pronounced for disadvantaged students. Wenger (2002) illustrates that increasing a state's dropout age is consistently predicted to lower the probability that an individual will drop out of high school. More specifically, she finds that the change in probability is equivalent to a decrease in the dropout rate of roughly 16%. The results in Oreopoulos (2009) also suggest that more restrictive compulsory schooling laws reduce dropout rates. Using less recent data, Lleras-Muney (2002) provides strong evidence that compulsory schooling laws were responsible for increased attendance between 1915 and 1939.

[9] U.S. Department of Justice, FBI, *Uniform Crime Reports: Arrests by Age, Sex, and Race* (Washington, DC: U.S. Department of Justice, FBI, and Ann Arbor, MI: Interuniversity Consortium for Political and Social Research, 1980–2008).

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

[11] It should be pointed out that "simple assaults" are actually referred to as "other assaults" in the UCR data codebook. However, because sexual and domestic offenses are given their own code, it is assumed that "other assaults" are mostly "simple assaults." This is likely a safe assumption given the age groups of interest.

[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, for example, Hindelang (1978, 1981).

[14] One worry is that a county might underreport arrests to suggest the MDA is bringing added benefits to the population. A benefit of the DDD approach is this issue is potentially addressed by differencing arrest rates across age groups. However, this concern is quelled only if a county underreports for the age groups 13 to 15 years and 16 to 18 years. If a county's underreporting specifically targets the 16- to 18-year-old population, then this remains a possible problem. I thank an anonymous referee for bringing this issue up.

[15] Lochner and Moretti (2004) report the following correlations: 0.96 for rape and robbery; 0.94 for murder, assault, and burglary; and 0.93 for auto theft.

TABLE 2.—DESCRIPTIVE STATISTICS FOR COUNTY PANEL DATA, 1980–2008

Variable	Mean	SD
Total crime arrest rate, 13- to 15-year-old males	31.59	33.28
Total crime arrest rate, 16- to 18-year-old males	61.70	49.06
Total crime arrest rate, 13- to 15-year-old females	10.40	13.46
Total crime arrest rate, 16- to 18-year-old females	14.78	14.93
Minimum dropout age = 18	0.239	0.427
Population density (thousands)	0.174	0.970
Percent black	0.088	0.140
Percent male	0.493	0.017
Percent aged 13 to 15	0.048	0.008
Percent aged 16 to 18	0.049	0.008
Real income per capita (2000 dollars)	21,849	5,779
Real minimum wage (2000 dollars)	5.157	0.535
Minimum legal drinking age = 19	0.089	0.285
Minimum legal drinking age = 20	0.009	0.097
Minimum legal drinking age = 21	0.845	0.362
Number of reporting agencies	4.621	7.877

The sample is based on the selection criteria described in the text. Unweighted means are presented. Arrest rates are arrests per 1,000 of the relevant age group population.

number of agencies reporting within a county for any given year.[16] Results from model specifications without these restrictions are presented in the sensitivity analysis.

B. Independent Variables

The state minimum dropout ages come from Oreopoulos (2009), the National Center for Education Statistics' *Digest of Education Statistics*, and various reports and policy briefs. Annual county-level demographic variables come from the U.S. Census Bureau. The regressions control for population density, the percentage black, the percentage male, and the percentages in the age ranges 13 to 15 and 16 to 18. Data on per capita personal income and the annual prevailing minimum wage are also included and come from the Bureau of Economic Analysis. These variables are deflated by the Consumer Price Index to convert to 2000 dollars. Data on each state's minimum legal drinking age come from Dee (2001). Table 2 presents descriptive statistics for all counties in the sample.

IV. Empirical Strategy

The empirical analysis is reduced form, based on the approach taken by a long line of researchers to evaluate the effects of county- and state-level variables on aggregate measures of crime.[17] As stated, this study aims to evaluate the impact of the minimum dropout age on juvenile arrest

rates by exploiting variation in state laws. The question now is: Are students who would have otherwise dropped out less likely to commit crimes when forced to stay in school?

To estimate the impact of the minimum dropout age on juvenile arrest rates, this paper uses a difference-in-difference-in-difference-type (DDD) empirical strategy.[18] This approach relies on statewide variation in compulsory schooling laws and 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 who are always below the minimum dropout age. Because all states have a minimum dropout age of at least 16, the control group is composed of 13- to 15-year-olds.[19] The treatment group consists of youth who are subject to changes in the law—those 16 to 18 years old.

The empirical framework relies on the assumption that criminal behavior among individuals who are below the minimum dropout age tracks the trend of individuals 16 to 18 years old except that they are not subject to more or less restrictive dropout laws. By using 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 below 18. In sum, this strategy compares the outcomes of youth who are affected by the minimum dropout age to the outcomes of youth who are not affected by the minimum dropout age (one "difference") in states with a minimum dropout age of 16 or 17 versus states with a minimum dropout age of 18 (a second "difference") over time (the third "difference"). This paper estimates the following equation:

$$\begin{aligned} ArrestRate_{ijst} = {} & \alpha + \beta_1 MDA18_{st} + \beta_2 age16to18_i \\ & + \beta_3 (MDA18_{st} * age16to18_i) + X_{jst}\beta_4 \\ & + C_j\beta_5 + T_t\beta_6 + Trend_s\beta_7 + \varepsilon_{ijst}, \quad (1) \end{aligned}$$

where i indexes the age group, j indexes the county, s indexes the state, and t indexes the year.[20]

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, *MDA18* is equal to 1 if the state has a minimum dropout age of 18 at time t

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[16] Following Gould et al. (2002), regressions were also considered where the sample was restricted to counties with an average population exceeding 25,000 between 1980 and 2008. This selection criterion is intended to capture a representative population and eliminate counties where arrest reports are more likely to be inaccurate. The results are similar when the sample is limited in this manner and are available on request.

[17] For examples, see Ludwig (1998) on the effects of concealed-gun-carrying laws on crime; Levitt and Donahue (2001) and Joyce (2009) on the effects of abortion rates on crime; Grinols and Mustard (2006) on the effects of casinos on crime; Carpenter (2008) on the effects of underage drunk driving laws on crime; and Mocan and Bali (2010) on the effects of unemployment on crime.

[18] Given the availability (or lack thereof) of yearly county-level high school dropout data, a two-stage estimation strategy was not possible.

[19] The one exception is Mississippi. From 1980 to 1993, Mississippi had a minimum dropout age of 14. The results are robust when Mississippi counties are excluded from the analysis.

[20] In a previous version of this paper, an indicator and interaction terms for *MDA17* were also included on the right-hand side of equation (1). Counties in MDA = 17 states are considered reference counties (along with counties in MDA = 16 states) in this version for the sake of brevity when discussing the results. More important, the trend among states has been to increase their MDA to 18. This paper highlights that point by focusing solely on indicators for MDA = 18 counties and provides results that are clearly interpretable in the context of the current policy environment. Results that include the *MDA17* variables are available on request.

and 0 otherwise. The variable *age16to18* is a dummy that controls for differences between 16- to 18-year-olds and 13- to 15-year-olds that are common across years. The variable X is a vector containing the county- and state-level controls described above. The variables C and T represent county fixed effects and year effects, respectively. The county fixed effects control for differences in counties that are common across years, while the year effects control for differences across time that are common to all counties and to individuals of all ages. The variable **Trend** represents a vector of linear state-specific time trends that account for time series variation within each state. In the online appendix, Table A2 shows results where equation (1) is altered to allow for differential treatment effects for 16-, 17-, and 18-year-olds.

The coefficient of interest is β_3. This interaction term coefficient represents the marginal effect of the policy on the treatment group relative to the control group. If increases in the MDA decrease crime among juveniles 16 to 18 years of age, then we expect β_3 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 those 16 to 18 years old to those 13 to 15 years old raises some concerns. This method, however, alleviates this issue because it also compares arrest rates of 16- to 18-year-olds in states with a minimum dropout age of 18 to arrest rates of 16- to 18-year-olds in states with a dropout age of 16 or 17. Second, expectations of when a student will be able to drop out may influence criminal behavior. For example, a 16-year-old in a state with a minimum dropout age of 17 may behave differently from a 16-year-old in a state with a minimum dropout age of 18 because the former anticipates being able to drop out sooner. Again, this approach mitigates these concerns because it compares individuals of different ages within states that have similar minimum dropout ages. This technique controls for the potential endogeneity of the minimum dropout age laws 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, Duflo, and Mullainathan (2004), standard errors are corrected for clustering at the state level. This procedure accounts for the possibility that standard errors may be biased due to serial correlation of the policy variable over time within a state.

A caveat is that 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 specific 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 MDA exemptions, the empirical strategy 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

Table 3 provides a breakdown of the mean arrest rates by age group and the prevailing MDA law for males and females, respectively. It is immediately apparent the two age groups display different levels of criminal behavior. Fortunately, the empirical strategy relies only on the assumption that the rates of crime between the two groups trend with each other over time. Interestingly, for many crimes, the mean rate of arrest is highest in MDA $= 18$ counties.[21] However, it is imperative to note these are only simple means; a more rigorous approach is required to address causality. The means are calculated such that a county in a state that changes its MDA is recorded under both dropout age regimes. For example, if a county is in a state that changes from an MDA $= 16$ to an MDA $= 18$, the mean rates of arrest are classified under an MDA $= 16$ before the policy change and under an MDA $= 18$ after the policy change.

Before discussing the results based on estimation of equation (1), it is useful to consider a more explicit test for whether changes in criminal behavior take place after MDA laws change. Figure 1 presents point estimates (with 95% confidence intervals) from a simple regression designed to capture intertemporal effects.[22] Two lead dummies, five lag dummies, and an indicator for the year a state law changed are considered independent variables in a regression that also includes county and year fixed effects.[23] The dependent variable is the arrest rate for 16- to 18-year-old males for all crimes (property $+$ violent $+$ drug crimes). The coefficient estimates for the lead dummies shown in figure 1 strongly suggest that states that increase their MDA do not have different arrest rates for 16- to 18-year-olds during the two years prior to a policy change. However, all lag dummies have coefficient estimates that are negative and relatively large in magnitude.[24] This indicates that arrest rates among the population of interest have fallen after increases in the MDA and motivates proceeding forward with a more careful empirical approach. In particular, this method does

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[21] Arson is the only crime where 13- to 15-year-olds appear to participate at higher rates than 16- to 18-year-olds for both males and females.

[22] Grinols and Mustard (2006) use this approach to analyze the effects of casinos on crime.

[23] For example, the first of the two lead dummies takes a value of 1 two years prior to a law change in a particular state and is equal to 0 otherwise. This variable is always equal to 0 for counties in states that do not change their MDA during the sample time frame.

[24] The coefficient estimates (with *p*-values for the *t*-statistics) for the lags are as follows: lag 1 $= -2.10$ (*p*-value $= 0.27$); lag 2 $= -3.34$ (*p*-value $= 0.16$); lag 3 $= -5.20$ (*p*-value $= 0.05$); lag 4 $= -3.21$ (*p*-value $= 0.14$); lag 5 $= -5.50$ (*p*-value $= 0.01$). For example, the estimated coefficient of lag 5 indicates that the arrest rate was lower by 5.5 arrests per 1,000 of the 16- to 18-year-old population five years after an increase in the MDA.

TABLE 3.—DESCRIPTIVE STATISTICS FOR ARREST RATES

A. Male Arrest Rates

	MDA ≤ 16			MDA = 17			MDA = 18		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
16- to 18-year-olds									
Larceny arrest rate	17.92	16.75	39,323	17.40	15.07	11,560	19.57	19.31	16,149
Burglary arrest rate	9.692	9.903	39,014	10.84	10.04	11,504	9.648	9.748	16,163
Auto theft arrest rate	2.468	3.951	38,928	2.903	5.493	11,413	3.162	4.945	16,066
Arson arrest rate	0.133	0.451	39,430	0.153	0.443	11,513	0.166	0.478	15,978
Property crime arrest rate	31.66	25.86	39,306	32.75	25.41	11,588	33.82	28.84	16,189
Murder arrest rate	0.071	0.297	39,773	0.122	0.543	11,515	0.063	0.273	16,177
Rape arrest rate	0.248	0.626	39,248	0.331	0.750	11,515	0.307	0.736	15,857
Robbery arrest rate	1.009	2.237	39,368	1.669	10.02	11,491	0.978	1.973	15,975
Aggravated assault arrest rate	3.072	4.290	39,314	3.631	6.056	11,458	3.195	4.023	15,944
Simple assault arrest rate	8.076	9.731	39,547	9.333	9.578	11,620	9.850	9.912	15,863
Violent crime arrest rate	13.36	14.51	39,662	16.12	21.97	11,673	15.38	13.67	15,986
Drug sale arrest rate	1.821	4.560	39,187	2.353	9.120	11,483	1.723	3.168	15,769
Drug possession arrest rate	9.287	13.59	39,500	10.20	14.35	11,679	13.78	16.10	15,828
Total drug arrest rate	11.67	16.10	39,545	13.50	22.82	11,727	16.21	17.40	15,855
Total crime arrest rate	58.61	46.52	39,528	64.03	59.91	11,665	67.62	45.66	16,089
13- to 15-year-olds									
Larceny arrest rate	12.17	14.91	39,290	11.30	13.39	11,512	15.19	17.83	16,095
Burglary arrest rate	4.956	6.902	38,995	5.811	7.493	11,493	6.124	7.617	16,084
Auto theft arrest rate	1.403	2.825	38,898	1.481	3.272	11,387	2.019	3.552	16,035
Arson arrest rate	0.167	0.517	39,608	0.163	0.508	11,574	0.272	0.671	15,920
Property crime arrest rate	19.77	21.87	39,260	19.87	21.33	11,533	24.76	25.75	16,161
Murder arrest rate	0.007	0.072	40,469	0.015	0.120	11,859	0.007	0.057	16,468
Rape arrest rate	0.085	0.315	39,765	0.138	0.414	11,600	0.144	0.438	15,929
Robbery arrest rate	0.306	1.079	39,886	0.630	6.717	11,560	0.352	1.014	16,086
Aggravated assault arrest rate	1.072	2.100	39,287	1.325	2.879	11,456	1.413	2.225	15,796
Simple assault arrest rate	4.065	7.017	39,447	5.022	8.042	11,557	6.619	8.862	15,754
Violent crime arrest rate	5.956	9.192	39,420	7.674	15.21	11,552	9.204	10.94	15,823
Drug sale arrest rate	0.305	1.366	39,604	0.392	2.454	11,575	0.327	0.873	15,870
Drug possession arrest rate	1.592	3.052	39,400	1.767	3.190	11,578	3.011	4.283	15,765
Total drug arrest rate	2.052	3.977	39,375	2.368	5.071	11,595	3.576	4.798	15,763
Total crime arrest rate	28.79	30.81	39,393	31.06	36.97	11,573	38.84	35.19	16,048

B. Female Arrest Rates

	MDA ≤ 16			MDA = 17			MDA = 18		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
16- to 18-year-olds									
Larceny arrest rate	6.520	8.443	39,293	6.284	7.776	11,681	7.614	9.385	15,913
Burglary arrest rate	0.490	1.071	39,096	0.478	1.099	11,649	0.632	1.312	15,899
Auto theft arrest rate	0.224	0.676	39,194	0.223	0.686	11,671	0.437	1.063	15,923
Arson arrest rate	0.005	0.052	40,387	0.006	0.048	12,035	0.008	0.067	16,343
Property crime arrest rate	7.641	9.147	39,248	7.387	8.403	11,705	9.168	10.30	15,938
Murder arrest rate	0.002	0.023	40,622	0.003	0.033	12,139	0.002	0.022	16,534
Rape arrest rate	0.000	0.012	40,964	0.000	0.004	12,242	0.000	0.015	16,665
Robbery arrest rate	0.047	0.186	40,095	0.081	0.716	11,927	0.059	0.217	16,190
Aggravated assault arrest rate	0.531	1.168	39,271	0.622	1.442	11,713	0.565	1.186	15,782
Simple assault arrest rate	2.740	4.479	39,410	3.118	4.226	11,802	3.790	5.460	15,652
Violent crime arrest rate	3.570	5.293	39,467	4.090	5.468	11,804	4.709	6.095	15,733
Drug sale arrest rate	0.211	0.704	39,322	0.227	0.794	11,732	0.212	0.754	15,790
Drug possession arrest rate	1.482	3.139	39,221	1.401	2.562	11,725	2.498	4.238	15,612
Total drug arrest rate	1.845	3.499	39,227	1.807	3.105	11,727	2.885	4.486	15,579
Total crime arrest rate	13.77	14.57	39,570	14.03	13.96	11,876	17.86	16.07	15,850
13- to 15-year-olds									
Larceny arrest rate	5.053	7.853	39,269	4.271	6.334	11,702	6.936	9.514	15,949
Burglary arrest rate	0.348	0.931	39,339	0.331	0.891	11,662	0.551	1.246	15,945
Auto theft arrest rate	0.268	0.854	39,331	0.234	0.847	11,681	0.545	1.300	15,923
Arson arrest rate	0.015	0.106	40,394	0.012	0.091	12,044	0.025	0.141	16,281
Property crime arrest rate	6.029	8.775	39,199	5.194	7.101	11,691	8.576	10.92	15,946
Murder arrest rate	0.000	0.003	41,002	0.000	0.008	12,251	0.000	0.005	16,649
Rape arrest rate	0.001	0.024	40,979	0.000	0.003	12,245	0.001	0.041	16,637
Robbery arrest rate	0.022	0.123	40,570	0.058	0.951	12,067	0.036	0.190	16,363
Aggravated assault arrest rate	0.273	0.789	39,542	0.348	0.984	11,717	0.351	0.862	15,842
Simple assault arrest rate	1.818	3.756	39,491	2.160	4.032	11,745	3.327	5.415	15,673
Violent crime arrest rate	2.240	4.274	39,411	2.752	5.210	11,735	3.950	6.011	15,710
Drug sale arrest rate	0.043	0.232	40,016	0.042	0.247	11,899	0.061	0.296	16,077
Drug possession arrest rate	0.380	1.016	39,410	0.356	0.978	11,738	0.827	1.559	15,736
Total drug arrest rate	0.470	1.171	39,351	0.457	1.142	11,765	0.962	1.736	15,703
Total crime arrest rate	9.282	12.59	39,382	8.941	11.86	11,752	14.26	15.76	15,877

The sample is based on the selection criteria described in the text. Unweighted means are presented. Arrest rates are arrests per 1,000 of the relevant age group population.

Figure 1.—Male Arrest Rate for All Crimes
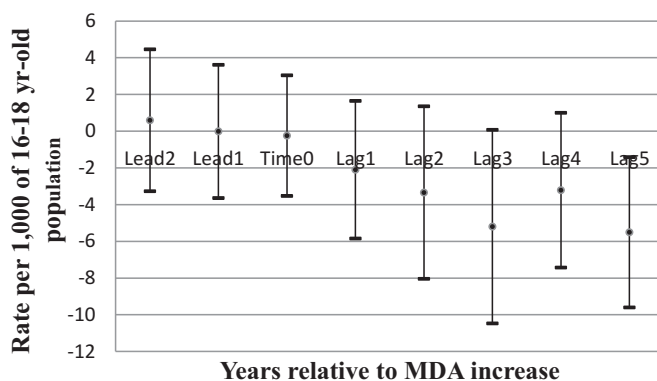
not account for important outside factors that may have occurred alongside MDA increases that also influenced arrest rates.[25]

Table 4 presents estimates for β_3 from equation (1) where each cell illustrates results from a separate regression. For males, the estimates are negative in sign and large in magnitude across all model specifications. With the exception of drug-related arrests, all estimates are statistically significant at the 10% level or better.[26] Though not reported for the sake of brevity, it is worth noting that β_1 from equation (1) is not statistically significant for any of the specifications for males in table 4. This implies that 13- to 15-year-old males in MDA = 18 states do not have statistically significantly different arrest rates than males of the same age in MDA = 16 or MDA = 17 states. The results in the bottom panel of table 4 illustrate a negative but statistically insignificant relationship between the MDA and the overall arrest rate among females. However, it does appear that a higher MDA reduces the rate of violent female offending.

The estimate from the full specification for males in column 3 of table 4 indicates that exposure to an MDA = 18 reduces the overall arrest rate for 16- to 18-year-olds by 10.27 incidences per 1,000 of the age group population. To put this estimate into perspective, this represents a 17.2% decrease from the mean arrest rate for 16- to 18-year-olds in states with an MDA = 16 or an MDA = 17. For male property crime arrests, an MDA = 18 is associated with a 9.9% reduction from the mean arrest rate for 16- to 18-year-olds in states with an MDA = 16 or an MDA = 17. For male violent crime arrests, an MDA = 18 is associated with a 22.5% reduction from the mean arrest rate for 16- to 18-year-olds in states with an MDA = 16 or an MDA = 17.

Because this paper relies on a reduced-form approach, it is important to consider whether the magnitudes of these effects are plausible. The Census analysis in the online appendix indicates that a one-year increase in the MDA is associated with roughly a 2 percentage point decrease in the dropout rate. According to the U.S. Department of Education, the high school completion rate was nearly 90% in 2009 (Chapman et al., 2011). This implies that roughly 20% of those who drop out would stay in school with a one-year increase in the MDA. Given that over 1.2 million youths drop out annually, this would mean that approximately 240,000 more students per year would stay in school with a higher MDA (Alliance for Excellent Education, 2007).[27] Using property crimes as an example, the UCR data indicate that 16- to 18-year-old males were responsible for roughly 175,000 arrests in 2008. A decrease of 9.9% means that over 17,000 fewer property crimes are committed annually when the dropout age is higher. Taken together, these figures imply that for every 100 students kept from dropping out, there would be over seven fewer property crimes committed. Although these are simple back-of-the-envelope calculations, these numbers are perhaps useful for an economic interpretation of the results.

A.   Male Arrest Rates by Crime Type

Table 5 focuses on male arrest rates and breaks down property, violent, and drug crimes by their respective components. For the individual property crime arrests, all coefficient estimates are negative in sign. Furthermore, with the exception of motor vehicle theft arrests, all estimates are statistically significant at the 10% level or better. Similarly, all coefficient estimates from the individual violent crime arrest models are negative in sign. Estimates for murder, rape, and simple assault are statistically significant at the 10% level or better, while estimates for robbery and aggravated assault are statistically insignificant. The decrease in the violent crime arrest rate appears to be driven in large part by simple assaults. This perhaps should come as no surprise because this particular crime is relatively common among juveniles.

Table 5 also reports results separately for the selling of drugs and the possession of drugs. Though not statistically significant at conventional levels, the coefficient estimate for selling-related arrests is relatively large in magnitude. There is no evidence that possession-related arrests are influenced by the MDA.

It is worth noting that an MDA = 18 shares a negative and statistically significant relationship with simple assaults for females. There is no evidence that other individual female offenses are influenced by the MDA.

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[25] When this approach is applied to 13- to 15-year-old male arrest rates, the "control" rates, there is no evidence of a relatively discrete and persistent drop following MDA increases. This provides further confidence that the results in figure 1 are illustrating a causal effect of changes in the dropout age.

[26] Because the county fixed effects explain most of the variation in crime, models without these were also considered in an even more basic specification. For males, the coefficient estimates remained negative and similar in magnitude to the results shown in table 4.

[27] This estimate is similar in magnitude to the results from Angrist and Krueger (1991). Li (2006) uses simulation to show that increasing the MDA to 18 will raise the percent who graduate high school from 89% to 94.1%. This implies that about half of those who drop out would stay in school with a higher MDA.

TABLE 4.—TEEN ARREST RATES AND THE MINIMUM DROPOUT AGE, 1980–2008

	All Crimes			Property Crime			Violent Crime			Drug Crime		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Males												
MDA18	−10.20*	−10.20*	−10.27*	−3.270**	−3.232**	−3.241**	−3.262**	−3.268**	−3.264**	−3.287	−3.275	−3.309
×age16to18	(5.331)	(5.321)	(5.323)	(1.303)	(1.296)	(1.295)	(1.468)	(1.466)	(1.468)	(3.431)	(3.426)	(3.436)
N	134,296	134,293	134,293	134,037	134,034	134,034	134,116	134,114	134,114	133,860	133,857	133,857
R^2	0.830	0.835	0.841	0.742	0.762	0.779	0.868	0.872	0.877	0.619	0.634	0.643
Females												
MDA18	−1.419	−1.448	−1.553	−0.739	−0.740	−0.749	−0.634**	−0.643**	−0.656**	0.029	0.030	0.027
×age16to18	(1.227)	(1.203)	(1.192)	(0.837)	(0.835)	(0.833)	(0.303)	(0.304)	(0.304)	(0.439)	(0.438)	(0.439)
N	134,307	134,304	134,304	133,727	133,725	133,725	133,860	133,857	133,857	133,352	133,349	133,349
R^2	0.747	0.756	0.773	0.709	0.718	0.733	0.717	0.727	0.746	0.586	0.599	0.611
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State trends	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Each cell represents a separate regression. The dependent variable is the arrest rate per 1,000 of the relevant age group population. The control group consists of individuals 13 to 15 years of age. Other covariates control for county demographic variables, population density, the minimum wage, the minimum legal drinking age, and the count of agencies reporting each year. County mean populations are used as weights. Standard errors are corrected for clustering at the state level. Significant at *10%, **5%, ***1%.

TABLE 5.—MALE TEEN ARREST RATES BY CRIME UYPE, 1980–2008

Coefficient on MDA18×age 16to18					
Individual Property Crimes		Individual Violent Crimes		Individual Drug Crimes	
Larceny	−1.574*	Murder	−0.102*	Selling	−1.731
	(0.806)		(0.055)		(1.151)
	N = 133,926		N = 136,258		N = 133,485
Burglary	−1.057*	Rape	−0.068*	Possession	−0.057
	(0.570)		(0.034)		(2.368)
	N = 133,250		N = 133,912		N = 133,747
Motor vehicle theft	−0.399	Robbery	−0.633		
	(0.470)		(0.571)		
	N = 132,724		N = 134,363		
Arson	−0.100**	Aggravated assault	−0.687		
	(0.040)		(0.738)		
	N = 134,020		N = 133,252		
		Simple assault	−1.655***		
			(0.512)		
			N = 133,785		

Each cell represents a separate regression. The dependent variable is the arrest rate per 1,000 of the relevant age group population. The control group consists of individuals 13 to 15 years of age. Other covariates control for county demographic variables, population density, the minimum wage, the minimum legal drinking age, and the count of agencies reporting each year. All regressions also include county fixed effects, year fixed effects, and state-specific time trends. County mean populations are used as weights. Standard errors are corrected for clustering at the state level. Significant at *10%, **5%, ***1% level.

TABLE 6.—TEEN ARREST RATES FOR PETTY DELINQUENCY, 1980–2008

Coefficient on MDA18×age16to18			
Males		Females	
Disorderly conduct	−5.368***	Disorderly conduct	−1.200***
	(1.986)		(0.363)
	N = 133,364		N = 133,713
	Mean = 8.022		Mean = 2.134
Vandalism	−0.247	Vandalism	−0.162**
	(0.325)		(0.061)
	N = 133,067		N = 133,910
	Mean = 5.611		Mean = 0.572
Curfew	0.184	Curfew	−0.338
	(0.729)		(0.320)
	N = 134,473		N = 135,392
	Mean = 2.061		Mean = 0.749
		Prostitution	0.020
			(0.102)
			N = 139,229
			Mean = 0.046

Each cell represents a separate regression. For context, each cell reports the mean arrest rate for 16- to 18-year-olds in states with an MDA lower than 18. The dependent variable is the arrest rate per 1,000 of the relevant age group population. The control group consists of individuals 13 to 15 years of age. Other covariates control for county demographic variables, population density, the minimum wage, the minimum legal drinking age, and the count of agencies reporting each year. All regressions also include county fixed effects, year fixed effects, and state-specific time trends. County mean populations are used as weights. Standard errors are corrected for clustering at the state level. Significant at *10%, **5%, ***1% level.

B. Less Serious Offenses

In addition to the crimes reported in table 5, it is also informative to consider less serious offenses that may be more relevant for these age groups. Table 6 displays results for disorderly conduct, vandalism, and curfew violation arrests for both sexes. Arrests for prostitution are also considered for females. An MDA = 18 is associated with roughly 5.4 and 1.2 fewer disorderly conduct arrests per 1,000 of the relevant age group population for males and females, respectively. Rates of female vandalism also share a negative and statistically significant relationship with the MDA. Male vandalism, male and female curfew violation, and female prostitution arrest rates do not share statistically significant relationships with the MDA.

C. Interaction Terms with Subsamples of the Population

When considering a policy change, it is vital to know whether the law has a homogeneous influence across different types of populations. In general, this information is of

TABLE 7.—INTERACTION TERMS AND MALE ARREST RATES, 1980–2008

	All Crimes	Property Crime	Violent Crime	Drug Crime
MDA18×age16to18 *	1.350	5.206***	0.468	−3.469
% black below median	(3.794)	(1.109)	(1.986)	(2.862)
Number	134,293	134,034	134,114	133,857
MDA18×age16to18 *	−1.403	1.256	−0.298	−2.396
income below median	(3.362)	(1.289)	(1.060)	(1.652)
Number	134,293	134,034	134,114	133,857

Each column represents a separate regression. The dependent variable is the arrest rate per 1,000 of the relevant age group population. The control group consists of individuals 13 to 15 years of age. Other covariates control for county demographic variables, population density, the minimum wage, the minimum legal drinking age, and the count of agencies reporting each year. All regressions also include an MDA18 indicator, an *age16to18* indicator, county fixed effects, year fixed effects, and state-specific time trends. The regressions in the top panel include an indicator for whether the percentage of the county's black population is below the sample median, and the regressions in the bottom panel include an indicator for whether the county's real income per capita is below the sample median. County mean populations are used as weights. Standard errors are clustered at the state-level. Significant at *10%, **5%, ***1%.

TABLE 8.—SENSITIVITY OF MALE ARREST RESULTS TO ALTERNATIVE SPECIFICATIONS, 1980–2008

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Baseline Estimate from Column 3 in Table 4	DD Estimate	log(arrest rate)	Add Age-Specific Trends	Add Age-by-Year and Age-by-State Fixed Effects	19–Year-Olds as Controls	No Sample Restrictions	Only Counties in States with Major Exemptions	Exclude California, Florida, NewYork, and Texas Counties
−10.27*	−7.32*	−0.132*	−13.00**	−5.364*	−3.400	−8.367*	−14.65**	−11.12***
(5.323)	(3.88)	(0.070)	(5.061)	(3.172)	(3.953)	(4.526)	(6.716)	(3.793)
N = 134,293	N = 71,841	N = 120,749	N = 134,293	N = 134,293	N = 134,477	N = 145,750	N = 93,034	N = 113,149

Each cell represents a separate regression. The dependent variable is the arrest rate per 1,000 of the relevant age group population for all crimes (property + violent + drug). Other covariates control for county demographic variables, population density, the minimum wage, the minimum legal drinking age, and the count of agencies reporting each year. All regressions also include county fixed effects, year fixed effects, and state-specific time trends. County mean populations are used as weights. Standard errors are corrected for clustering at the state level. Significant at *10%, **5%, ***1%.

interest to policymakers whose goal is to affect specific populations or areas where the policy may be most effective. Table 7 reports estimates for male arrest rates based on interaction terms with potentially important subsamples of the population.[28] In the upper panel of table 7, the variable of interest is interacted with a dummy variable indicating whether the percentage of the county's population that is African American is below the sample median.[29] The most striking result is for property crimes, where it appears that a higher MDA may be more effective at reducing crime in areas with a relatively large African American population. This result is of interest because dropout and arrest rates are historically higher among blacks than whites.

In the bottom panel of table 7, the variable of interest is interacted with a dummy variable indicating whether the county's income per capita is below the sample median. While three of the four estimates are negative in sign, they are not statistically significant at conventional levels.

D. *Sensitivity of Results to Alternative Specifications*

Table 8 investigates the sensitivity of the results to a range of alternative specifications. Column 1 reports the estimate from column 3 in table 4 to serve as a baseline reference for the impact of an MDA = 18 on overall male arrest rates.

In column 2, the estimate from a standard difference-in-difference (DD) regression is reported. This model is simi-

lar to equation (1) but does not utilize the arrest rates for 13- to 15-year-olds as control trends. While this estimate is smaller in magnitude than the baseline estimate, it is relatively large in size and statistically significant at the 10% level. Table A3 in the online appendix illustrates DD results for sparser specifications for both sexes.

In column 3, the sensitivity of the results to using the log transformation of the arrest rate is assessed. While other papers use this as their dependent variable (Lochner & Moretti, 2004), it comes with the drawback that zero values must be discarded. The estimate in column 3 indicates the results are robust to this transformation.

In column 4, linear age-specific time trends are added to the baseline specification. Age-specific trends are designed to account for time series variation particular to each age group. The DDD coefficient estimate is slightly larger in magnitude and more precisely measured under this alternative specification.

Column 5 adds age-by-year and age-by-state fixed effects to the baseline model.[30] The age-by-year fixed effects serve a similar purpose as the age-specific trends in that they allow each age group to have its own time trend. The age-by-year effects are, however, less restrictive because they do not impose linearity. The age-by-state fixed effects are included to allow for separate shifts in the arrest rates for 16- to 18-year-olds in different states. When these terms are added, the coefficient estimate of interest remains negative in sign and statistically significant at the 10% level. The

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[28] Results for females are available from the author on request.
[29] Unfortunately, it is not possible to observe race for the age-specific UCR arrest data.

[30] This amounts to adding eighty new variables to the baseline specification that already contains county fixed effects, year effects, and state-specific trends.

TABLE 9.—MALE ARREST RATES FOR MALES 19 TO 21 YEARS OLD, 1980–2008

	(1)	(2)	(3)	(4)
	All Crimes	Property Crime	Violent Crime	Drug Crime
$MDA18 \times age19to21$	−1.545	0.263	−1.503	−0.074
	(5.476)	(3.401)	(0.987)	(2.556)
	$N = 201,399$	$N = 200,795$	$N = 201,188$	$N = 200,711$

Each cell represents a separate regression. The dependent variable is the arrest rate per 1,000 of the relevant age group population. The *MDA18* variable represents a three-year lagged indicator. This is done so as to represent the dropout age regime that was in place when the 19- to 21-year-old age group was in high school. Control group is 13- to 18-year-olds. Other covariates control for county demographic variables, population density, the minimum wage, the minimum legal drinking age, and the count of agencies reporting each year. All regressions also include county fixed effects, year fixed effects, and state-specific time trends. County mean populations are used as weights. Standard errors are clustered at the state level. Significant at *10%, **5%, ***1%.

magnitude of the estimate decreases but still implies a relatively large effect. In this case, an MDA = 18 leads to roughly 5.36 fewer arrests per 1,000. This represents an approximate 9% decrease from the mean rate of arrests for 16- to 18-year-olds in states with an MDA = 16 or an MDA = 17.

Column 6 illustrates results where 19-year-olds serve as the control group. Regardless of the state, 19-year-olds are never legally obligated to attend school. One may argue that 19-year-olds serve as a better control group because they are more similar to 16- to 18-year-olds than are 13- to 15-year-olds. However, a potential issue with this specification is that 19-year-olds in MDA = 18 states may have been less likely to commit crime when younger and, as a result, may be less likely to commit crime at age 19. If this is the case, then the impact of MDA laws on 16- to 18-year-olds will be understated. While the result in column 6 is negative in sign, it is smaller in magnitude than the baseline estimate and is measured imprecisely.

In column 7, the sample is not restricted by the criteria described in section III. In this case, the estimate is only slightly smaller in magnitude than the baseline result and remains statistically significant at the 10% level.

Column 8 illustrates results where only counties in states that have an MDA = 16 throughout the entire period or that offer a major exemption to their dropout age law are included in the sample.[31] 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.[32] The coefficient estimate under this specification is slightly larger in magnitude and more precisely estimated than the baseline result. This implies the minimum dropout age set by law is itself an important factor in determining juvenile arrest rates.

Finally, the sensitivity of the results to large populations is examined in column 9 of table 8. This is an important consideration because the regressions are population weighted. California, Florida, New York, and Texas contribute over

20,000 observations to the full sample.[33] Additionally, California and Texas both increased their dropout age to 18 during the sample time period. When counties from these states are dropped, the main result holds: increases in the MDA reduce arrest rates among 16- to 18-year-olds.

E.   Investigating the Potential Mechanisms through Which Education Reduces Crime

Education may reduce crime because schooling has an incapacitating effect on youth. The incapacitation mechanism is inherent in a time allocation problem where youth choose between investing in education, participating in the labor force, and committing crime (Lochner, 2010).[34] If increasing the minimum dropout age has an incapacitating effect on youth only, then these laws should have no impact on individuals of ages above which the law binds. However, if human capital effects are an important channel through which education affects crime, then MDA laws should have a lasting influence on criminal behavior that goes beyond high school. More schooling increases future wage rates and, as a result, the opportunity costs of crime. Furthermore, punishment is likely to be more costly for individuals with additional years of schooling.[35]

To investigate this further, table 9 includes 19- to 21-year-olds in the sample.[36] The regression model follows the baseline DDD specification, but the policy indicator is defined as the minimum dropout age that was in place three years prior. This is done so as to better match the 19- to 21-year-old age group with the MDA regime that was in place when they were in high school. The control group consists of males ages 13 to 18 years old. Arrest rates for 16- to 18-

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[31] As an example, individuals in New Mexico can drop out one year before reaching their state's MDA of 18 if they have obtained a work permit. In Arkansas, youth can drop out a year early if they attend an adult education program at least ten hours per week. Counties in states that always have an MDA = 16 are kept as "control" counties.

[32] Counties from ten states plus Washington, DC, are dropped from observation under this sample restriction.

[33] Eight out of the top 10 and 40 out of the top 100 most populous counties are in these four states.

[34] It is possible that criminal behavior is merely pent up after an increase in the minimum dropout age and the result is an increase in offending when individuals leave school at a later date. This paper finds no evidence, however, to support this hypothesis. I thank Lan Shi for conversations regarding this point.

[35] Arrow (1997) suggests that youth may also learn important values in school that alter their tastes for crime. For example, schooling may decrease criminal behavior by affecting the psychic costs of breaking the law. Schooling may also generate important social interaction effects. Keeping youth in school longer may promote physical altercations and facilitate the coordination of crime (Jacob & Lefgren, 2003). On the other hand, youth who stay in school may be less likely to form peer groups that promote delinquency.

[36] Again, results for females are available on request.

year-olds are included as control rates because, in principle, the MDA in place when these individuals were three years younger should have no impact on their current offending behavior.

The results shown in table 9 are negative in sign for three of the four specifications, however, none of these estimates are statistically significant at conventional levels. Although imprecisely measured, the coefficient estimate for the violent crime equation is relatively large in magnitude.[37] Taken together, the estimates in this paper indicate that the effects of MDA laws are relatively large at ages where the law binds (16- to 18-year-olds). Though this does not rule out other mechanisms, these results are consistent with the notion that incapacitation effects are important to the relationship between the MDA and juvenile crime.[38] Unfortunately, due to limitations of the data, further interpretation of these results should be made with caution.[39]

F. MDA Laws and Measures of Police Enforcement

A final concern is that increases in the minimum dropout age are made alongside increases in police effort. If police officers exert more effort toward reducing juvenile crime when MDA laws are made more restrictive, then one might incorrectly attribute decreases in crime rates to the MDA policy. To examine this further, observable measures of police enforcement are regressed on MDA law indicators where states with an MDA = 16 serve as the reference category.[40] The dependent variables are annual state-level measures of police expenditures per capita and the number of sworn officers per capita. These data cover the period 1982 to 2005 and come from the Bureau of Justice Statistics.

If effects are spurious due to increased policing, then measures of police enforcement should be positively associated with more restrictive MDA legislation. Table 10 provides no evidence that higher MDA laws coincide with increases in police effort.[41] Estimates in column 2 actually

TABLE 10.—MDA LAWS AND POLICE ENFORCEMENT, 1982–2005

	(1)	(2)
	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	1,152	1,058
R^2	0.971	0.981
State FE	Yes	Yes
Year FE	Yes	Yes
State trends	Yes	Yes

Each column is a separate state-level regression. The dependent variable in column 1 is the number of sworn police officers per capita. The dependent variable in column 3 is police protection expenditures per capita in 2000 dollars. All regression models control for the fraction of the population aged 15 to 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. State populations are used as weights. Standard errors are corrected for clustering at the state level. Significant at *10%, **5%, ***1%.

suggest that police expenditures per capita are lower in states with an MDA = 18. As Lochner and Moretti (2004) point out, 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 MDA laws and not stricter police enforcement.

VI. Do MDA Laws Displace Problems to Schools?

The results provide strong evidence that increasing the minimum dropout age has a negative effect on juvenile arrest rates. Yet it is important to bear in mind that these estimates do not fully consider the potential displacement of delinquency from the streets to schools. If a youth commits a crime within school that is punished by arrest, then this is reflected in the results presented here. 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 decrease in the perception of school safety. Evidence suggests that students who fear victimization at school are more likely to stay home (Pearson & Toby, 1992).

The goal here is to provide a brief treatment along this line of inquiry. This section employs restricted-use state-identified versions of the 1993–2007 National Youth Risk Behavior Surveys (YRBS), which economists have used to study a wide range of topics concerning policy evaluations and youth behavior.[42] The national surveys are conducted every other year by the Centers for Disease Control and Prevention and provide a nationally representative sample

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[37] The sensitivity of these results to alternative control groups was examined. This paper considered 13- to 15-year-olds and 16-to 18-year-olds separately as controls. Estimates where only 16- to 18-year-olds served as controls were always insignificant. When 13- to 15 year-olds were the controls, the violent crime equation returned a negative and statistically significant coefficient estimate on the interaction term of interest. The implied magnitude of this effect was smaller than that for 16- to 18-year-olds in the baseline violent crime specification shown in table 4.

[38] Table A4 in the online appendix shows results for white-collar crimes for 19- to 21-year-olds.

[39] Other results considered specifications for 19- to 21-year-olds with a series of lagged indicators for the timing of policy changes. These estimates provided similar evidence as to the results reported in table 9.

[40] Both regression models control for the fraction of the population aged 15 to 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.

[41] 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.

[42] For other studies that use the YRBS data, see Gruber and Zinman (2001) on trends in youth smoking; Carpenter and Stehr (2008) on the effects of mandatory seatbelt laws on seatbelt use, motor vehicle fatalities, and crash-related injuries; and Anderson (2010) on the effect of an anti-methamphetamine campaign on teen meth use.

TABLE 11.—DO MDA LAWS DISPLACE PROBLEMS TO SCHOOLS? EVIDENCE FROM YRBS DATA

Coefficients on *MDA18*	(1) Everyone	(2) Males	(3) Females
Missed school out of fear for	0.032***	0.019	0.044**
own safety during past month	(0.008)	(0.018)	(0.017)
N	113,727	55,927	57,800
Mean of dependent variable	0.062	0.061	0.063
Had sexual intercourse during	0.025	−0.009	0.061**
past month	(0.016)	(0.040)	(0.025)
N	106,441	51,699	54,742
Mean of dependent variable	0.412	0.419	0.406
Ever been pregnant			0.026
			(0.018)
N			42,303
Mean of dependent variable			0.093

Each cell represents a separate regression. The dependent variable in the top panel is equal to 1 if the respondent missed school out of fear for his or her own safety during the past month, and is equal to 0 otherwise. The dependent variable in the middle panel is equal to 1 if the respondent had sexual intercourse during the past month and is equal to 0 otherwise. The dependent variable in the bottom panel is equal to 1 if the respondent has ever been pregnant and is equal to 0 otherwise. For context, each cell reports the mean rate for individuals in states with an MDA lower than 18. At the individual level, all regression models control for age, grade, and race. All regression models also include state fixed effects, year fixed effects, and state-specific time trends. Standard errors are clustered at the state level. Significant at *10%, **5%, ***1%

of U.S. high school students.[43] The primary purpose of the YRBS is to gather information on youth activities that influence health.[44] The YRBS also asks students questions pertaining to in-school safety. In the top panel of table 11, the dependent variable of interest is a dummy for whether the respondent has missed school in the past month for fear of his or her own safety.

Standard two-way fixed effects models are estimated to gauge the extent to which student responses differ by their state's MDA law.[45] Table 11 illustrates that females in MDA = 18 states are more likely to report missing school for fear of their own safety than females attending schools in MDA = 16 or MDA = 17 states. Not only do these results highlight the potential for negative peer effects due to stricter dropout laws, but they suggest that female students may be more susceptible to these effects than male students. To explore asymmetric effects further, the second panel presents estimates on the relationship between MDA laws and whether the respondent reports having had sexual intercourse during the past month. These results suggest that females attending schools with an MDA = 18 are statistically significantly more likely to report have had recent sex. The bottom panel shows results for teenage pregnancy.

[43] Though intended to be nationally representative, not all fifty states are represented in any given year the survey has been conducted.
[44] See Anderson (2010) for a more thorough discussion of the YRBS data.
[45] More specifically, the following equation is estimated:

$$Y_{ist} = \alpha + \beta_1 MDA18_{st} + X_{ist}\beta_2 + S_s\beta_3 + T_t\beta_4 + Trend_s\beta_5 + \varepsilon_{ist},$$

where *i* indexes the individual, *s* indexes the state, and *t* indexes the year. On the right-hand side, *MDA18* is the same as described above and *X* is a vector of individual-level controls. *S* and *T* represent state and time fixed effects, respectively. *Trend* is a vector of linear state-specific time trends. All regressions are estimated with linear probability models and are weighted by the sample weights provided with the YRBS data. Standard errors are clustered at the state level.

While the coefficient estimate is positive in sign and large in magnitude, it is not statistically significant at conventional levels.[46]

Though intended to be brief, these results emphasize important potential unintended consequences of increases in the minimum dropout age. Future research should explore these issues further. Due to negative peer effects that displaced delinquents might generate, future research will also want to consider the impact that stricter MDA laws might have on the academic outcomes of students who stay in school regardless of the minimum dropout age. This could be important for the short- and long-run outcomes of these individuals.

VII. Conclusion

Juvenile crime in the United States is widespread and a major concern for policymakers. 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 school attendance on juvenile arrest rates by exploiting state-level variation in minimum dropout age laws in the United States.

Using a difference-in-difference-in-difference-type empirical strategy and age-specific county arrest data, this paper finds that minimum dropout age requirements have a significant and negative effect on juvenile crime. Results from the preferred specification suggest that a minimum dropout age of 18 decreases arrest rates among 16- to 18-year-olds by approximately 17%. The negative effect holds and is sizable for property crime, violent crime, and drug crime arrests; however, the estimated effects are usually not statistically significant for drug-related arrests. In addition, the magnitude of the property crime effect is greater for counties with proportionally large African American populations. This indicates that MDA laws may be more relevant for at-risk subsamples of the general population. While other mechanisms cannot necessarily be ruled out, the results are consistent with an incapacitation effect: keeping teenagers in school decreases the time and opportunity available to commit 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 roughly $190 million could be saved annually on the nation's average value of lost property if all

[46] Of course, because these surveys are conducted in school, these estimates could be picking up the fact that females who are kept in school due to stricter dropout laws may be more likely to report staying home for fear of their own safety or having had recent sexual intercourse. To check against these possibilities, the regressions were run on the subsample of females under the age of 16. Under this specification, the estimate for the missing school outcome becomes larger in magnitude and more precisely estimated. On the other hand, the estimate for recent sexual intercourse becomes statistically insignificant.

states were to set an MDA = 18.[47] Though this figure does not reflect the social cost of property crime, it is nevertheless useful in describing the effect of MDA laws. Furthermore, these cost savings likely pale in comparison to potential benefits reaped from more difficult-to-measure variables associated with keeping young people in school. Cohen (1998) estimates that a high school dropout causes roughly $300,000 in external costs during his or her lifetime. To put this number into further perspective, consider that roughly 1.2 million youths drop out of high school every year and that the average public expenditure per pupil enrolled in elementary and secondary schools is approximately $10,000 (Alliance for Excellent Education, 2007; National Center for Education Statistics, 2008). High school graduation incentive programs have been estimated to cost around $12,000 per student (Greenwood et al., 1996).

Despite the benefits, it is important to bear in mind that these estimates do not fully consider the potential displacement of delinquency and other risky behaviors from the streets to schools. As section VI highlights, this is an important area for future research. It is possible that other students bear costs when an increase in the minimum dropout age forces more delinquents to remain in school. Furthermore, it is also important to consider that these laws may have asymmetric effects between male and female students. Policymakers should take these potential consequences into consideration when weighing the costs and benefits associated with an increase in the minimum dropout age. Future research should also evaluate 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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[47] From this paper's analysis, an MDA = 18 is associated with an approximate 10% decrease in property crime arrests for 16- to 18 year-old males. According to the UCR data, this group is responsible for nearly 17% of all male property crimes. Taken together, these estimates imply that if all states had an MDA = 18, property crime arrests for the entire male population would decrease by roughly 1.7%. Given that the FBI estimates the nation's cost of lost physical property due to property crimes to be $17.2 billion per year and that males are arrested for roughly 65% of all property crimes, this implies an annual cost savings of approximately $190 million. This calculation is based on estimates for 2008. Interestingly, this estimate is similar to the cost savings associated with introducing zero-tolerance drunk-driving laws (see Carpenter, 2007).

REFERENCES

Acemoglu, Daron, and Joshua Angrist, "How Large Are Human Capital Externalities? Evidence from Compulsory Schooling Laws" (pp. 9–59), in Ben Bernanke and Kenneth Rogoff, eds., NBER Macroeconomics Annual 2000 (Cambridge, MA: MIT Press, 2001).
Alliance for Excellent Education, The High Cost of High School Dropouts: What the Nation Pays for Inadequate High Schools (Washington, DC: Alliance for Excellent Education, 2007).
Anderson, D. Mark, "Does Information Matter? The Effect of the Meth Project on Meth Use among Youths," Journal of Health Economics 29 (2010), 732–742.
Angrist, Joshua, and Alan Krueger, "Does Compulsory School Attendance Affect Schooling and Earnings?" Quarterly Journal of Economics 106 (1991), 979–1014.
Apel, Robert, Shawn D. Bushway, Raymond Paternoster, Robert Brame, and Gary Sweeten, "Using State Child Labor Laws to Identify the Causal Effect of Youth Employment on Deviant Behavior and Academic Achievement," Journal of Quantitative Criminology 24 (2008), 337–362.
Arrow, Kenneth, "The Benefits of Education and the Formation of Preferences," in Jere Behrman and Nevzer, eds., The Social Benefits of Education (Ann Arbor: University of Michigan Press, 1997).
Arum, Richard, and Irenee R. Beattie, "High School Experience and the Risk of Adult Incarceration," Criminology 37 (1999), 515–540.
Becker, Gary S., "Crime and Punishment: An Economic Approach," Journal of Political Economy 76 (1968), 169–217.
Belfield, Clive, and Henry Levin, "High School Dropouts and the Economic Losses from Juvenile Crime in California," California Dropout Research Project Report 16, University of California–Santa Barbara (2009).
Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How Much Should We Trust Differences-in-Differences Estimates?" Quarterly Journal of Economics 119 (2004), 249–276.
Black, Sandra, Paul Devereux, and Salvanes Kjell, "Staying in the Classroom and out of the Maternity Ward? The Effect of Compulsory Schooling Laws on Teenage Births," Economic Journal 118 (2008), 1025–1054.
Buonanno, Paolo, and Leone Leonida, "Non-Market Effects of Education on Crime: Evidence from Italian Regions," Economics of Education Review 28 (2009), 11–17.
Carpenter, Christopher, "Heavy Alcohol Use and Crime: Evidence from Underage Drunk-Driving Laws," Journal of Law and Economics 50 (2007), 539–557.
Carpenter, Christopher, and Mark Stehr, "The Effects of Mandatory Seatbelt Laws on Seatbelt Use, Motor Vehicle Fatalities, and Crash-Related Injuries among Youths," Journal of Health Economics 27 (2008), 642–662.
Chapman, Chris, Jennifer Laird, Nicole Ifill, and Angelina KewalRamani, "Trends in High School Dropout and Completion Rates in the United States: 1972–2009," Compendium Report (Washington, DC: National Center for Education Statistics, US Department of Education, 2011).
Cohen, Mark, "The Monetary Value of Saving a High-Risk Youth," Journal of Quantitative Criminology 14 (1998), 5–33.
Corman, Hope, and H. Naci Mocan, "A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City," American Economic Review 90 (2000), 584–604.
Dee, Thomas, "The Effects of Minimum Legal Drinking Ages on Teen Childbearing," Journal of Human Resources 36 (2001), 823–838.
Deming, David, "Better Schools, Less Crime?" Quarterly Journal of Economics 126 (2011), 2063–2115.
Fagan, Jeffrey, and Edward Pabon, "Contributions of Delinquency and Substance Use to School Dropout among Inner-City Youths," Youths and Society 21 (1990), 306–354.
Farrington, David, Bernard Gallagher, Lynda Morley, Raymond St. Ledger, and Donald West, "Unemployment, School Leaving and Crime," British Journal of Criminology 26 (1986), 335–356.
Freeman, Richard B., "Why Do So Many Young American Men Commit Crimes and What Might We Do about It?" Journal of Economic Perspectives 10 (1996), 25–42.
French, Michael T., and Johanna C. Maclean, "Underage Alcohol Use, Delinquency, and Criminal Activity," Health Economics 15 (2006), 1261–1281.
Gottfredson, Michael, "Youth Employment, Crime, and Schooling," Developmental Psychology 21 (1985), 419–432.
Gould, Eric, Bruce Weinberg, and David Mustard, "Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997," this REVIEW 84 (2002), 45–61.
Greenwood, Peter, Karyn Model, Peter Rydell, and James Chiesa, Diverting Children from a Life of Crime: Measuring Costs and Benefits (Santa Monica, CA: Rand Corporation, 1996).
Grinols, Earl, and David Mustard, "Casinos, Crime, and Community Costs," this REVIEW 88 (2006), 28–45.
Grogger, Jeffrey, "Local Violence and Educational Attainment," Journal of Human Resources 32 (1997), 659–682.
——— "Market Wages and Youth Crime," Journal of Labor Economics 16 (1998), 756–791.
Gruber, Jonathan, and Jonathan Zinman, "Youth Smoking in the United States: Evidence and Implications," in Jonathan Gruber, ed., Risky

Behavior among Youths: An Economic Analysis (Chicago: University of Chicago Press, 2001).

Hindelang, Michael, "Race and Involvement in Common Law Personal Crimes," *American Sociological Review* 43 (1978), 93–109.

——— "Variations in Sex-Race-Age-Specific Incidence Rates of Offending," *American Sociological Review* 46 (1981), 461–474.

Hjalmarsson, Randi, "Criminal Justice Involvement and High School Completion," *Journal of Urban Economics* 63 (2008), 613–630.

Jacob, Brian A., and Lars Lefgren, "Are Idle Hands the Devil's Workshop? Incapacitation, Concentration, and Juvenile Crime," *American Economic Review* 93 (2003), 1560–1577.

Joyce, Ted, "A Simple Test of Abortion and Crime," this REVIEW 91 (2009), 112–123.

Kline, Patrick, "The Impact of Juvenile Curfew Laws on Arrests of Youth and Adults," *American Law and Economics Review* 14 (2012), 44–67.

Levitt, Steven, "Juvenile Crime and Punishment," *Journal of Political Economy* 106 (1998), 1156–1185.

Levitt, Steven, and John Donahue III. "The Impact of Legalized Abortion on Crime," *Quarterly Journal of Economics* 116 (2001), 379–420.

Li, Mingliang, "High School Completion and Future Youth Unemployment: New Evidence from High School and Beyond," *Journal of Applied Econometrics* 21 (2006), 23–53.

Lleras-Muney, Adriana, "Were Compulsory Attendance and Child Labor Laws Effective? An Analysis from 1915 to 1939," *Journal of Law and Economics* 45 (2002), 401–435.

——— "The Relationship between Education and Adult Mortality in the U.S.," *Review of Economic Studies* 72 (2005), 189–221.

Lochner, Lance, "Education, Work, and Crime: A Human Capital Approach," *International Economic Review* 45 (2004), 811–843.

——— "Education Policy and Crime," NBER working paper 15894 (2010).

Lochner, Lance, and Enrico Moretti, "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports," *American Economic Review* 94 (2004), 155–189.

Luallen, Jeremy, "School's Out . . . Forever: A Study of Juvenile Crime, At-Risk Youths and Teacher Strikes," *Journal of Urban Economics* 59 (2006), 75–103.

Ludwig, Jens, "Concealed-Gun-Carrying Laws and Violent Crime: Evidence from State Panel Data," *International Review of Law and Economics* 18 (1998), 239–254.

Mocan, Naci, and Turan Bali, "Asymmetric Crime Cycles," this REVIEW 92 (2010), 899–911.

National Center for Education Statistics, *Digest of Education Statistics* (Washington, DC: National Center for Education Statistics, 2008).

Oreopoulos, Philip, "The Compelling Effects of Compulsory Schooling: Evidence from Canada," *Canadian Journal of Economics* 39 (2006a): 22–52.

——— "Estimating Average and Local Average Treatment Effects of Education When Compulsory Schooling Laws Really Matter," *American Economic Review* 96 (2006b), 152–175.

——— "Would More Compulsory Schooling Help Disadvantaged Youth? Evidence from Recent Changes to School-Leaving Laws," in Jonathan Gruber, ed., *The Problems of Disadvantaged Youth: An Economic Perspective* (Chicago: University of Chicago Press, 2009).

Pearson, Frank, and Toby Jackson, *Perceived and Actual Risks of School-Related Victimization*, final report to the National Institute of Justice (1992).

Tauchen, Helen, Ann Witte, and Harriet Griesinger, "Criminal Deterrence: Revisiting the Issue with a Birth Cohort," this REVIEW 76 (1994), 399–412.

Thornberry, Terence, Melanie Moore, and R.L. Christenson, "The Effect of Dropping Out of High School on Subsequent Criminal Behavior," *Criminology* 23 (1985), 3–18.

Waldfogel, Joel, "The Effect of Criminal Conviction on Income and the Trust Reposed in the Workmen," *Journal of Human Resources* 29 (1994a), 62–81.

——— "Does Conviction Have a Persistent Effect on Income and Employment?" *International Review of Law and Economics* 14 (1994b), 103–119.

Wenger, Jennie, "Does the Dropout Age Matter? How Mandatory Schooling Laws Impact High School Completion and School Choice," *Public Finance and Management* 2 (2002), 507–534.

Witte, Ann, and Helen Tauchen, "Work and Crime: An Exploration Using Panel Data," *Public Finance* 49: suppl. (1994), 155–167.