Are Young Criminals Rational?

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October 4, 2025

Abstract

We develop a model in which individuals accumulate two types of human capital: legal and crime-specific, both of which grow through learning by doing. Juveniles in their final year before losing juvenile status anticipate higher future costs of crime, giving them an incentive to shift effort toward legal work. The model therefore predicts that individuals on the verge of this transition are more likely to desist from crime even before reaching the age of criminal majority. Using FBI arrestee data, we empirically validate this prediction. Exploiting policy changes in four states that raised the age of criminal majority from 17 to 18, we find causal evidence that juveniles in their final year while legally treated as juveniles commit fewer crimes than comparable age groups.

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1 Introduction

A central policy question in juvenile justice is whether young offenders should be punished as adults or treated with more leniency to emphasize rehabilitation. In the United States, states take different positions on this issue, which can be observed in the setting of the Age of Criminal Majority (ACM). The ACM refers to the minimum age at which an individual is legally treated as an adult for criminal offenses. For instance, if the ACM is set at 17, then after one's 17th birthday, they are no longer considered a juvenile but are treated as an adult when committing a crime. Currently, most U.S. states set the ACM at either 17 or 18, with some states recently raising it from 17 to 18. A number of studies examine how such policy shifts from 17 to 18 affect juvenile crime rates (Arora, 2023; Circo and Scranton, 2020; Hjalmarsson, 2009; Loeffler and Chalfin, 2017; Mueller-Smith et al., 2023).

In Becker's classic framework, individuals commit a crime if the expected benefits outweigh the expected costs (Becker, 1968). Building on this foundation, subsequent studies link crime to human capital mechanisms, showing that education, juvenile justice involvement, and early labor market experiences shape criminal behavior (Aizer and Doyle, 2015; Anderson, 2014; Bayer et al., 2009; Carvalho and Soares, 2016; Deming, 2011; Lochner, 2004; Sviatschi, 2022).

In this study, we distinguish between two types of human capital, legal and crime-specific. Both accumulate through learning by doing and raise future returns. This becomes especially relevant around the age of criminal majority. In the last year as a juvenile, individuals know that the cost of crime will rise once they are treated as adults, which gives them an incentive to invest in legal human capital before the transition.

Next, we validate this explanation using FBI arrestee data. For causal inference, we focus on states that raised the ACM from 17 to 18 and find that juveniles in their final year of being treated as juveniles commit less crime compared to adjacent age groups.

2 Theory

We begin by introducing two types of human capital in our model: crime and legal work. An individual's productive activities include both crime and legal work, and the total time devoted to production in a given year is normalized to 1. If x_t of the time is allocated to crime, then $(1 - x_t)$ is allocated to legal work.

First, we define the following components of the model and discuss how returns from crime are determined:

- x_t: the amount of time the individual invests in crime during year t.
- x_{t-1}: the amount of time the individual invested in crime during the previous year $(t - 1)$.
- p: the probability of being arrested.
- $f(x_{t-1})$: accumulated criminal skills at year t, modeled as a function of past investment x_{t-1}.

Combining these, we assume that the returns from crime in year t are given by

$$v_t \;=\; f(x_{t-1}) \cdot (1 - p) \cdot x_t \tag{1}$$

It is natural to assume that the value of production is a function of the time invested, x_t. However, equal time investments do not necessarily yield the same output, since factors such as technology and skill also play an important role. We capture these factors with $f(x_{t-1})$, where criminal skills and proficiency are modeled as a function of the time x_{t-1} spent in crime in the previous year. This reflects the idea that greater direct participation in crimes enhances one's skills and efficiency.

Of course, it may also be possible to enhance skills through education at schools, but in the case of crime, there are no institutions that teach such skills formally. Thus, one may reasonably assume that direct participation in real-world criminal activities is practically the only way to learn. This is the so-called 'learning by doing,' which we assume to be the only method of acquiring criminal skills.

Another assumption is that current criminal skills depend solely on the time invested in crime during the preceding year. While it is possible that experience from two years ago may also matter, we argue that last year's activity is far more relevant for two main reasons.

First, criminal activities evolve rapidly. New tools and methods appear each year, and once a technique is recognized by the police, they intensify efforts to suppress it. As a result, criminals must continually adapt, making last year's experience more relevant for acquiring the latest skills.

Second, crime is often organized in teams. Even for burglary, where one person could act alone, collaboration typically improves efficiency by allowing participants to divide tasks between scouting targets, breaking in, and selling stolen goods. However, if an individual did not participate last year, they may struggle to rejoin established groups and lose the benefits of teamwork. In practice, this forces them to reconstruct their networks entirely, reducing the value of older experience.

Based on these reasons, we assume that this year's criminal skills, $f(x_{t-1})$, are determined solely by last year's criminal activity, x_{t-1}. We interpret $f(x_{t-1})$ in multiplicative terms. If last year's skills are denoted by a, then this year's level becomes $a \cdot f(x_{t-1})$. By normalizing last year's skills to 1, this year's skills are simply $f(x_{t-1})$. Since learning by doing implies improvement, we assume that for any $x_{t-1} > 0$ it holds that

$$f(x_{t-1}) > 1 \tag{2}$$

The term $(1-p)$ in equation (1) represents the probability of committing a crime without being arrested. The idea is that no benefit is realized if the individual is arrested.

Next, we discuss how the returns from legal work are determined. Recall that $(1 - x_t)$ of total time is allocated to legal work. Using a similar approach to that of criminal production, we assume that the returns from legal work in year t are given by

$$w_t \;=\; \gamma \cdot g(1 - x_{t-1}) \cdot (1 - x_t) \tag{3}$$

Here, $g(1 - x_{t-1})$ indicates that returns from legal work also depend on the skills and knowledge accumulated through past experience. These follow the principle of learning by doing, as they are shaped by participation in legal activities during the previous year. The parameter γ captures the relative skill level of legal work in year $t - 1$ compared to crime, where the skill level of crime in year $t - 1$ is normalized to 1.

To capture the learning effect in legal work, we similarly assume that for $(1 - x_{t-1}) > 0$,

$$g(1 - x_{t-1}) > 1 \tag{4}$$

Combining (1) and (3), the total return in year t from allocating time between crime and legal work is given by

$$\pi_t \;=\; v_t + w_t \;=\; f(x_{t-1}) \cdot (1-p) \cdot x_t \;+\; \gamma \cdot g(1-x_{t-1}) \cdot (1-x_t) \tag{5}$$

In this case, the total value the individual produces over the two periods ($t-1$ and t) is given by

$$\pi_{(t-1,\,t)} \;=\; 1 \cdot x_{t-1} \;+\; \gamma \cdot (1-x_{t-1}) \;+\; f(x_{t-1}) \cdot (1-p) \cdot x_t \;+\; \gamma \cdot g(1-x_{t-1}) \cdot (1-x_t) \tag{6}$$

Note that in year $t-1$ the term $(1-p)$ does not appear, since the individual is assumed to be a juvenile under the age of criminal majority. If the individual is also a juvenile in year t, then $p = 0$ as well and thus $(1-p) = 1$. Therefore, for all terms in year $t-1$, the probability of being arrested is not taken into account.

If an individual rationally allocates time between crime and legal work, the allocation is determined by solving the following maximization problem.

Maximizing $\pi_{(t-1,t)}$ with respect to x_t and x_{t-1} yields the following first-order conditions:

$$\frac{\partial \pi_{(t-1,\,t)}}{\partial x_t} \;=\; f(x_{t-1}) \cdot (1-p) \;-\; \gamma \cdot g(1-x_{t-1}) \tag{7}$$

$$\frac{\partial \pi_{(t-1,\,t)}}{\partial x_{t-1}} \;=\; 1-\gamma \;+\; f'(x_{t-1}) \cdot (1-p) \cdot x_t \;-\; \gamma \cdot g'(1-x_{t-1}) \cdot (1-x_t) \tag{8}$$

Equation (7) does not depend on x_t. Hence, unless it happens to equal zero in special cases, its value will generally be either strictly positive or strictly negative.

First, suppose that committing a crime always lead to arrest, i.e. $p = 1$. Then (7) can be written as:

$$-\gamma \cdot g(1-x_{t-1}) < 0 \tag{9}$$

which is strictly negative. Hence the optimal choice is $x_t = 0$, and the individual does not commit crimes since no benefit can be obtained.

Even if the arrest probability is less than one ($p < 1$), if $\gamma \cdot g(1-x_{t-1})$ is sufficiently large, then (7) will be negative. Again, γ represents the baseline skills and knowledge in legal work in year $t-1$, while $g(1-x_{t-1})$ captures the additional skills accumulated through last year's participation. Thus, a large value of $\gamma \cdot g(1-x_{t-1})$ indicates substantial prior investment in legal work.

In this case, even when $p < 1$, the negative term $-\gamma \cdot g(1 - x_{t-1})$ dominates the positive term $f(x_{t-1})(1-p)$, so that (7) is negative and the optimal choice is $x_t = 0$. This means that even if the individual is still a juvenile under the age of criminal majority at time t (with $p = 0$), they will abstain from crime when skills and knowledge are sufficiently accumulated through legal work.

Thus, an individual will choose $x_t > 0$ (i.e., commit crime) only if two conditions hold simultaneously: (1) the probability of arrest is less than one ($p < 1$), and (2) the individual's legal skills are sufficiently low, with limited expectation of improvement.

Furthermore, since equation (7) does not depend on x_t, the model implies that the optimal choice is always a corner solution: either $x_t = 0$ (no crime) when (7) is negative, or $x_t = 1$ (full-time crime) when (7) is positive. The probability of an interior solution, with $0 < x_t < 1$, is zero.

Now consider equation (8). From equation (7), we know that the individual chooses either $x_t = 0$ or $x_t = 1$. If the individual chooses $x_t = 1$ (allocating all time to crime in year t), then equation (8) can be written as:

$$1 - \gamma \ + \ f'(x_{t-1}) \cdot (1 - p) \tag{10}$$

In (10), the only negative term is $-\gamma$. If the absolute value of $-\gamma$ is sufficiently small so that (10) is positive, then we have

$$\frac{\partial \pi_{(t-1,\, t)}}{\partial x_{t-1}} > 0 \tag{11}$$

which implies $x_{t-1} = 1$. In this case, the individual devotes all time to crime in both year $t - 1$ and year t.

Especially if the individual is still a juvenile under the age of criminal majority in year t, then $(1 - p) = 1$, and (8) can be written as:

$$1 - \gamma + f'(x_{t-1}) \tag{12}$$

which increases the probability that (8) is positive.

On the other hand, suppose the individual in year t allocates all of their time to legal productive activities, i.e. $x_t = 0$. Then equation (8) can be rewritten as

$$1 - \gamma \; - \; \gamma \cdot g'(1 - x_{t-1}) \tag{13}$$

This means that if an individual ceases all criminal activity in year t but still committed a crime in year $t-1$ (so that $x_{t-1} > 0$), then (13) must take a positive value. This occurs only when

$$\gamma + \gamma \cdot g'(1 - x_{t-1}) < 1 \tag{14}$$

In other words, such behavior is possible only if the individual's baseline skill in legal work (γ) is very low and the marginal gain in legal skills from participation in legal work, $g'(1 - x_{t-1})$, is also very small.

In particular, under the assumption that criminal skills in year $t-1$ are normalized to 1, if the level of legal skills γ already exceeds 1, then (13) immediately becomes negative. In this case, the individual will not commit crime at all in year $t-1$.

Therefore, for someone who is certain not to commit crime in year t but nevertheless commits crime in year $t-1$, the condition $\gamma + \gamma \cdot g'(1 - x_{t-1}) < 1$ must hold. This condition can only be satisfied when legal skills and learning ability are significantly weaker than those associated with crime. However, in reality, most individuals do not fall into this category, which explains why the number of law-abiding citizens is much larger than the number of criminals.

If the individual is no longer a juvenile in year t and the police's arrest probability p is sufficiently high, they will not commit crime in that year. Furthermore, if the condition $\gamma + \gamma \cdot g'(1 - x_{t-1}) > 1$ holds, the individual will refrain from committing crime already in year $t-1$, despite still being a juvenile at that time.

However, if the condition $\gamma + \gamma \cdot g'(1 - x_{t-1}) < 1$ holds during their final year as a juvenile, the individual will continue committing crime.

Finally, comparing equation (10) with equation (13), we can observe that (13) always takes a smaller value:

$$1 - \gamma \; - \; \gamma \cdot g'(1 - x_{t-1}) \; < \; 1 - \gamma + f'(x_{t-1}) \cdot (1 - p). \tag{15}$$

Because equation (13) is always smaller and thus more likely to be negative, the scenario with $x_t = 0$ (full legal work in year t) is more likely than the scenario with $x_t = 1$ (full criminal activity, as in equation (10)). It follows that the probability of $x_{t-1} = 0$ (no crime in year $t - 1$) is greater when $x_t = 0$ than when $x_t = 1$.

As shown in equation (7), once the individual is no longer a juvenile in year t, a positive arrest probability ($p > 0$) increases the probability of choosing $x_t = 0$ (full legal work). Equation (15) further shows that when $x_t = 0$ is chosen in year t, the probability of $x_{t-1} = 0$ (no crime in year $t - 1$) is also higher.

Taken together, our model implies that an individual who expects to lose juvenile status in the following year, and therefore anticipates ceasing criminal activity in the future, is more likely to stop committing crime already in the current year, even while still legally treated as a juvenile. This prediction is consistent with the findings from our empirical analysis.

3 Data and descriptive statistics

We use data from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program, which compiles crime statistics reported by local law enforcement agencies through the Summary Reporting System (SRS). The SRS has historically provided the most comprehensive coverage of law enforcement agencies in the United States, and our analysis mainly relies on this source.

The United States has a decentralized law enforcement system that includes various types of agencies, such as the International Association of Chiefs of Police (IACP), the Major Cities Chiefs Association (MCCA), the National Sheriffs' Association (NSA), and the Major County Sheriffs of America (MCSA). Each of these agents has the authority to make arrests, but they differ in their size and the areas they cover. All agencies are encouraged to report the aggregate number of arrestees by age and gender each month. These reports constitute the SRS dataset, which is used in this study.

We use agency-level arrestee data from the Summary Reporting System (SRS) covering 2005–2019. To construct a balanced panel, we restrict the sample to agencies that reported arrests in every month from January 2005 through December 2019. The final sample consists of 710 agencies located in 287 counties across 9 states. Four of these states raised the ACM from 17 to 18 during the sample period (Connecticut, Massachusetts, Mississippi, and New Hampshire), while five maintained an ACM of 18 through 2019 (Georgia, Michigan, Missouri, Texas, and Wisconsin). Table 1 summarizes ACM policies across all 50 states as of 2019, along with relevant institutional details.

Table 2 shows that the number of arrestees increases with age. Among younger cohorts (ages 10–15), the number of male arrestees is roughly twice that of females, whereas in older cohorts men outnumber women by about three to one. Table 3 shows that the age distribution of arrestees is remarkably similar across states, despite differences in population size, overall crime levels, and reporting coverage by agencies.

Figure 1 illustrates the total number of arrests over time, showing both a significant overall decline in crime and clear seasonality in arrest patterns. To address these patterns, we include both year and month fixed effects in the regression analyses.

Finally, Table 4 presents the balance test, showing that the states that raised the age of criminal majority from 17 to 18 and those that kept it at 17 were well balanced in the baseline.

4 Econometric analyses and results

In this section, we use a balanced panel dataset of monthly arrests for each agency, aggregated by age, gender, and offense type. Although a number of studies have examined the effect of changes in the age of criminal majority (ACM) (Arora, 2023; Circo and Scranton, 2020; Hjalmarsson, 2009; Loeffler and Chalfin, 2017; Lovett and Xue, 2025; Mueller-Smith et al., 2023; Oka, 2009), the primary focus of this paper is on the behavior of juveniles in their final year of being treated as minors. However, a simple comparison between states that maintained an ACM of 17 and those that maintained an ACM of 18 cannot be interpreted causally. Therefore, we exploit policy changes in states that raised the ACM from 17 to 18.

We employ two identification strategies. The first is a standard two-way fixed effects (TWFE) model:

$$Y_{it} = \beta \cdot 1\{ACM = 18\}_{it} + \alpha_i + \delta_t + \epsilon_{it}, \tag{16}$$

where Y_{it} denotes the outcome of interest (e.g., the share of arrestees in a given age group) for agency i at time t. The indicator variable $1\{ACM = 18\}_{it}$ equals one if agency i is in a state where the ACM is set to 18 at time t, and zero otherwise. α_i are agency fixed effects, and δ_t are time fixed effects.

For Y_{it}, we use five different variables and interpret them jointly:

$$\frac{\text{10–12 Arrestees}}{\text{10–17 Arrestees}}, \quad \frac{\text{13–14 Arrestees}}{\text{10–17 Arrestees}}, \quad \frac{\text{15 Arrestees}}{\text{10–17 Arrestees}}, \quad \frac{\text{16 Arrestees}}{\text{10–17 Arrestees}}, \quad \frac{\text{17 Arrestees}}{\text{10–17 Arrestees}}.$$

The idea is that by using the proportion as the dependent variable, we can examine whether juveniles who are at the last age of being treated as juveniles commit less crime compared to other teenagers. For example, in the setting where several states increased the ACM from 17 to 18, we can validate our hypothesis by checking whether $\frac{\text{17 Arrestees}}{\text{10–17 Arrestees}}$ has decreased significantly.

This identification strategy has several advantages. First, it can be applied to datasets where reporting rates of agencies differ across states. For example, if we were to use the standard measure of crime rate (criminals per total population) as the dependent variable, the results would not be persuasive when the number of agencies reporting fluctuates across states and over time.

Second, this approach allows us to uncover a new channel that cannot be observed when analyzing crime rates or the absolute number of criminals. Specifically, it enables us to examine how the ACM setting affects juveniles in their final year of juvenile status. While the existing literature has primarily focused on the channel whereby weaker punishment increases crime, our approach makes it possible to directly compare across age groups and capture relative changes. In doing so, we show that juveniles at the threshold of losing juvenile status may commit fewer crimes relative to other teenagers.

Table 5 reports the results. We first construct three separate datasets by offense type: property crimes (robbery, burglary, larceny, forgery, and fraud), violent crimes (assault and manslaughter), and drug-related crimes. We then conduct the same analysis for each dataset separately. The results are straightforward. For property crimes, the proportion of 17-year-olds significantly decreased by 3.2% (relative to a control mean of 35.4%), while the proportions of 15- and 16-year-olds increased by 1.2% and 1.1%, respectively. For violent and drug-related crimes, we find no evidence of such effects.

These results are consistent with our theory. For property crimes, the findings align closely with the predictions of our model. In contrast, for violent and drug-related crimes, we find no significant effects, which also supports our theoretical framework. Our model assumes that individuals rationally decide whether to commit crime by comparing costs and benefits. Thus, the theory applies well to rational decision-making but not to crimes that are impulsive (such as violent offenses) or addictive (such as drug-related offenses).

Moreover, our framework emphasizes that human capital accumulates through learning by doing, which increases the returns to crime. Property crimes fit this mechanism because repeated participation enhances the skills required to steal properties and sell them. Violent and drug-related crimes, however, are less likely to involve skill accumulation through learning by doing, which also explains why we do not observe similar effects in those cases.

Additionally, we estimate an event study specification to examine the dynamic effects of the policy change:

$$Y_{it} = \sum_{\tau=-5}^{6} \beta_\tau \text{ RaiseACM}_i \cdot 1\{t = \tau\} + \alpha_i + \delta_t + \varepsilon_{it}, \tag{17}$$

where Y_{it} denotes the outcome of interest for agency i at time t. RaiseACM_i is an indicator equal to one if agency i is located in a state that raised the ACM from 17 to 18 during 2005–2019, and zero otherwise. The coefficients β_τ capture the dynamic effects of the policy in treated states relative to control states for each event-time period τ, with period -1 serving as the baseline and period 0 denoting the first year of the policy change. For instance, in Connecticut, where the ACM was raised from 17 to 18 starting in July 2012, we define event time 0 as July 2012 through June 2013. As before, α_i are agency fixed effects and δ_t are time fixed effects.

Figure 2 presents the event study results for property crimes, using $\frac{\text{17 Arrestees}}{\text{10–17 Arrestees}}$ as the dependent variable. The estimates show that raising the ACM from 17 to 18 leads to a decline of about 2.5–5%, and this effect becomes slightly stronger over time. We find no heterogeneity by gender.

This result is also consistent with our theoretical framework. If rational juveniles reduce crime relative to other age groups, the downward trend may intensify over time as they come to better understand the new policy and observe how older peers respond. Hence, the event study evidence further supports the predictions of our model.

5 Conclusion

This study develops a theoretical framework in which individuals accumulate two types of human capital, legal work and crime, through learning by doing. Unlike the existing literature that emphasizes how weaker punishment incentives increase crime, our model highlights a new channel: juveniles on the verge of losing their juvenile status may rationally reduce crime in anticipation of higher future costs.

The key implication is that forward-looking behavior can lead to crime reduction even before the legal transition occurs. Using FBI arrest data, we provide empirical evidence consistent with this prediction. This mechanism helps explain why most individuals choose to invest in legal work rather than crime, and shows that changes in the age of criminal majority influence juvenile behavior not only through the severity of punishment but also dynamically through expectations about the future.

6 Figures

Figure 1: Half-season trends of home winning percentage & average attendance, 2009-2024

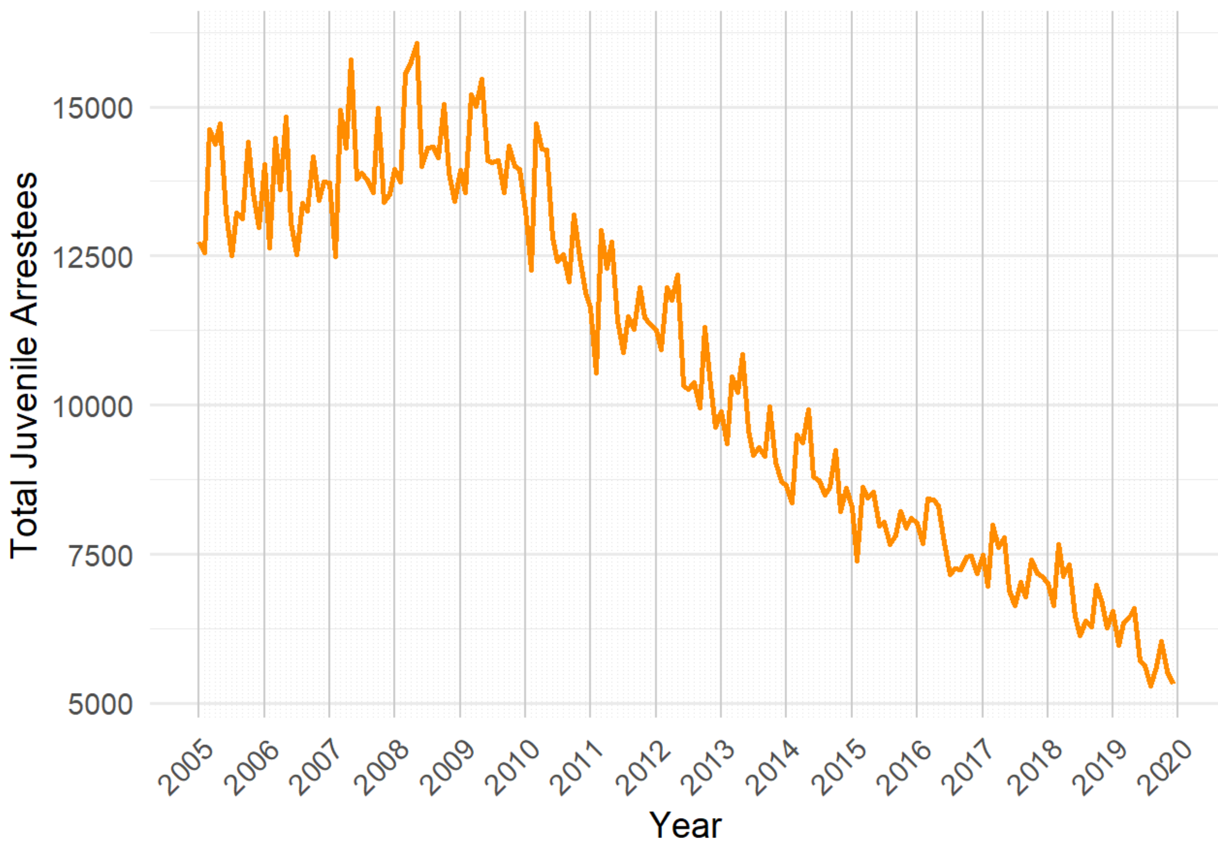
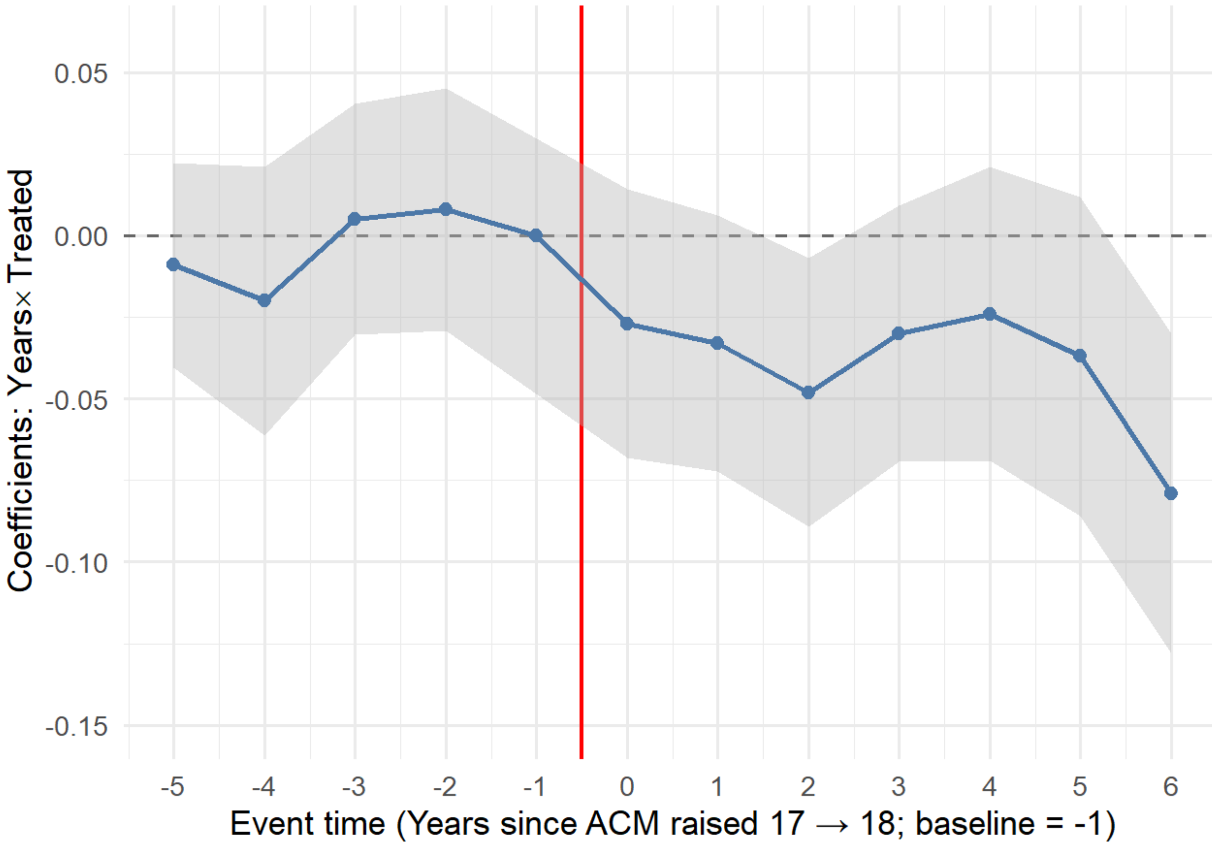


Figure 2: Event Study Estimates of ACM Reform



Notes: This figure presents event study estimates of the ACM reform, along with 95% confidence intervals.

7 Tables

Table 1: Institutional changes in the age of criminal majority (2019)

State	**ACM change (implementation)**
Panel A: Treatment Group	
Connecticut	16 → 17 (2010.07.01); 17 → 18 (2012.07.01)
Massachusetts	17 → 18 (2013.09.18)
New Hampshire	17 → 18 (2015.06.20)
Mississippi	17 → 18 (2011.07.01[1])
Panel B: Control Group	
Missouri	Remained 17
Wisconsin	Remained 17[2]
Georgia	Remained 17
Michigan	Remained 17
Texas	Remained 17
Panel C: Treatment Group, but not used in our analysis	
Alabama	16 → 17 (1975); 17 → 18 (1976)
Illinois	17 → 18 (2010.01.01[3]; 2014.01.01[4])
Louisiana	17 → 18 (2019.03.01[5]; 2020.07.01[6])
New York	16 → 17 (2018.10.01); 17 → 18 (2019.10.01)
North Carolina	16 → 18 (2019.12.01[7])
Rhode Island	18 → 17 (2007.07.01); 17 → 18 (2007.11.07)
South Carolina	17 → 18 (2019.07.01)
Vermont	17 → 18 (2020.07.01); 18 → 19 (2022.07.01)[8]
Wyoming	19 → 18 (1993)
Panel D: Always Treated Group, Not used in our analysis	
Alaska, Arizona, Arkansas, California, Colorado, Delaware, District of Columbia, Florida, Hawaii, Idaho, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Minnesota, Montana, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Dakota, Tennessee, Utah, Virginia, Washington, West Virginia	Remained 18

Notes: The table summarizes institutional changes in the age of criminal majority across ten U.S. states. Dates in the parentheses are statutory implementation dates.

[1]Still 17 for any act which, if committed by an adult, would be punishable by life imprisonment or death.
[2]Set to 18 until 1996; then 17.
[3]For misdemeanors.
[4]For felonies.
[5]For non-violent offenses as defined in R.S. 14:2.
[6]For delinquent acts of violence.
[7]For misdemeanors and low-level felonies.
[8]Act 201 of 2018. Vermont law also allows juvenile jurisdiction through age 21 under youthful offender

Table 2: Summary statistics of key variables.

Variable	**N**	**Mean**	**SD**	**Min**	**Max**
State	9				
County	287				
Law enforcement agency	710				
10–12 Arrestee					
Total	127,800	0.525	1.691	0	44
Male	127,800	0.364	1.232	0	33
Female	127,800	0.161	0.658	0	18
13–14 Arrestee					
Total	127,800	1.833	5.613	0	158
Male	127,800	1.198	3.836	0	111
Female	127,800	0.635	2.060	0	57
15 Arrestee					
Total	127,800	1.636	4.909	0	131
Male	127,800	1.089	3.458	0	97
Female	127,800	0.547	1.735	0	49
16 Arrestee					
Total	127,800	2.077	5.929	0	153
Male	127,800	1.416	4.278	0	110
Female	127,800	0.660	1.960	0	58
17 Arrestee					
Total	127,800	2.712	7.244	0	175
Male	127,800	1.924	5.446	0	132
Female	127,800	0.788	2.147	0	54
18 Arrestee					
Total	127,800	3.163	9.711	0	488
Male	127,800	2.307	7.377	0	358
Female	127,800	0.856	2.621	0	130
19 Arrestee					
Total	127,800	3.044	9.481	0	352
Male	127,800	2.226	7.250	0	269
Female	127,800	0.819	2.489	0	105

provisions.

Table 3: State-level summary statistics by treatment status (counts and percentages, 2005–2019).

State	**Agencies**	**Total Number of Arrestees (2005–2019)**					
		10–12	13–14	15	16	17	18–19
Panel A. ACM raised from 17 to 18							
Connecticut	50	3,639	14,493	14,060	17,456	20,539	48,592
		(3.06%)	(12.20%)	(11.84%)	(14.70%)	(17.29%)	(40.90%)
Massachusetts	80	2,576	11,329	10,773	13,807	17,540	41,677
		(2.64%)	(11.59%)	(11.02%)	(14.13%)	(17.95%)	(42.67%)
Mississippi	7	618	2,257	2,027	2,561	3,330	9,128
		(3.10%)	(11.33%)	(10.17%)	(12.85%)	(16.72%)	(45.83%)
New Hampshire	30	867	3,922	3,599	5,079	6,948	13,430
		(2.56%)	(11.59%)	(10.63%)	(15.01%)	(20.52%)	(39.68%)
Panel B. ACM remained at 18							
Georgia	6	257	1,015	932	1,228	2,863	6,657
		(1.98%)	(7.83%)	(7.20%)	(9.48%)	(22.10%)	(51.41%)
Michigan	161	9,695	34,285	32,772	42,222	61,949	128,865
		(3.13%)	(11.07%)	(10.58%)	(13.63%)	(20.00%)	(41.59%)
Missouri	68	7,976	24,576	20,780	27,602	38,155	73,446
		(4.14%)	(12.76%)	(10.79%)	(14.34%)	(19.82%)	(38.16%)
Texas	235	30,846	108,224	95,100	120,247	155,629	338,565
		(3.64%)	(12.75%)	(11.20%)	(14.17%)	(18.34%)	(39.90%)
Wisconsin	73	10,573	34,194	29,045	35,200	42,961	74,591
		(4.67%)	(15.10%)	(12.82%)	(15.54%)	(18.96%)	(32.91%)

Notes: Each cell reports the total number of arrestees by age group (2005–2019). The second row for each state shows percentages relative to the state total.
"Agencies" refers to the number of distinct law enforcement agencies reporting in each state.

Table 4: Balance Tests: Arrestee Ratios

	(1) Control mean	(2) Difference	(3) t-test p-value	(4) K-S p-value
Property				
$\frac{\textit{10–12 Arrestees}}{\textit{10–17 Arrestees}}$	0.051	0.007	0.749	0.246
$\frac{\textit{13–14 Arrestees}}{\textit{10–17 Arrestees}}$	0.224	-0.008	0.839	0.189
$\frac{\textit{15 Arrestees}}{\textit{10–17 Arrestees}}$	0.182	0.018	0.602	0.502
$\frac{\textit{16 Arrestees}}{\textit{10–17 Arrestees}}$	0.240	-0.000	0.991	0.862
$\frac{\textit{17 Arrestees}}{\textit{10–17 Arrestees}}$	0.303	-0.017	0.674	0.750
Violent				
$\frac{\textit{10–12 Arrestees}}{\textit{10–17 Arrestees}}$	0.075	-0.013	0.495	0.999
$\frac{\textit{13–14 Arrestees}}{\textit{10–17 Arrestees}}$	0.260	-0.059	0.128	0.155
$\frac{\textit{15 Arrestees}}{\textit{10–17 Arrestees}}$	0.176	0.022	0.496	0.192
$\frac{\textit{16 Arrestees}}{\textit{10–17 Arrestees}}$	0.212	0.108**	0.017	0.039**
$\frac{\textit{17 Arrestees}}{\textit{10–17 Arrestees}}$	0.277	-0.058	0.134	0.490
Drug				
$\frac{\textit{10–12 Arrestees}}{\textit{10–17 Arrestees}}$	0.015	-0.009	0.296	1.000
$\frac{\textit{13–14 Arrestees}}{\textit{10–17 Arrestees}}$	0.130	-0.005	0.904	0.999
$\frac{\textit{15 Arrestees}}{\textit{10–17 Arrestees}}$	0.130	-0.023	0.575	1.000
$\frac{\textit{16 Arrestees}}{\textit{10–17 Arrestees}}$	0.240	0.093	0.224	0.403
$\frac{\textit{17 Arrestees}}{\textit{10–17 Arrestees}}$	0.485	-0.055	0.517	0.377

Notes: This table reports the results of the balance test using arrest ratios. The balance test does not include fixed effects when conducting mean difference test using the t-test. The p-values from Kolmogorov–Smirnov test for distribution equality are reported in the column 'KS test p-value'. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

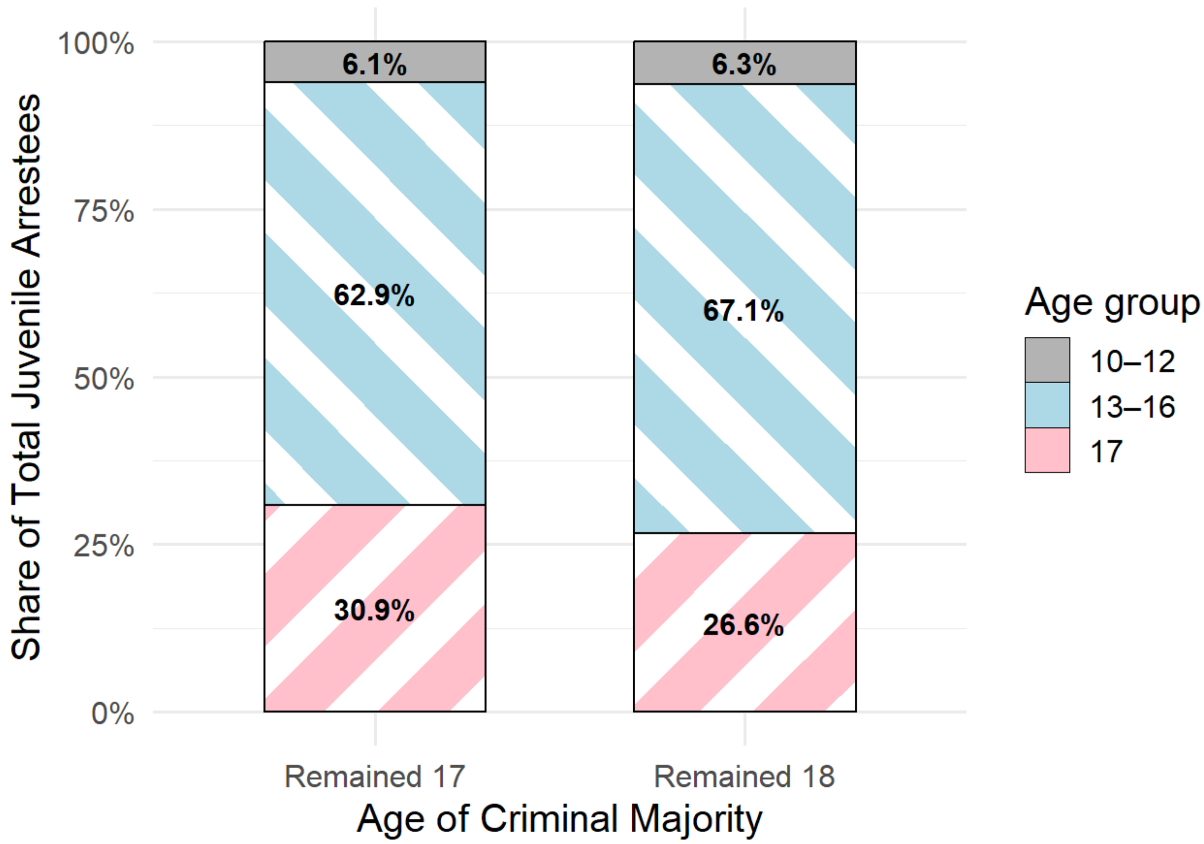
Table 5: Treatment Effects by Age Ratio and Crime Type

	Property (N=42,747)			Violent (N=42,525)			Drug (N=25,550)		
	Total (1)	Male (2)	Female (3)	Total (4)	Male (5)	Female (6)	Total (7)	Male (8)	Female (9)
$\frac{\textit{10–12 Arrestees}}{\textit{10–17 Arrestees}}$	0.000	0.001	-0.001	-0.004	-0.008	-0.012*	-0.001	-0.001	-0.007
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.003)	(0.003)	(0.006)
Control mean	0.047	0.050	0.045	0.087	0.097	0.075	0.014	0.013	0.020
$\frac{\textit{13–14 Arrestees}}{\textit{10–17 Arrestees}}$	0.008	0.002	0.019*	-0.004	-0.011	-0.002	0.004	-0.006	0.054**
	(0.007)	(0.008)	(0.011)	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.025)
Control mean	0.182	0.185	0.182	0.244	0.238	0.267	0.103	0.099	0.138
$\frac{\textit{15 Arrestees}}{\textit{10–17 Arrestees}}$	0.012**	0.011*	0.013	0.005	0.002	0.019**	0.009	0.011	-0.002
	(0.006)	(0.007)	(0.011)	(0.006)	(0.007)	(0.009)	(0.013)	(0.012)	(0.019)
Control mean	0.175	0.178	0.175	0.187	0.181	0.204	0.134	0.133	0.153
$\frac{\textit{16 Arrestees}}{\textit{10–17 Arrestees}}$	0.011*	0.020**	-0.006	0.010	0.015*	0.006	0.017	0.010	0.008
	(0.007)	(0.008)	(0.011)	(0.008)	(0.009)	(0.011)	(0.016)	(0.017)	(0.030)
Control mean	0.241	0.239	0.247	0.215	0.213	0.220	0.240	0.243	0.234
$\frac{\textit{17 Arrestees}}{\textit{10–17 Arrestees}}$	-0.032***	-0.034***	-0.025	-0.007	-0.001	-0.010	-0.029	-0.014	-0.053*
	(0.010)	(0.011)	(0.016)	(0.010)	(0.011)	(0.010)	(0.020)	(0.020)	(0.030)
Control mean	0.354	0.349	0.351	0.266	0.270	0.234	0.509	0.511	0.455

Notes: The table reports treatment effects by crime type. Columns (1)–(3) show Property, (4)–(6) Violent, and (7)–(9) Drug, each split into Total, Male, and Female. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

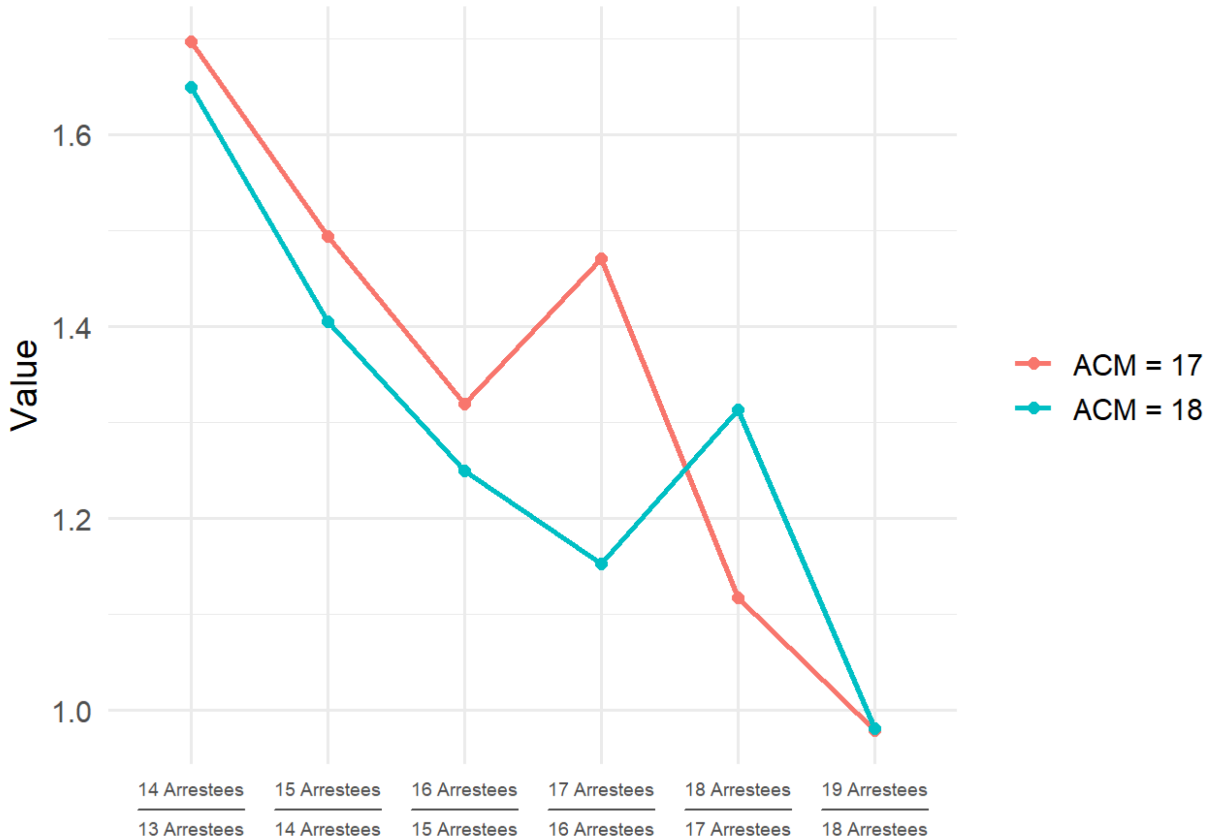
Appendix Figures & Tables

Figure A1: Age distribution of juvenile arrestees: Comparison between states where ACM remained at 17 and states where ACM remained at 18, 2005–2019



Notes: This figure plots the proportion of arrestees by age group among juveniles (ages 10–17). The comparison is between states that kept the ACM at 17 and those that kept it at 18 throughout the 2005–2019 period.

Figure A2: Arrestee Ratios Across Sequential Age Groups



Notes: This figure shows the comparison of arrestee ratios across sequential age groups (14/13 through 19/18), highlighting differences between states with an age of criminal majority (ACM) set at 17 versus 18.

Table A1: Treatment Effects by Age Group and Crime Type

	Property (N=53,100)			Violent (N=55,620)			Drug (N=36,900)		
	Total	Male	Female	Total	Male	Female	Total	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
10 Arrestees	0.315***	0.194***	0.122***	0.071	0.071	-0.000	0.004	0.007	-0.003
	(0.058)	(0.037)	(0.024)	(0.061)	(0.044)	(0.019)	(0.013)	(0.010)	(0.003)
Control mean	0.529	0.347	0.183	0.518	0.364	0.154	0.073	0.057	0.016
13 Arrestees	1.041***	0.600***	0.441***	0.238	0.191	0.047	0.075	0.058	0.018
	(0.201)	(0.125)	(0.091)	(0.193)	(0.131)	(0.065)	(0.093)	(0.078)	(0.017)
Control mean	2.053	1.300	0.753	1.455	0.911	0.545	0.529	0.419	0.111
15 Arrestees	0.841***	0.505***	0.336***	0.150	0.120	0.030	0.123	0.115	0.008
	(0.178)	(0.116)	(0.079)	(0.132)	(0.088)	(0.047)	(0.108)	(0.094)	(0.016)
Control mean	1.913	1.209	0.704	1.055	0.661	0.394	0.656	0.540	0.116
16 Arrestees	1.044***	0.634***	0.410***	0.163	0.147	0.016	0.064	0.085	-0.021
	(0.214)	(0.139)	(0.092)	(0.132)	(0.091)	(0.043)	(0.164)	(0.150)	(0.018)
Control mean	2.434	1.530	0.904	1.136	0.737	0.398	1.039	0.875	0.164
17 Arrestees	1.130***	0.721***	0.408***	0.119	0.127	-0.008	0.142	0.188	-0.046
	(0.243)	(0.165)	(0.095)	(0.137)	(0.097)	(0.042)	(0.271)	(0.245)	(0.030)
Control mean	2.958	1.875	1.083	1.218	0.837	0.381	1.915	1.626	0.288

Notes: The table reports treatment effects by crime type using absolute counts of arrestees. Columns (1)–(3) show Property, (4)–(6) Violent, and (7)–(9) Drug, each split into Total, Male, and Female. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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