Juvenile Crime and Anticipated Punishment[*]

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Abstract

Are juvenile offenders deterred by criminal sanctions? Existing research indicates that they are not, as offending decreases only marginally when individuals cross the age of criminal majority and begin to face harsher, adult-level sanctions. Dynamic models of criminal behavior predict, however, that these small reactions close to the age threshold may mask larger responses away from, or in anticipation of, the age threshold. I use raise-the-age reforms in the United States to show that juvenile crime increases when the age of criminal majority is increased. As predicted by dynamic models of crime, these effects are driven by age groups well below the age of criminal majority. Further, the increase is driven by crime categories that are most likely to be related to street gangs as per the FBI's National Gang Report, consistent with a model of criminal capital accumulation. Alternative mechanisms like peer effects are discussed, but are not supported by the data. In sum, this paper focuses on crime as a dynamic process, and shows that offenders can respond in anticipation of increases in criminal sanctions. Accounting for these anticipatory responses can overturn the conclusion that harsh sanctions do not deter juvenile crime.

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1 Introduction

Recent research in economics and criminology finds that the threat of punitive sanctions does not deter young offenders from engaging in crime (Chalfin & McCrary, 2014). This finding has informed the public policy shift towards increasing rehabilitation efforts and reducing punitive sanctions for younger offenders. This approach is reflected in states across the United States, many of which are increasing the age of criminal majority - the age at which young delinquents are transferred to the adult criminal justice system.

The view that punitive sanctions do not deter young offenders is not supported by qualitative evidence. Young offenders report consciously desisting from criminal activity close to the age of criminal majority, driven by the differences they perceive in the treatment of juvenile and adult criminals (Glassner *et al.* 1983, Hekman *et al.* 1983). Law enforcement officials also voice concerns about the potential for heightened juvenile gang recruitment and violence in response to raising the age of criminal majority.[1] While this divergence may be driven by methodological differences, it may also be explained by two features of the empirical literature. One, adolescent crime is modeled as a series of on-the-spot decisions, with no dependence on previous criminal involvement. Two, if crime is underreported at a higher rate for juveniles (those below the age of criminal majority) than adults, empirical estimates may be picking up the combined effect of changes in sanctions and under-reporting.[2]

This paper tackles each of these issues to provide novel evidence about the deterrent effect of sanctions on juvenile crime. I first formalize a dynamic model in which individuals evaluate the costs and benefits of crime, but also accumulate criminal experience as they commit crime. Each period, returns to crime increase with accumulated criminal experience, and decrease in expected sanctions. When the age of criminal majority (henceforth, ACM) is raised from seventeen to eighteen, this framework predicts that all individuals younger than seventeen should increase criminal activity, not just 17-year-olds. This indicates that we may be able to deal with the issue of under-reporting, since we do not need to rely exclusively on estimates based on 17-year-olds, who now face lower sanctions, but also higher rates of under-reporting.[3]

I present evidence consistent with these predictions using both self-reported data on criminal

[1] For instance, see https://home.chicagopolice.org/community/gang-awareness/ and https://www.dnainfo.com/new-york/20170330/new-york-city/raise-the-age-juvenile-justice-16-17-year-old-charged-adults

[2] Among others, Greenwood (1995), Chalfin & McCrary (2014), Costa *et al.* (2016) and Loeffler & Chalfin (2017) discuss concerns about differential under-reporting for juvenile and adult crimes. The difference is likely driven by the fact that law enforcement officials must meet additional requirements to arrest and hold juveniles in custody.

[3] Focusing on younger age groups has the additional advantage of not being confounded by incapacitation effects. Since juvenile sentences are often shorter than adult sentences, reported increases in 17-year-old crime may be driven by reduced incapacitation, or shorter sentences. This confound does not affect 13-16-year-olds, who face identical sentences after the ACM change.

involvement, and law enforcement data on arrests. As a first litmus test, I use self-reported data to show that criminal involvement is lower among adolescents in states that set the ACM at seventeen, as compared to states that set the ACM at eighteen. The bulk of the analysis, however, uses data on age- and offense- specific arrests to show that the link between higher ACMs and greater criminal involvement is causal.

To identify the impact of the ACM on arrests, I use changes to the ACM across states in the U.S. in a difference-in-difference-in-differences framework.[4] Arrest rates for 13-16-year-olds increase significantly when the ACM is raised from seventeen to eighteen. This increase is driven by offense categories that are most likely to be related to street gangs as per the FBI's National Gang Report, including serious crimes such as homicide, robbery and burglary, indicating that general crime trends are unlikely to explain away the findings.[5] Arrest rates for 17-year-olds do not increase significantly, consistent with previous work. I provide suggestive evidence that this is at least partly due to a simultaneous increase in under-reporting of crime committed by 17-year-olds.

A back-of-the-envelope calculation shows that for every 17-year-old diverted from adult sanctions, jurisdictions bore social costs on the order of $124,000 due to the increase in juvenile (13-16-year-old) offending, as well as the additional costs of incarcerating 17-year-olds in juvenile facilities.[6] While these estimates show that raising the ACM is not costless, these findings should not be taken as an unequivocal rejection of raise the age reforms. Rather, they highlight the need for more research to quantify the benefits of these policies, which are not well understood. For instance, proponents of raising the ACM usually argue that being processed as a juvenile will lower recidivism, which is not supported by recent studies (Entorf 2011, Pichler & Römer 2013, Loeffler & Grunwald 2015). Understanding both the costs and benefits of these policies is of particular relevance today, as states have continued to raise their ACMs, sometimes well above eighteen - Vermont, for instance, has raised the ACM to twenty-one for some offenses, while states like Connecticut, Illinois, and Massachusetts have introduced legislation to do the same.[7]

Before diving into the analysis, I provide evidence that under-reporting of juvenile crime is a significant issue, and may qualify the conclusions of studies that do not take these effects into

[4]The difference-in-difference-in-differences framework compares those who are predicted to be affected by the ACM increase (adolescents close to the ACM) with individuals that are not (those further from the ACM, adults older than 21) across treatment and control states, before and after the ACM change.

[5]The objective of this separation exercise is not to suggest that other crimes cannot react to the ACM change - in fact, they may react strongly if there is enough overlap between "gang" and "non-gang" crimes. Instead, the aim is to test whether the types of crime that fit the framework of criminal capital accumulation actually do respond to the ACM change.

[6]Juvenile incarceration costs more than adult incarceration. For instance, in Connecticut and Massachusetts, two of the treatment states, the cost per inmate in juvenile facilities is three times that in adult facilities (Justice Policy Institute, 2014).

[7]For more details, see https://www.bostonglobe.com/metro/2019/07/09/crime-bill-would-redefine-juveniles-age/maHshbBT6QaaX9ooVDVidN/story.html

account. Using both arrest and offense data, I show that reported crime increases sharply as individuals surpass the ACM, which varies across states within the U.S.[8] I use the National Incident Based Reporting System (NIBRS) data for the years 2006-14 to show that reported crime increases sharply at age seventeen in states that set the ACM at seventeen, while this increase appears at age eighteen in states that set the ACM at eighteen. This pattern shows up irrespective of whether we use arrests made or offenses known to measure criminal activity, and even when we restrict attention to the most serious types of crime. These findings are consistent with local law enforcement officials exercising discretion over whether to report offenses, and are likely driven by the fact that additional requirements must be met to hold juveniles in custody, including a strict 48 hour deadline to file charges.

If juvenile crime is under-reported at higher rates than adult crime, comparing individuals just below the ACM with those just above will pick up the effects of differential sanctions *and* differential rates of under-reporting. Specifically, if the ACM is increased from seventeen to eighteen, 17-year-olds may be less deterred due to the sanction decrease, but we are also less likely to observe any crime they do commit, because of a corresponding decrease in reporting rates (since they are now treated as juveniles, and booking juveniles is more costly for police officers). To get around this issue, this paper proposes an alternative method to estimate deterrence effects - examining responses among cohorts for whom the degree of under-reporting is held fixed.

To identify cohorts that increase criminal activity in response to the change in the ACM, but are not affected by changes in under-reporting, I turn to the theoretical framework. In each period, rational, forward-looking individuals weigh the costs and benefits of crime to maximize lifetime utility. Benefits include both the immediate return to crime and the increase in future return to crime (via the accumulation of criminal capital). This framework is motivated by research which shows that criminal capital increases the return to future offending (Bayer *et al.* 2009, Pyrooz *et al.* 2013, Carvalho & Soares 2016, Sviatschi 2017).[9]

This framework generates two main predictions. First, criminal involvement may decrease as adolescents approach the ACM. This is because the value of criminal capital diminishes considerably once adolescents are treated as adults and face higher criminal sanctions. This decline in the net return to future offending causes criminal activity to decline even before adolescents have reached the ACM.[10] Second, when the ACM is raised from seventeen to eighteen, this framework

[8]This approach is analogous to the strategies employed in Costa *et al.* (2016) and Loeffler & Chalfin (2017).

[9]Juveniles may also lose human capital while incarcerated (Hjalmarsson 2008, Aizer & Doyle 2015), increasing the relative return to criminal capital and perpetuating long-term offending.

[10]Criminologists have hypothesized that offenders may desist from criminal activity as they approach the age of majority (Reid 2011). Abrams (2012) also documents reactions in anticipation of gun-law changes, rationalized by a model of forward-looking behavior in which individuals respond by not making investments related to a criminal career.

predicts that all individuals below eighteen should increase criminal activity, not just 17-year-olds. This is because the value of criminal capital increases for each age group that faces an extended period of low sanctions. This increase in the net return to future offending causes criminal activity to increase among 17-year-olds, as well as individuals younger than seventeen.

In light of these predictions, I turn to the empirical analysis. As a first step, I use the National Longitudinal Survey of Youth (1997-2001) to document self-reported patterns of criminal involvement by age, separating states by their ACM. Cross-sectional variation in the ACM across states is used to provide evidence consistent with the predictions of the model. One, criminal involvement among adolescents is significantly lower in states that set the ACM at seventeen, as compared to those that set it at eighteen. Two, point estimates indicate that criminal involvement is lower at each age, not just seventeen, in states that set the ACM at seventeen instead of eighteen. Third, the decline in criminal involvement starts well below, or well in anticipation of, the ACM. These patterns are consistent with the model, but remain suggestive.

To estimate the causal impact of the ACM on adolescent crime, I use recent changes to the ACM in Connecticut, Massachusetts, New Hampshire and Rhode Island. Estimates are based on a difference-in-difference-in-differences strategy, which leverages variation in the policy across age groups, states and time. I first show that the overall arrest rate for 13-17-year-olds increases when the ACM is raised from seventeen to eighteen. This increase is driven by offenses associated with a medium or high level of street gang involvement.[11] Second, arrest rates increase for each age group under seventeen; the estimate for 17-year-olds, however, does not increase significantly. Next, I examine offense-specific arrest rates, and find that juvenile arrests for drug, homicide, robbery, theft, burglary and vandalism increase by over fifteen per cent of the mean. Arrest rates for offenses that are not associated with street gangs, such as driving under the influence and liquor law violations, do not increase for any of the age groups under eighteen. This indicates that it is not a general increase in juvenile crime that is driving the findings. I show that these results are robust to a number of checks, such as using alternative age groups as controls, accounting for geographical spillovers, and extending the study sample to include all states in the U.S. I also discuss a number of alternative explanations for the results, and argue that mechanisms such as peer effects and contemporaneous juvenile justice reforms are inconsistent with the finer points of the data.

[11] These are identified using the FBI's 2015 National Gang Report, in which agencies identify crimes most commonly associated with street gangs, and include homicide, assault, robbery, theft, vandalism, and drug offenses.

1.1 Related Literature

This paper contributes to the literature on whether sanctions can deter crime in general, and adolescent crime in particular. The evidence on whether harsh sanctions can deter crime is mixed (Nagin 2013, Chalfin & McCrary 2014, O' Flaherty & Sethi 2014). Sentence enhancements and poor prison conditions have been shown to deter adult criminals (Katz *et al.* 2003, Helland & Tabarrok 2007, Drago *et al.* 2009, Abrams 2012, Hansen 2015). Research on young offenders, however, finds mixed results. Some studies leveraging the discontinuity in sanction severity at the ACM fail to find evidence of deterrence (Hjalmarsson 2009a, Costa *et al.* 2016, Lee & McCrary 2017, Loeffler & Chalfin 2017, Damm *et al.* 2017[12]), while others do (Levitt 1998, Oka 2009, Munyo 2015, Lovett & Xue 2018). This paper finds evidence of deterrence and is consistent with the latter set of papers, but is also able to reconcile the two sets of findings. For instance, Loeffler & Chalfin (2017) also study the impact of raising the ACM on juvenile crime; however, cohorts *below* the original ACM are used as the control group. If younger cohorts also respond to the ACM increase, as is shown in the current paper, then this approach would bias their estimates of deterrence towards zero.

More broadly, this paper contributes to research on how individuals account for future events when making decisions. Studies in public finance and labor economics show that individuals react in anticipation of events like the exhaustion of unemployment benefits (Mortensen 1977, Lalive *et al.* 2006), job losses (Hendren 2016), and education access (Khanna 2016). This paper adds to the literature that uses a dynamic approach to study the effect of criminal sanctions (Flinn 1986, O'Flaherty 1998, Imai & Krishna 2004, Mocan *et al.* 2005, McCrary 2010, Munyo 2015). Prior research argues that adolescents' ongoing psychosocial maturation and present-bias would make it unlikely that dynamic deterrence effects on juveniles could be sizable (Steinberg & Scott 2003, Lee & McCrary 2017). The results of this paper, however, indicate that there may be heterogeneity in present-bias among juveniles, and that those who are forward-looking, or less present-biased, respond to the higher ACM by continuing to offend at older ages. Accounting for these anticipatory responses indicates that criminal sanctions can deter juvenile offenders.

The rest of this paper is organized into six sections. Section 2 provides background information on juvenile crime in the U.S., and the criminal justice system's approach to juvenile delinquency since the 1990s. Section 3 describes the datasets used in this paper, and shows that juvenile crime is likely under-reported at higher rates than adult crime. Section 4 lays out a theoretical frame-

[12] Damm *et al.* (2017) study effects at the age of criminal *responsibility*, the age at which individuals are transferred from the social service system to the juvenile justice system; most papers focus on the age of criminal *majority*, the age at which individuals are transferred from the juvenile to the adult criminal justice system. Individuals between the ages of criminal *responsibility* and *majority* in Denmark benefit from a number of sentencing policies and options not available for adults (Kyvsgaard, 2004), which makes the comparison to the US setting inexact.

work in which individuals accumulate criminal capital, and generates predictions on the response to changes in the ACM. Section 5 describes the difference-in-difference-in-differences specification used to estimate the causal impact of the ACM. Section 6 exploits policy variation in the Northeastern states in the U.S. to show causal evidence consistent with the theoretical framework, argues that alternative explanations are unlikely to be consistent with all of the findings, and presents a partial cost-benefit analysis. Section 7 concludes.

2 Setting

This section provides a brief description of juvenile crime trends in the U.S., and policy responses to these trends. Changes to the ACM across the U.S. are described at some length, as they are used to estimate the causal impact of sanctions on juvenile crime in later sections. I then use criminological studies and national gang surveys to identify which offenses are most commonly associated with street gangs, institutions that may provide juveniles with opportunities to build criminal experience in the U.S. Finally, I use data on self-reported criminal involvement to show that juvenile crime is higher in states with higher ACMs, even among age groups below the ACM.

2.1 Juvenile Crime: Trends & Policy Responses

The roots of the juvenile justice system in the U.S. can be traced back to the nineteenth century, when the desire to remove juveniles from overcrowded adult prisons led to the development of separate facilities for juveniles, as well as alternative options like out-of-home placement and probation. The juvenile justice system in the U.S. today also includes a separate system of juvenile courts, where decisions are made by an individual judge instead of a jury. For those facing incarceration, sentence lengths are shorter and living conditions are better in juvenile facilities (Myers 2003, Lee & McCrary 2017). Additionally, it is easier to expunge or seal one's criminal records if the offense was committed as a juvenile (Litwok 2014).

States vary in who they treat as juveniles under their criminal justice systems. The ACM - the lowest age at which offenders are automatically processed as adults in the criminal justice system - has varied considerably across time and space within the U.S.[13] Table A.1 displays a complete list of states and their ACMs in 2019, and whether states have had a different ACM in the past. While the majority of states set the ACM at seventeen or eighteen, the ACM has varied from nineteen in Wyoming in 1993 to sixteen in Connecticut, New York and North Carolina in the 2010s. In the last few years, states have gone further and Vermont raised the ACM to twenty-one for some offenses,

[13]Some states have statutory exclusion laws in place, which allow offenders younger than the ACM to be tried as adults for serious offenses like murder.

while states like Connecticut, Illinois and Massachusetts proposed bills to do the same.[14]

Trends in juvenile crime explain some of the variation in the ACM over time. Figure A.1 plots juvenile and adult arrest rates in the U.S. for the period 1980-2012. Noticing the sharp increase in juvenile arrest rates in the 1990s (a trend that was not mirrored by adult arrest rates) states began to "get tough" on juvenile crime, passing laws that increased the severity of juvenile sanctions. Between 1992 and 1975, all but three states passed legislation easing the transfer of juveniles into the adult system, instituted mandatory minimum sentences for serious offenses, reduced juvenile record confidentiality, increased victim rights or simply raised the ACM (Snyder & Sickmund 2006). As shown in Table A.1, New Hampshire, Wisconsin and Wyoming lowered their ACMs during this period. However, the simultaneous enactment of policy changes in other states makes it unlikely that a difference-in-difference analysis would isolate the causal effect of the ACM on crime. The empirical analysis, therefore, relies on more recent changes in states' ACMs (where the identification assumptions for a difference-in-difference-in-differences design are more likely to be satisfied). These changes are described in detail below.

2.2 ACM Changes in the 2000s

Juvenile crime rates have fallen consistently since the 1990s, generating public support for easing juvenile sanctions and raising the ACM in states that set it below eighteen. ACM changes were also catalyzed by the passage of the 2003 Prison Rape Elimination Act (PREA), a federal law aimed at preventing sexual assault in prison facilities. The PREA went into effect in 2018, and requires offenders under eighteen to be housed separately from adults in correctional facilities, *irrespective* of the state's ACM. Naturally, this requirement is harder to meet in states that incarcerate 16- and 17-year-olds along with older inmates in adult facilities, and most "raise-the-age" reforms have taken place in states with ACMs below eighteen.[15]

Since 2003, ten states have passed legislation to raise their ACM to eighteen.[16] The empirical analysis uses ACM changes in all states during the period covered by the data, 2006-15. The most robust set of estimates, however, are based on six contiguous states in the Northeast - Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont. These states provide an arguably ideal setting in which to study the impact of ACM changes, for two distinct reasons. First, each of these states has introduced legislation to change the ACM since the passage of the PREA, and each has been successful. This lends credibility to the assumption that the actual timing

[14]For more details, see https://www.bostonglobe.com/metro/2019/07/09/crime-bill-would-redefine-juveniles-age/maHshbBT6QaaX9ooVDVidN/story.html

[15]A state's ACM is usually an artifact of the time period in which it established its juvenile justice system. For instance, New York set its ACM at sixteen in 1909, while other states settled upon higher ACMs over the ensuing decades.

[16]These are listed in Table A.1.

of legislation passage was unrelated to local crime trends. Second, their geographical proximity makes it likely that unobserved factors evolved similarly across the states. Therefore, most of the empirical analysis is based on estimates from this subsample.

2.3 Street Gangs in the U.S. & Gang-Related Crime

This section uses criminological studies and national gang surveys to characterize adolescent involvement in street gangs in the U.S. Crimes most likely to be related to street gangs are examined separately in the empirical analysis. The objective of this separation exercise is not to suggest that other crimes cannot react to the ACM change - in fact, they may react strongly if there is enough overlap between "gang" and "non-gang" crimes. Instead, the aim is to test whether the types of crime that fit the framework of criminal capital accumulation actually do respond to the ACM change.

Gangs[17] are a growing problem in the United States. Following a steady decline until the early 2000s, annual estimates of gang prevalence and gang-related violent, property and drug crimes have steadily increased (Egley *et al.* 2010, National Gang Center 2012).[18] Street gangs are central to the discussion of juvenile crime for two reasons. One, a large proportion of gang members are juveniles - the 2011 National Youth Gang Survey estimates that over a third of all gang members are under the age of eighteen, and Pyrooz & Sweeten (2015) estimate that there are currently over a million juvenile gang members in the U.S. Two, gang members contribute disproportionately to overall crime, particularly to violent adolescent crime. For instance, Fagan (1990) and Thornberry (1998) documented that while gang membership ranged from 14 to 30 per cent across six cities - Rochester, Seattle, Denver, San Diego, Los Angeles and Chicago - gang members contributed to at least 60 percent of drug dealing offenses and 60 percent of general delinquency and serious violence.[19]

Which crimes are most commonly associated with street gangs in the U.S.? Past work has shown that gang members are not crime specialists (Fagan 1990, Thornberry 1998, Klein & L. Maxson 2010, National Gang Center 2012). This finding is confirmed by the FBI's 2015 National Gang Report, which collected information from law enforcement agencies about the degree of street gang involvement in various criminal activities.[20] I define gang-related offenses as those for which street

[17]The FBI National Crime Information Center defines a gang as three or more persons that associate for the purpose of criminal or illegal activity.

[18]Also see https://www.usnews.com/news/articles/2015/03/06/gang-violence-is-on-the-rise-even-as-overall-violence-declines

[19]Crime definitions varied by city. Recent research has also shown that this heightened delinquency cannot simply be attributed to individual selection effects (Barnes *et al.* 2010), and is likely to be associated with gang affiliation itself.

[20]The survey question asked respondents to indicate whether gang involvement in various criminal activities in their jurisdiction was High, Moderate, Low, Unknown or None.

gang involvement is reported as moderate or high in this report. These include eleven offense categories - homicide, robbery, assault, burglary, theft (including motor vehicle theft), stolen property offenses, forgery and fraud, vandalism, weapon law violations and drug offenses.[21]

The empirical analysis also examines responses among offense categories with at most a low level of street gang involvement - arson, embezzlement, gambling, offenses against the family and children, driving under the influence and liquor laws, disorderly conduct (including drunkenness), and suspicion (including vagrancy and loitering).[22] The absence of an increase in these "non-gang" crimes is used to support the hypothesis that general crime trends are not driving the deterrence results.

TABLE 1. SELF-REPORTED CRIMINAL INVOLVEMENT

	All Age Groups	Age $\leq$ 21	Age > 21
1(Age of Criminal Majority=18)	0.010*** (0.003)	0.013*** (0.005)	0.003 (0.003)
Female	-0.070*** (0.003)	-0.103*** (0.005)	-0.028*** (0.003)
Black	0.0003 (0.004)	0.0004 (0.006)	0.004 (0.003)
Hispanic	-0.005 (0.005)	-0.008 (0.007)	-0.003 (0.004)
Constant	0.135*** (0.004)	0.207*** (0.006)	0.047*** (0.004)
Mean	0.105	0.163	0.032
Observations	95,952	53,457	42,495
Clusters	8,220	8,062	7,587

Notes: This table displays results from an OLS regression of self-reported criminal involvement on the age of criminal majority. Data comes from the 1997 National Longitudinal Survey of Youth, and includes individuals in states that set the ACM at seventeen or eighteen. Standard errors are clustered at the individual level. * p < 0.1, ** p < 0.05, *** p < 0.01.

[21]This crime pattern is broadly corroborated by Klein & L. Maxson (2010).

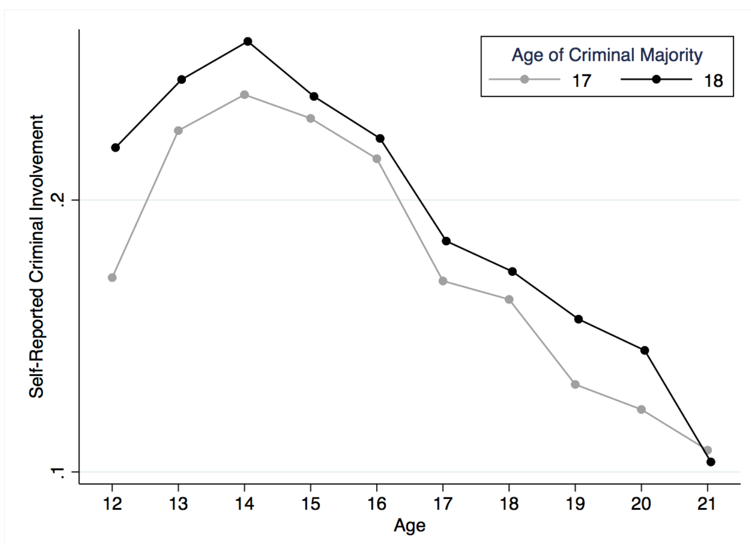
[22]I exclude from the empirical analysis the following offense categories - sex offenses, since the UCR definition of offenses classified as rape changed in 2013; runaways, a status offense which only applies to juveniles and would be expected to mechanically increase when 17-year-olds are treated as juveniles; uncategorized crimes, due to the lack of interpretability for these results. These three categories account for around 27% of total arrests.

2.4 Self-Reported Criminal Involvement

In order to motivate the theoretical framework and empirical analysis that follows, I examine patterns of criminal involvement by age using self-reported panel data. Data comes from the National Longitudinal Survey of Youth, described in more detail in Section 3. Starting in 1997, around 9,000 youths were asked about criminal involvement (property, drug, assault and theft offenses) in the twelve months preceding an annual interview. I use these self-reports to examine (1) whether criminal involvement is lower in states that set the ACM at seventeen instead of eighteen and (2) whether criminal involvement is lower even before individuals reach the ACM.

Table 1 reports results from a regression of criminal involvement on an indicator for whether the ACM is eighteen, controlling for the individual's sex and race. Since the regression uses a panel dataset that tracks the same individuals over time, standard errors are clustered at the individual level. Individuals in states that set the ACM at eighteen are one percentage point more likely to have committed a crime within the last twelve months, a 9.5 per cent increase relative to the mean. Separating the sample into adolescent (age 21 and below) and older (ages 22 and above) individuals, we see that this relationship is driven by heightened criminal involvement among adolescents, while there is no statistically significant difference for adults across the two groups of states.

FIGURE 1. SELF-REPORTED CRIMINAL INVOLVEMENT



Notes: This graph displays results from OLS regressions of self-reported criminal involvement on age fixed effects, separating states by their age of criminal majority; the black line displays coefficients for states that set the ACM at eighteen, and the grey line displays coefficients for states that set the age at seventeen. Data comes from the 1997 National Longitudinal Survey of Youth.

Figure 1 examines whether this relationship between criminal involvement and the ACM begins even before individuals have reached the ACM. The grey line displays coefficients from a regression of criminal involvement on age fixed effects for states that set the ACM at seventeen, while the black line displays the analogous relationship for individuals in states that set the ACM at eighteen. Irrespective of the ACM, there is a clear upward trend until fourteen, and a steady decline thereafter. The most notable feature of this graph, however, is that the coefficients are higher at *all* ages in states that set the ACM at eighteen. In Section 4, I show that this pattern is consistent with a model in which individuals are forward looking, who may respond rationally to the anticipated increase in sanctions at the ACM by lowering criminal activity at younger ages. The empirical analysis then proceeds to show that this relationship is causal - raising the ACM leads to an immediate increase in criminal activity at all ages below the ACM, and a delayed increase in criminal activity by age groups above the ACM.

3 Data and Under-Reporting

This section describes the data sets used in the empirical analysis, and presents evidence that crimes by those below the ACM are more likely to go unreported than crimes by those above. Accounting for this variation in reporting is one of the key contributions of this paper.

3.1 Data Sources

Local law enforcement agencies in the U.S. report crime statistics to federal agencies through the Uniform Crime Reports (UCR) or the National Incident Based Reporting System (NIBRS). The UCR covers more law enforcement agencies in the U.S., while the NIBRS presents a more detailed picture of crime within the agencies that it covers. The empirical analysis uses both of these data sources.

The UCR arrest data contain monthly counts of criminal activity within an agency's jurisdiction, with subtotals by arrestee age and sex under each offense category. As of 2015, law enforcement agencies representing over ninety per cent of the U.S. population submitted their crime data via the UCR. The main estimates in this paper are based on a balanced sample of agencies reporting crime via the UCR for the period 2006-15.

The NIBRS collects detailed information on each crime occurrence known to the police, and generates data as a by-product of automated records management systems. Importantly, offender profiles are generated independent of arrest using victim and witness statements. This allows us to examine separately whether reporting behavior, not just arrest behavior, is influenced by the age of the offender. As of 2012, law enforcement agencies representing twenty eight per cent of the population submitted their crime data via the NIBRS.

Finally, I use self-reported data to complement law enforcement reports on criminal activity. Self-reported data comes from the National Longitudinal Survey of Youth 1997 (NLSY97), a nationally representative sample of approximately 9,000 youths who were twelve to sixteen years old as of December 31, 1996. This dataset includes self-reports on criminal involvement (property, drug, assault and theft offenses) in the twelve months preceding the survey, starting in the year 1997. I use these responses as representative of the age at which the respondent spent the majority of the previous twelve months, and create age profiles for criminal involvement, separating states by their ACM in Section 2.4.

3.2 Juvenile Crime Data: Evidence of Under-Reporting

Criminal activity is not directly observable, so researchers usually rely on proxies like arrest and offense data generated by local law enforcement agencies. A shared concern of papers that use such data is that many steps lie between the criminal offense and the generation of an official report (Costa *et al.* 2016, Loeffler & Chalfin 2017).[23] Official data cannot reflect, for instance, the amount of crime which is not reported to the police, or crime that goes unrecorded due to the discretionary practices of individual officers.[24]

This issue is particularly salient for research on the effects of age-based criminal sanctions. This is because offense and arrest reports are *more* likely to be generated if offenders are treated as adults by the criminal justice system.[25] Law enforcement officials must comply with additional supervisory requirements while juveniles are held in custody - unlike adults, juveniles cannot be dropped off at the local or county jail. Furthermore, juveniles can only be detained for 48 hours while charges are filed in juvenile court. These additional costs make it less likely that juvenile offenders are officially arrested or charged, and therefore, less likely to have their offenses included in official crime statistics. This is problematic for studies that compare individuals on either side of the ACM, because crime is reported at higher rates for individuals that face *lower* incentives to commit crime (individuals above the ACM). If the drop in crime committed is offset by the increased probability of a crime being reported, we may find small or null deterrence estimates. The latter effect may even dominate the former, leading to a *rise* in reported crime exactly when the incentives to commit crime decrease, as in Costa *et al.* (2016). Similarly, Loeffler & Chalfin (2017) show that arrests dip sharply for 16-year-olds in Connecticut, coincident with the first year in which they are transitioned from the adult to the juvenile justice system.

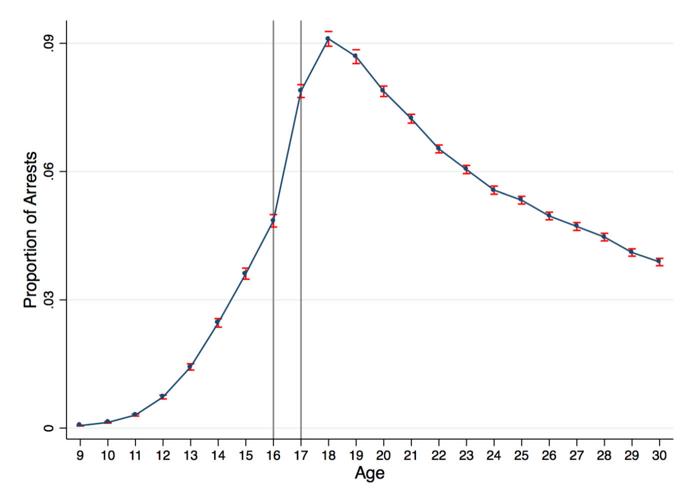
[23]How crime statistics are generated is also a long-standing concern in criminology - see Black (1970), Black (1971) and Smith & Visher (1981).

[24]The National Crime Victimization Surveys from 2006-10 reported that less than half of all violent victimizations are reported to the police. Moreover, crimes against victims in the age group 12 to 17 were most likely to go unreported.

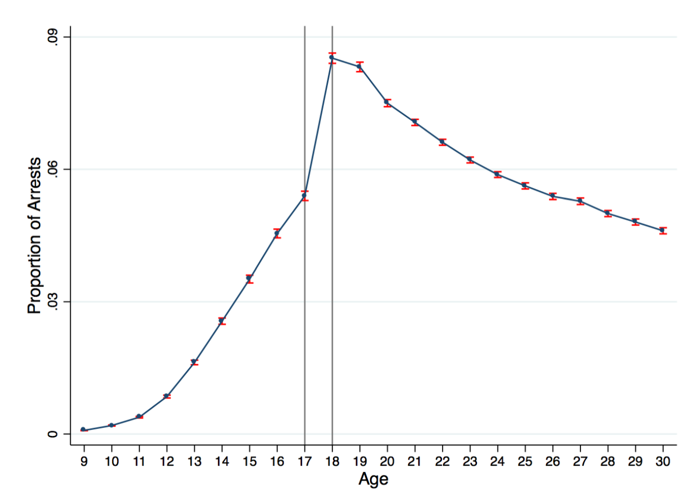
[25]For additional discussion, see Loeffler & Grunwald (2015) and Loeffler & Chalfin (2017).

FIGURE 2. CRIME REPORTING INCREASES AT AGE OF CRIMINAL MAJORITY

(A) AGE OF CRIMINAL MAJORITY = 17



(B) AGE OF CRIMINAL MAJORITY = 18



Notes: This graph uses monthly NIBRS arrest data at the law enforcement agency level for 2006-14. Standard errors are clustered at the agency level, and 95% confidence intervals are marked in red. Figures A.2 and A.3 present analogous results for offenses known to the police and arrests for gang-related crimes respectively.

I use an analogous argument to show that under-reporting falls at the ACM across the U.S. Reported crime increases sharply at age seventeen in states that set the ACM at seventeen, while this increase appears at age eighteen in states that set the ACM at eighteen. Using monthly data at the law enforcement agency level for the years 2006-14, Panel A of Figure 2 displays the proportion of arrests attributable to each age group in states that set the ACM at seventeen. Panel B repeats this exercise for states that set the ACM at eighteen. The spike in recorded crime is striking as we transition from the age just before the threshold (sixteen or seventeen) to the age where individuals are treated as adults by the criminal justice system (seventeen or eighteen). This indicates that under-reporting falls as individuals cross the ACM. Existing research that compare juveniles with adults is, therefore, likely to be reporting an estimate of deterrence that is adulterated by the effect of reduced under-reporting.

What are possible workarounds to get at true measures of deterrence? One way to circumvent this issue is to use data that is less likely to be under-reported. For instance, Costa *et al.* (2016) study violent death rates around the ACM in Brazil as a proxy for involvement in violent crime, as death rates are more likely to be accurately measured than police reports. They also highlight the main drawback of this measure - violent death rates may not be reflective of trends in other types of crime. In a similar vein, some studies on crime in the U.S. use data on offenses known to the police instead of arrests (Loeffler & Chalfin 2017, Abrams 2012), since the latter are more likely to be affected by police officer behavior. However, the age-crime profiles with spikes at the ACM are true irrespective of whether we use arrests or offenses. Figure A.2 recreates the age-crime profile, using the proportion of offenses attributable to each age group instead of arrests. There is a clear spike in the proportion of offenses attributable to 18-year-olds in states that set the ACM at eighteen, but not in states that set the ACM at seventeen. This indicates that data on offenses, not just arrests, by those below the ACM may suffer from under-reporting as well.[26]

This paper proposes an alternative method to estimate deterrence effects - examining responses among cohorts for whom the degree of under-reporting is held fixed. I test for responses to increases in the ACM among individuals who are always treated as juveniles, i.e. those to the left of the former ACM. Since these age groups are treated as juveniles both before and after the ACM change, the degree of under-reporting for these groups should be unchanged. If adolescents to the left of the threshold increase criminal activity when the ACM is moved further away from them, and the degree of under-reporting is unchanged, reported crime should increase as well. This response allows us to measure deterrence, since juveniles are responding to lower sanctions in the future by increasing offending in the current period, and under-reporting is less likely to dilute the estimates.

4 Theoretical Framework

This section presents a model of criminal behavior in which current criminal activity increases the return to future criminal offending, and individuals are aware of the increase in sanctions at the ACM. This framework isolates a deterrence response by identifying cohorts that increase

[26] Figure A.3 recreates the age-crime profile, using the proportion of gang-related crime arrests attributable to each age group. There continues to be a spike in the proportion attributable to 17-year-olds in states that set the ACM at seventeen, and a spike for 18-year-olds in states that set the ACM at eighteen.

criminal activity in response to the change in the ACM, and then pinpoints cohorts for which under-reporting confounds are unlikely to be an issue.

In Becker (1968)'s seminal framework, individuals commit crime if the benefits of criminal activity outweigh the costs. Motivated by recent empirical research[27] this model is extended to allow individuals to accumulate criminal experience, and thereby increase the return to future criminal activity.[28] The key insight of this approach is that crime may be undertaken for its immediate benefits, as well as longer-term benefits. This in turn predicts that crime may be deterred by lowering the long-term return to criminal offending. The remainder of this section is devoted to the intuition behind each of these predictions, while specifics of the theoretical framework are relegated to Appendix A.3.

4.1 Criminal Activity Under Anticipated Adult Sanctions

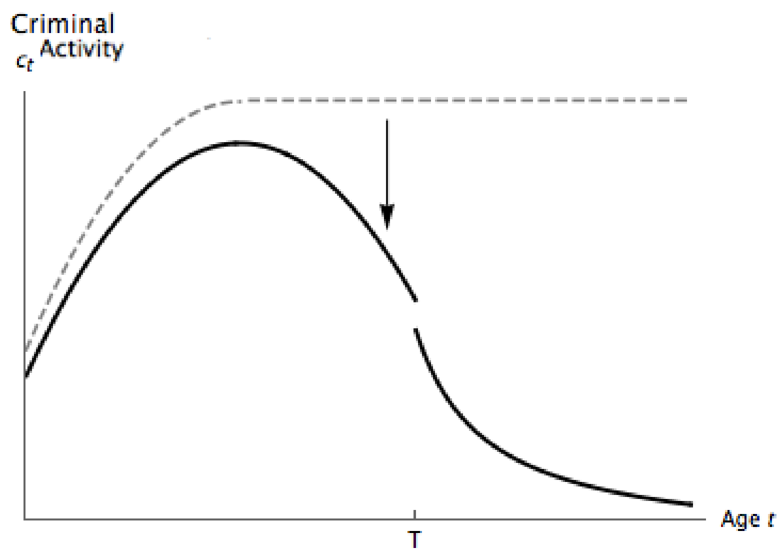
As in prior work, dynamic incentives generate clear predictions about the effects of sanctions on criminal activity (Imai & Krishna 2004, Mocan *et al.* 2005, Munyo 2015). These predictions are summarized by Figure 3. As a benchmark, the dashed lines represent the optimal level of crime c at each age t if sanctions were *not* to increase at the ACM T. Under this benchmark scenario, criminal activity continues to increase until the steady level level of criminal experience is reached, and is sustained thereafter.

The anticipation of adult sanctions beginning at age T, however, generates alternative predictions. These predictions are summarized by the (undashed) black line in Figure 3. At the beginning of adolescence, adult sanctions entail only small deterrence effects. As individuals approach the ACM T, however, adult sanctions begin to generate larger deterrence effects on crime. This is because the older the age (closer to T) at which an individual commits crime, the shorter the duration for which they can benefit from its returns as a juvenile. This lowers the lifetime return to investing in criminal capital, and lowers criminal activity even *before* an individual has reached the ACM. Finally, the increase in sanctions at T will lower the immediate return to criminal activity, leading to a discontinuous decrease criminal activity at age T. The main takeaway from this Figure is that the increase in sanctions should lead to a decrease in crime at the ACM, but it also leads to a decrease in crime *before* individuals have reached the ACM. It is this anticipatory response that the

[27] Pyrooz *et al.* (2013) and Carvalho & Soares (2016) show that embeddedness and wages in gangs increase with participation in gang-related crime. Also see Levitt & Venkatesh (2000) who find that gang members are motivated by the symbolic value attached to upward mobility in drug gangs, as well as the tournament for future riches. Criminal experience may also reduce the probability of being caught and thereby increase the net benefit of future crime.

[28] This is similar to Mocan *et al.* (2005) and Munyo (2015) wherein both work- and crime-specific human capital evolve with past choices. Also related are Lee & McCrary (2017), who use a dynamic extension of Becker (1968) and the static model of time allocation by Grogger (1998) in which individuals allocate time between leisure, formal work and criminal activity. However, the return to crime is assumed to be independent of previous criminal involvement in both of these studies.

FIGURE 3. CRIMINAL ACTIVITY UNDER ANTICIPATED ADULT SANCTIONS



Notes: This figure summarizes the qualitative predictions of the model. The dashed line displays crime c at each age t if sanctions were not to increase at the age of criminal majority T. The undashed line shows that when sanctions increase at the age of criminal majority T, crime c_t is predicted to decrease discontinuously at T, but is also lower **prior** to age T.

empirical analysis in Section 6 attempts to capture.

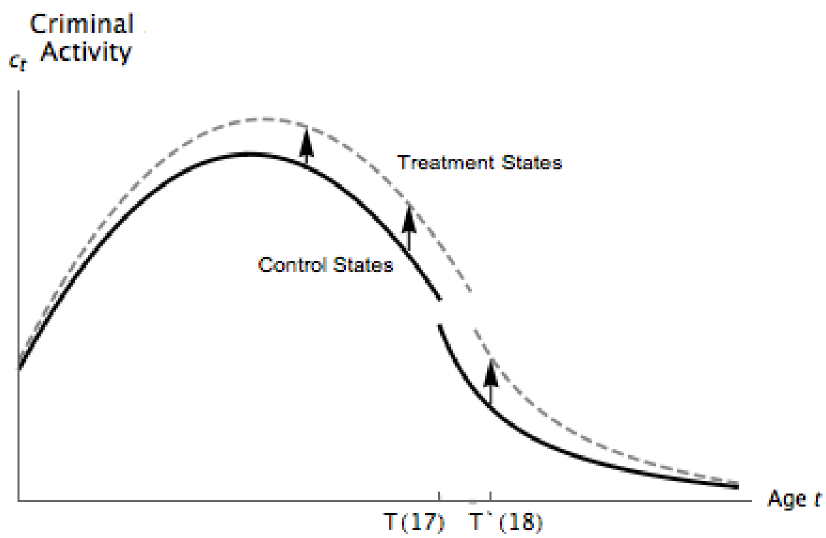
4.2 Increasing the Age of Criminal Majority

This section describes the model's predictions in response to an increase in the ACM from T to T', summarized by Figure 4. The model predicts that three groups should increase criminal activity - age groups below T, age groups between T and T', and age groups above T'. In Figure 4, T and T' are are marked as the age thresholds 17 and 18 in parentheses, in reference to the empirical analysis in Section 6, which estimates the impact of raising the ACM from seventeen to eighteen.

The first group to benefit from the ACM increase is individuals below the original threshold T. When the ACM is increased, individuals younger than T will face lower, juvenile-level sanctions for an additional year. This increases the lifetime return to committing crime and gaining criminal experience. In response, individuals below the age of T are predicted to increase criminal activity, and accumulate additional criminal experience. Moreover, this response is unlikely to be offset by changes in reporting behavior because those below T are treated as juveniles both before and after the policy change. Any increase in criminal activity by this group can, therefore, be interpreted as a clean measure of the effect of sanctions on crime.

The second set of beneficiaries are those aged between T and T'. This group was subject to higher, adult level sanctions before the policy change, but is subject to lower, juvenile level sanc-

FIGURE 4. CRIMINAL ACTIVITY UNDER DELAYED ADULT SANCTIONS



Notes: This figure summarizes the qualitative predictions of raising the age of criminal majority (ACM) from T to T'. The undashed line displays crime c at each age t if the ACM was was T, and the dashed line displays the analogous relationship if the ACM was set at a higher age T'. T and T' are marked as the age thresholds 17 and 18 in parentheses, in reference to the empirical analysis, which estimates the impact of raising the ACM from seventeen to eighteen.

tions after the policy change, at least until they reach age T'. This causes an increase in criminal activity through two separate channels - first, the immediate return to criminal activity is higher, because expected sanctions if caught in the current period are lowered; second, the lifetime return to committing crime is higher, since individuals can benefit from criminal experience as juveniles for up to a year. However, this group is also subject to a simultaneous increase in under-reporting since they were treated as adults previously, but are now treated as juveniles by the criminal justice system. Therefore, we may not observe an increase in official crime statistics for age groups between T and T', even if the decrease in sanctions leads to an increase in criminal activity.

Finally, an ACM increase from T to T' will also lead to a delayed increase in criminal activity at age T' and above. This increase will be driven by individuals entering age T' with higher levels of criminal experience than under the ACM T. This will raise the return to committing crime in the current period, which in turn is predicted to increase criminal activity for those aged T' and above. Since these age group are treated as adults both before and after the ACM change, this response is unlikely to be offset by changes in reporting behavior, and we should observe an increase in reported crime. This is another clean measure of the effect of sanctions on crime.[29]

[29] Increases in criminal activity by age groups other than those between T and T' may also be consistent with alternative explanations such as peer effects, which are discussed but argued against in Section 6.6.

5 Empirical Strategy

This section describes the difference-in-difference-in-differences (DDD) framework used to identify the impact of the ACM on adolescent offending. I also describe an event study specification, which is used to examine year-by-year effects of the ACM change, and rule out differential pre-trends.

Throughout this section, I refer to the group of states that raised the ACM during the study period 2006-15 as the treatment states, and the group with no such change as the control states. The DDD technique compares those who are predicted to be affected by the ACM increase (adolescents, aged 21 and below) with individuals that are not (older adults, aged 22 and above) across the two groups of states, before and after the ACM change. Examining effects on age groups below and above seventeen (the original ACM) allows us to test all of the model's predictions about the impact of the policy change. The DDD estimate relies on the assumption that in the absence of the ACM change, the difference in outcomes between adolescent ($\leq$ 21) and older adult ($\geq$ 22) cohorts in treatment states after the ACM change would have evolved similarly to the difference in outcomes between these cohorts in control states before the ACM change went into effect.

Central Specification

Table A.1 specifies when the ACM was modified in each of the treatment states. This information is used to estimate the following equation:

$$C_{alst} = \beta_0 + \beta_1 ADOL_a * TREAT_s * POST_{st} + \gamma_{as} + \gamma_{st} + \gamma_{at} + \varepsilon_{alst}$$

C_{alst} is a measure of the crime rate among age group a in location l in state s in month t. As a measure of the crime rate, I use the number of arrestees aged a per 100,000 residents in location l. Age-state interactions γ_{as} allow for permanent differences across age groups in different states. Age-time interactions γ_{at} control flexibly for national trends that may affect one age group more than another. State-time interactions γ_{st} control flexibly for factors changing at the state-time level that could affect the outcomes of interest.

The coefficient of interest is β_1, the DDD estimate of the effect of an ACM increase on adolescent offending. $ADOL_a$ is an indicator variable that equals one for age groups 21 and under. This allows us to capture the ACM's effects not just on 17-year-olds, but on four age groups below and above seventeen (the original ACM), consistent with the model's predictions.[30] $TREAT_s$ is

[30] In Section 6.5, I show that the estimated increase in juvenile crime is robust to redefining the control group to include only younger or older cohorts.

an indicator variable that equals one if state s raised its ACM during the study period 2006-15.[31] $POST_{st}$ is an indicator variable that equals one if the ACM change in state s is in effect at time t. Since treatment varies at the age level within each state, standard errors ε_{alst} are clustered at the age-state level.

Event Study Specification

In order to examine the year-by-year impact of the ACM change, I use the following event study specification:

$$C_{alst} = \sum_{i \geq -n} \beta_i ADOL_a * TREAT_s * POST^i_{st} + \gamma_{as} + \gamma_{st} + \gamma_{at} + \varepsilon_{alst}$$

C_{alst} is a measure of the crime rate among age group a in location l in state s in month t. $POST^i_{st}$ are indicator variables that equal 1 if the ACM was increased in state s exactly i years before period t. For instance, Connecticut raised its ACM from seventeen to eighteen on July 1, 2012, so the $POST^1$ dummy equals 1 for Connecticut during July 2012 - June 2013, the $POST^2$ dummy equals 1 for Connecticut for the period July 2013 - June 2014, and so on. Also notice that i may take on negative values, which allows us to test for differences prior to the policy's implementation. Regressions continue to control for age-state, state-time and age-time interactions. Standard errors are clustered at the age-state level to adjust for serial correlation.[32]

6 Results

In this section, I show that postponing the threat of adult sanctions leads to an increase in adolescent offending. When the ACM is increased from seventeen to eighteen, individuals aged seventeen and under increase criminal activity. This increase is driven by offenses related to street gangs, including drug, homicide, robbery, theft, vandalism and burglary offenses. Further, this increase is concentrated among 13-16-year-olds, consistent with the argument that a simultaneous increase in under-reporting of crime by 17-year-olds would obfuscate any effects on this age group. I also show that the ACM increase leads to a delayed increase in crime by 18-year-olds, consistent with the predictions of the model. The section concludes by presenting a range of robustness checks, discussing alternative mechanisms that may explain the results, and a back-of-the-envelope calculation of the social costs of raising the ACM.

[31]Rhode Island *lowered* its ACM from 18 to 17 for the period July - November 2007. $TREAT_{s=Rhode\,Island}$ takes on the value -1, which ensures that β_1 can be interpreted as the impact of an increase in the ACM.

[32]Since Rhode Island only changed its ACM for four months before reversing it back, I include it in the control group for the event study regressions.

6.1 Juvenile Crime

I first test whether increasing the ACM from seventeen to eighteen led to an increase in arrest rates for 13-17-year-olds. These results are presented in the first column of Table 2, which shows that the monthly arrest rate increased by around 0.41, or 8 per cent of the mean, for each age group in the range 13-17. The second column reports analogous estimates for offenses with a medium or high level of street gang involvement, based on the FBI's 2015 National Gang Report. Here we see that the previously documented increase is entirely driven by offenses associated with street gangs, for which arrest rates increase by 0.43, or 11 per cent of the mean. The third column reports analogous estimates for offenses with at most a low level of street gang involvement, such as driving under the influence and liquor law violations. These offense categories do not respond to the increase in the ACM - the estimated coefficient is small (less than 1.5 per cent of the mean) and statistically indistinguishable from zero. Taken together, the last two columns support the argument that juvenile offending can respond to criminal sanctions, and that this increase may be observed for the most serious types of offending (homicide, robbery, etc).

TABLE 2. IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY
13-17-YEAR-OLDS

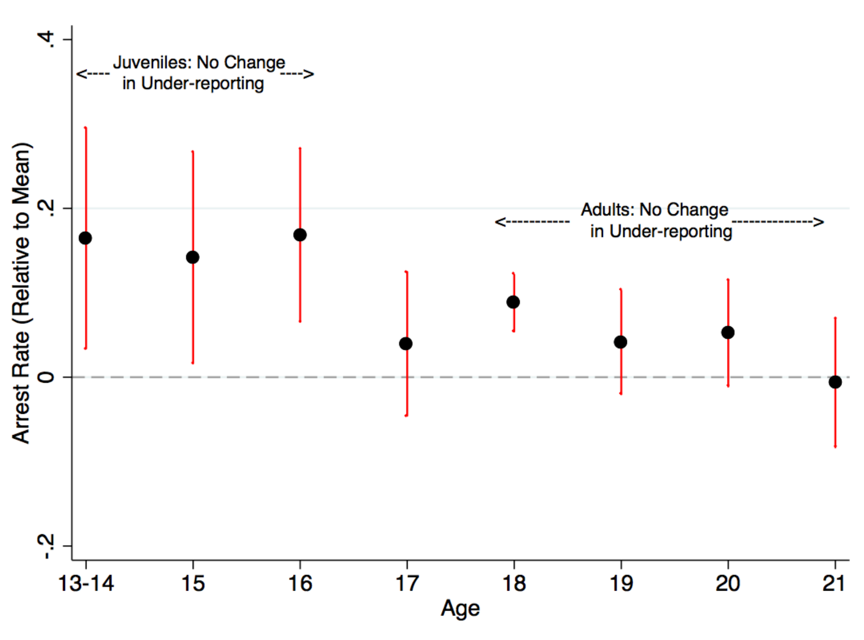
	Arrest Rate		
	All Offenses	Gang-Related Offenses	Other Offenses
DDD Estimate	0.411**	0.431***	-0.019
	(0.170)	(0.115)	(0.137)
Mean	5.217	3.915	1.301
Observations	945,000	945,000	945,000
Clusters	90	90	90

Notes: This table displays estimates of the impact of an increase in the age of criminal majority from seventeen to eighteen, using data from the Uniform Crime Reports for 2006-15. The outcome is the age-specific monthly arrest rate, defined as the number of arrests by age per 100,000 residents. The sample includes the six contiguous states of Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont, each of which introduced legislation to raise the age of criminal majority during the study period. Each regression includes state-time, age-time and age-state fixed effects. Standard errors are clustered at the age-state level. *** p<0.01, ** p<0.05, * p<0.1.

6.2 Age-Specific Estimates

The previous section presents an overview of the impact of the ACM increase on juvenile crime. In this section, I present age-specific estimates of the impact of the ACM increase on gang-related offenses. As predicted by the model, I show that the ACM increase also leads to a delayed increase in offending by those older than seventeen, since these adolescents are now entering adulthood with higher levels of criminal experience, and their return to offending will be higher than previous cohorts'.

FIGURE 5. IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY
AGE-SPECIFIC ESTIMATES

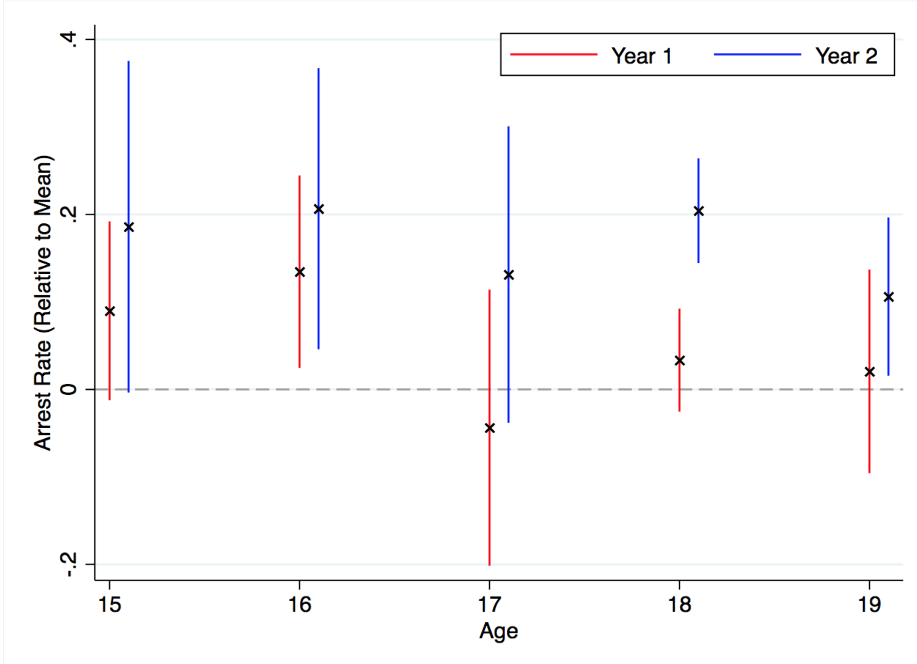


Notes: Point estimates reflect the age-specific impact (and 95% confidence intervals) of an increase in the age of criminal majority from seventeen to eighteen. To enable comparisons across age groups, each estimate is divided by the age group's mean arrest rate. This figure uses the ACM increase dates of July 2012 for Connecticut, September 2013 for Massachusetts, and July 2015 for New Hampshire.

Figure 5 displays the estimated impact on each group in the age range 13-21. To enable comparisons across age groups, each estimate is normalized by the age group's mean arrest rate. 13- and 14-year-olds are clubbed together because the Uniform Crime Reports only report collective data for 13- and 14-year-old arrestees. Arrest rates increase for 13-16-year-olds by over 15 per cent of the mean, and for 18-year-olds by over 8 per cent of the mean. The smaller, statistically insignificant estimate for 17-year-olds is particularly conspicuous, consistent with the argument that 17-year-olds are exposed simultaneously to lower sanctions as well as an increase in under-reporting. The latter effect appears to offset the effect of lower sanctions, which can be observed much more clearly for those aged 13-16 and 18. To show that the increase in arrest rates for those *above* the ACM is not immediate, but lagged, Figure 6 shows age- and year-specific impacts for the first two years following the ACM increase. There is no evidence of an increase for age groups above the ACM in the first year following the ACM change; this increase only appears in the following year, consistent with the predictions of the model.

Next, I use an event study specification to examine the year-by-year impact of the ACM in-

FIGURE 6. INITIAL IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY



Notes: Point estimates reflect the age- and year-specific impact of an increase in the age of criminal majority from seventeen to eighteen. The red lines display the 95% confidence intervals for the effect in the first year, while the blue lines reflect analogous estimates for the second year following the ACM increase. This figure uses the ACM increase dates of July 2012 for Connecticut, September 2013 for Massachusetts, and July 2015 for New Hampshire.

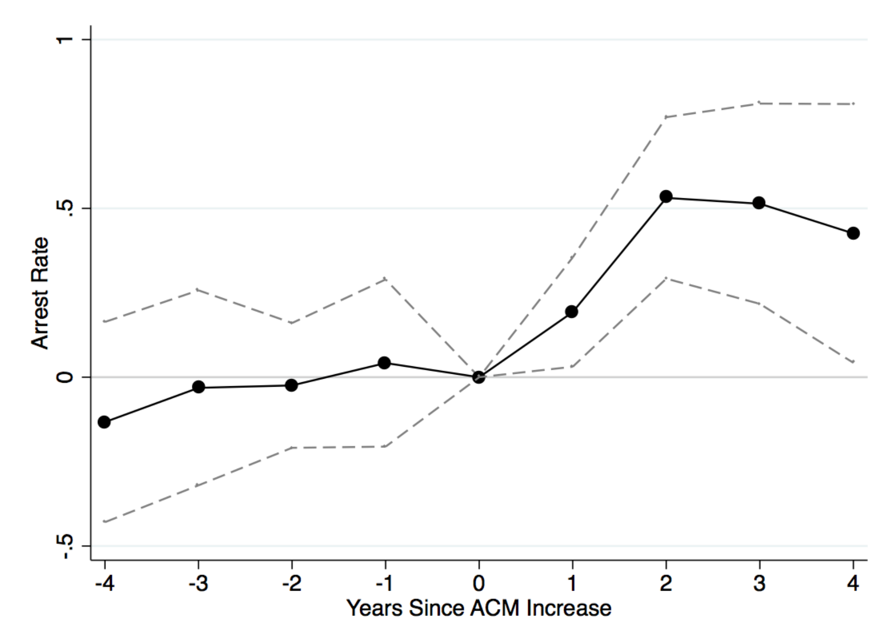
crease on gang-related arrests. Figure 7 displays DDD coefficients for five years before and four years after the policy's implementation. As expected from quasi-random implementation dates, there is no statistical difference between the treatment and control group coefficients prior to the ACM increase, indicating that differential pre-trends are not driving the main results. There is a clear increase in arrest rates starting in the first year of the ACM change, with the effect size increasing over time.

6.3 Offense-Specific Estimates

Since the results presented above may be driven by a handful of frequently occurring offenses, I also examine effects for arrest rates by offense category. This includes ten offense categories associated with street gang activity, and nine offense categories that are not.

Table 3 displays DDD estimates of the increase in arrests for offenses with a medium or high level of street gang involvement. These estimates are displayed separately for 13-16-year-olds, 17-year-olds and 18-21-year-olds. I find that the arrest rate for 13-16-year-olds increases by over 15 per cent of the mean for drug offenses and by over 20 per cent of the mean for homicide, rob-

FIGURE 7. DYNAMIC IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY
13-21-YEAR-OLDS



Notes: Point estimates reflect the year-by-year impact (and 95% confidence intervals) of an increase in the age of criminal majority from seventeen to eighteen. This figure uses the ACM increase dates of July 2012 for Connecticut, September 2013 for Massachusetts, and July 2015 for New Hampshire.

bery, theft, burglary and vandalism offenses. This increase is not observed for 17-year-olds, and is only observed for a subset of offenses for 18-21-year-olds. Overall, the evidence points to a consistent increase across gang-related crime categories for 13-16-year-olds, but the effects on older age groups are less precisely estimated, with precise increases restricted to less serious categories like burglary and vandalism.

To show that general crime trends are unlikely to explain the effects documented above, I also examine the effect of the ACM increase on crime categories that are less likely to involve street gangs. Table 4 displays DDD estimates for nine offense categories, separately for 13-16-year-olds, 17-year-olds and 18-21-year-olds. There appears to be no consistent response by 13-16- or 17-year-olds for these offense categories, since many of the estimates are negative, and most are statistically indistinguishable from zero. There is a statistically significant increase in the 18-21-year-old arrest rate for disorderly conduct and liquor law violations. However, the estimated impact of the ACM increase on all other offense categories is small (relative to the mean) and statistically indistinguishable from zero. Overall, Table 4 does not show evidence of a consistent pattern for any of the age groups.

TABLE 3. OFFENSE-SPECIFIC IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY OFFENSES RELATED TO STREET GANGS

Age Group	**13-16**	**17**	**18-21**
Drug Crimes	0.095***	0.011	-0.013
	(0.031)	(0.087)	(0.072)
Mean	0.505	1.714	2.070
Homicide	0.002***	-0.0005	0.002*
	(0.001)	(0.001)	(0.001)
Mean	0.001	0.002	0.005
Assault	-0.037	-0.013	0.020
	(0.049)	(0.069)	(0.026)
Mean	0.957	1.483	1.385
Robbery	0.011**	0.005	-0.017**
	(0.005)	(0.013)	(0.008)
Mean	0.051	0.100	0.091
Theft	0.291***	0.121	0.098*
	(0.063)	(0.122)	(0.058)
Mean	0.898	1.860	1.594
Stolen Property Offenses	0.046***	0.137***	0.071***
	(0.012)	(0.023)	(0.012)
Mean	0.090	0.198	0.179
Burglary	0.048***	0.060	0.045**
	(0.012)	(0.042)	(0.020)
Mean	0.199	0.362	0.316
Vandalism	0.115***	0.093	0.097***
	(0.020)	(0.057)	(0.019)
Mean	0.411	0.671	0.473
Weapon Law Violations	0.0004	-0.026**	0.003
	(0.006)	(0.011)	(0.006)
Mean	0.056	0.085	0.090
Fraud & Forgery	-0.035***	0.014	0.055***
	(0.013)	(0.015)	(0.015)
Mean	0.032	0.105	0.255
Observations	882,000	756,000	945,000
Clusters	84	72	90

Notes: This table displays estimates of the impact of an increase in the age of criminal majority from seventeen to eighteen, using age- and offense-specific data from the Uniform Crime Reports for 2006-15. Offense categories are restricted to those with a medium or high level of street gang involvement, based on the FBI 2015 National Gang Report. The sample includes six contiguous states in the Northeast that introduced legislation to raise the age of criminal majority during 2006-15 - Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont. Each regression includes state-time, age-time and age-state fixed effects. Standard errors are clustered at the age-state level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4. OFFENSE-SPECIFIC IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY
OTHER OFFENSES

Age Group	**13-16**	**17**	**18-21**
Arson	-0.007*	-0.004	0.003
	(0.004)	(0.003)	(0.002)
Mean	0.0210	0.0170	0.0100
Embezzlement	0.002	-0.001	0.001
	(0.002)	(0.003)	(0.003)
Mean	0.003	0.007	0.002
Offenses against the Family & Children	-0.005	-0.032	-0.004
	(0.010)	(0.020)	(0.005)
Mean	0.0320	0.0380	0.0450
Driving Under the Influence	-0.137***	-0.069	0.073
	(0.028)	(0.054)	(0.048)
Mean	0.0180	0.216	0.837
Liquor Laws	0.069	0.276	0.657***
	(0.065)	(0.277)	(0.241)
Mean	0.298	1.352	1.784
Drunkenness	0.022	0.100	0.016
	(0.028)	(0.153)	(0.047)
Mean	0.0760	0.288	0.383
Disorderly Conduct	-0.068	0.061	0.128***
	(0.048)	(0.051)	(0.044)
Mean	0.409	0.679	0.654
Gambling	-0.0003	0.001	0.0005
	(0.0004)	(0.001)	(0.0007)
Mean	0.0004	0.002	0.002
Vagrancy, Suspicion, Curfew, Loitering	-0.009***	-0.007***	0.001
	(0.002)	(0.002)	(0.002)
Mean	0.00800	0.0150	0.0120
Observations	882,000	756,000	945,000
Clusters	84	72	90

Notes: This table displays estimates of the impact of an increase in the age of criminal majority from seventeen to eighteen, using age- and offense-specific data from the Uniform Crime Reports for 2006-15. Offense categories are restricted to those with at most a low level of street gang involvement, based on the FBI 2015 National Gang Report. The sample includes six contiguous states in the Northeast that introduced legislation to raise the age of criminal majority during 2006-15 - Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont. Each regression includes state-time, age-time and age-state fixed effects. Standard errors are clustered at the age-state level. *** p<0.01, ** p<0.05, * p<0.1.

6.4 Demographic Heterogeneity

In this section, I examine whether some demographic groups are more responsive to the increase in the ACM than others. The first panel of Table 5 shows a significant increase in arrest rates for males of each age except seventeen, while the second panel shows a similar pattern of positive, but smaller coefficients for females. Since the mean for male arrest rates is higher, the pattern of increase is similar in relative terms for both groups.

TABLE 5. IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY
DEMOGRAPHIC HETEROGENEITY

	Male 13-14	**Male 15**	**Male 16**	**Male 17**
DDD Estimate	0.274***	0.413***	0.736***	0.261
	(0.082)	(0.087)	(0.182)	(0.215)
Mean	1.185	2.130	3.262	4.567
	Female 13-14	**Female 15**	**Female 16**	**Female 17**
DDD Estimate	0.232**	0.240*	0.258**	0.215
	(0.098)	(0.131)	(0.119)	(0.144)
Mean	0.512	0.898	1.327	1.781
	White 0-17	**Black 0-17**	**Other 0-17**	
DDD Estimate	1.609***	-0.076	0.155	
	(0.475)	(0.400)	(0.109)	
Mean	14.67	3.177	0.173	
Observations	756,000	756,000	756,000	756,000
Clusters	72	72	72	72

Notes: Regressions estimate the impact of an increase in the age of criminal majority from seventeen to eighteen. Each regression controls for state, year and age fixed effects, as well as state-year, age-year and age-state fixed effects. Standard errors are clustered at the age-state level. The UCR data does not contain age specific arrests by race, only the number of arrests under eighteen separated by race; Hispanic arrestees are not reported separately and may belong to any of the race categories. *** p<0.01, ** p<0.05, * p<0.1.

The Uniform Crime Reports also include data on arrests for individuals aged seventeen and under by race (though finer data on age- and race-specific arrests are not included). The last panel of Table 5 shows that the deterrence estimates are largely driven by an increase in the arrest rate for White adolescents (an increase equivalent to 11 per cent of the mean), while the response among Black and Other adolescents is statistically indistinguishable from zero.[33] This finding is actually

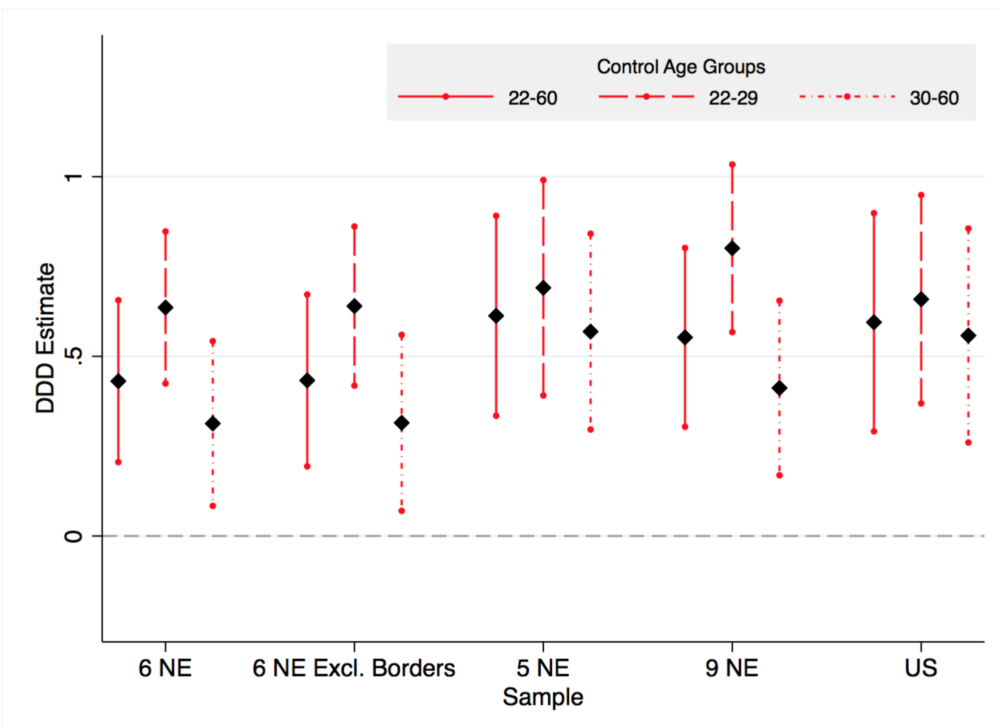
[33] Agencies do not separately report arrests for Hispanic arrestees, who can be included in any of the race categories.

supported by other studies on the effect of sanctions on juvenile crime. For instance, Lovett & Xue (2018) find that White youth are responsive to the sanction hike at the ACM, while Black youth are not. This pattern is consistent with effective treatment differing across race groups. If youth of color are more likely to be charged in adult courts (Juszkiewicz, 2009) or face harsher sanctions within the juvenile justice system (Eren & Mocan, 2018), raising the ACM will change their incentives less than those of White youth. In this situation, it would not be surprising to find larger effects for White adolescents and smaller effects for adolescents belonging to other race groups, as documented in Table 5.

6.5 Robustness Checks

This section shows that the main results are robust to a number of checks such as using alternative age groups as controls, accounting for geographical spillovers, and extending the study sample to include all states in the U.S. The outcome of interest is the 13-17-year-old arrest rate based on gang-related offenses.

FIGURE 8. ROBUSTNESS CHECKS



Notes: This figure displays estimates (and 95% confidence intervals) of the impact of an increase in the age of criminal majority from seventeen to eighteen for different subsets of the data. This figure uses the ACM increase dates of July 2012 for Connecticut, September 2013 for Massachusetts, and July 2015 for New Hampshire.

Alternative Age Groups as Controls

Heretofore, the analysis has used individuals aged 22 and above as control groups. To show that the estimated increase in juvenile arrests is not driven by this choice, this section shows that the estimates remain positive and statistically significant when the control group is redefined to only include younger (below 30) or older (30 and above) age groups. In Figure 8, the estimates corresponding to the six Northeastern states (labelled 6 NE) show how the point estimate and corresponding confidence interval vary when we use those aged 22-60, 22-29, or 30-60 as control groups. The estimates remain statistically significant and economically meaningful in magnitude for each of the three choices.

Geographical Spillovers

One possible mechanism behind the increase in juvenile crime is that crime is simply shifting over from treatment to control states, with no increase in overall crime. I attempt to shed light on this hypothesis by re-estimating the DDD estimates after excluding jurisdictions that border treatment and control states.[34] These are the second set of estimates displayed in Figure 8, labelled 6 NE excluding borders. This exercise does not meaningfully alter the estimates, indicating that geographical spillovers are not the main drivers of the findings.

Other Juvenile Justice Reforms

A natural worry with studies that exploit ACM changes is that they are likely to have been accompanied by other juvenile justice reforms. This worry is partly assuaged by the fact that I show evidence for a delayed reaction to the ACM by 18-year-olds, who are treated as adults both before and after the ACM change, and would be unaffected by other reforms that explicitly target juveniles.

Amongst the treatment states, Connecticut implemented a range of juvenile justice reforms such as reducing in-school arrests in 2009 and discontinuing the detention of juveniles for non-criminal cases in 2007. These reforms were not implemented in the same year as the ACM increase, and the event study estimates show that these policies did not have a large impact prior to the ACM change. Moreover, these policies serve to reduce the number of juvenile arrests, which would lead to an underestimate of the true effect of the ACM increase. To show this formally, I restrict attention to the three treatment states that implemented the ACM change without an accompanying package of reforms, as well as the two control states New York and Vermont. In

[34]Table A.3 displays the list of police agencies that are dropped from the analysis.

Figure 8, the third set of estimates (labelled 5 NE) show how the estimates change when we exclude Connecticut from the sample. The estimated increase is larger, consistent with the fact that accompanying reforms would reduce juvenile arrests. Further, this increase is robust to redefining which age groups serve as the control group.

Including Additional States

As a final check, I show that the main results are robust to widening the sample to include additional states. The fourth set of estimates displayed in Figure 8 use all nine states in the Northeast, even those that did not introduce legislation to raise the ACM during the study period (Maine, New Jersey, and Pennsylvania). The fifth set of estimates use data from all states in the UCR, which now includes two additional treatment states - Illinois (post 2009) and Mississippi (post June 2011). Both sets of estimates show a large, statistically significant increase in the juvenile gang-related arrest rate. This increase is observed irrespective of which age groups are used as controls.

6.6 Alternative Mechanisms: Discussion

The preceding analysis shows that when the ACM is raised, age groups below the original ACM increase gang-related criminal activity. This paper focuses on criminal capital accumulation as the main driver of these results. However, these results could ostensibly be due to other mechanisms. For instance, criminal activity by 17-year-olds may encourage offending by younger cohorts (peer effects), or criminal activity may have intrinsic inter-temporal complementarities that generate repeated behavior (habit formation). In this section, I argue that these and other mechanisms are inconsistent with the finer points of the data.

Three features characterize the response to the increased ACM. First, age groups below the original ACM increase criminal activity. Second, this increase is only observed for crimes like homicide, robbery, theft, vandalism and drug offenses. Three, there is a delayed increase in criminal activity by age groups above the ACM. Any discussion of the mechanism behind these responses must be consistent with each of these findings.

Habit Formation

The mechanism of criminal capital formation is actually reminiscent of Becker & Murphy (1988)'s model of habit formation, in which consumption today increases the marginal utility of consumption the following period. Under this set up, agents may rationally form habits (repeated consumption) by internalizing these inter-temporal complementarities. Applied to the current setting, this model would require the utility or intrinsic return from crime to be an increasing function of prior criminal involvement.

This study cannot empirically distinguish criminal capital formation from habit formation. Thus, the extent to which they can be differentiated depends on which types of crime we would expect to be subject to habit formation or intrinsic utility complementarities. Casual intuition suggests that offenses associated with alcohol, widely accepted as having strong inter-temporal complementarities, should increase if habit formation is an important driver of the observed effects. However, arrest rates for drunkenness, driving under the influence and other liquor law violations either decrease or do not increase significantly in response (Table 3). Therefore, it seems unlikely then that habit formation can provide a complete explanation for the findings.

Peer Effects

An alternative explanation for the fact that age groups surrounding the ACM increase criminal activity is peer effects. 17-year-olds increase criminal activity in response to lower sanctions (which we do not observe due to the offsetting decrease in reporting behavior) and this increase spills over on to their younger and older peers.

This explanation is not consistent with the fact that we only observe an increase in arrest rates for the most serious offenses, which carry the harshest sentences. Further, the increase in arrest rates for 18-year-olds is delayed, which is not consistent with a simple model of peer effects. Additionally, prior research finds that peer effects are strongest for less serious crimes, and are less likely to be present for crimes such as robbery (Bayer *et al.* 2009, Damm & Gorinas 2016, Billings & Schnepel 2017). This is not the pattern documented in the present study (Tables 3 and 4), which makes it less likely that peer effects provide a complete explanation for the observed effects.

Leniency Towards Juveniles

A reasonable concern when studying the effects of higher ACMs is that these may be accompanied by a more lenient approach by the state towards juvenile offenders. The resulting leniency may then result in an increase in juvenile offending. However, this explanation is not consistent with the observed increase in 18-year-old arrests, who should be unaffected by the increased leniency. Further, the effect of leniency by law enforcement agencies is usually to reduce, not increase, arrests. For instance, Connecticut's 2009 School Based Diversion Initiative trains schools to identify children with behavioral health needs, who are then diverted away from the juvenile justice system towards mental health programs. Under this scenario, the DDD estimates would actually provide an underestimate of the effects of the ACM increase on juvenile crime.

Gang Leaders as Decision Makers

An alternative explanation for the observed pattern of results is that adolescents themselves do not exert full control over the decision to commit crime. Instead, other forward-looking individuals such as gang leaders understand that the return to crime is an increasing function of prior criminal activity, and decide on how much crime each individual will commit. Since we do not observe the decision-making process behind each crime - only whether it was committed or not - the results are entirely consistent with this explanation. However, this scenario is still consistent with a deterrence response - raising the ACM increases juvenile crime by reducing deterrents for gang leaders, who are likely to care about the long-term profitability of their criminal enterprises, as opposed to the juveniles themselves.

6.7 Some Costs of Raising the Age of Criminal Majority

This section uses a back-of-the-envelope calculation to estimate the social costs of raising the ACM. This is a partial estimation exercise, as I make multiple assumptions and focus only on two sources of social cost increases due to the ACM change - the increase in criminal offending by 13-16-year-olds, and the costs of transferring 17-year-olds to more expensive juvenile facilities. For every 17-year-old that is now processed through the juvenile justice system, this exercise results in estimates of $124,000 in social costs. In terms of policy recommendations, I discuss whether these costs are expected to be offset by the benefits of raising the ACM, and whether local jurisdictions can employ additional tools to anticipate and offset these crime increases.

The first source of social costs due to the ACM change is the increase in criminal offending by age groups below seventeen. For each crime category, I use the arrest-to-offense ratio from the 2015 Uniform Crime Reports to predict the increase in the number of offenses by 13-16-year-olds.[35] The first two columns of Table 6 display estimates of the increase in monthly arrest rates of 13-16-year-olds for homicide, robbery, aggravated assault, burglary, motor vehicle theft, larceny, stolen property, vandalism, forgery, fraud and drug offenses following the ACM increase as well as the arrest-to-offense ratio for each of these crimes. The third column displays McCollister *et al.* (2010)'s estimates of social costs by offense, which include costs imposed directly on victims and indirectly on the criminal justice system in the form of legal, police and corrections costs.[36] The

[35] This ratio does not include offenses that are not reported to the police and is, therefore, an underestimate of the total increase in offending. This method will also underestimate the increase in offending if juveniles are arrested at lower rates than adults.

[36] McCollister *et al.* (2010) employ cost-of-illness and jury compensation methods to estimate both the tangible and intangible costs of crime. I use their estimates for three reasons - first, they provide the most recent set of estimates; second, they provide cost estimates for more offense categories than Donohue III (2009); third, their estimates for the overlapping set of offenses are broadly similar to those of other studies like Donohue III (2009) and Cohen *et al.* (2004). I exclude McCollister *et al.* (2010)'s estimates of offenders' productivity losses while incarcerated, since individuals

fourth column displays the annual increase in costs (including incarceration[37]) by offense type due to the uptick in offending, evaluated at the average agency population of 29,882. The crime increase among 13-16-year-olds led to an annual increase of $386,143 in social costs, two thirds of which is accounted for by homicide offenses.

TABLE 6. SOCIAL COSTS OF INCREASE IN JUVENILE OFFENDING

Offense	**Arrest Rate Increase 13-16-Year-Olds**	**Arrest-Offense Ratio**	**Unit Cost* 2015 $**	**Estimated Cost 2015 $**
Homicide	0.005	61.5	9,717,787	283,301
Robbery	0.035	29.3	41,842	17,922
Aggravated Assault	-0.058	54.0	115,383	-44,439
Burglary	0.184	12.9	6,359	32,524
Motor Vehicle Theft	0.036	13.1	11,241	11,077
Larceny	0.514	21.9	3,706	31,190
Stolen Property	0.145	19.4	7,526	20,170
Vandalism	0.356	19.4	4,575	30,104
Forgery	0.008	19.4	5,066	749
Fraud	-0.014	19.4	4,809	-1,244
Drug Crimes	0.105	20.0	2,544	4,789
Total				**$386,143**

Notes: The Arrest Rate Increase column is based on DDD regressions estimating the impact of an increase in the age of criminal majority from seventeen to eighteen. The Arrest-Offense Ratio column uses the ratio of arrests to offenses known in the 2015 UCR data. The Unit-Cost column relies on McCollister *et al.* (2010), who incorporate cost-of-illness and jury compensation methods to estimate the tangible and intangible costs of crime. The Estimated Cost column displays the annual estimated increase in social costs by offense type, evaluated at a population of 29,882, the mean for law enforcement agencies in the six Northeastern states.

The second source of social costs is the transfer of 17-year-olds to juvenile facilities. Juvenile incarceration costs in the treatment states average $544 per day (Justice Policy Institute, 2014), while the equivalent estimate for adult incarceration is $198 (Vera Institute of Justice, 2017).[38] My estimate of the number of such transfers is based on a number of steps, summarized in Table 7. The first column shows the monthly arrest rate for 17-year-olds in the study sample, and the second displays the ratio of offense-specific juvenile arrests to juvenile court cases in 2015, based on the Uniform Crime Reports and the National Center for Juvenile Justice (2015). I combine this

below seventeen are unlikely to be a part of the formal labor force. I also supplement these estimates with Mueller-Smith (2016)'s social cost of drug offenses estimate of $2,544. I exclude simple assault and weapon law violations due to the absence of social cost estimates for these offenses.

[37]This is likely to be an underestimate, since juvenile incarceration costs over twice as much as adult incarceration. I also do not account for the fact that 13-16-year-old offenders who are incarcerated may be more likely to recidivate in the future.

[38]Since New Hampshire is not included in the Vera Institute of Justice (2017) report, I use the Vera Institute of Justice (2012) estimates assuming that its costs grew at the same rate as Connecticut and Rhode Island, who provided information in both surveys. Estimates are in 2015 USD.

with offense-specific incarceration rates for 17-year-olds[39] along with expected sentence lengths specific to each offense category (person, property, drug and public order), relying on data from the Office of Juvenile Justice and Delinquency Prevention and the National Center for Juvenile Justice (2015). The last two columns use the incarceration cost estimates of $544 and $198 mentioned above. The increase in costs due to the transfer of 17-year-olds from adult to juvenile facilities is around $390,000.[40] Adding in the costs due to heightened offending by 13-16-year-olds gives us an estimate of approximately $776,000 in social costs as a result of the ACM increase.

What are the benefits of raising the ACM? Proponents of raising the ACM argue that rates of recidivism are likely lower after being processed by the juvenile justice system. Recent studies show, however, that incarceration in juvenile facilities also has a large impact on recidivism (Aizer & Doyle, 2015) and that adult incarceration may actually lower recidivism for marginal offenders (Entorf 2011, Pichler & Römer 2013, Loeffler & Grunwald 2015).[41] Therefore, I do not focus on lower recidivism as the primary benefit of raising the age; instead, I focus on the 17-year-olds who will be diverted away from adult prisons, and will usually have the option to expunge their criminal records. My estimate of the number of 17-year-olds that will receive this benefit is displayed by offense type in the fourth column of Table 7, which sums up to a total of 6.24 17-year-olds.

The question for policymakers is whether costs of $124,410 per 17-year-old are exceeded by the potential benefits. There are many reasons why it might. One, the expungement of criminal records may boost employment and average annual real earnings by around $6,000 (Selbin *et al.* , 2017); two, the transfer to juvenile facilities may lower the risk of assault faced by the average juvenile convict - McCollister *et al.* (2010) estimate victim costs alone of over $200,000 for sexual assault and $100,000 for aggravated assault;[42] three, if more 17-year-olds receive probation instead of incarceration sentences, Bayer *et al.* (2009) and Aizer & Doyle (2015)'s findings indicate that we may see an increase in high school completion rates and a decrease in recidivism. It is worth reiterating, however, that these benefits are not well understood, and more research is needed to shed light on how large these benefits are, and which subgroups benefit the most. In the meantime, policymakers implementing these reforms can be proactive in understanding that there are real

[39] Here, I make three assumptions. One, the proportion of 17-year-olds adjudicated delinquent that receive placement sentences (instead of probation sentences) does not change after the increase in the ACM. Two, the cost of probation for a 17-year-old does not change when the ACM is raised to eighteen. Third, the completed duration of incarceration does not depend on the ACM, an assumption supported by the findings of Fritsch *et al.* (1996) and Fagan (Jan/Apr. 1996.).

[40] If the marginal incarceration cost is around half of the average cost in both juvenile and adult facilities, as found by Owens (2009) in Maryland, the cost increase will be around $195,000.

[41] Hjalmarsson (2009b) and Gandelman & Munyo (2015) also show that juvenile incarceration can lower post-release recidivism when compared to non-carceral sanctions.

[42] It is difficult to quantify the change in assault risk faced by adolescents across different types of facilities. For instance, Beck & Hughes (2004) document that rates of reported sexual assault are six times higher in juvenile correctional facilities than in adult facilities across the U.S. This is at least partly driven by state laws specifying that all sexual acts involving youth below certain ages are nonconsensual.

TABLE 7. ADDITIONAL COSTS OF INCARCERATING 17-YEAR-OLDS

Offense	Monthly Arrest Rate	% Referred to Court	% Placed/ Incarcerated	Annual Incarcerations	Duration (Months)	Cost Adult Facilities	Cost Juvenile Facilities
Homicide	0.002	1.000	0.28	0.002	8.18	97	267
Robbery	0.100	1.000	0.28	0.100	8.18	4859	13374
Aggravated Assault	0.236	0.897	0.28	0.213	8.18	10349	28487
Burglary	0.362	1.000	0.25	0.325	5.72	11042	30395
Larceny	1.780	0.927	0.25	1.479	5.72	50252	138319
Motor Vehicle Theft	0.080	0.907	0.25	0.065	5.72	2208	6079
Other Assaults	1.246	1.000	0.28	1.251	8.18	60785	167312
Arson	0.017	1.000	0.25	0.015	5.72	510	1403
Stolen Property	0.198	0.859	0.25	0.153	5.72	5198	14309
Other Property Crimes	0.112	1.000	0.25	0.100	5.72	3398	9352
Vandalism	0.671	1.000	0.25	0.602	5.72	20454	56300
Weapon Law Violations	0.085	0.979	0.29	0.087	4.38	2263	6230
Prostitution, Commercialized Vice	0.002	1.000	0.29	0.002	4.38	52	143
Drug Abuse Violations	1.714	1.000	0.16	0.983	4.78	27911	76824
Other Public Order Offenses	2.614	0.092	0.29	0.25	4.38	6504	17903
Other Person Offenses	0.038	1.000	0.28	0.038	8.18	1846	5082
Liquor Laws, Drunkenness	1.640	0.126	0.29	0.215	4.38	5594	15397
Disorderly Conduct	0.693	0.497	0.29	0.358	4.38	9314	25637
Total				**6.238**		222,636	612,813
Additional Cost							**390,177**

Notes: The monthly arrest rate column is based on UCR 2006-15 data for the six Northeastern states. % referred to court uses the ratio of offense-specific juvenile arrests to juvenile court cases in 2015, based on the UCR and National Center for Juvenile Justice (2015), and is capped at 100%. % incarcerated also relies on National Center for Juvenile Justice (2015). The annual number of incarcerations is evaluated at a population of 29,882, the mean for law enforcement agencies in the six Northeastern states. Cost estimates are in 2015 $, and based on estimates from Vera Institute of Justice (2017) and Justice Policy Institute (2014). Other Property Crimes include Forgery, Counterfeiting, Fraud and Embezzlement; Other Public Order Offenses include Gambling, Driving Under the Influence, All Other Non-Traffic Offenses; Other Person Offenses include Offenses against the Family and Children; Disorderly Conduct includes Vagrancy, Curfew and Loitering Violations. Offenses omitted include manslaughter by negligence, for which the arrest rate is 0; runaways, a status offense which only applies to juveniles; rape and sex offenses, since the UCR definition for these offenses changed in 2013.

costs associated with these policies, and try to offset some of these effects by expanding services such cognitive behavioral therapy and job training to reduce juvenile criminal involvement (Heller 2014, Heller *et al.* 2017).

7 Conclusion

Research shows that criminal involvement can persist into long-term offending, as individuals accumulate skills and experience pertinent to the crime sector (Bayer *et al.* 2009, Pyrooz *et al.* 2013, Carvalho & Soares 2016, Sviatschi 2017) or lose human capital valued in the non-crime sector (Hjalmarsson 2008, Aizer & Doyle 2015). However, most research on the deterrent effects of the age of criminal majority has overlooked these inter-temporal complementarities.

In this paper, I show that accounting for these dynamic incentives can change how we look for and measure deterrence. This approach also helps us deal with the issue of increased underreporting as individuals cross the age of criminal majority, which may have biased existing studies towards finding no evidence of deterrence. Using policy variation in the Northeastern states since 2006, I find that raising the age of criminal majority increases arrest rates for 13-17-year-olds. This rise in arrests is driven by offenses commonly associated with street gangs, including property, drug and violent offenses. Using a back-of-the-envelope calculation, I show that for every 17-year-old diverted from adult sanctions, jurisdictions bore costs on the order of $124,000 due to the increase in juvenile offending, and the costs of incarcerating 17-year-olds in (more expensive) juvenile facilities.

More research is needed to quantify the potential benefits of raising the ACM, which are not well understood. These estimates are crucial for identifying policies that actually lower levels of juvenile crime, recidivism, and incarceration in the long run. They are also of particular policy relevance today, as states have continued the push to raise the age of criminal majority - in 2016, Vermont increased the age of criminal majority to twenty one for certain offenses, while Connecticut, Massachusetts, and Illinois have each introduced legislation to do the same.[43]

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[43]For more details, see https://www.bostonglobe.com/metro/2019/07/09/crime-bill-would-redefine-juveniles-age/maHshbBT6QaaX9ooVDVidN/story.html

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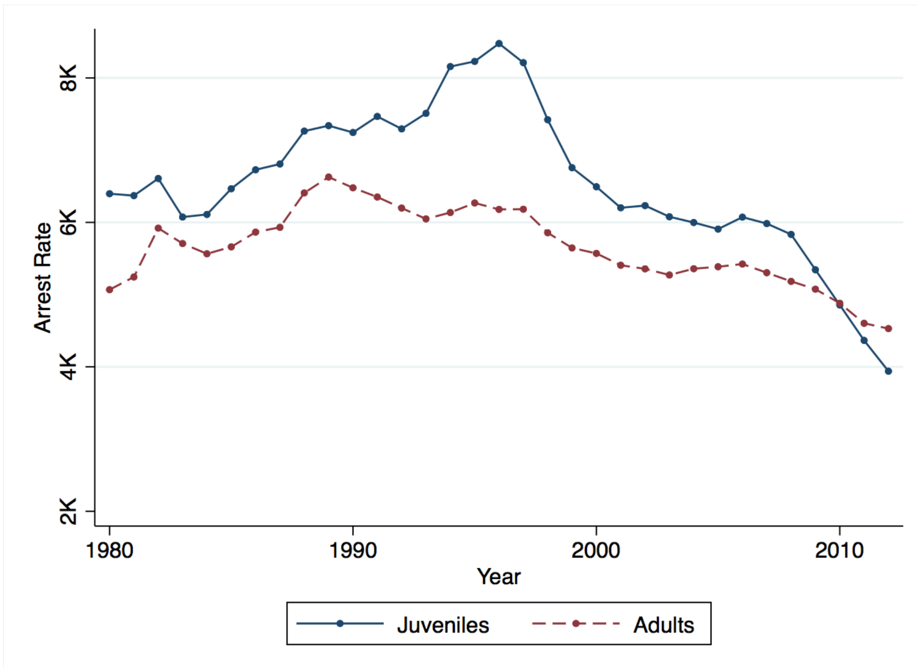
Appendix

A.1 Figures

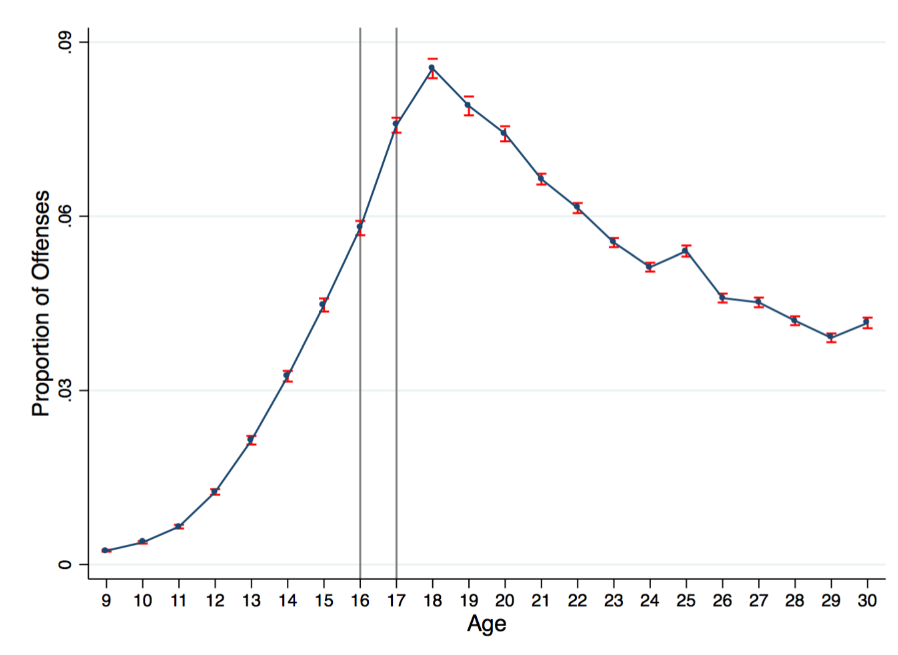
FIGURE A.1. JUVENILE AND ADULT ARRESTS PER 100,000 PERSONS



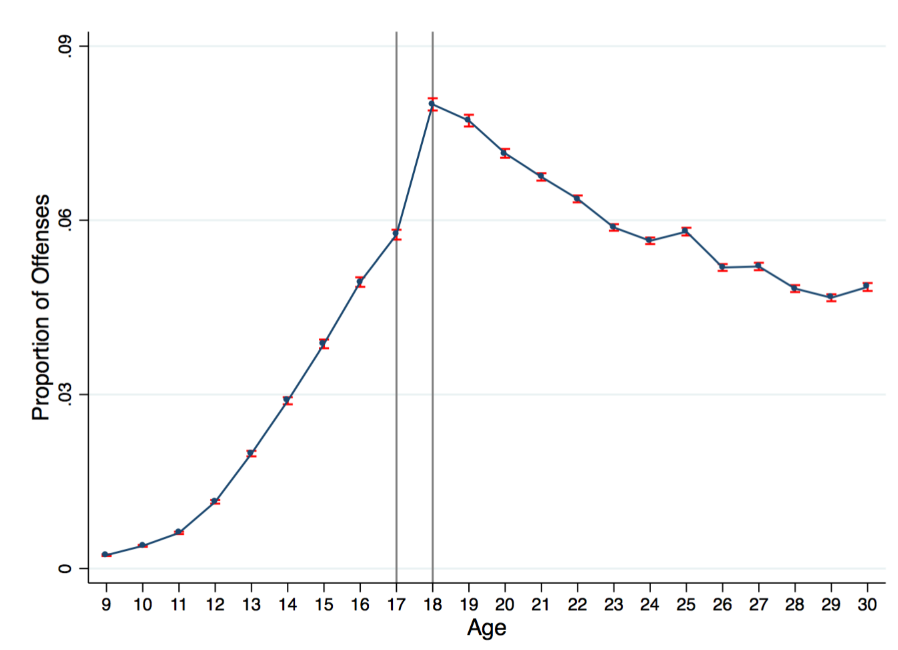
Data Source: Bureau of Justice Statistics.

FIGURE A.2. PROPORTION OF OFFENSES KNOWN BY AGE

(A) AGE OF CRIMINAL MAJORITY = 17



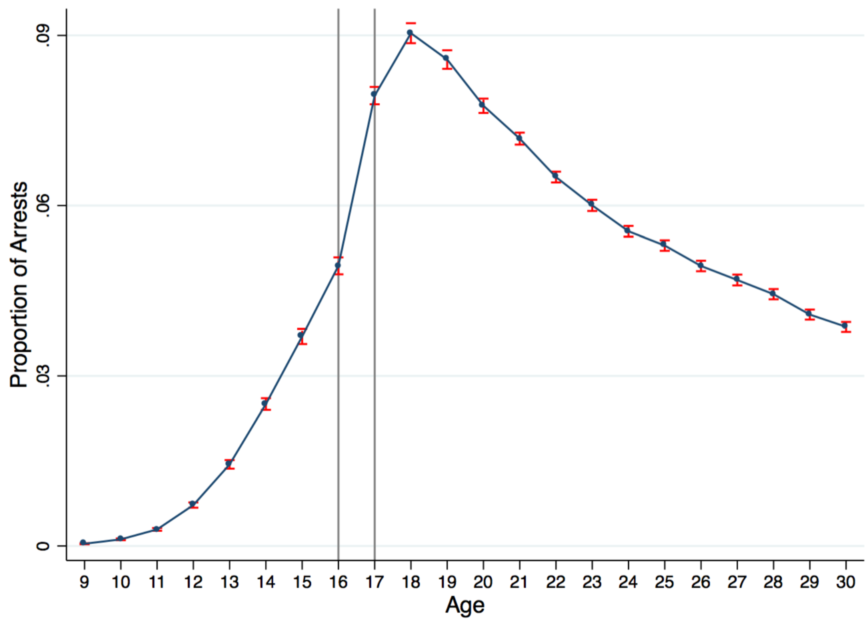
(B) AGE OF CRIMINAL MAJORITY = 18



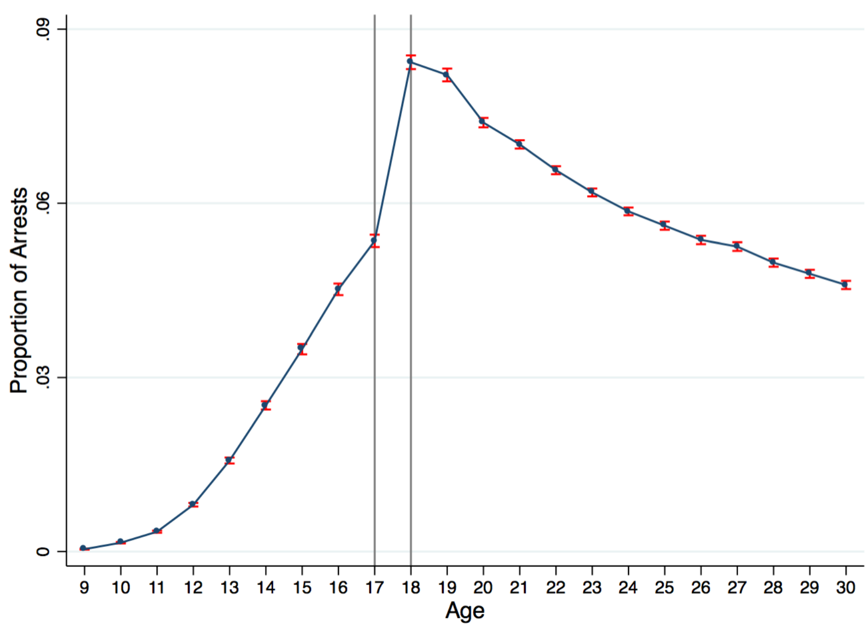
Notes: This graph uses monthly NIBRS data at the law enforcement agency level for 2006-14. Standard errors are clustered at the agency level, and 95% confidence intervals are marked in red.

FIGURE A.3. PROPORTION OF GANG-RELATED CRIME ARRESTS BY AGE

(A) AGE OF CRIMINAL MAJORITY = 17



(B) AGE OF CRIMINAL MAJORITY = 18



Notes: This graph uses monthly NIBRS data at the law enforcement agency level for 2006-14. Standard errors are clustered at the agency level, and 95% confidence intervals are marked in red.

A.2 Tables

TABLE A.1. STATES' AGE OF CRIMINAL MAJORITY OVER TIME

State	ACM in 2017	Changes
Alabama	18	16 until 1975, 17 until 1976
Connecticut	18	16 until 12/31/2009, 17 until 6/30/2012
Illinois	18	17 for misdemeanors until 12/31/2009 17 for felonies until 12/31/2013
Louisiana	18	17 until 2016
Massachusetts	18	17 until 9/18/2013
Mississippi	18	17 for misdemeanors until 6/30/2011^{+} Still 17 for some felonies
Missouri	17	Will change to 18 on 1/1/2021
New Hampshire	18	18 until 1996, 17 until 6/20/2015
New York	16	17 on 10/1/2018; 18 since 10/1/2019
North Carolina	16	Will change to 18 on 12/1/2019 for misdemeanors, low-level felonies
Rhode Island	18	18 until 30/6/2007, 17 until 11/7/2007
South Carolina	18	17 until 2016
Vermont	18	22 for nonviolent crimes since 7/1/2018
Wisconsin*	17	18 until 1996
Wyoming	18	19 until 1993
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	18	-
Georgia, Michigan*, Texas*	17	-

*Legislation introduced to raise ACM, not succeeded to date: Wisconsin AB387 introduced 9/23/13, failed 4/8/14; Texas: HB 122 introduced 11/14/16, passed House on 4/20/17; Michigan: HB 4607 introduced 5/11/7. $^{+}$ https://www.ncjrs.gov/pdffiles1/ojjdp/232434.pdf

TABLE A.2. SUMMARY STATISTICS

	Full Sample	Northeastern States
Population	36,103.72	29,881.60
(Thousands)	(103,627.17)	(71,916.27)
Arrest Rates		
All Offenses		
Total	406.75	266.88
	(907.08)	(231.02)
Under 21	123.77	85.91
	(214.83)	(103.47)
Violent Offenses		
Total	50.82	40.90
	(82.57)	(40.97)
Under 21	14.40	11.73
	(29.86)	(16.94)
Property Offenses		
Total	67.70	47.34
	(274.25)	(84.21)
Under 21	23.66	16.83
	(85.56)	(40.95)
Drug Offenses		
Total	3.81	2.87
	(3.27)	(2.79)
Under 21	1.48	1.17
	(1.62)	(1.39)
Agencies	4,618	525

Notes: Standard deviations in parentheses. Data is at the agency-month level from the Uniform Crime Reports for 2006-15. Northeastern States refers to the six contiguous states in the Northeast that introduced legislation to raise the age of criminal majority during 2006-15 - Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont. Arrest rates are measured as the number of arrests for every 100,000 residents. Violent crime offenses include murder, rape, assault, and robbery. Property crime offenses include burglary, theft, motor vehicle theft, arson, forgery, counterfeiting, fraud, embezzlement, and stolen property offenses.

TABLE A.3. JURISDICTIONS BORDERING TREATMENT AND CONTROL STATES

State	Border Municipalities	Police Agencies
Connecticut	Salisbury, Sharon, Kent, Sherman, New Fairfield, Danbury, Ridgefield, Wilton, New Canaan, Stamford, Greenwich	Connecticut State Police, Danbury, Ridgefield, Wilton, New Canaan, Stamford, Greenwich
Massachusetts	Williamstown, Hancock, Richmond, West Stockbridge, Alford, Edgemont, Mount Washington, Clarksburg, Monroe, Florida, Rowe, Heath, Colrain, Leyden, Bernardston, Northfield	Wiliamstown, Egremont, State Police: Berkshire County, State Police: Franklin County, Bernardston
New York	Petersburg, Berlin, Stephentown, Northeast (Millerton), Amenia, Dover, Pawling, Patterson, Southeast (Brewster), North Salem, Lewisboro, Pound Ridge, North Castle, Harrison, Rye Brook, Port Chester	Millerton, Rensselaer, Brewster, Lewisboro, Pound Ridge, North Castle, Harrison, RyeBrook, Port Chester, Dutchess, Putnam, Westchester Public Safety
Vermont	Canaan, Lemington, Bloomfield, Brunswick, Maidstone, Guildhall, Lunenburo, Concord, Waterford, Barnet, Rye Gate, Newbury, Bradford, Fairlee, Thetford, Norwich, Hartford, Hartland, Windsor, Weathersfield, Springfield, Rockingham, Westminster, Putney, Dummerston, Brattleboro, Vernon, Guilford, Halifax, Whitingham, Readsboro, Stamford, Pownal	Canaan, State Police: St. Johnsbury, Bradford, Thetford, Norwich, Hartford, State Police: Royalton, Windsor, Weathersfield, Springfield, State Police: Bratteboro, Bratteboro, Vernon, State Police: Shaftsbury

Notes: This table displays the list of police agencies that are located along the borders of treatment and control states. Section 6.5 shows that excluding these agencies does not materially change the results, indicating that geographical spillovers are unlikely to be the primary drivers of the findings.

A.3 Theoretical Framework

Adolescents are indexed by age t and have preferences that are represented by an intertemporally separable utility function $u(c_t, k_t, s_t)$. At each at age, adolescents decide how much crime c_t to commit, knowing that they will face criminal sanctions s_t if caught. The return to criminal activity is an increasing, concave function of criminal capital k_t.

$$u(c_t, k_t, s_t) = R(k_t)\, c_t - p(c_t)\, s_t$$

$$R_k \geq 0 \qquad R_{kk} \leq 0$$

$$c_t \geq 0$$

The probability of facing criminal sanctions $p(.)$ is assumed to be an increasing convex function of criminal activity c_t.[44]

$$p_c \geq 0 \qquad p_{cc} \geq 0$$

Criminal activity adds to an individual's stock of criminal capital, which depreciates at the rate δ. Therefore, the change in criminal capital at each age is current criminal activity ("investment") less depreciation.

$$\dot{k_t} = c_t - \delta k_t$$

$$0 < \delta < 1$$

Sanctions s for criminal offenses are a function of age t, and increase sharply as adolescents surpass the ACM T.

$$s_t = \begin{cases} S_J & t < T \\ \\ S_A & t \geq T \end{cases} \qquad\qquad 0 < S_J < S_A$$

Individuals are forward-looking and maximize lifetime utility. Future flow utility is discounted at the rate $\rho \in (0, 1)$. The intertemporal separability of the utility function allows us to write lifetime utility U_t as the discounted sum of flow utilities u_t.

$$U_t = \int_t^{\infty} e^{-\rho(\tau - t)} u(c_\tau, k_\tau, s_\tau) d\tau$$

At each age t, individuals choose how much crime to commit c_t to maximize lifetime utility, subject to the criminal capital accumulation equation and an initial level of criminal capital k_0.[45]

$$V_t = Max_{c_t} \int_t^{\infty} e^{-\rho(\tau - t)} u(c_\tau, k_\tau, s_\tau) d\tau$$

$$\text{s.t. } \dot{k_t} = c_t - \delta k_t$$

Dynamics Under Fixed Sanctions

I first solve for the optimal level of c_t when sanctions s_t do not vary with t (or that $s = S_J = S_A$). In essence, this shows how individuals would behave if they were treated as juveniles for their entire lifetime.

$$\mathcal{H}(c_t, k_t) = u(c_t, k_t, S_J) + \lambda_t(c_t - \delta k_t)$$

[44] This assumption is motivated by the fact that serious offenses are more likely to result in an arrest. For instance, the 2015 Uniform Crime Reports show that less than 40 per cent of homicide offenses did not result in an arrest, while the analogous estimate for robbery was over 70 per cent.

[45] k_0 determines the return to criminal activity for an individual with no criminal experience, and can be thought of as the criminal experience of one's peer group, or an inexperienced individual's access to criminal opportunities.

c_t, the control variable, can be chosen freely; k_t is the state variable, since its value is determined by past decisions; λ_t, the costate variable, is the shadow value of the state variable k_t. The Maximum Principle generates three conditions characterizing the optimum path for (c_t, k_t, λ_t):

$$\begin{array}{lllllll} \mathcal{H}_c & = & 0 & \Longrightarrow & R(k_t) - p_c(c_t)S_J + \lambda_t & = & 0 \quad (2a) \\ \mathcal{H}_k & = & \rho\lambda_t - \dot{\lambda}_t & \Longrightarrow & R_k(k_t)c_t - \delta\lambda_t & = & \rho\lambda_t - \dot{\lambda}_t \quad (2b) \\ & & & & lim_{t\to\infty}e^{-\rho t}\lambda_t k_t & \leq & 0 \quad (2c) \end{array}$$

Equation $(2a)$ pins down the optimal level of criminal activity at each age, and can be rewritten as

$$p_c(c_t)S_J = R(k_t) + \lambda_t$$

Individuals choose c_t to equate the marginal cost of crime $p_c(c_t)S_J$ with the marginal benefits of crime. Benefits from crime consist of the current return $R(k_t)$ plus the value of an additional unit of criminal capital in the future λ_t. This implies that expectations about future decisions will influence the valuation of criminal capital in the current period. For instance, lower returns in the future λ_t can decrease c_t today even if immediate returns $R(k_t)$ remain high.

Equation $(2b)$ can be integrated to obtain the following expression

$$\lambda_t = \int_t^\infty e^{-(\rho+\delta)(\tau-t)}R_k(k_\tau)c_\tau d\tau$$

λ_t represents the shadow value of criminal capital k_t, and is equal to the present discounted value of future marginal returns to criminal capital. This implies that expectations about future decisions will influence the valuation of criminal capital in the current period. For instance, if criminal activity is expected to decrease in the future, λ_t will decrease even if returns to c_t are high in the current period t.

Equation $(2c)$ specifies that the value of criminal capital cannot accumulate at a rate faster than the discount rate on the optimal path. This ensures that optimizing individuals do not accumulate criminal capital that they do not intend to utilize.

Using $R(k_t) = k_t^\alpha$, $\alpha \in (0,1)$, $p(c_t) = c_t^2$, and re-arranging the capital accumulation equation and first order conditions, dynamics in the model can be summarized by:

$$\dot{k}_t = c_t - \delta k_t = \tfrac{1}{2S_J}(k_t^\alpha + \lambda_t) - \delta k_t$$

$$\dot{\lambda}_t = (\rho+\delta)\lambda_t - \alpha c_t k_t^{\alpha-1} = (\rho + \delta - \tfrac{\alpha}{2S_J}k_t^{\alpha-1})\lambda_t - \tfrac{\alpha}{2S_J}k_t^{2\alpha-1}$$

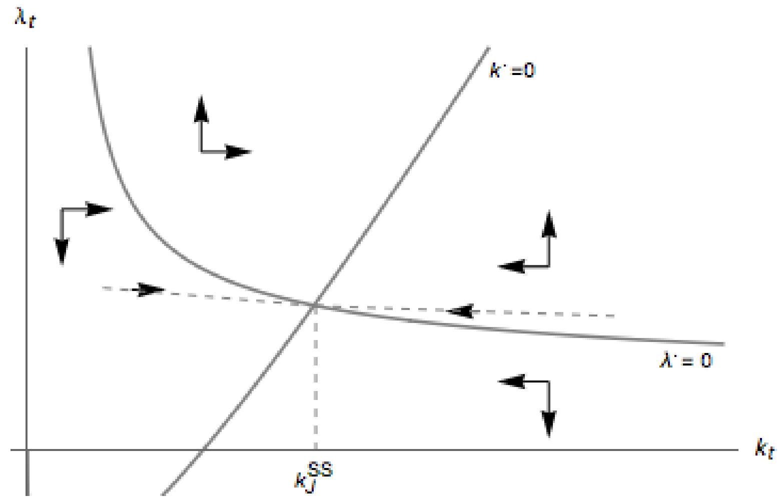
Figure A.4 displays the $\dot{k}_t = 0$ and $\dot{\lambda}_t = 0$ loci graphically.[46] The arrows show how k_t and λ_t must evolve in order to satisfy conditions $(2a)$ and $(2b)$, given their initial values. The $\dot{k}_t = 0$ and $\dot{\lambda}_t = 0$ loci intersect at the steady state level of capital of criminal capital k_J^{SS} - optimizing individuals will not increase or decrease their stock of criminal capital beyond

$$k_J^{SS} = [\tfrac{1}{2S_J\delta}\{\tfrac{\alpha}{(\rho+\delta)} + 1\}]^{\frac{1}{1-\alpha}}$$

The steady state value of criminal capital decreases in criminal sanctions S_J, depreciation rate δ and the rate at which future utility is discounted ρ; k_J^{SS} increases with the returns to additional criminal capital α. This is explicitly calculated in Section A.3.1.

[46]This figure is drawn using the following parameter values: $\alpha = 0.4, \delta = 0.3, \rho = .05, s = 10$.

FIGURE A.4. SADDLE PATH UNDER AGE-INDEPENDENT SANCTIONS



This system of differential equations exhibits saddle path stability for a wide range of parameter values, as detailed in Section A.3.2.[47] Recall that the initial value of capital k_0 is assumed to be given, while the shadow value of capital λ_0 is free to adjust. Saddle path stability indicates that there is a unique value of λ_0 (on the saddle path, shown as the dashed line) such that k_t and λ_t converge to the steady state. If λ_0 starts below the saddle path, the individual eventually crosses into the region where both k_t and λ_t are falling indefinitely. If λ_0 starts above the saddle path, the individual eventually crosses into the region where both k_t and λ_t are rising indefinitely. Both of these cases will violate the transversality condition $(2c)$.[48]

Thus, given an initial value k_0, optimizing individuals will move along the saddle path towards k_J^{SS}. If an individual's initial k_0 is lower than the steady state k_J^{SS}, c_t and k_t will increase until $k_t = k_J^{SS}$, and criminal activity will stabilize at

$$c_J^{SS} = \frac{1}{2S_J}[(k_J^{SS})^\alpha + \lambda_J^{SS}]$$

The dashed lines in Figure A.6 represent this evolution graphically. In the absence of adult sanctions, both criminal activity and criminal capital increase as individuals age, and converge towards their respective steady states.

Dynamics Under Anticipated Adult Sanctions

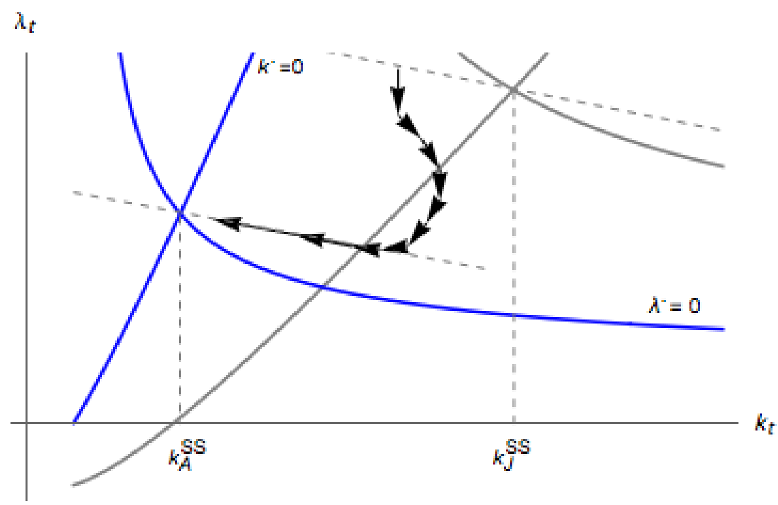
In this section, I describe the optimal response to the anticipation of higher sanctions S_A for $t \geq T$. Graphically, individuals anticipate that both the $\dot{k_t} = 0$ and $\dot{\lambda_t} = 0$ loci will shift to the left for $t \geq T$, as shown in Figure A.5. The $\dot{k_t} = 0$ locus shifts up and to the left because the increase in sanctions makes it more expensive to replenish depreciated capital. The $\dot{\lambda_t} = 0$ locus shifts down because c_t is expected to fall in the future (due to higher costs) and this lowers the future return to criminal capital. Figure A.5 also shows that the new steady state level of criminal capital k_A^{SS} will be lower than k_J^{SS}:

$$k_A^{SS} = [\frac{1}{2S_A\delta}\{\frac{\alpha}{(\rho+\delta)} + 1\}]^{\frac{1}{1-\alpha}} < k_J^{SS}$$

[47] For instance, $0 < \alpha \leq 0.5$ is a sufficient condition for saddle path stability.

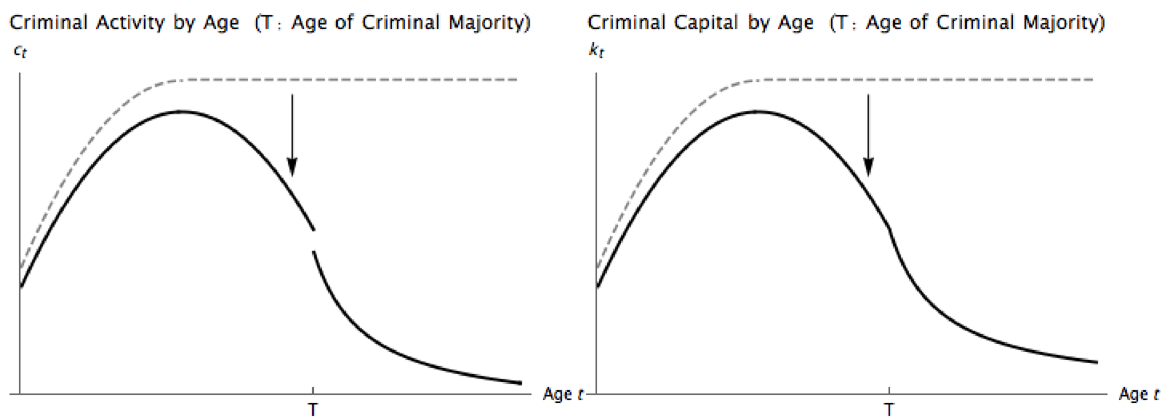
[48] There is a lower bound k_{min} (defined in Section A.3.3) such that no capital accumulation will take place if $k_0 < k_{min}$ (the asymptote of the $\dot{\lambda_t} = 0$ locus on the k-axis). I focus on individuals for whom $k_{min} < k_0 < k_J^{SS}$ and describe c_t and k_t as they move along the saddle path towards k_J^{SS}.

FIGURE A.5. SADDLE PATH UNDER AGE-DEPENDENT SANCTIONS



The optimal response to an anticipated rise in sanctions is characterized by two pieces of information. First, while the lower sanctions S_J are in effect, the original $\dot{k_t}$ and $\dot{\lambda_t}$ functions still dictate the evolution of k_t and λ_t - graphically, the original arrows indicate how $\dot{k_t}$ and $\dot{\lambda_t}$ evolve while $t < T$. Second, the shadow value of criminal capital λ_t cannot jump (decrease discontinuously) at time T, since no new information about sanctions is learned at time T. Instead, λ_t will jump down (decrease discontinuously) when the individual first learns about the higher sanctions S_A. This will ensure that the individual moves toward the new saddle path during $t < T$, and is on the new saddle path at time T. After time T, the individual moves up along the saddle path, decumulating criminal capital until they reaches the new steady state k_A^{SS}.

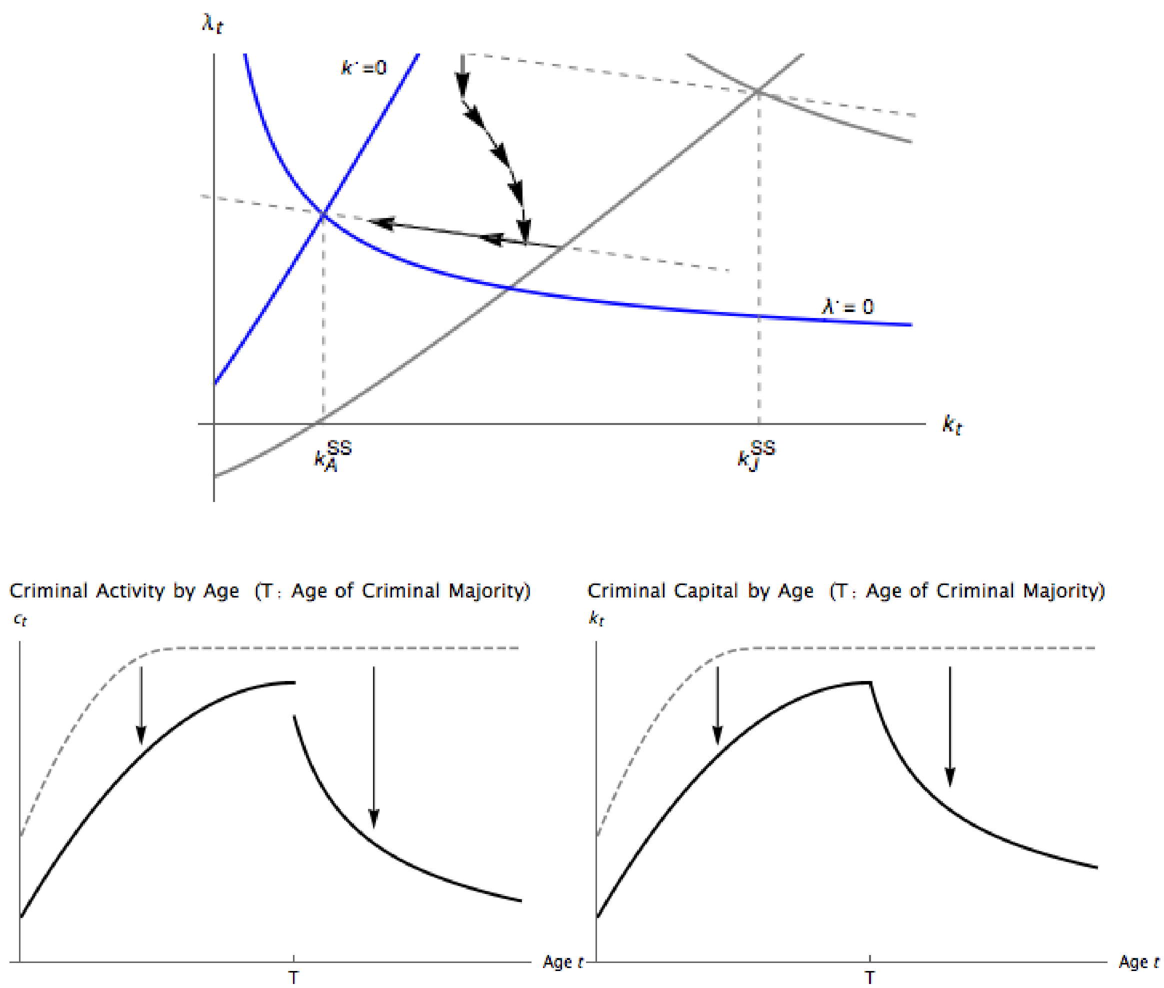
FIGURE A.6. c_t AND k_t UNDER ANTICIPATED ADULT SANCTIONS



Notes: This figure summarizes the qualitative predictions of the model. The dashed lines display the optimal paths for c_t and k_t if sanctions stay fixed at S_J. The undashed line shows that when sanctions increase at the age of criminal majority T, crime c_t is predicted to decrease discontinuously at T, but is also lower **prior** to age T. k_t is also lower **prior** to age T.

Figure A.6 shows how this has implications for criminal activity and criminal capital as individuals age into adulthood. While individuals are below the ACM T, they will first add to their stock of criminal capital k_t, and later begin to decumulate k_t as they approach T. Since the change in k_t depends on c_t net of depreciation, this also tells us about the behavior of c_t, which first increases and then decreases as individuals approach T. Optimal c_t drops discontinuously when individuals surpass T and face higher sanctions, and continues to decline as k_t declines (since k_t determines the return to crime). We can see that deterrence shows up as a discontinuous drop in c_t at T, but deterrence effects also generate lower c_t and k_t prior to reaching the threshold T. This is a deterrence effect because in the absence of adult sanctions, c_t and k_t would have converged towards their original steady state levels (represented by the dashed grey lines).

FIGURE A.7. ALTERNATE PATHS FOR c_t, k_t AND λ_t UNDER ANTICIPATED ADULT SANCTIONS



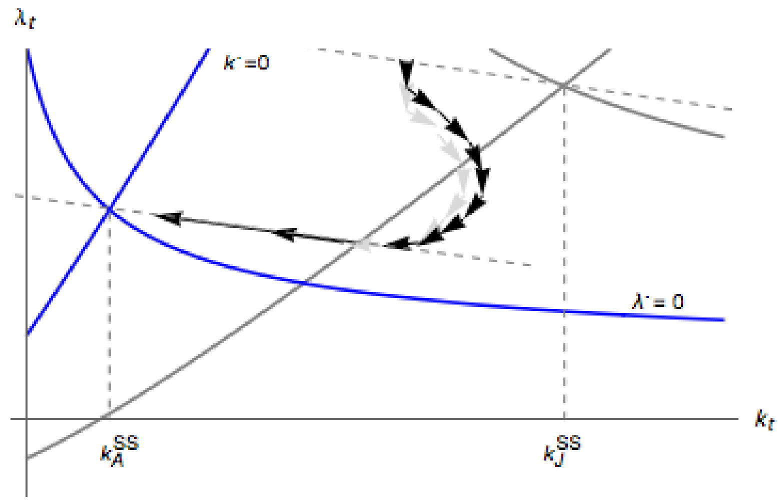
Notes: This figure displays paths for c_t, k_t and λ_t that are also consistent with optimizing behavior. The dashed lines mark optimal paths for c_t and k_t if sanctions stayed fixed at S_J. Importantly, k_t and c_t are lower than they would be in the absence of adult sanctions, even **before** the age of criminal majority T.

Figure A.7 presents an alternate saddle path for k_t that is consistent with optimizing behavior. In this situation, k_t and c_t continue to increase until age T, but are lower than they would be in the absence of adult sanctions. As individuals cross the threshold T and begin to face harsher sanctions, c_t decreases discontinuously. From this point onwards, k_t begins to converge to the lower steady state k_A^{SS}, and c_t follows suit. The predicted responses to an increase in the age of criminal majority T, discussed in Section 4.2, remain similar under both of these scenarios.

Increasing the Age of Criminal Responsibility

This section focuses on the subset of adolescents who are both informed of the age threshold, and forward looking ($\rho < \infty$).[49] The model predicts that that when the ACM is raised from T to T', groups close to T should increase criminal activity.

FIGURE A.8. RESPONSE TO AN INCREASE IN T



When the age threshold is raised from T to T', the optimal response must continue to satisfy two requirements, shown graphically in Figure A.8. First, while the lower sanctions S_J are in effect the original $\dot{k}_t$ and $\dot{\lambda}_t$ functions still dictate the evolution of k_t and λ_t. Second, the shadow value of criminal capital λ_t must decrease *less* to ensure that the individual is on the new saddle path at age T', i.e. one year later. The individual moves toward the new saddle path during $t < T'$, and is on the new saddle path at age T'. Once past T', the individual moves up along the new saddle path, decumulating criminal capital until they reach the new steady state k_A^{SS}. For the case in which criminal capital decumulation only begins at T, the same argument applies - λ_t will decrease by less to ensure that the individual is on the new saddle path at age T' instead of T.

For age groups below the new threshold T', returns to criminal activity are higher, reflected by the smaller drop in λ_t. This will lead to an increase in c_t for age groups below the old threshold T, but also between the two thresholds T and T'. For age groups close to but above the new threshold T', k_t is higher than under the old threshold T. This leads to higher (albeit decreasing) returns to criminal activity as individuals approach the adult steady state. Therefore, c_t is higher for groups to the right of T' as well when the threshold is raised from T to T'.

A.3.1 Steady State k_t and λ_t

This section calculates the the steady state values of k_t and λ_t. Dynamics in the model can be summarized by the following equations:

[49] Individuals who are not forward looking ($\rho = \infty$) will maximize flow utility, and not lifetime utility. This means that they will not internalize the future benefits of criminal capital while making decisions. The maximization problem is a static one (as in Becker 1968), in which individuals commit crime if the current benefits outweigh the current costs. Therefore, the amount of criminal activity that individuals at age t with criminal capital k_t will undertake is given by $c_t = \frac{k_t^\alpha}{2s_t}$. In this case, criminal activity should decrease sharply when sanctions s_t rise as individuals cross the ACM, and the only tests for deterrence are to compare juveniles on either side of the threshold, or examine the behavior of the "newly juvenile group" (the group between T and T') when the age threshold is moved from T to T'.

$$\dot{k}_t = c_t - \delta k_t = \frac{k_t^\alpha + \lambda_t}{2s_t} - \delta k_t$$

$$\dot{\lambda}_t = (\rho + \delta)\lambda_t - \frac{\alpha c_t}{k_t^{1-\alpha}}$$

At the adult steady state, $\dot{k}_t = 0$

$$c_t = \delta k_t \implies \lambda_t = 2s_t \delta k_t - k_t^\alpha$$

At the adult steady state, $\dot{\lambda}_t = 0$ as well

$$(\rho + \delta)\lambda_t = \frac{\alpha c_t}{k_t^{1-\alpha}}$$

Substituting in $c_t = \delta k_t$

$$(\rho + \delta)\lambda_t = \alpha k_t^\alpha$$

Using $\lambda_t = 2s_t \delta k_t - k_t^\alpha$ and assuming $k_A^{SS} \neq 0$

$$\begin{aligned} (\rho + \delta)(2s_t \delta k_t - k_t^\alpha) &= \alpha k_t^\alpha \\ \implies (\rho + \delta)(2s_t \delta k_t^{1-\alpha} - 1) &= \alpha \\ \implies k_A^{SS} &= [\tfrac{1}{2s_t\delta}\{\tfrac{\alpha}{(\rho+\delta)} + 1\}]^{\frac{1}{1-\alpha}} \end{aligned}$$

The steady state value of criminal capital decreases in criminal sanctions s, depreciation rate δ and the rate at which future utility is discounted δ. However, k_A^{SS} increases with the returns to additional criminal capital, represented by α.

A.3.2 Saddle Path Stability

This section shows that the system of differential equations exhibits saddle path stability close to the steady state. A first order Taylor approximation is used to linearize the system around the steady state values.

This system can be written in matrix form:

$$\begin{bmatrix} k_t \\ \lambda_t \end{bmatrix} \approx \begin{bmatrix} \frac{\alpha(\rho+\delta)-(\alpha+\rho+\delta)}{\alpha+\rho+\delta} & \frac{1}{2s_t} \\ (1-2\alpha)(\rho+\delta) + \alpha(1-\alpha) & (\rho+\delta)(1 - \frac{\delta\alpha}{\alpha+\rho+\delta}) \end{bmatrix} \begin{bmatrix} k_t - k^* \\ \lambda_t - \lambda^* \end{bmatrix} = [A] \begin{bmatrix} k_t - k^* \\ \lambda_t - \lambda^* \end{bmatrix}$$

The necessary and sufficient condition for saddle-path stability is that the determinant of A is negative. This condition is met if $0 < \alpha < \frac{1}{2}$ since

$$\frac{\alpha(\rho+\delta)-(\alpha+\rho+\delta)}{\alpha+\rho+\delta} < 0$$

$$\frac{1}{2s_t} > 0$$

$$(1-2\alpha)(\rho+\delta) + \alpha(1-\alpha) > 0$$

$$(\rho+\delta)(1 - \frac{\delta\alpha}{\alpha+\rho+\delta}) > 0$$

However, this is a subset of the parameter values that satisfy the condition $|A| < 0$. Values of (α, ρ, δ) that satisfy $(1-2\alpha)(\rho+\delta) + \alpha(1-\alpha) > 0$ also guarantee saddle path stability.

A.3.3 k_{min}

$$
\begin{aligned}
& \dot{\lambda}_t &=& \quad 0 \\
\implies & \lambda_t &=& \quad [\tfrac{\alpha}{2S_J} k_t^{2\alpha-1}] / [\rho + \delta - \tfrac{\alpha k_t^{\alpha-1}}{2S_J}] \\
\implies & \lambda_t &=& \quad \tfrac{\alpha k_t^{\alpha}}{2S_J(\rho+\delta)k_t^{1-\alpha} - \alpha} \\
& &\to& \quad \infty \\
& &\text{as}& \quad k_t \to \tfrac{\alpha}{2S_J(\rho+\delta)}^{\frac{1}{1-\alpha}} = k_{min}
\end{aligned}
$$