

Juvenile Crime and Anticipated Punishment*

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Abstract

Recent research suggests that the threat of harsh sanctions does not deter juvenile crime. This is based on the finding that criminal behavior reduces only marginally as individuals cross the age of criminal majority, the age at which they are transferred from the juvenile to the more punitive adult criminal justice system. Using a model of criminal capital accumulation, I show theoretically that these small reactions close to the age threshold mask larger reactions away from, or in anticipation of, the age threshold. The key prediction of this framework is that when the age of criminal majority is raised from seventeen to eighteen, all individuals under eighteen will increase criminal activity, not just seventeen year olds. I exploit recent changes to the age of criminal majority in the United States to show evidence consistent with this prediction - arrests of 13-16 year olds rise significantly for offenses associated with street gangs, including homicide, robbery, theft, burglary and vandalism offenses. Consistent with previous work, I find that arrests of 17 year olds do not rise systematically in response. I provide suggestive evidence that this null effect may be due to a simultaneous increase in under-reporting of crime by 17 year olds. Last, I use a back-of-the-envelope calculation to show that for every seventeen year old who was diverted from adult punishment, jurisdictions bore social costs of over \$65,000 due to the increase in juvenile offending.

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1 Introduction

Recent research in economics and criminology suggests 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 shift is reflected in states across the U.S., many of which have recently increased the age of criminal majority - the age at which 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. For instance, 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).¹ While this divergence may be driven by methodological differences, it may also be explained by two limitations 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 ACM) than adults, previous estimates may be picking up the combined effect of deterrence and under-reporting.

This paper addresses both of these shortcomings. I first formalize a theoretical model in which individuals not only evaluate the costs and benefits of crime in each period, but also accumulate criminal capital as they commit crime. Each period, returns to crime increase with accumulated criminal capital and decrease in potential sanctions. When the age of criminal majority (henceforth, ACM) is raised from seventeen to eighteen, this framework predicts that individuals younger than seventeen should also increase criminal activity, not just seventeen year-olds. This suggests 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 seventeen year-old arrests.

I present evidence consistent with these predictions using recent variation in the ACM in the United States. To examine juvenile offending that benefits from criminal capital, I use crimes most commonly associated with street gangs, which provide an environment for juveniles in the U.S. to build criminal experience and access additional criminal opportunities. Using a difference-in-differences framework, I show that arrest rates in the age group thirteen-sixteen for these crimes increase significantly when the ACM is raised from seventeen to eighteen. Arrest rates for seventeen year-olds do not increase significantly, consistent with previous work. I provide suggestive evidence that this may be due to a simultaneous increase in under-reporting of crime by this co-

¹Similarly, law enforcement officials often voice concerns about the potential for heightened juvenile gang recruitment and violence in response to raising the age of criminal majority. For instance, see <https://www.dnainfo.com/new-york/20170330/new-york-city/raise-the-age-juvenile-justice-16-17-year-old-charged-adults>

hort. Overall, these results indicate that the deterrence effects of the ACM can be large, particularly when we look for reactions in anticipation of the age threshold.

The theoretical framework used in this paper is motivated by research which shows that criminal experience increases the return to future offending (Sviatschi 2017, Carvalho & Soares 2016, Bayer *et al.* 2009, Pyrooz *et al.* 2013).² 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).³

This framework generates two main predictions. First, criminal involvement will 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.⁴ Second, when the ACM is raised from seventeen to eighteen, this framework predicts that all individuals below eighteen should increase criminal activity. 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 seventeen year olds, as well 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 patterns of criminal involvement and gang-membership by age, separating states by their ACM. Cross-sectional variation in the ACM across states is used to provide evidence consistent with the two main predictions of the model. One, criminal involvement and gang membership (used as a proxy for criminal capital) decline as adolescents approach the ACM. Two, this decline starts at a later age in states that set the ACM at eighteen, as compared to those that set it at seventeen. These patterns are consistent with the model, but remain suggestive.

For the core of the empirical analysis, I use recent variation in the ACM in Connecticut, Massachusetts, New Hampshire and Rhode Island to estimate the causal impact of the ACM on adolescent crime. Estimates are based on a difference-in-differences strategy, and the identification assumption is that the timing of the law change is exogenous. I first show that the monthly arrest rate for sixteen year olds increases by over ten per cent, but does not increase significantly for other age groups under eighteen. Second, I use a crime index based on offenses most likely

²Juveniles may also lose human capital while incarcerated (Aizer & Doyle 2015, Hjalmarsson 2008), increasing the return to criminal capital and perpetuating long-term offending.

³O'Flaherty (1998) also shows that decision makers who confront a long sequence of criminal opportunities act differently from those who confront a single opportunity.

⁴Criminologists 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.

to be related to street gangs⁵ and find a significant increase for each age group under seventeen; the index for seventeen year olds, however, does not increase significantly. Next, I examine arrest rates separately for each of these offenses - the arrest rate for theft, burglary, vandalism, robbery and homicide offenses by thirteen-sixteen year olds increases by over ten per cent; arrest rates for seventeen year olds, however, do not increase significantly. Last, I examine demographic heterogeneity, and find that these effects are entirely driven by arrests of White male adolescents. In sum, these results suggest that deterrence effects are not negligible, particularly for serious offending.⁶

Last, I show that reported crime increases sharply as individuals surpass the ACM, which varies across states within the U.S.⁷ 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 or offenses known to measure criminal activity, and even when we restrict attention to the most serious crimes. These findings are consistent with the fact that local law enforcement officials exercise discretion over how to handle offenders, and that additional requirements must be met to hold juveniles in custody including a strict 48 hour deadline to file charges.⁸

Deterrence estimates are likely to enter the calculus of state governments deciding where to set the ACM. Proponents of raising the ACM usually argue that crime rates will be lower in the long run because incarceration in juvenile facilities reduces recidivism. However, this benefit must be weighed against the costs of reduced deterrence, as documented in this paper. Further, juvenile incarceration is an expensive proposition, outstripping the costs of adult prison in the states under consideration by a factor of two or three.⁹ A back-of-the-envelope calculation suggests that the increase in juvenile crime cost the jurisdiction of an average law enforcement agency around \$430,000 in social costs, including both the costs of heightened offending and additional incarceration costs. On the benefit side, the increase in the ACM meant that the average law enforcement agency subjected 5.4 fewer seventeen-year olds to adult sanctions. Therefore, policymakers should evaluate whether diverting a seventeen year old from adult sanctions is worth \$80,000 in benefits associated with the absence of a criminal record like lower recidivism and higher employment.

⁵These offenses include homicide, assault, robbery, weapon law violations, theft, burglary, vandalism and drug crimes, based off of the FBI's 2015 National Gang Report, in which agencies identify crimes most commonly associated with street gangs.

⁶This is consistent with [Bushway et al. \(2013\)](#)'s findings that seasoned offenders were more responsive to fluctuations in law enforcement practices (Oregon 2000 - 2005).

⁷This is analogous to the strategies employed in [Costa et al. 2016](#) and [Loeffler & Chalfin 2017](#).

⁸[Greenwood 1995](#) and [Chalfin & McCrary 2014](#) also note that juveniles may be arrested at different rates for the same crime.

⁹For instance, in Connecticut and Massachusetts, the cost per inmate in juvenile facilities is three times that in adult facilities ([Justice Policy Institute 2014](#)).

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 (Chalfin & McCrary 2014, O' Flaherty & Sethi 2014, Nagin 2013). Past studies have shown that it is possible to deter adult criminals - sentence enhancements in the U.S. were shown to deter crimes involving firearms and drunk driving (Abrams 2012, Hansen 2015), California's three strikes law reduced felony arrests among offenders with two strikes (Helland & Tabarrok 2007) and in Italy even poor prison conditions were found to deter adult crime (Katz *et al.* 2003). However, research on young offenders finds that sanction severity does not deter crime.¹⁰ These studies leverage the discontinuity in sanction severity at the ACM (Lee & McCrary 2017, Hjalmarsson 2009, Costa *et al.* 2016, Hansen & Waddell 2014) or exploit variation in the ACM over time (Loeffler & Chalfin 2017, Loeffler & Grunwald 2015b, Anna *et al.* 2017) to identify deterrence effects. Since these studies assume that the return to crime is independent of previous criminal experience, the only test for deterrence is whether offending rates for those above the ACM are lower than those below.¹¹ If crime reporting increases once individuals reach the ACM, this test will lead to an underestimate of the deterrence effect. This paper shows that accounting for changes in reporting behavior requires looking at cohorts away from the ACM to measure deterrence effects, and that these can be sizable.

This paper also seeks to contribute to the literature on how individuals think and behave in order to develop alternative approaches to criminal deterrence. These approaches include Cognitive Behavioral Therapy (CBT), which helps adolescents develop alternative ways of processing and reacting to information in order to reduce criminal activity (Heller *et al.* 2017). The Gang Resistance Education And Training (G.R.E.A.T.) program, implemented in middle schools across America, also employs CBT techniques and has been found to reduce gang involvement, but has not significantly reduced violent offending (Pyrooz 2013). While interventions like CBT target those who have not managed to extricate themselves from violent networks, I focus on the fact that some adolescents may already possess the forward-looking behavior associated with reduced automaticity. It is possible that these adolescents respond to the higher ACM by staying in gangs longer, and continuing to offend at higher rates until a later age.

The results of this paper also contribute to the broader literature on how individuals account

¹⁰An exception is Levitt 1998, who studies juvenile crime in the U.S. during 1978-92, during which there were no changes in any state's ACM. He finds that as individuals transition from the juvenile to the adult system, crime falls by more in states where the adult system is more punitive relative to the juvenile system. However, punitiveness is measured by the proportion of juveniles in custody, which could be driven by a greater likelihood of arrest. Increasing the probability of arrest, without increasing sanction severity, has been shown to be an effective crime deterrent (Chalfin & McCrary 2014, O' Flaherty & Sethi 2014).

¹¹Anna *et al.* (2017) test for "role-model" effects on age groups below the age of criminal *responsibility*, the age at which individuals are transferred from the social service system to the criminal justice system. However, individuals between the age of criminal *responsibility* and the age of *majority* in Denmark benefit from a number of sentencing policies and options not available for adults (Kyvsgaard 2004), which makes it difficult to compare the treatment to the US setting.

for future events when making decisions. For instance, the public finance literature has documented that individuals react in anticipation of events like the exhaustion of unemployment benefits (Mortensen 1977, Lalive *et al.* 2006), job losses (Hendren 2016) and even access to higher education (Khanna 2016). My findings are also consistent with an extensive margin response - juveniles who wish to reduce offending may leave criminal lifestyles such as gang membership entirely, rather than continue on as gang members who reduce offending once they cross the age threshold.

The rest of this paper is organized into five sections. Section 2 provides background information on juvenile crime trends and law enforcement approaches to juvenile delinquency since the 1990s. Section 3 lays out the theoretical framework of how juveniles accumulate criminal capital, and generates predictions on the response to changes in the ACM. Section 4 describes how these predictions are tested in the data. Section 5 exploits policy variation in the Northeastern states in the U.S. to show evidence consistent with the theoretical framework, and presents the cost-benefit analysis. Section 6 concludes.

2 Setting and Data

This section provides a brief description of juvenile crime trends in the U.S., policy responses to these trends, and the data sets used in the empirical analysis. Policy changes in the Northeastern states in the U.S. are described at some length, because they are used to identify the impact of the ACM on juvenile offending. I also provide suggestive evidence that criminal activity is more likely to be recorded (and hence, observable to the researcher) if the offender in question is above the ACM. Accounting for this variation in observability is one of the key contributions of this paper.

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 abandoned and delinquent juveniles, as well as alternative options like out-of-home placement and probation for juvenile offenders. The juvenile justice system in the U.S. today comprises of both separate facilities for housing juveniles as well as a separate system of juvenile courts, in which the focus is on protecting and rehabilitating youthful offenders, usually disbursed via the individualized attention of a judge (as opposed to a jury).

However, there exists substantial variation in the definition of juveniles within the U.S. The age of criminal majority - the lowest age at which offenders can be treated as adults by the criminal

justice system¹² - has varied considerably across time and space within the U.S. Table 1 displays a complete list of states by the age of criminal majority in 2017, and whether it has had a different age of criminal majority in the past. While the majority of states set the ACM at seventeen or eighteen, the ACM has varied from nineteen in 1993 Wyoming to sixteen in Connecticut, New York and North Carolina in the 2010s. Recently, Connecticut, Illinois and Vermont have even proposed bills to raise the age of criminal majority to twenty-one.

Trends in juvenile crime help explain some of the variation in the ACM over time. Figure A.1 plots juvenile and arrest rates in the U.S. for the period 1980-2013. 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 age of criminal majority (Snyder & Sickmund 2006). As shown in Table 1, New Hampshire, Wisconsin and Wyoming lowered their ACMs during this period. However, the simultaneous enactment of policy changes in other states makes it hard to disentangle the effect of the ACM from the effect of all of these other policies. Since the identification assumptions necessary for a difference-in-difference analysis are unlikely to be satisfied in this context, I turn to more recent changes in the ACM.

ACM Changes in the 2000s

This section describes recent changes to the ACM across states in the U.S. As Figure A.1 shows, juvenile crime rates have fallen consistently since the 1990s. This decline has lent support to the legislative push to raise the ACM in states that set it below eighteen. Many of these 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 goes 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 will be more costly to implement in states that set the ACM below eighteen and incarcerate sixteen and seventeen year old along with older inmates in adult facilities.

The Northeastern states of Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont provide an arguably ideal setting in which to study the impact of ACM changes. The first reason is that there existed tremendous heterogeneity in the ACM within these states in 2003. Connecticut and New York set the ACM at sixteen, Massachusetts and New Hampshire

¹²Some states have statutory exclusion laws in place, which allow offenders younger than the ACM to be tried as adults for serious felonies like murder.

TABLE 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 misdemeanours 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 ^a Still 17 for other felonies
New Hampshire	18	18 until 1996, 17 until 6/20/2015
New York	16	Will change to 17 on 10/1/2018 change to 18 on 10/1/2019
Rhode Island	18	18 until 30/6/2007, 17 until 11/7/2007
South Carolina	18	17 until 2016
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, Vermont, Virginia, Washington, West Virginia	18	-
Georgia, Michigan*, Missouri*, Texas*	17	-
North Carolina*	16	-

*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; North Carolina: HB 725, introduced 4/10/13, passed House on 5/21/14; Missouri: HB 274 introduced 12/19/1; Michigan: HB 4607 introduced 5/11/7.

^a<https://www.ncjrs.gov/pdffiles1/ojdp/232434.pdf>

at seventeen, and Rhode Island and Vermont at eighteen.¹³ Second, each of these states has introduced legislation to change the ACM since the passage of the PREA, and five have been successful. The identifying assumption that the actual timing of legislation passage is random is more believable, given that each state's neighbors had also introduced similar legislation within the same time frame. Last, their geographical proximity makes it likely that unobserved factors are similar across the states.

Two other states recently raised the ACM - Illinois raised the age for misdemeanors in 2010 and for all felonies in 2014, while Mississippi raised the age for misdemeanors and some felonies in 2011. Three reasons prevent the inclusion of these states into the study sample. First, the law change is not identical to that of the Northeast, since the ACM is raised only for a subset of offenses each time. Second, data is unavailable for most agencies in Illinois. Third, traditional control groups are unavailable, since none of these states' neighbors introduced legislation to change the ACM during the study period. Therefore, I focus on the Northeastern states for the bulk of my empirical analysis.

Arrest and Offense Data: Proxies for Criminal Activity

Criminal activity is not directly observable, so researchers 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 (Loeffler & Chalfin 2017, Costa *et al.* 2016), such as the victim's decision to file an official report.¹⁴ Official data cannot reflect, for instance, the amount of crime which is not reported to the police¹⁵ or crime that goes unreported due to the discretionary practices of individual officers.

Studies examining the effects of age-based criminal sanctions particularly worry that offense and arrest reports are *more* likely to be generated if offenders are treated as adults by the criminal justice system.¹⁶ This is because 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 forty eight 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 that their offenses are included in official crime statistics. This is problematic for studies that compare individuals on either side

¹³A 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.

¹⁴How crime statistics are generated is also a long-standing concern in criminology - see Black (1970), Black (1971) and Smith & Visser (1981).

¹⁵The 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.

¹⁶For instance, see Loeffler & Grunwald (2015a) and Loeffler & Chalfin (2017).

of the ACM, because reported crime will be higher for individuals that face lower incentives to commit crime (individuals above the ACM). If the drop in actual crime is largely offset by the increased probability of a crime being reported, we are likely to find very small 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. [Costa et al. \(2016\)](#) examine biases in criminal statistics by testing for discontinuous *increases* in crime as individuals surpass the age of criminal majority in Brazil. They find a significant increase in non-violent crimes by individuals just above the age threshold, which suggests that under-reporting falls once offenders can be charged criminally as adults. An analogous strategy is followed by [Loeffler & Chalfin \(2017\)](#), who show that arrests dip sharply for sixteen year olds in Connecticut, as they are transitioned from the adult to the juvenile justice system.

I use an analogous argument to provide evidence suggestive of reduced under-reporting at the ACM in the U.S. - I 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. Using monthly data at the law enforcement agency level for the years 2006-14, Panel A of Figure 6 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 is suggestive of reduced under-reporting as individuals cross the age of criminal majority. Therefore, existing papers that compare juveniles with adults are likely to report 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 manipulated. For instance, [Costa et al. \(2016\)](#) study violent death rates around the ACM in Brazil as a proxy for involvement in violent crime. They argue that this is an improvement over police records because death certificates that include the probable cause of death are necessary for burial and mandated by the national government. They also highlight the main drawback of this measure - violent death rates may not be reflective of trends in other, less violent crimes. In a similar vein, some studies on crime in the U.S. use data on offenses 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 profile described above is true irrespective of whether crime is defined as 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 eighteen 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

offenders below the ACM (not just arrestees) may suffer from under-reporting as well. Therefore, using offense data provides a partial solution to the misreporting issue.

This paper proposes an alternative method to estimate deterrence effects. I examine 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 of crime is unchanged. If adolescents to the left of the threshold increase criminal activity when the ACM is moved further away from them, reported crime should increase. Furthermore, this response is a deterrence effect, since juveniles are responding to the expectation of lower sanctions in the future by increasing offending in the current period.

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

This section uses criminological studies and national gang surveys to characterize youthful involvement in street gangs in the United States. Crimes most likely to be related to street gangs are the focus of the empirical analysis. All other crime categories are used as "placebo" tests, to show that general crime trends are not driving the results.

Gangs¹⁷ 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 (National Gang Center 2012, Egley *et al.* 2010).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 over a million juvenile gang members in the U.S. today. Two, gang members contribute disproportionately to overall crime, particularly to violent adolescent crime. For instance, Thornberry (1998) and Fagan (1990) 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 sixty percent of drug dealing offenses and sixty 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 (National Gang Center 2012, Thornberry 1998,

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

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

¹⁹Crime 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.

Fagan 1990, Klein & L. Maxson 2010). 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 gang involvement is reported as moderate or high. I end up with eleven UCR offense categories - homicide, robbery, assault, burglary, theft (including motor vehicle theft), stolen property offenses, counterfeiting and fraud, vandalism, weapon law violations, prostitution and sex offenses (excluding rape), and drug sale and manufacture.²¹

Gangs provide a setting in which juveniles can accumulate criminal experience and access additional criminal opportunities, lending support to the assumptions of the theoretical framework. Additionally, previous involvement with law enforcement makes gang members more likely to be informed about changes in the ACM. These two features mean that gang-related crimes are expected to react in line with the predictions of the model. Therefore, I use these eleven gang-related offenses to test the main predictions of my model. I use other offenses as placebo tests - the absence of changes in these crimes is used to rule out the hypothesis that general crime trends are driving the deterrence results.

Data

Local law enforcement agencies in the United States choose to report crime statistics to federal agencies in one of two ways - the Uniform Crime Reports (UCR) and the National Incident Based Reporting System (NIBRS). This paper makes use of both of these data sources; 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 Uniform Crime Reports have been compiled by the Federal Bureau of Investigation (FBI) since 1930. UCR data contain monthly data on criminal activity within the 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 have submitted their crime data via the UCR. However, the UCR system does not account for multiple offenses,²² nor does it account for seriousness within offense categories.

These drawbacks of the UCR system led to the creation of the National Incident Based Reporting System (NIBRS). The NIBRS collects information on each crime occurrence known to the police, and generates data as a by-product of local, state and federal automated records management sys-

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

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

²²In an incident wherein multiple offenses were committed, only the crime that has the highest rank order in the list of ordered categories will be counted in the monthly totals.

tems. 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 have submitted their crime data via the NIBRS.

To examine how juveniles accumulate criminal experience by offending and associating with delinquent peers, I use the National Longitudinal Survey of Youth 1997 (NLSY97). The NLSY97 is 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 gang membership and criminal involvement (property, drug, assault and theft offenses) in the preceding twelve months for each year between 1997 and 2001. 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 gang membership and criminal involvement, separating states by their ACM.²³

3 Theoretical Framework

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

Life-Cycle Model of Crime with an Anticipated Threshold

In [Becker \(1968\)](#)'s seminal framework, individuals undertake criminal activity if the benefits of crime outweigh the costs. I extend this model to allow individuals to accumulate criminal capital as they undertake criminal activity over their life course.²⁴ In line with recent work,²⁵ criminal capital increases the return to future crime, likely through access to criminal networks and additional opportunities to commit crime.²⁶ The setup is similar to a standard model of optimal capital

²³[Pyrooz & Sweeten \(2015\)](#) create gang membership by age profiles, but do not separate states by their ACM.

²⁴[Lee & McCrary \(2017\)](#) also use a dynamic extension of [Becker \(1968\)](#)'s framework, but do not allow for inter-temporal complementarities in criminal activity. Closely related is 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 decreasing, and independent of previous criminal involvement.

²⁵See [Pyrooz et al. \(2013\)](#) and [Carvalho & Soares \(2016\)](#), who 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.

²⁶This insight is also similar to that of the rational addiction literature, which argues that individual decision making reflects knowledge of inter-temporal complementarities in consumption. See [Becker & Murphy \(1988\)](#) for a theoretical exposition.

accumulation (Barro & Sala-i Martin 1995), except that individuals can only benefit from criminal capital by committing more crime in the future.

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 age, adolescents decide how much criminal activity c_t to undertake, 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 .

$$u(c_t, k_t, s_t) = R(k_t).c_t - Prob(Caught).s_t$$

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

$$c_t \geq 0$$

The probability of facing criminal sanctions $p(\cdot)$ is assumed to be an increasing convex function of criminal activity c_t .²⁷

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

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

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 .

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

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

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

²⁷This assumption is motivated by the fact that serious offenses are more likely to be reported to the police. For instance, the 2010 National Victimization Survey reports that less than 15 per cent of motor vehicle thefts were not reported to the police, while the analogous estimate for all other thefts was over 65 per cent.

At each age t , individuals choose how much crime to undertake c_t to maximize lifetime utility, subject to the criminal capital accumulation equation.

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

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

To solve this maximization problem, we first set up the current value Hamiltonian. Assume for now that sanctions s_t do not vary with t (or that $s = S_J = S_A$). The initial level of criminal capital k_0 is given.²⁸

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

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) :

$$\mathcal{H}_c = 0 \quad \implies \quad R(k_t) - p_c(c_t)S_J + \lambda_t = 0 \quad (2a)$$

$$\mathcal{H}_k = \rho\lambda_t - \dot{\lambda}_t \quad \implies \quad R_k(k_t)c_t - \delta\lambda_t = \rho\lambda_t - \dot{\lambda}_t \quad (2b)$$

$$\lim_{t \rightarrow \infty} e^{-\rho t} \lambda_t k_t \leq 0 \quad (2c)$$

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 additional benefits of criminal activity. 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 .

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

²⁸ k_0 determines the return to criminal activity for an individual with no criminal experience, and may be influenced by the criminal experience of one's peer group or access to criminal opportunities.

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) is essentially the Transversality Condition in a standard capital accumulation setup (Barro & Sala-i Martin 1995) - on the optimal path, the value of criminal capital should not accumulate at a rate faster than the discount rate, so that individuals do not accumulate criminal capital that do not intend to utilize.

Dynamics Under Fixed Sanctions

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

$$\begin{aligned}\dot{k}_t &= c_t - \delta k_t = \frac{1}{2S_J}(k_t^\alpha + \lambda_t) - \delta k_t \\ \dot{\lambda}_t &= (\rho + \delta)\lambda_t - \alpha c_t k_t^{\alpha-1} = (\rho + \delta - \frac{\alpha}{2S_J} k_t^{\alpha-1})\lambda_t - \frac{\alpha}{2S_J} k_t^{2\alpha-1}\end{aligned}$$

Figure 1 displays the $\dot{k}_t = 0$ and $\dot{\lambda}_t = 0$ loci graphically.²⁹ The arrows show how k_t and λ_t must behave 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 - optimizing individuals will not wish to increase or decrease their stock of criminal capital once they've accumulated $k = k_J^{SS}$. In the Appendix, I show that that the steady state level of k is given by

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

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 system of differential equations exhibits saddle path stability if $0 < \alpha \leq 0.5$.³⁰ 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 means 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).³¹

²⁹This figure is drawn using the following parameter values: $\alpha = 0.4$, $\delta = 0.3$, $\rho = .05$, $s = 10$.

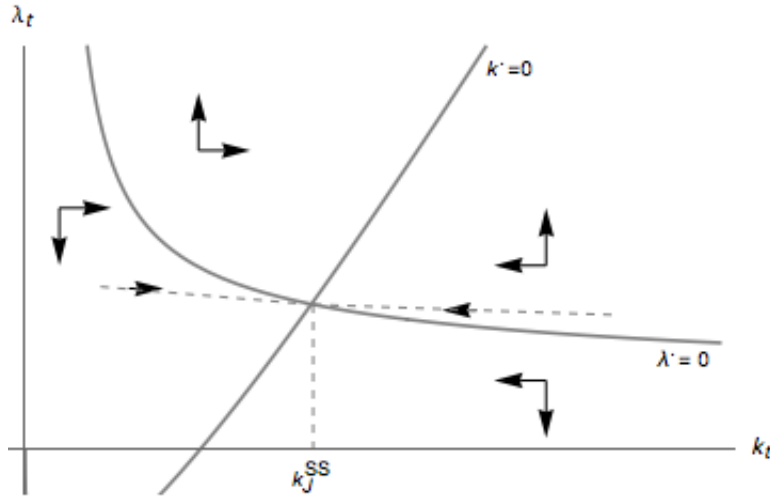
³⁰I show this formally in the Appendix.

³¹There is a lower bound k_{min} 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} .

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

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

FIGURE 1: SADDLE PATH UNDER AGE-INDEPENDENT SANCTIONS



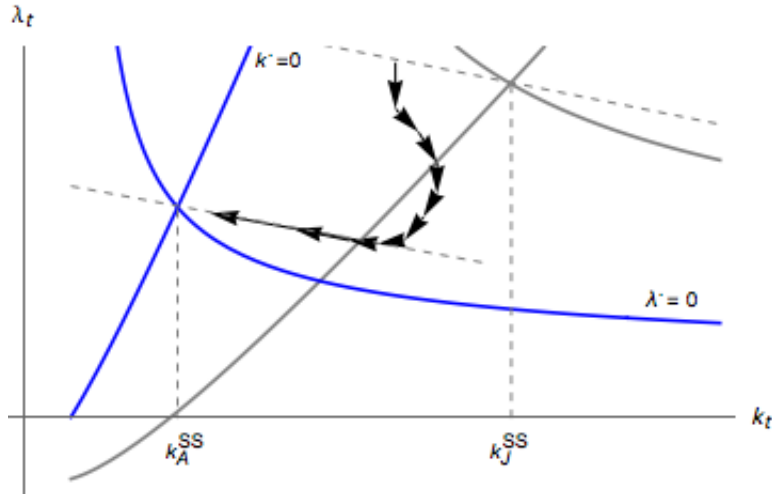
Dynamics Under Anticipated Adult Sanctions

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 2. 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 2 also shows that the new steady state level of criminal capital k_A^{SS} will be lower than k_J^{SS} .

To characterize the optimal response to an anticipated rise in sanctions, we use 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 . As Figure 2 shows, this ensures that the individual moves toward the new saddle path during

$t < T$, and is on the new saddle path at time T . The individual then moves up along the saddle path, decumulating criminal capital until he reaches the new steady state k_A^{SS} .

FIGURE 2: CRIMINAL CAPITAL ACCUMULATION UNDER ANTICIPATED ADULT SANCTIONS



These dynamics dictate how criminal activity and criminal capital evolve as individuals age into adulthood. Figure 2 shows that 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). Figure 3 plots the evolution of both k_t and c_t over time. We can see from Figure 3 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 dotted grey lines).³²

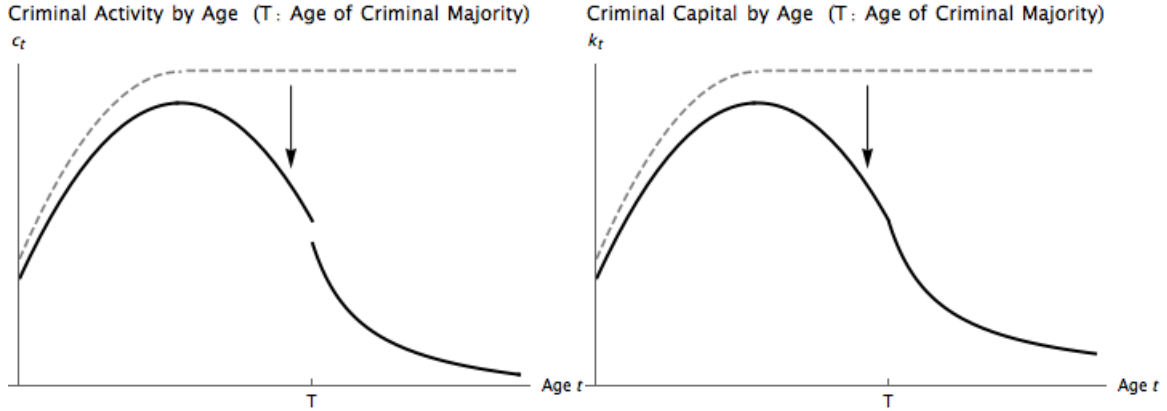
Comparative Statics

Entry Decisions

In the above analysis, each individual's non-crime utility was normalized to zero. It is straightforward to show that if the outside option (or alternative to crime) improves, individuals are less likely to commit crime in the first place.

³²It is not necessary that (k_t, λ_t) cross the original $\dot{k}_t = 0$ locus, as shown in Appendix Figures A.3 and A.4. Here, k_t and c_t continue to increase until age T , but are lower than they would be in the absence of adult sanctions. The predicted response to an increase in the age of majority T remains the same.

FIGURE 3: c_t AND k_t UNDER ANTICIPATED ADULT SANCTIONS



Notes: The dashed line marks the optimal paths for c_t and k_t if sanctions stay fixed at S_J .

Entry decisions are also influenced by the initial stock of criminal capital k_0 , since it determines the payoff to crime. Individuals who begin with a high initial stock of criminal capital, perhaps because they live in areas where returns to crime are high or their peers are criminally active, are predicted to be more likely to begin offending, leading to a self-perpetuating cycle of increases in criminal capital and criminal activity. This prediction is consistent with papers that document very large geographic heterogeneity in criminal offending, including the existence of crime "hot spots" (Eriksson *et al.* 2016, O' Flaherty & Sethi 2014).

Myopic Juveniles

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

$$c_t = \frac{k_t^\alpha}{2s_t}$$

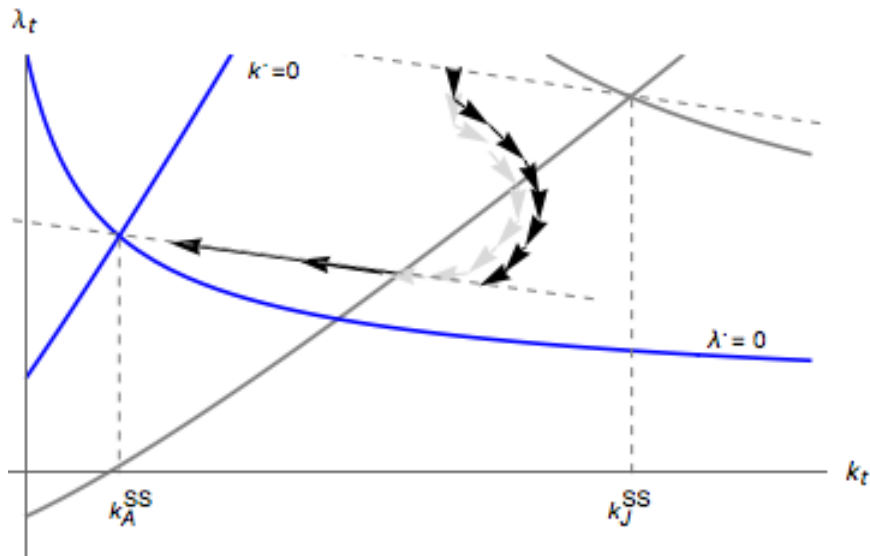
In this case, criminal activity should decrease sharply when sanctions s_t rise as individuals cross the ACM, and the only tests for deterrence are to compare juveniles on either side of the threshold, or examine the behavior of the "newly juvenile group" (the group between T and T') when the age threshold is moved from T to T' . However, past estimates of the change in criminal activity at the threshold have either been small (Lee & McCrary 2017) or negligible (Hjalmarsson 2009, Costa *et al.* 2016). This paper argues that these small effects could be due to mismeasurement of official data,

but also because individuals who are deterred by the threat of adult sanctions may exit criminal lifestyles even before reaching the threshold.

Forward-Looking Adolescents

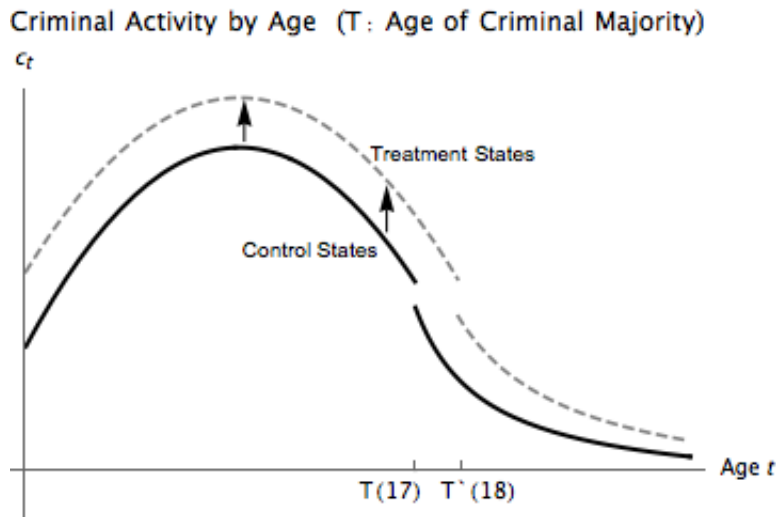
This section focuses on the subset of adolescents who are both informed of the age threshold, and forward looking ($\rho < \infty$). Predictions based on their reaction to changes in the ACM are tested in Section 5 using recent policy variation in the Northeastern states. If the age threshold rises from T to T' , all individuals below T' will benefit from this change, since each of them will face lower sanctions (if caught) for an additional year. In response, individuals will begin to increase criminal activity and accumulate additional criminal capital, as shown in Figures 4 and 5. For instance, a sixteen year old who would have reduced criminal offending and exited his gang before he turned seventeen (T), may postpone exit for an additional year when the ACM is shifted to eighteen. This will show up as an increase in gang membership and criminal offending by sixteen year olds. Moreover, this response is unlikely to be offset by changes in reporting behavior because sixteen year olds are treated as juveniles both before and after the policy change.

FIGURE 4: RESPONSE TO AN INCREASE IN T



The age group between T and T' - those who were treated as adults before the policy change, but juveniles after - should also increase criminal activity c_t . However, if this policy change is accompanied by a simultaneous increase in under-reporting, we may not observe an increase in official crime statistics for this age group.

FIGURE 5: CRIME RESPONSE TO AN INCREASE IN T



Suggestive Evidence from the NLSY

To provide suggestive evidence consistent with the predictions of the model, I examine the age profile of self-reported gang membership and criminal involvement using data from the National Longitudinal Survey of Youth. A panel of 8,984 adolescents were asked about gang membership and criminal involvement (property, drug, assault and theft offenses) in the twelve months preceding the interview. I use these self-reports to examine whether (1) gang membership and criminal involvement decreases prior to the ACM and (2) whether this decrease begins earlier in states that set the ACM at seventeen instead of eighteen.

The first panel of Figure 7 displays the relationship between gang membership and age for male adolescents in all U.S. states that set their ACM at 17 or 18 (as in Pyrooz & Sweeten 2015). Gang membership peaks at ages fifteen and sixteen and declines at ages seventeen and above. The second panel of Figure 7 also shows the age profile of male gang membership, but separates states by their ACM. Here, we find evidence suggestive of earlier exit in states that set the ACM at seventeen, consistent with the predictions of the model. In particular, gang membership peaks earlier (at fifteen) and begins its decline earlier (at sixteen) in states that set the ACM at seventeen. In states that set the ACM at eighteen, gang membership peaks at sixteen, and then declines at ages seventeen and eighteen. Figure A.6 shows that including female survey respondents leads to similar patterns of gang membership.

Figure 8 examines whether the relationship between criminal involvement and age varies with the ACM. The first panel depicts this relationship for male adolescents in all U.S. states that set their ACM at 17 or 18 - we see a clear upward trend until sixteen, and a sharp decline at seventeen.

The second panel also displays the age-crime relationship but separates states by their ACM. Two points are worth noting about this graph. One, criminal involvement is higher for all age groups under eighteen. Two, the decline in criminal involvement begins earlier (at age sixteen) in states that set the ACM at seventeen, and appears later, at age seventeen, in states that set the ACM at eighteen. Both patterns are consistent with the predictions of the model. Figure A.7 repeats this analysis for the sample including female survey respondents, and shows that the patterns of criminal involvement by age are similar. In Section 5, I show that one of the causes of this pattern of higher criminal involvement for all age groups under eighteen is the higher age of criminal majority.

4 Empirical Strategy

This section describes the difference-in-differences strategy used to identify the impact of ACM increases on juvenile offending. As described above, crime by the age cohort that is shifted from above the ACM to below the ACM may experience a simultaneous increase in under-reporting.³³ Therefore, I also examine responses among younger cohorts, for whom crime reporting behavior is less likely to be affected by the ACM law change. The identifying assumption is that the timing of ACM changes is exogenous, conditional on included covariates.

Central Specification

The first test for the impact of the increase in ACM is a straightforward difference-in-difference specification:

$$y_{l,t}^a = \beta ACM_{l,t} + \gamma_l + \gamma_t + \gamma_{ms} + \omega X_{l,t} + \varepsilon_{l,t}$$

Here, $y_{l,t}^a$ is a measure of the crime rate among age group a , in originating agency l in month t . As a measure of the crime rate, I use the number of arrestees aged a per 100,000 residents in agency l 's jurisdiction as the outcome of interest. $ACM_{l,t}$ is a dummy variable that takes on the value one if agency l belongs to a state that raised its ACM in month t or before month t , and zero otherwise.³⁴ To account for permanent differences across law enforcement agencies, I include agency fixed effects γ_l . Time fixed effects γ_t account for national crime trends. State-specific month-of-the-year fixed effects γ_{ms} account for state-specific seasonality. $X_{l,t}$ represents two monthly control variables at the originating agency level - population covered by the agency's jurisdiction,

³³This age group may also face shorter sentences (reduced incapacitation), so observed increases in crime may not be driven by reduced deterrence.

³⁴Rhode Island *lowered* its ACM from 18 to 17 for the period July - November 2007. I assume that $ACM_{l,t}$ takes on the value -1 during this period, which ensures that β can be interpreted as the impact of an increase in the ACM.

as well as the arrest rate in the age group 18-20. The first control is relevant because more populous localities are strongly correlated with higher crime rates; the latter absorbs local trends in arrests for youthful offenders.

Difference-in-difference studies that use one-time changes are usually concerned about the over-rejection of null hypotheses due to serial correlation (Bertrand *et al.* 2004). To deal with this concern, standard errors $\varepsilon_{l,t}$ are clustered at the originating agency level l .³⁵

Event Study Specification

In order to examine the year-by-year impact of the ACM change, I use an event study specification. Agencies are grouped together based on the number of years since implementation of the ACM change. This results in the following specification:

$$y_{l,t}^a = \sum_{i \geq -n} \beta_i ACM_{l,t}^i + \gamma_l + \gamma_t + \gamma_{ms} + \omega X_{l,t} + \varepsilon_{l,t}$$

$y_{l,t}^a$ is a measure of the crime rate among age group a as described above. $ACM_{l,t}^i$ are dummy variables that take on the value 1 if the ACM increased in agency l exactly i years before period t . For instance, Connecticut raised its ACM from 17 to 18 on July 1, 2012, so the ACM^1 dummy will be 1 for the period July 2012 - June 2013, the ACM^2 dummy will be 1 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 location and time fixed effects (γ_l and γ_t), state seasonality (γ_{ms}) as well as agency-level controls $X_{l,t}$. Standard errors are clustered at the agency level.³⁶

5 Results

In this section, I show that delaying the threat of adult sanctions leads to an increase in juvenile offending. When the age of criminal majority is increased from 17 to 18, individuals aged 17 and under increase criminal activity. Increases of over 10 per cent are observed for offenses related to street gangs, including homicide, robbery, theft, stolen property, vandalism and burglary offenses. Since seventeen year-olds are exposed to multiple treatments - lower sanctions³⁷ and an increase in under-reporting, the focus of the empirical analysis is on the response of 13-16 year olds. Their

³⁵This allows errors to be serially correlated within each law enforcement agency, but assumes independence across agencies. The assumption that local shocks to crime are independent across agencies is supported by the finding that crime tends to be concentrated within certain localities (Glaeser *et al.* (1996), O'Flaherty & Sethi (2014)). I show that results are robust to relaxing this assumption in Section 5.5.

³⁶Since Rhode Island only changed its ACM for four months, I include it in the control group for the event study regressions.

³⁷Sanctions are also shorter, leading to a simultaneous reduction in incapacitation.

responses are taken to be clean measures of deterrence because they are responding to the threat of lower sanctions in the future by increasing crime in the current period, and are not exposed to a simultaneous increase in under-reporting.

The setting for the empirical tests is the Northeastern States - Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont. Each of these states has experimented with raising the ACM since 2005, lending credibility to the assumption that the actual timing of ACM changes within these states has been exogenous. These results are based on a balanced panel of agencies that submit data via the Uniform Crime Reports for the period 2006-15.

5.1 Total Crime

I first test whether the overall arrest rate for 13-17 year olds increased following the ACM increase. Table 2 displays the estimated increase in arrest rate across a variety of specifications. The first column shows a significant increase of about 3.5 arrests per 100,000 people each month (12 per cent of the mean) and this estimate does not change materially when we account for state seasonality (state-specific month-of-the-year fixed effects) in the second column. The third column shows that controlling for population and local crime trends (arrest rate for 18-20 year olds) reduces this estimate to 2.4 (8 per cent of the mean) but remains statistically significant. The fourth column accounts for both state seasonality and local controls, and finds that the estimate rises slightly to 2.5 and remains significant at the 5 per cent level. The last column displays the specification used for most of the empirical analysis. Each column clusters standard errors at the originating agency level.

Next, I use an event study specification to examine the year-by-year impact of the ACM increase. Using the specification from column (4) of Table 2, Figure 9 displays β^i coefficients for five years before and four years after the policy's implementation. Panel A shows a clear break in trend during the first year of the ACM increase, and this effect increases over time. To show that local crime trends are not driving these results, I repeat this analysis for three other age groups. Panel B displays the effect on average arrest rate for individuals in four age groups - 13-17, 18-29, 30-39 and 40-49 year olds. There is no evidence of an increase in crime for the age groups 18-29, 30-39 and 40-49 after the ACM increase. Consistent with this graph, I show in the robustness section that results do not change materially when I control for different measures of local crime.

One interpretation of the above results is that the increase in juvenile crime is driven by the reversal of incapacitation effects - seventeen year-olds now face shorter sentences and are able to commit more crime out on the streets. However, this argument would not hold for 13-16 year olds who face identical sentences after the age of criminal majority is raised to eighteen. Below, I show that 13-16 year olds are the main drivers of this increase in offending, and that this is likely to

be a deterrence response since these age groups do not witness a simultaneous change in under-reporting and/or incapacitation.

5.2 Crime Indices: Gang-Related and Other Crime

To examine which types of crime are driving this increase in the arrest rate, I create two crime indices. Each index is the equally weighted average of the z-scores³⁸ of its components.³⁹ The first index uses arrest rates for nine offense categories associated with street gangs - homicide, robbery, assault, burglary, theft (including motor vehicle theft and stolen property offenses), forgery and fraud, vandalism, weapon law violations, and drug sales. The second index uses arrest rates for the remaining eight offense categories that are not associated with street gangs - arson, embezzlement, drug possession, gambling, offenses against the family and children, driving under the influence and liquor laws, disorderly conduct (including drunkenness), and suspicion (including vagrancy and loitering). 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 model and are most likely to react to the ACM change actually do respond.

Table 3 displays the difference-in-difference coefficients for each of these indices, measuring separately the impact on arrest rates of four age groups - 17 year olds, 16 year olds, 15 year olds and 13-14 year olds.⁴⁰ In line with previous research, I find that the impact of an increase in the ACM on 17 year old arrests is not significantly different from zero, for both gang-related and other crimes. I show below that this appears to be driven by an increase in under-reporting of crime by 17-year olds following the ACM increase.

For each of the age groups below seventeen, however, I find a positive and statistically significant increase in the gang-crime index. This increase is not mirrored by an increase in the index based on other crime categories, as shown in Panel B. This indicates that general crime trends may not be driving the effects on gang-related crime.

Figure 10 displays year-by-year estimates from an event study specification to show that this increase in 13-16 year old arrests began following the ACM increase. Panel A displays results for the gang-related crime index - while arrest rates for 13-16 year olds show a clear trend break when the ACM change is implemented, arrest rates for 17 year olds actually dip during the first year of the policy's implementation. This is in line with a surge in under-reporting of 17-year old offenders, who are now treated as juveniles by the criminal justice system. Panel B displays

³⁸z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation.

³⁹Results are robust to using scores based on inverse variance weighting and are available on request.

⁴⁰The Uniform Crime Reports only report collective data for 13 and 14 year old arrestees.

analogous results for the index based on all other offenses, which shows no evidence of an increase around the ACM change for any of the age groups.

5.3 Impact By Offense Type

In this section, I present results for arrest rates by offense category. This includes ten offense categories associated with street gang activity, and the five most common offenses not related to gangs.

5.3.1 Offenses Related to Gangs

Tables 4 and 5 display difference-in-difference estimates separately for property and violent crimes that are most likely to be related to gangs. I find that the arrest rate for 13-16 year olds increases by over ten per cent for theft offenses, and by over twenty per cent for burglary, vandalism, forgery, robbery and homicide offenses. The coefficient on drug sales is large (around eighteen per cent of the mean) and positive, but not statistically significant from zero. The bottom panels of each of these tables shows that 17-year old arrest rates for these offenses do not systematically increase in response to the change in ACM.

5.3.2 Other Offenses

To show that general crime trends may not explain the effects documented above, I examine the effect on crime categories that are unrelated to gang activity. Table 6 displays difference-in-difference estimates for each of the four age groups for the five most common offenses that are not related to gangs. I find that the impact of the ACM increase on disorderly conduct, liquor law violations, drug possession, offenses against families and children, and arson are not significantly different from zero. This findings holds for arrest rates of seventeen year-olds as well as age groups under seventeen.

5.4 Demographic Heterogeneity

In this section, I examine which gender and race groups are driving the increase in gang-related crime. The first panel of Table 7 shows a significant increase in the crime index for males of each age except 17, while the second panel shows that no increase is found among females. This finding may be due to the low involvement of females in criminal enterprises like gangs - for instance, the 2011 National Youth Gang Survey reports that the proportion of female gang members did not exceed 8 per cent over the period 1998-2010.

The UCR data also report the number of arrests of individuals aged seventeen and under by race. The last panel of Table 7 shows that the deterrence estimates are entirely driven by an increase

in the arrest rate for White adolescents.⁴¹ There appears to be no response among adolescents belonging to other race groups. This is surprising because the National Youth Gang Survey reports that in 2011 around 58 per cent of gang members were White/Hispanic while 35 per cent were Black. However, this pattern is consistent with effective treatment differing across race groups - if youth of color are disproportionately charged in adult courts (as reported in [Juszkiewicz 2009](#)), raising the ACM may 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.

5.5 Robustness Checks

This section implements a variety of robustness checks to rule out alternative mechanisms, and deals with issues of over-rejection due to serial correlation.

Clustering at the Age-State Level

The previous analysis studies age-specific arrest rates and clusters standard errors at the agency level. This allows errors to be correlated across time within agency jurisdictions, but assumes that errors are independent across agencies. However, we may want to allow for arbitrary correlation of errors across agencies within each state, since the treatment variable for each age group varies only at the state level.

This sections shows that clustering standard errors at the age-state level does not materially change the results. Recall that treatment differs across age groups - for instance, treated 13-year-olds face an additional year as juveniles four years in the future, while treated 16-year-olds face an additional year as juveniles one year later. That is, effective treatment varies at the age level within each state. To estimate the impact of the ACM increase on juvenile crime while clustering standard errors at the age-state level, I stack arrest rates for three age groups a (13-14, 15 and 16 year olds) and use the following empirical specification:

$$y_{a,l,s,t} = \sum_a \beta^a ACM_{s,t} + \gamma_s + \gamma_t + \gamma_{ms} + \gamma_a + \omega X_{l,s,t} + \varepsilon_{a,l,s,t}$$

$y_{a,l,s,t}$ is the arrest rate for age group a in agency l of state s in month t . Regressions control for state, time and age fixed effects ($\gamma_s, \gamma_t, \gamma_a$), state seasonality (γ_{ms}) and agency-level measures of population and youthful (age 18-20) arrests ($X_{l,s,t}$). β^a is the impact of the ACM increase on age group a . Standard errors are clustered at the age-state level, which allows errors to be serially correlated for each age group within each state, but assumes independence across age groups within each state.

⁴¹Agencies do not separately report arrests for Hispanic arrestees, who can be included in any of the race categories.

Table 10 presents estimates of the average impact ($\frac{\beta^{13,14} + \beta^{15} + \beta^{16}}{3}$) of the ACM increase on the gang-related crime index and ten offense-specific arrest rates. Standard errors are clustered at the age-state level, and are estimated using the wild bootstrap method prescribed by Cameron *et al.* (2008), since the number of clusters is small (eighteen). The top panel shows a significant increase in the gang crime index as well as arrest rates for property crimes like theft, stolen property burglary and vandalism offenses. The bottom panel shows that the increase in homicide offenses remains statistically significant at the 5 per cent level.

Clustering at the State Level

In this section, I extend the sample to include all states in the US and show that clustering at the state level actually strengthens the main results. Illinois, which raised the ACM for felonies in 2014 is used as an additional treatment state.⁴² The specification used is as follows:

$$y_{l,s,t}^a = \beta ACM_{s,t} + \gamma_s + \gamma_t + \gamma_{ms} + \omega X_{l,s,t} + \varepsilon_{a,l,s,t}$$

Standard errors are clustered at the state level, which allows errors to be serially correlated within each state.

Table 11 shows the estimated impact of the ACM increase on offenses related to street gangs - the impact on the gang crime index is nearly identical to previously reported estimated, while the impact on most property, violent and even drug sale offenses are positive and statistically significant. Figure A.5 displays event study estimates, and shows that pre-trends are not driving these findings.

Panel Length

The main empirical analysis used a balanced panel of law enforcement agencies over a ten year period. In this section, I show that extending the balanced panel to additional time periods does not materially change the results. Table A.1 displays effects on the gang crime index based on arrest rates for the age group 13-16 after restricting attention to a balanced sample of agencies over a period of eleven, twelve, thirteen or fourteen years. The coefficient of interest is largely unchanged, and remains statistically significant at the 1 per cent level.

Population Outliers

In this section, I show that the results are not driven by a handful of agencies that cover the most populous jurisdictions. I exclude jurisdictions with populations above the 95th percentile, and re-

⁴²The analysis excludes Mississippi since it only raised the ACM for a subset of offenses and is not directly comparable to treatment in the other states. Results are robust to including Mississippi and are available on request.

estimate the impact of the ACM increase on the gang-related crime index. The first column of Table A.2 displays the results, and shows that the coefficient is materially unchanged and remains significant at the 1 per cent level.

Alternative Crime Controls

In this section, I show that the results are robust to controlling for alternative measures of local crime. The last three columns of Table A.2 show that the estimated effect of the ACM increase on the gang-crime index does not change if we control for the analogous crime index in the age group 18-24, 25-29 or 30-34, and remains statistically significant at the 1 per cent level.

5.6 Some Costs of Raising the Age of Criminal Majority

This section uses a back-of-the-envelope calculation to compare the social costs of raising the ACM with its expected benefits. This is necessarily a partial estimation exercise, since 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 increase in costs from transferring seventeen year-olds to more expensive juvenile facilities. These estimates are then contrasted with the expected benefits of raising the ACM, primarily via the reduction in the number of seventeen year olds with criminal records.

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 UCR data to predict the increase in the number of offenses by 13-16 year olds.⁴³ The first two columns of Table 8 displays the estimates of the increase in monthly arrest rates of 13-16 year olds for homicide, robbery, larceny, motor vehicle theft, stolen property, burglary, vandalism, fraud and forgery 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 estimate of societal costs by offense type, which include costs imposed directly on victims and indirectly on the criminal justice system in the form of legal, police and corrections costs.⁴⁴ The fourth column displays the annual increase

⁴³This 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 offending if juveniles are arrested at lower rates than adults.

⁴⁴[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 offenses than another recent study [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 below seventeen are unlikely to be a part of the formal labor force.

in costs (including incarceration⁴⁵) by offense type due to the uptick in offending, evaluated at the average treatment agency population of 27,200. Overall, the crime increase among 13-16 year olds led to an increase of \$357,000 in societal costs, two thirds of which is accounted for by homicide offenses.

The second source of social costs is the transfer of seventeen 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).⁴⁶ My estimate of the number of such transfers is based on the Office of Juvenile Justice and Delinquency Prevention's data on offense-specific probation and incarceration rates for seventeen year olds, displayed in Table 9.⁴⁷ The sixth column displays completed sentence lengths specific to each offense category (person, property, drug and public order) also reported by the OJJDP. The increase in costs due to the transfer of seventeen year-olds from adult to juvenile facilities is just under \$75,000.⁴⁸

What are the benefits of raising the ACM? Proponents of raising the ACM argue that juvenile justice policies reduce recidivism. However, recent studies show that incarceration in juvenile facilities has a large impact on recidivism (Aizer & Doyle 2015) and that adult incarceration may actually lower recidivism for marginal offenders (Loeffler & Grunwald 2015a). Therefore, I do not focus on lower recidivism as the primary benefit of raising the age; instead, I estimate the number of seventeen year-olds who will be diverted away from adult prisons and will not receive criminal records. This estimate is displayed by offense type in the fourth column of Table 9, which sums up to a total of 5.35 seventeen year-olds.

The question for policymakers is whether a cost increase of \$80,000 per seventeen year-old is exceeded by the potential benefits. There are three reasons why it might - one, the expungement of criminal records has been shown to boost employment rates and average annual real earnings (Selbin *et al.* 2017) and has also been associated with an increase in college completion rates (Lit-

⁴⁵This 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.

⁴⁶Since 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.

⁴⁷Here, I make three assumptions. One, the proportion of seventeen 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 seventeen 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.).

⁴⁸If 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 \$37,500.

wok 2014); 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 \$220,000 for sexual assault and \$24,000 for aggravated assault; three, if more seventeen year olds receive probation instead of incarceration sentences, *Aizer & Doyle (2015)* and *Bayer et al. (2009)*'s findings indicate that we may see an increase in high school completion rates and a decrease in recidivism.

6 Conclusion

Recent research shows that criminal involvement can persist into long-term offending, as individuals accumulate skills and experience pertinent to the crime sector (*Sviatschi 2017, Carvalho & Soares 2016, Bayer et al. 2009, Pyrooz et al. 2013*) or lose human capital valued in the non-crime sector (*Aizer & Doyle 2015, Hjalmarsson 2008*). However, existing research on the deterrence effects of sanctions does not account for these inter-temporal complementarities in the returns to crime.

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 under-reporting as individuals cross the age of criminal majority, which may have biased existing studies towards finding effects of no deterrence.⁴⁹ Using policy variation in the Northeastern states since 2006, I find that raising the age of criminal majority increases overall arrest rates for 13-17 year olds. This rise in arrests is driven by offenses commonly associated with street gangs, including both property and violent offenses. Using a back-of-the-envelope calculation, I show that for every seventeen year-old who was diverted from adult sanctions, jurisdictions bore costs of \$65,000 due to this increase in juvenile offending. Policymakers deciding where to set the age of criminal majority should evaluate whether these costs are outweighed by the potential benefits of lower recidivism and assault risk faced by seventeen year olds, as well as the increase in educational attainment and employment associated with fewer seventeen year olds having criminal records.

Incorporating dynamic incentives into models of criminal decision making appears to be a rich area for future work. While this paper applies this approach to study the deterrence effects of criminal sanctions, it may also be applied to understand the effects of other features of the criminal justice system. For instance, if criminal capital is slow to depreciate, the dynamic approach would indicate that the positive effects of rehabilitative services are likely to be much larger when evaluated over the long term.

⁴⁹This strategy also helps avoid the confound of incapacitation effects - seventeen year olds in the juvenile system may face shorter sentences and spend more time out on the streets where they can commit crime. Therefore, a positive effect of the ACM hike on 17-year-old crime may be due to reduced incapacitation instead of reduced deterrence.

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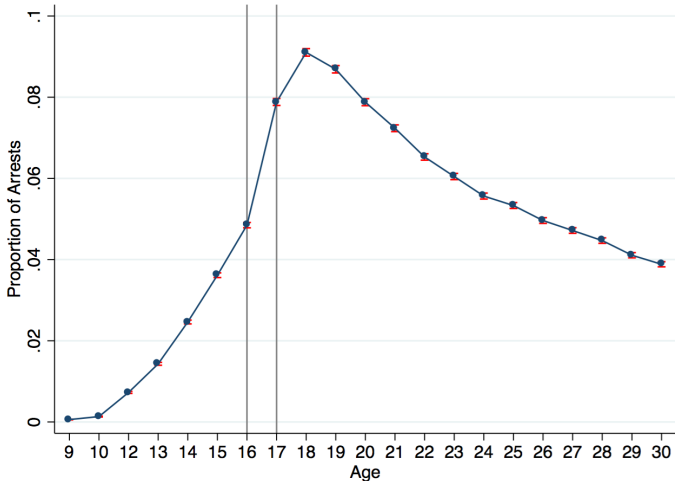
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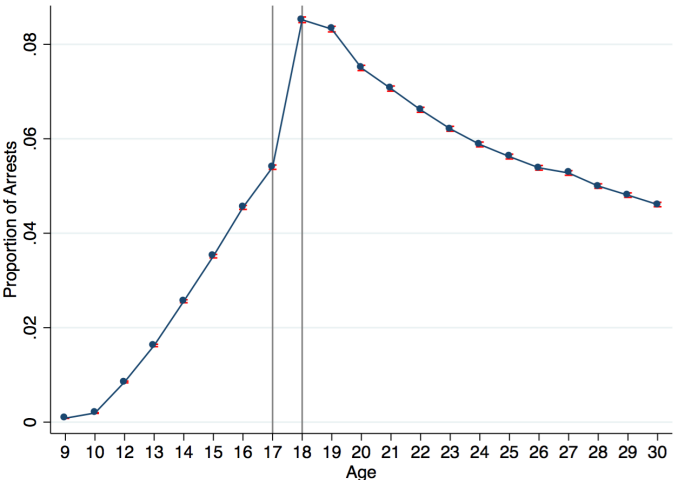
Figures

**FIGURE 6: CRIME REPORTING INCREASES AT AGE OF CRIMINAL MAJORITY
PROPORTION OF ARRESTS BY AGE 2006-14**

(A) AGE OF CRIMINAL MAJORITY = 17



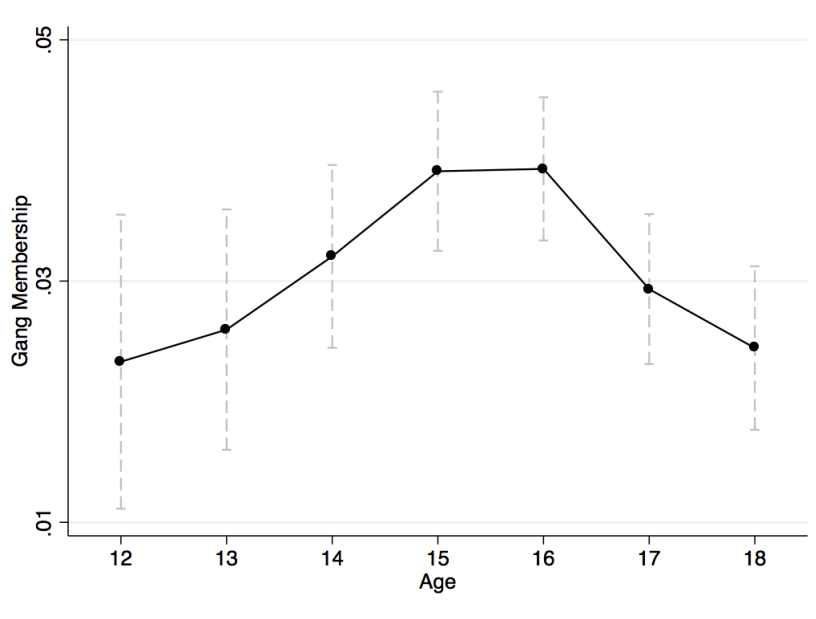
(B) AGE OF CRIMINAL MAJORITY = 18



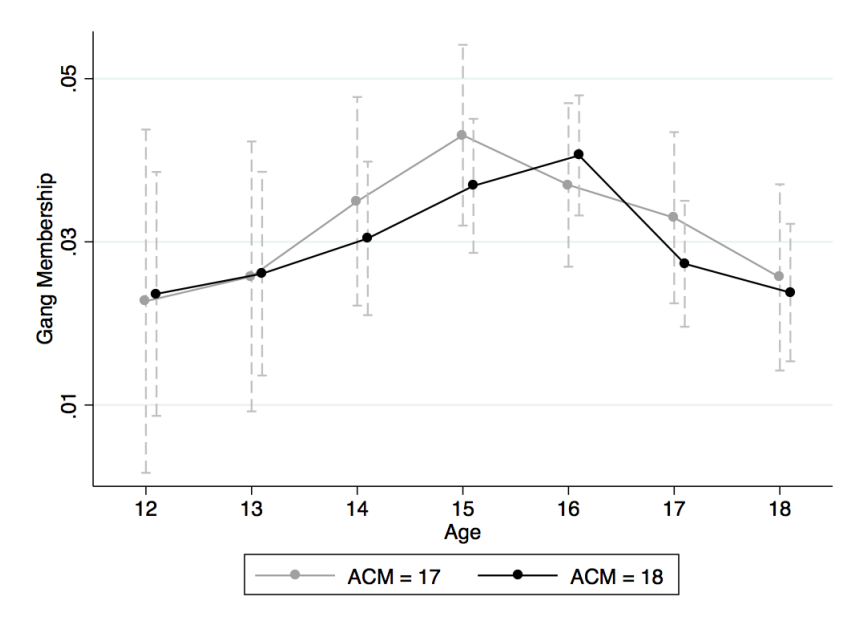
Notes: Uses monthly NIBRS data at the agency level from 39 states. Confidence intervals in red.

FIGURE 7: GANG MEMBERSHIP-AGE PROFILE

(A) ALL STATES



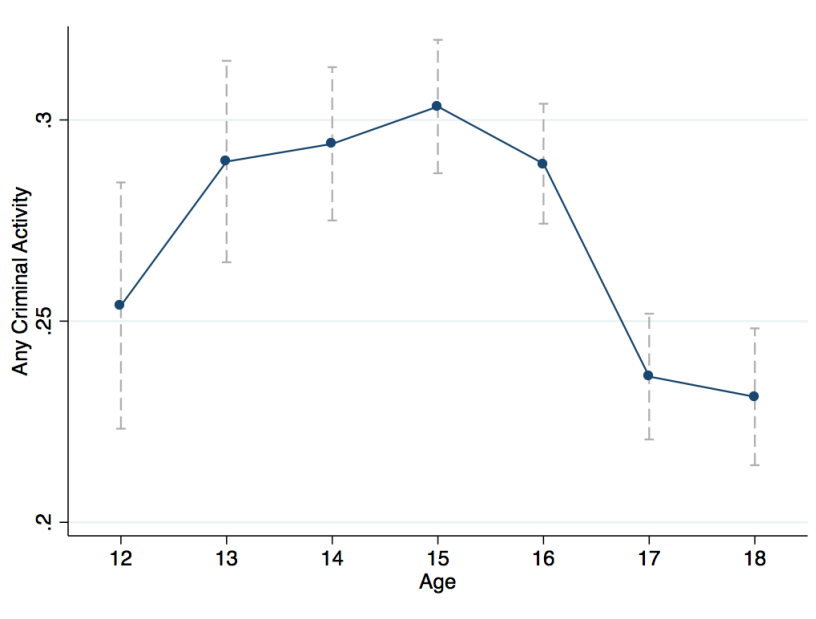
(B) GANG MEMBERSHIP-AGE PROFILE BY AGE OF CRIMINAL MAJORITY



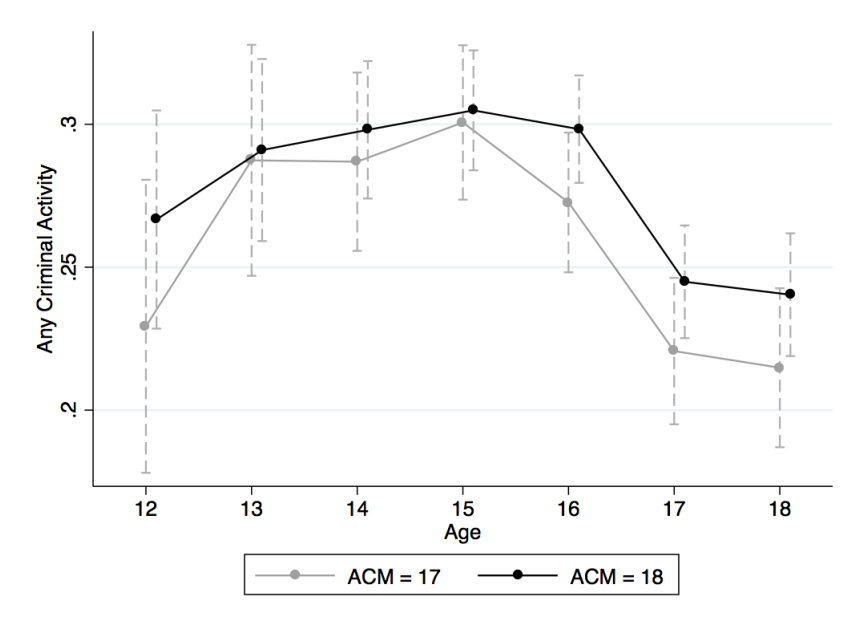
Notes: This graph uses the NLSY97 male self-reported data on gang membership. The coefficients are estimates from a regression of gang membership on age-fixed effects.

FIGURE 8: CRIMINAL INVOLVEMENT-AGE PROFILE

(A) ALL STATES



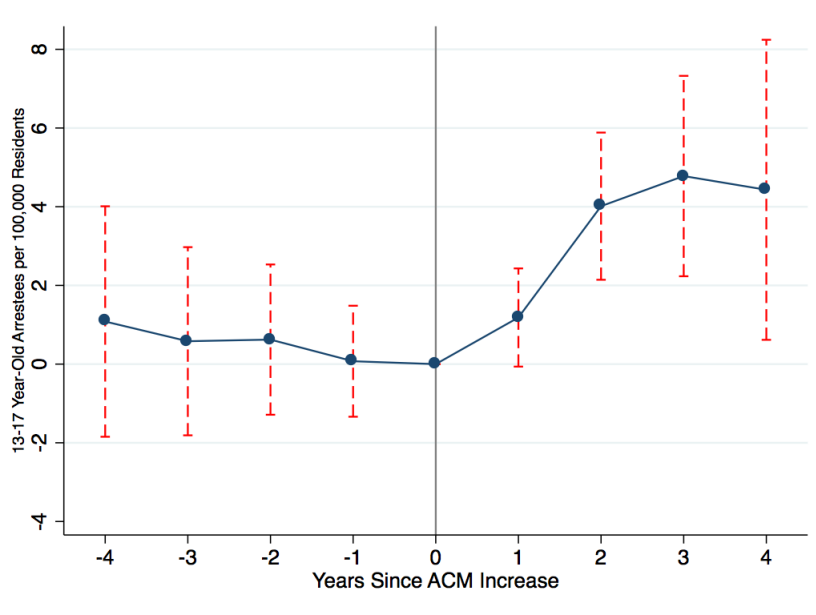
(B) CRIMINAL INVOLVEMENT-AGE PROFILE BY AGE OF CRIMINAL MAJORITY



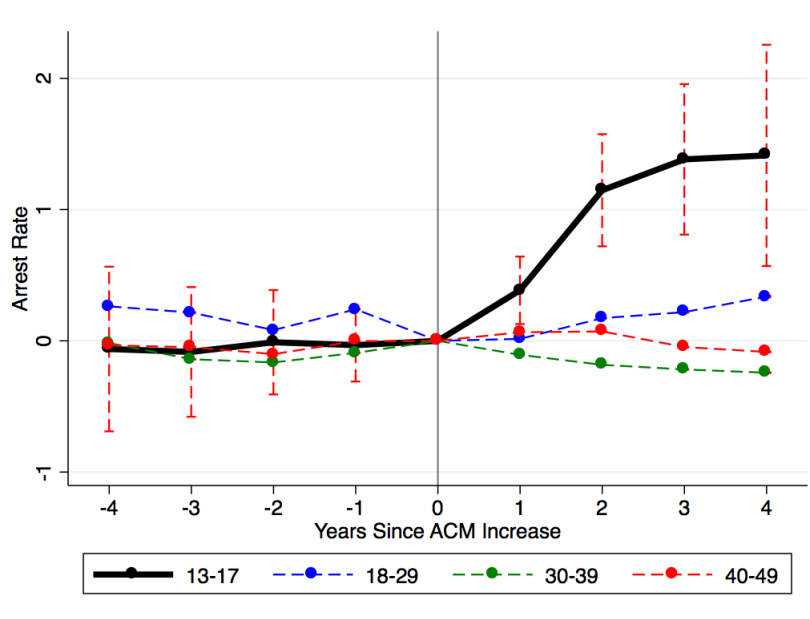
Notes: This graph uses the NLSY97 male self-reported data on criminal involvement. The coefficients are estimates from a regression of criminal involvement on age-fixed effects.

**FIGURE 9: IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY
ARREST RATE OF 13-17 YEAR OLDS**

(A) 13-17 YEAR OLDS



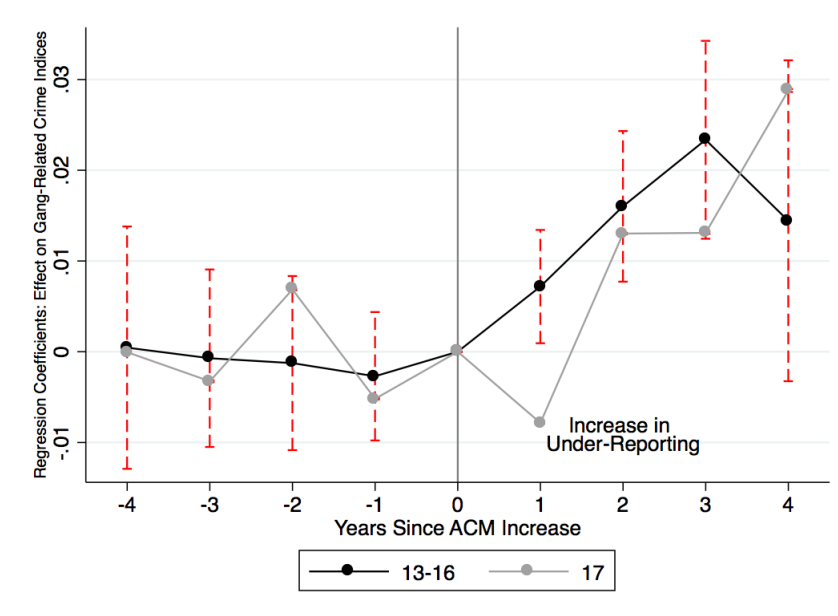
(B) UNRELATED TO TRENDS IN OTHER AGE GROUPS



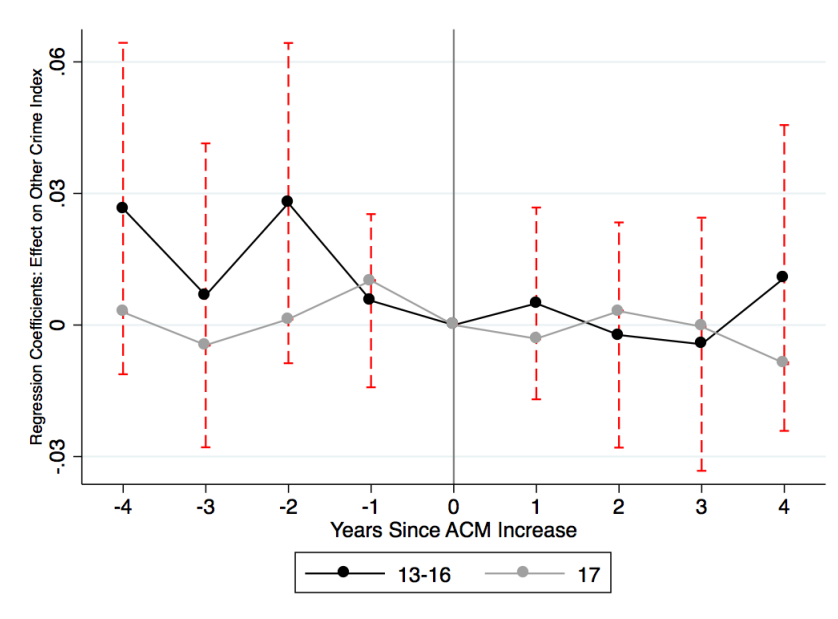
Notes: The outcome variable is total (average) arrests per 100,000 residents for each age group in the first (second) panel. This figure uses the ACM implementation dates of July 2012 for Connecticut, September 2013 for Massachusetts, and July 2015 for New Hampshire. The second panel controls for pre-treatment trends among treated and control states.

FIGURE 10: IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY ON CRIME INDICES

(A) OFFENSES RELATED TO GANGS



(B) OTHER OFFENSES



Notes: This figure uses the ACM implementation dates of July 2012 for Connecticut, September 2013 for Massachusetts, and July 2015 for New Hampshire. The outcome variable is a crime index based on the equally weighted sum of z-scores of its components; the z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation. For definitional details, see Table 3.

Tables

TABLE 2: IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY ON THE ARREST RATE OF 13-17 YEAR OLDS

Specification	(1)	(2)	(3)	(4)
ACM Increase	3.534*** (1.111)	3.634*** (1.114)	2.391** (1.009)	2.508** (1.018)
Dep Var Mean	30.55	30.55	30.55	30.55
Agencies	525	525	525	525
Observations	63,000	63,000	63,000	63,000
Agency F.E.	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
State Seasonality		Yes		Yes
Controls			Yes	Yes

Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrest rate in the age group 18-20. Standard errors are clustered at the agency level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

TABLE 3: IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY ON CRIME INDICES

	Age Group			
	17	16	15	13-14
Crime Index: Gang-Related Offenses				
ACM Increase	0.006 (0.005)	0.015*** (0.005)	0.015*** (0.005)	0.017*** (0.006)
Dep Var Mean	-0.019	-0.030	-0.019	-0.024
Crime Index: Other Offenses				
ACM Increase	-0.003 (0.007)	0.006 (0.009)	-0.046* (0.028)	-0.003 (0.007)
Dep Var Mean	-0.002	0.000	0.060	0.008
Agencies	525	525	525	525
Observations	63,000	63,000	63,000	63,000
Agency F.E.	Yes	Yes	Yes	Yes
State Seasonality	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Regressions estimate the impact of an increase in ACM from 17 to 18. Each crime index is the equally weighted sum of z- scores of its components; the z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation. Controls at the agency-month level include log of population and arrests for the same offense categories in the age group 18-20. Standard errors are clustered at the originating agency level. *** p<0.01, ** p<0.05, * p<0.1

Index for Gang-Related Offenses is the equally weighted average of nine z-scores, one each for for homicide, robbery, assault, burglary, theft (including motor vehicle theft and stolen property offenses), forgery and fraud, vandalism, weapon law violations, and drug sales.

Index for Other Offenses is the equally weighted average of eight z-scores, one each for for arson, embezzlement, drug possession, gambling, offenses against the family and children, driving under the influence and liquor laws, disorderly conduct (including drunkenness), and suspicion (including vagrancy and loitering).

TABLE 4: IMPACT OF AN INCREASE IN THE ACM ON ARRESTS FOR PROPERTY CRIMES

	Theft	Stolen Property (Buying, Selling)	Burglary	Vandalism	Fraud, Forgery & Counterfeiting
13-16 Year Old Arrests					
ACM Increase	0.427* (0.248)	0.167*** (0.035)	0.171*** (0.061)	0.315*** (0.112)	0.049** (0.020)
Dependent Variable Mean	3.175	0.314	0.709	1.527	0.111
17 Year Old Arrests					
ACM Increase	-0.059 (0.126)	0.123*** (0.027)	0.044 (0.035)	0.062 (0.074)	0.061*** (0.014)
Dependent Variable Mean	1.860	0.198	0.362	0.671	0.105
Originating Agencies	525	525	525	525	525
Observations	63,000	63,000	63,000	63,000	63,000
Agency F.E.	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes	Yes
State Seasonality	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrests for the same offense categories in the age group 18-20. Standard errors are clustered at the originating agency level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 5: IMPACT OF AN INCREASE IN THE ACM ON ARRESTS FOR VIOLENT CRIMES AND DRUG SALES

	Robbery	Homicide	Assault	Weapon Law Violations	Drug Sales & Manufacturing
13-16 Year Old Arrests					
ACM Increase	0.043* (0.023)	0.005** (0.002)	-0.196 (0.187)	0.029 (0.025)	0.035 (0.026)
Dependent Variable Mean	0.176	0.003	3.475	0.207	0.196
17 Year Old Arrests					
ACM Increase	0.014 (0.013)	-0.000 (0.001)	-0.029 (0.079)	-0.016 (0.016)	-0.008 (0.025)
Dependent Variable Mean	0.100	0.002	1.483	0.085	0.185
Originating Agencies	525	525	525	525	525
Observations	63,000	63,000	63,000	63,000	63,000
Agency F.E.	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes	Yes
State Seasonality	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrests for the same offense categories in the age group 18-20. Standard errors are clustered at the originating agency level. *** p<0.01, ** p<0.05, * p<0.1.

**TABLE 6: IMPACT OF AN INCREASE IN THE ACM ON ARRESTS FOR
NON-GANG-RELATED OFFENSES**

	Disorderly Conduct (Incl. Drunkenness)	Liquor Laws (Incl. DUI)	Drug Possession	Offenses Against Families & Children	Arson
13-16 Year Old Arrests					
ACM Increase	-0.099 (0.179)	0.126 (0.083)	0.120 (0.091)	0.018 (0.054)	-0.027 (0.017)
Dependent Variable Mean	1.711	0.999	1.429	0.113	0.0810
17 Year Old Arrests					
ACM Increase	0.116 (0.077)	-0.051 (0.116)	0.003 (0.096)	-0.024 (0.018)	-0.004 (0.005)
Dependent Variable Mean	0.967	1.568	1.507	0.0380	0.0170
Originating Agencies Observations	525 63,000	525 63,000	525 63,000	525 63,000	525 63,000
Agency F.E.	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes	Yes
State Seasonality	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrests for the same offense categories in the age group 18-20. Standard errors are clustered at the originating agency level. *** p<0.01, ** p<0.05, * p<0.1

**TABLE 7: IMPACT OF ACM INCREASE ON GANG-RELATED CRIME INDEX
BY DEMOGRAPHIC GROUP**

Gender & Age	Male 17	Male 16	Male 15	Male 13-14
ACM Increase	0.005 (0.005)	0.015*** (0.004)	0.014*** (0.004)	0.016*** (0.005)
Dep Var Mean	-0.0190	-0.0250	-0.0170	-0.0200
Gender & Age	Female 17	Female 16	Female 15	Female 13-14
ACM Increase	0.004 (0.005)	0.001 (0.004)	0.006 (0.005)	0.008 (0.005)
Dep Var Mean	-0.007	-0.019	-0.009	-0.015
Race & Age	White 0-17	Black 0-17	Indian 0-17	Asian 0-17
ACM Increase	0.026*** (0.006)	0.005 (0.007)	0.002 (0.005)	-0.002 (0.009)
Dep Var Mean	-0.0240	-0.0490	-0.008	0.0140
Agencies	525	525	525	525
Observations	63,000	63,000	63,000	63,000
Agency F.E.	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

UCR data does not contain age specific arrests by race, only the number of arrests under 18 separated by race; Hispanic arrestees are not reported separately and may belong to any of the race categories. Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrests for the same offense categories in the age group 18-20. Standard errors are clustered at the originating agency level. *** p<0.01, ** p<0.05, * p<0.1

TABLE 8: SOCIAL COSTS OF INCREASE IN JUVENILE OFFENDING

	Coefficient	Arrest-Offense Ratio	Unit Cost* 2015 \$	Estimated Cost 2015 \$
Homicide	0.005	61.5	9,717,787	234,489
Robbery	0.035	29.3	41,842	16,182
Burglary	0.177	12.9	6,359	28,515
MV Theft	0.028	13.1	11,241	7,860
Larceny	0.379	21.9	3,706	20,975
Stolen Property	0.153	19.4	7,526	19,426
Vandalism	0.330	19.4	4,575	25,441
Forgery	0.012	19.4	5,066	1,046
Fraud	0.033	19.4	4,809	2,677
Total				\$ 356,612***

Offenses not shown include manslaughter by negligence, prostitution and commercialized vice, gambling, vagrancy and suspicion, for which the arrest rate is 0, and runaways - a status offense which only applies to juveniles. Evaluated at a population of 27221, the mean for treatment agencies. I exclude effects on sex offenses (excluding rape) because the UCR definition of rape changed in 2013.

TABLE 9: SEVENTEEN YEAR OLDS: CHANGE IN ANNUAL COST OF INCARCERATION

Offense	Monthly Arrest Rate	Adjudicated Delinquent (Per 1000)	Waived to Adult Court (Per 1000)	Adjudicated Delinquent (Number)	Placement / Incarceration (Per 1000)	Duration (Months)	Cost Adult Facilities	Cost Juvenile Facilities
Homicide	0.001	408	65	0.0014	171	8.18	29	80
Rape	0.02	408	65	0.0285	171	8.18	578	1592
Robbery	0.058	459	84	0.0949	227	8.18	2279	6273
Aggravated Assault	0.141	401	36	0.1916	143	8.18	3319	9135
Burglary	0.157	405	29	0.2139	152	5.72	2728	7510
Larceny-theft	1.234	219	9	0.8908	44	5.72	6082	16740
Motor vehicle theft	0.046	388	17	0.0593	172	5.72	894	2460
Other Assaults	0.901	243	9	0.7217	65	8.18	9378	25812
Arson	0.008	330	4	0.0087	77	5.72	68	187
Forgery & Counterfeiting	0.013	272	14	0.0117	77	5.72	112	309
Fraud	0.012	272	14	0.0108	77	5.72	105	290
Embezzlement	0.006	272	14	0.0054	77	5.72	51	140
Stolen property	0.079	420	12	0.1097	138	5.72	1223	3367
Vandalism	0.354	277	8	0.3229	69	5.72	2732	7519
Weapons-carry, posses, etc.	0.054	372	16	0.0667	135	4.38	630	1733
Sex offenses	0.025	375	4	0.0307	118	8.18	471	1297
Drug Abuse Violations	0.85	258	8	0.7221	44	4.78	3495	9621
Family/Children Offenses	0.035	282	17	0.0328	62	8.18	350	963
Driving Under Influence	0.127	163	6	0.068	21	4.38	229	630
Liquor laws	0.967	163	6	0.518	21	4.38	1735	4777
Drunkenness	0.209	163	6	0.112	21	4.38	375	1031
Disorderly conduct	0.35	207	4	0.2376	26	4.38	775	2134
All other non-traffic	1.412	189	2	0.8735	42	4.38	5050	13900
Curfew & Loitering	0.019	207	4	0.0129	26	4.38	42	115
Subtotal							42730	117615
Total				5.35				74,885

49

Offenses not shown include manslaughter by negligence, prostitution and commercialized vice, gambling, vagrancy and suspicion, for which the arrest rate is 0, and runaways - a status offense which only applies to juveniles. Evaluated at a population of 27221, the mean for treatment agencies. Cost estimates are in 2015 \$.

TABLE 10: IMPACT OF AN INCREASE IN THE AGE OF MAJORITY ON GANG-RELATED CRIME CLUSTERING BY AGE X STATE

	Crime Index	Theft	Stolen Property	Burglary	Vandalism	Fraud, Forgery
ACM Increase	0.013** (0.004)	0.128* (0.067)	0.045*** (0.011)	0.056*** (0.018)	0.109*** (0.033)	0.014 (0.0084)
Dep. Var. Mean	-0.003	1.058	0.105	0.236	0.509	0.037
		Robbery	Homicide	Assault	Weapons	Drug Sales
ACM Increase		0.011 (0.007)	0.0014** (0.0005)	-0.079 (0.085)	0.007 (0.008)	0.012 (0.007)
Dep. Var. Mean		0.059	0.001	1.158	0.069	0.065
Clusters	18	18	18	18	18	18
Observations	189,000	189,000	189,000	189,000	189,000	189,000

Regressions estimate the impact of an increase in ACM from 17 to 18. The outcome variable for the last five columns is the number of arrests in the age group 13-16 per 100,000 people. Each regression includes month and state fixed effects, as well as controls at the agency-month level (natural log of population and arrests for the same offense categories in the age group 18-20). Standard errors are clustered at the state X age level and estimated using the wild bootstrap. *** p<0.01, ** p<0.05, * p<0.1

TABLE 11: IMPACT OF AN INCREASE IN THE AGE OF MAJORITY ON GANG-RELATED CRIME CLUSTERING BY STATE

	Crime Index	Theft	Stolen Property	Burglary	Vandalism	Fraud, Forgery
ACM Increase	0.013*** (0.004)	0.919*** (0.315)	0.089*** (0.028)	0.264*** (0.091)	0.551* (0.278)	0.024 (0.018)
Dep. Var. Mean	-0.003	5.383	0.286	1.198	1.943	0.131
		Robbery	Homicide	Assault	Weapons	Drug Sales
ACM Increase		0.060* (0.035)	0.004*** (0.001)	0.276 (0.342)	0.154*** (0.050)	0.041** (0.018)
Dep. Var. Mean		0.253	0.009	4.459	0.453	0.346
Clusters	48	48	48	48	48	48
Observations	552,708	552,708	552,708	552,708	552,708	552,708

Regressions estimate the impact of an increase in ACM from 17 to 18. The outcome variable for the last five columns is the number of arrests in the age group 13-16 per 100,000 people. Each regression includes month and state fixed effects, as well as controls at the agency-month level (natural log of population and arrest rate for the same offense categories in the age group 18-20). Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1

Appendix

A.10.1 Solving the Model

This section calculates the the steady state values of k_t and λ_t , and shows that the system exhibits saddle path stability close to the steady state.

A.10.1.1 Steady State k_t and λ_t

Dynamics in the model can be summarized by the following equations:

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

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

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 $k_A^{SS} \neq 0$

$$(\rho + \delta)(2s_t \delta k_t - k_t^\alpha) = \alpha k_t^\alpha$$

$$\implies (\rho + \delta)(2s_t \delta k_t^{1-\alpha} - 1) = \alpha$$

$$\implies k_A^{SS} = \left[\frac{1}{2s_t \delta} \left\{ \frac{\alpha}{(\rho + \delta)} + 1 \right\} \right]^{\frac{1}{1-\alpha}}$$

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.10.1.2 Saddle Path Stability

To show that the system of differential equations exhibits saddle path stability, I use a first order Taylor approximation 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 is easily shown since

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

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

$$(1-2\alpha)(\rho+\delta) + \alpha(1-\alpha) > 0 \quad \text{if } \alpha < \frac{1}{2}$$

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

A.10.1.3 k_{min}

$$\dot{\lambda}_t =$$

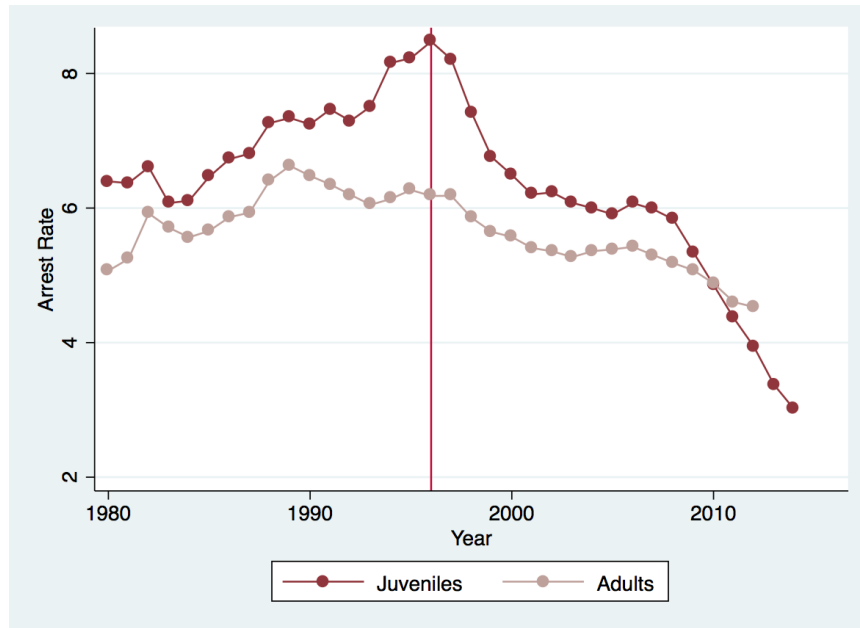
$$\implies \lambda_t = \left[\frac{\alpha}{2S_J} k_t^{2\alpha-1} \right] / \left[\rho + \delta - \frac{\alpha k_t^{\alpha-1}}{2S_J} \right]$$

$$\implies \lambda_t = \frac{\alpha k_t^\alpha}{2S_J(\rho+\delta)k_t^{1-\alpha}-\alpha}$$

$$\rightarrow \infty$$

$$\text{as } k_t \rightarrow \frac{\alpha}{2S_J(\rho+\delta)}^{\frac{1}{1-\alpha}} = k_{min}$$

FIGURE A.1: ADULT AND JUVENILE ARREST RATES



Notes: Based on data released by the Office of Juvenile Justice and Delinquency Prevention.

**TABLE A.1: IMPACT OF ACM INCREASE ON GANG-CRIME INDEX FOR 13-16 YEAR OLDS
ROBUSTNESS TO VARYING PANEL LENGTH**

Panel Length (Years)	14	13	12	11
ACM Increase	0.016*** (0.005)	0.016*** (0.005)	0.017*** (0.005)	0.016*** (0.004)
Dep Var Mean	-0.0220	-0.0240	-0.0230	-0.0240
Agencies	364	389	433	491
Observations	61,152	60,684	62,352	64,812
Agency F.E.	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
State Seasonality	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrests for the same offense categories in the age group 18-20. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

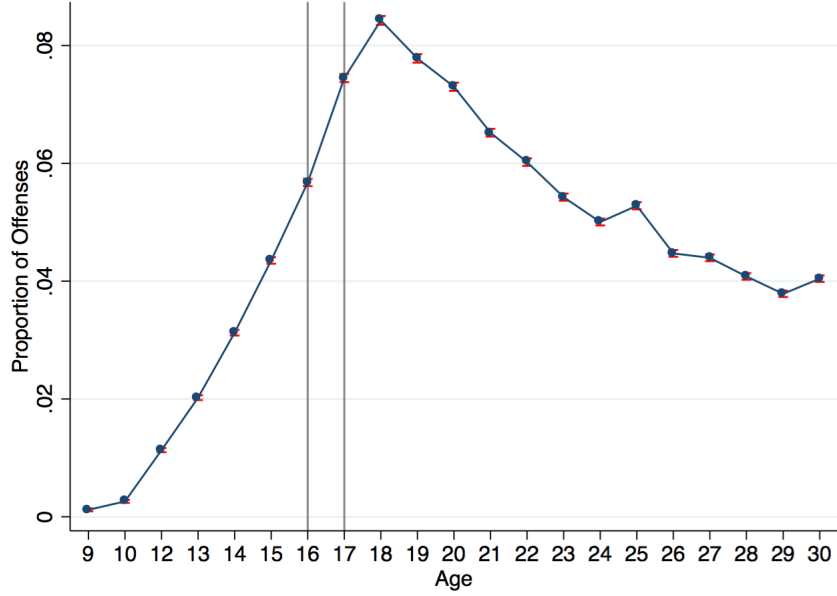
**TABLE A.2: IMPACT OF ACM INCREASE ON GANG-CRIME INDEX FOR 13-16 YEAR OLDS
ROBUSTNESS TO POPULATION OUTLIERS AND LOCAL CRIME CONTROLS**

Specification	Excluding Population Outliers	Crime Control: Arrest Rate for Ages		
		18-24	25-29	30-34
ACM Increase	0.017*** (0.004)	0.016*** (0.004)	0.016*** (0.004)	0.016*** (0.004)
Dep Var Mean	-0.0260	-0.0240	-0.0240	-0.0240
Observations	59,436	63,000	63,000	63,000
Agency F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Originating Agencies	497	525	525	525

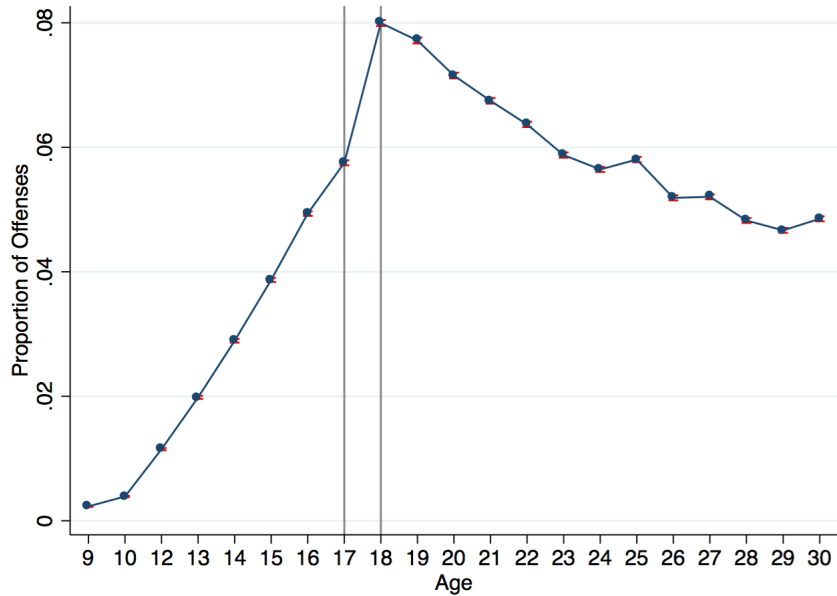
Regressions estimate the impact of an increase in ACM from 17 to 18. Controls at the agency-month level include log of population and arrests for the same offense categories in varying age groups. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

FIGURE A.2: PROPORTION OF OFFENSES BY AGE 2006-14

(A) AGE OF CRIMINAL RESPONSIBILITY = 17

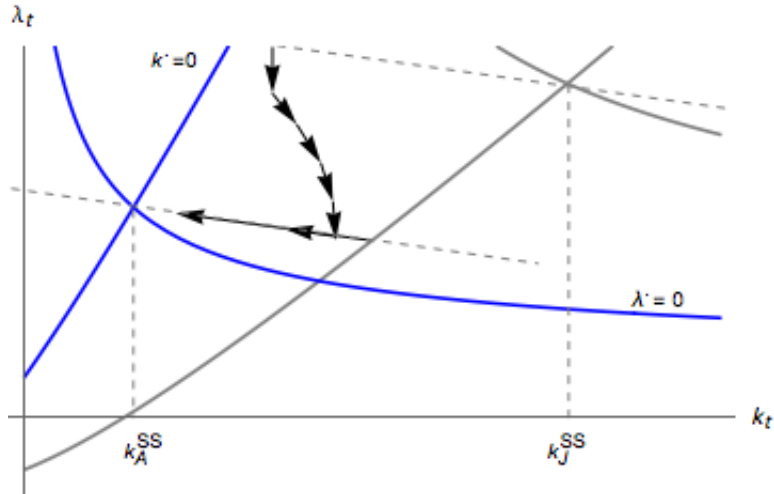


(B) AGE OF CRIMINAL RESPONSIBILITY = 18



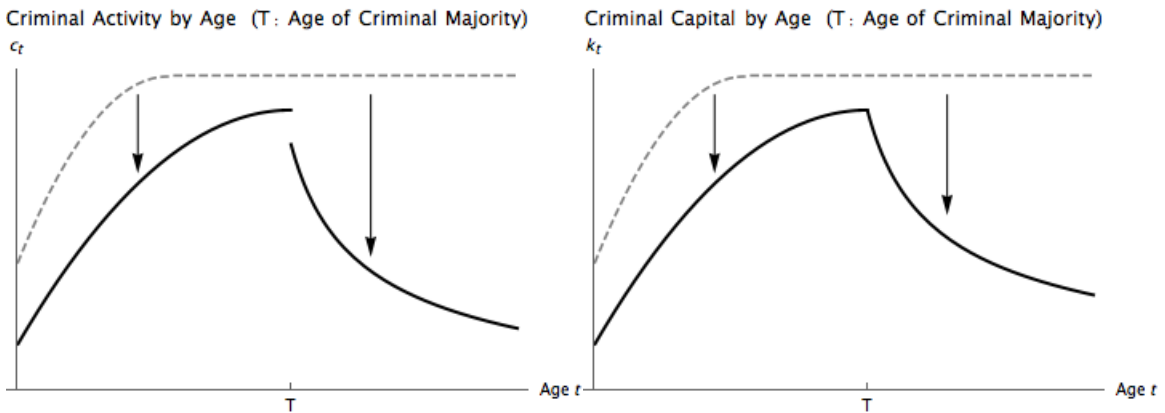
Notes: This graph uses monthly data at the law enforcement agency level from 39 states in the NIBRS data. Confidence intervals are shown in red.

FIGURE A.3: CRIMINAL CAPITAL ACCUMULATION UNDER ANTICIPATED ADULT SANCTIONS



Notes: This figure presents an alternative path for k_t that is consistent with optimizing behavior.

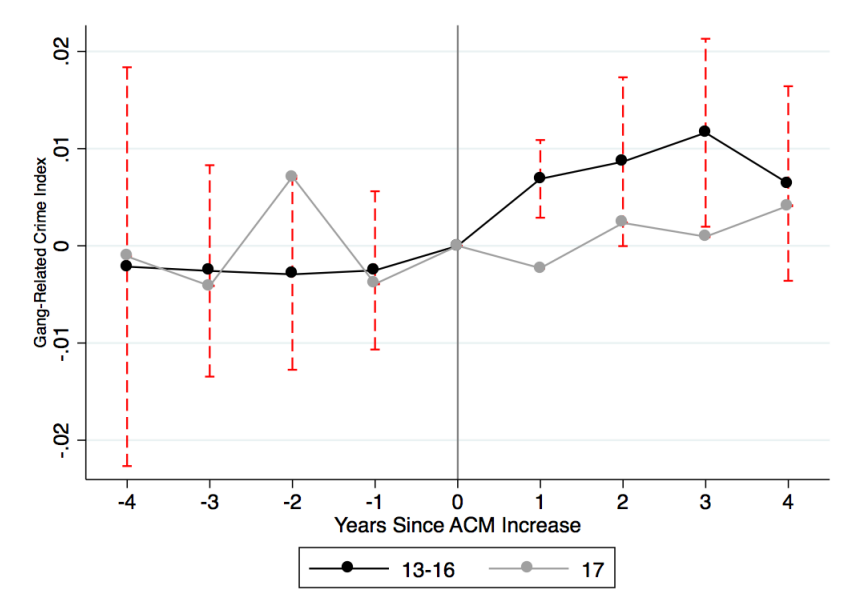
FIGURE A.4: c_t AND k_t UNDER ANTICIPATED ADULT SANCTIONS



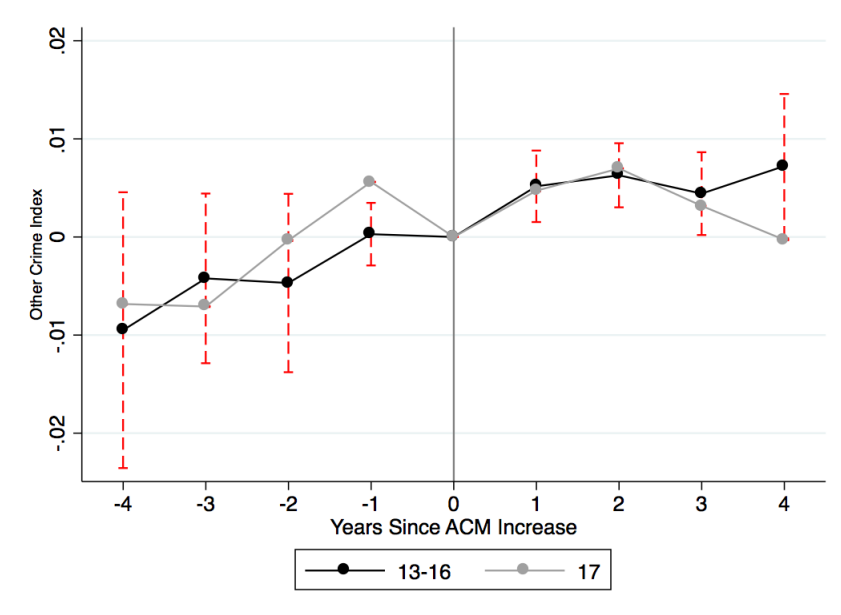
Notes: This figure displays optimal paths for c_t and k_t under the scenario displayed in the above phase diagram. The dashed line marks the optimal paths for c_t and k_t if sanctions stay fixed at S_J .

FIGURE A.5: IMPACT OF AN INCREASE IN THE AGE OF CRIMINAL MAJORITY ON ARRESTS FOR GANG-RELATED CRIMES

(A) OFFENSES RELATED TO GANGS



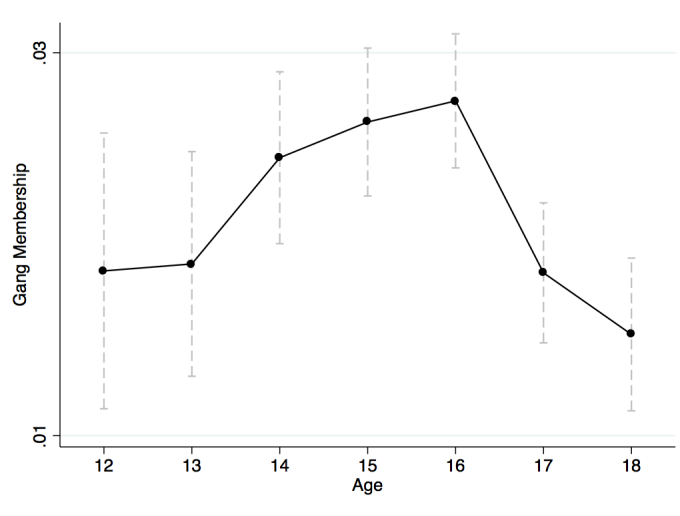
(B) OTHER OFFENSES



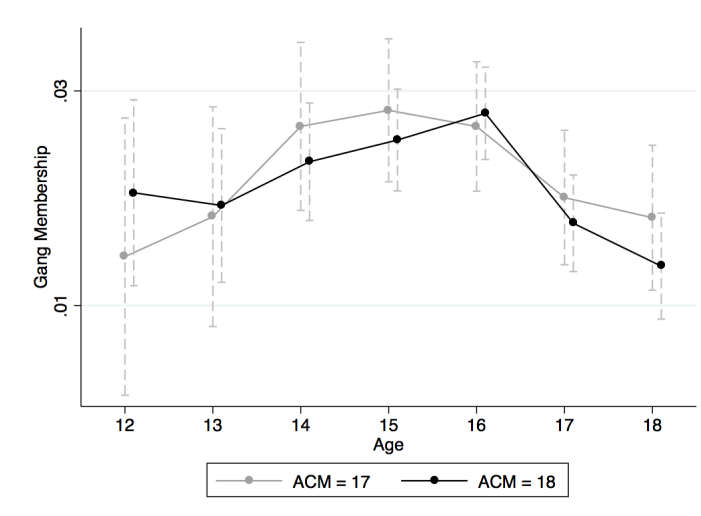
Notes: This figure uses the ACM implementation dates of July 2012 for Connecticut, September 2013 for Massachusetts, January 2014 for Illinois, and July 2015 for New Hampshire. Standard errors clustered at the state level.

FIGURE A.6: GANG MEMBERSHIP-AGE PROFILE

(A) ALL STATES



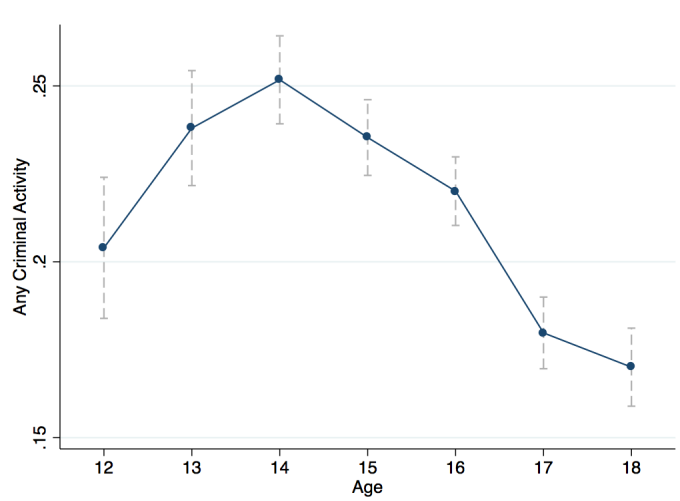
(B) GANG MEMBERSHIP-AGE PROFILE BY AGE OF CRIMINAL MAJORITY



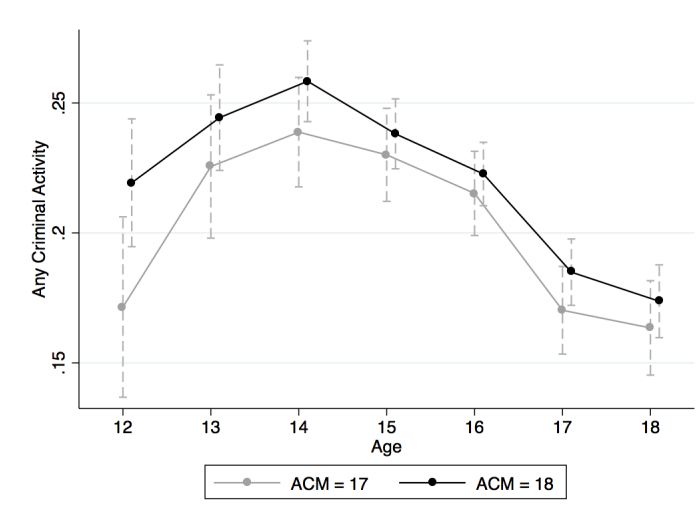
Notes: This graph uses the NLSY97 self-reported data on gang membership. The coefficients are estimates from a regression of gang membership on age-fixed effects.

FIGURE A.7: CRIMINAL INVOLVEMENT-AGE PROFILE

(A) ALL STATES



(B) CRIMINAL INVOLVEMENT-AGE PROFILE BY AGE OF CRIMINAL MAJORITY



Notes: This graph uses the NLSY97 self-reported data on criminal involvement. The coefficients are estimates from a regression of criminal involvement on age-fixed effects.