Online Appendix

for Juvenile Crime and Anticipated Punishment

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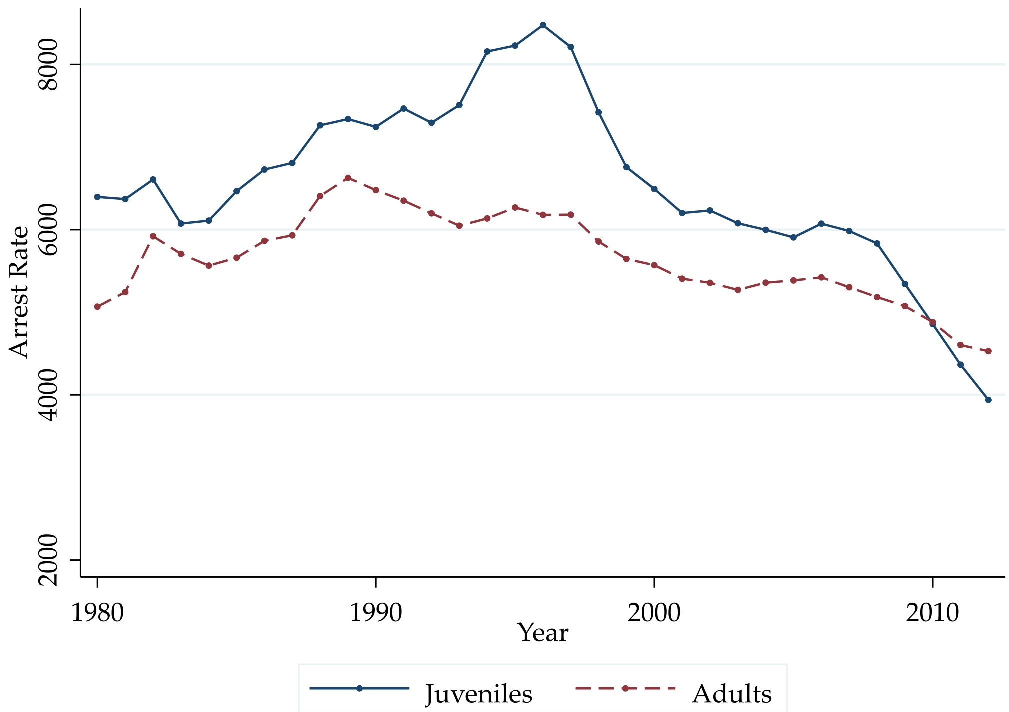
A.1 Figures

Figure A.1. Juvenile and Adult Arrest Rates in the U.S. 1980-2012



Notes: This graph displays the juvenile arrest rate and adult arrest rate per 100,000 individuals between 1980-2012 in the United States. Source: Office of Juvenile Justice and Delinquency Prevention, Office of Justice Programs, U.S. Department of Justice (OJJDP, 1980-2012)

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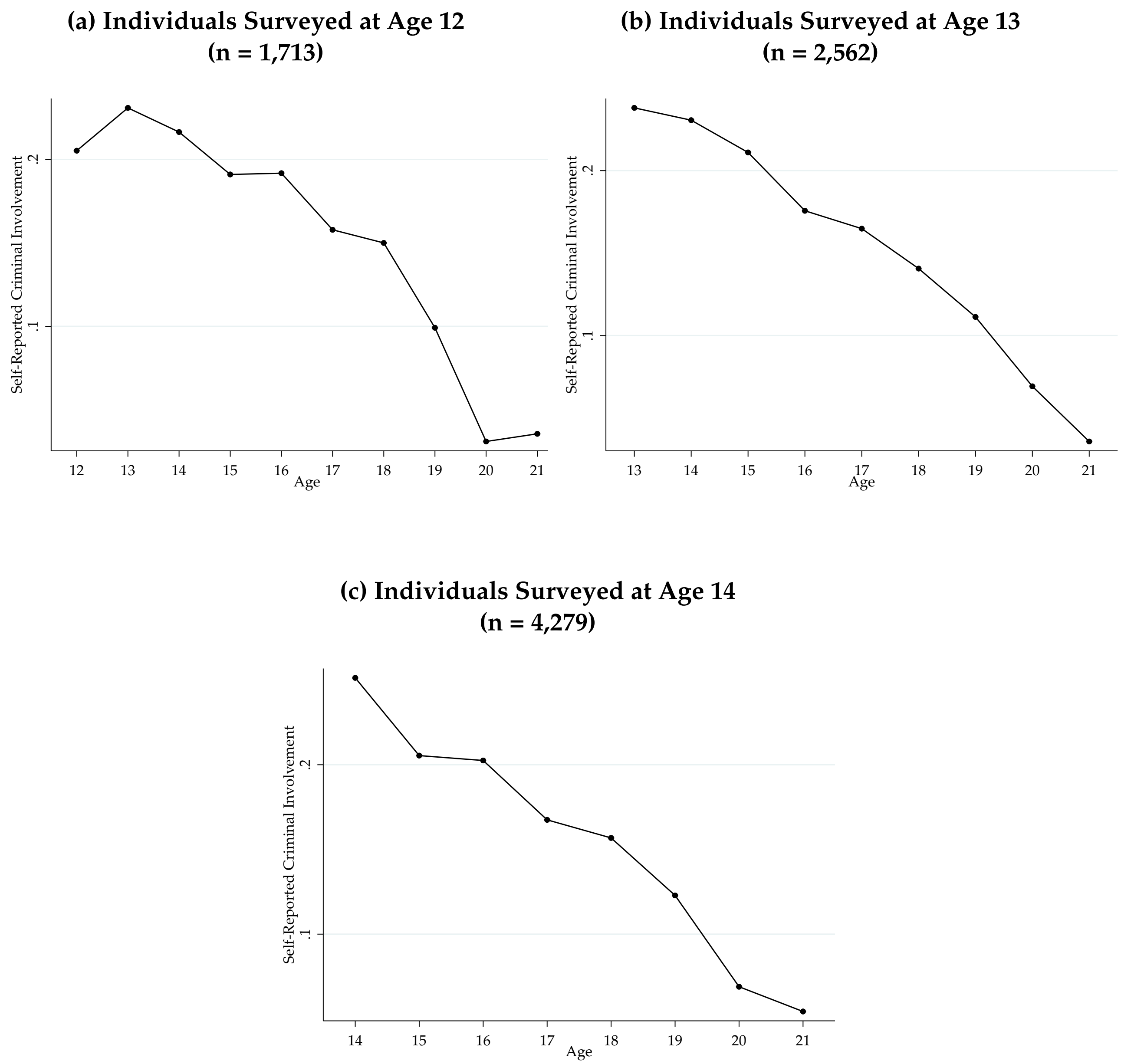
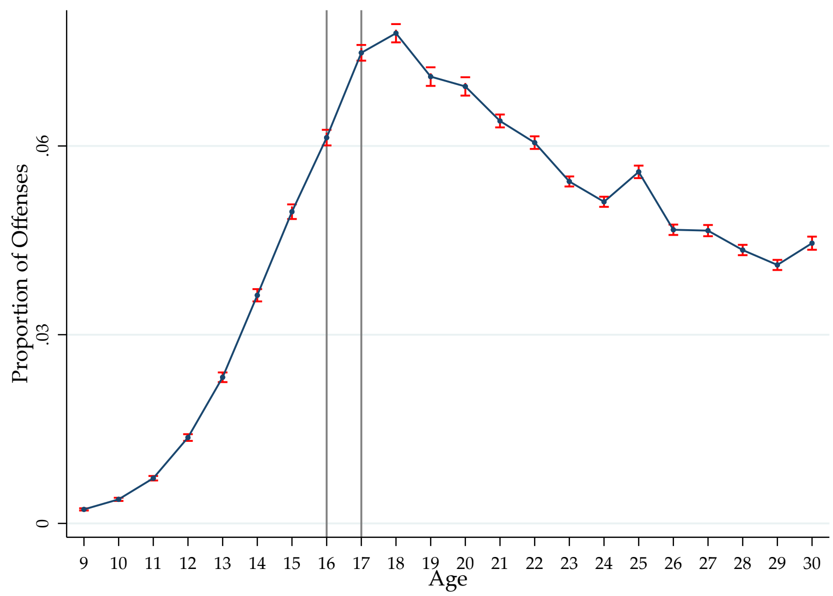
Figure A.2. Self-Reported Criminal Involvement by Age



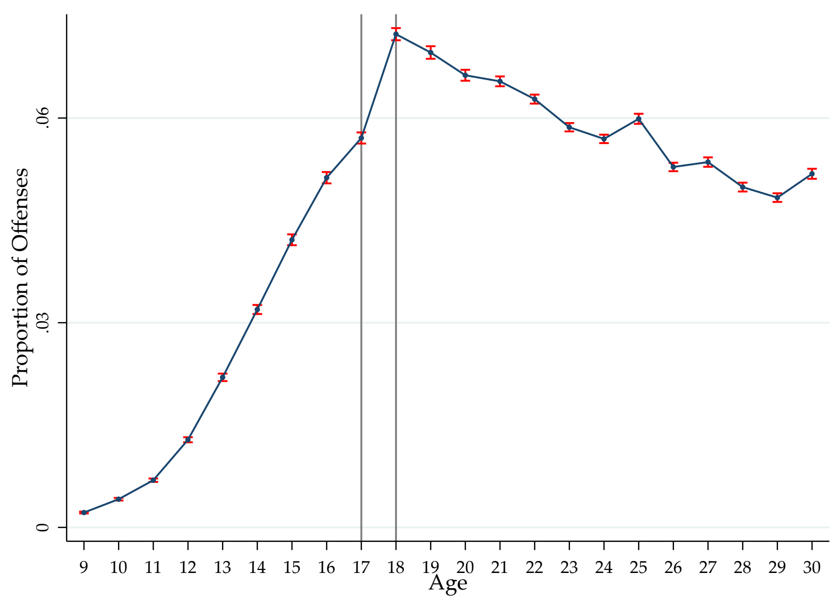
Notes: These graphs display results from OLS regressions of self-reported criminal involvement on age fixed effects, restricting attention to individuals who are observed at least once at age 12, 13, or 14 in Panels (a), (b) and (c) respectively. Source: 1997-2015 data from the National Longitudinal Survey of Youth.

Figure A.3. Index Offenses Recorded by Police Increase at Age of Criminal Majority

(a) Age of Criminal Majority = 17



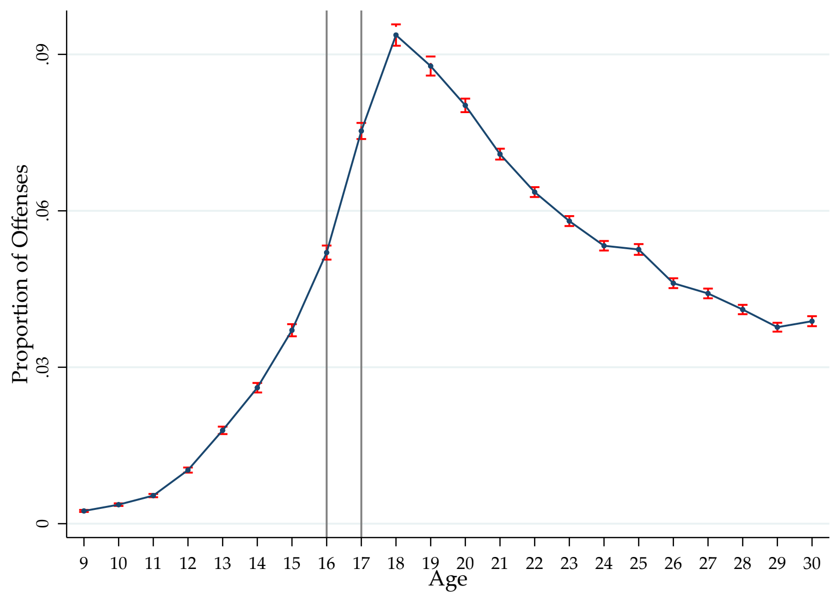
(b) Age of Criminal Majority = 18



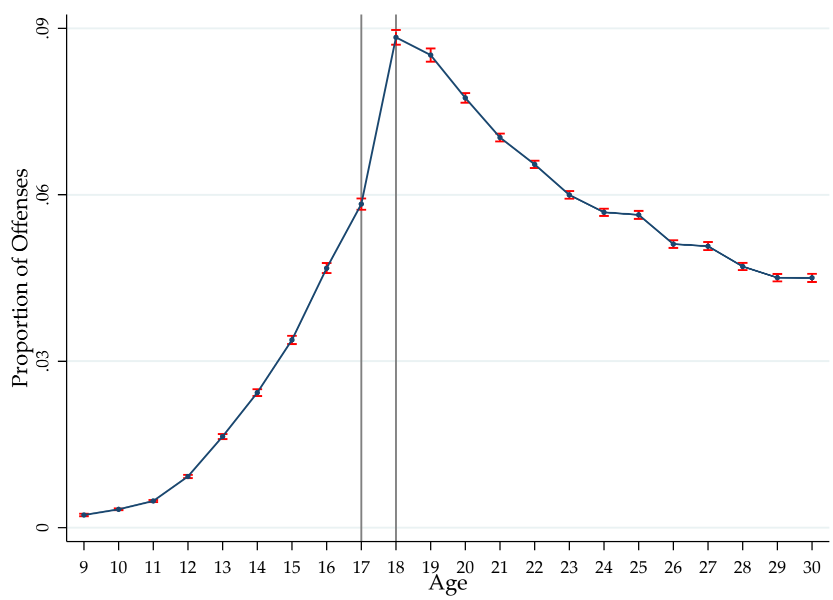
Notes: These graphs display results from OLS regressions of the proportion of offenses known for six Index crimes (homicide, assault, robbery, burglary, larceny, and motor vehicle theft) at the law enforcement agency level on age fixed effects. Standard errors are clustered at the agency level, and 95% confidence intervals are marked in red. Source: 2006-14 National Incident-Based Reporting System data.

Figure A.4. Non-Index Offenses Recorded by Police Increase at Age of Criminal Majority

(a) Age of Criminal Majority = 17



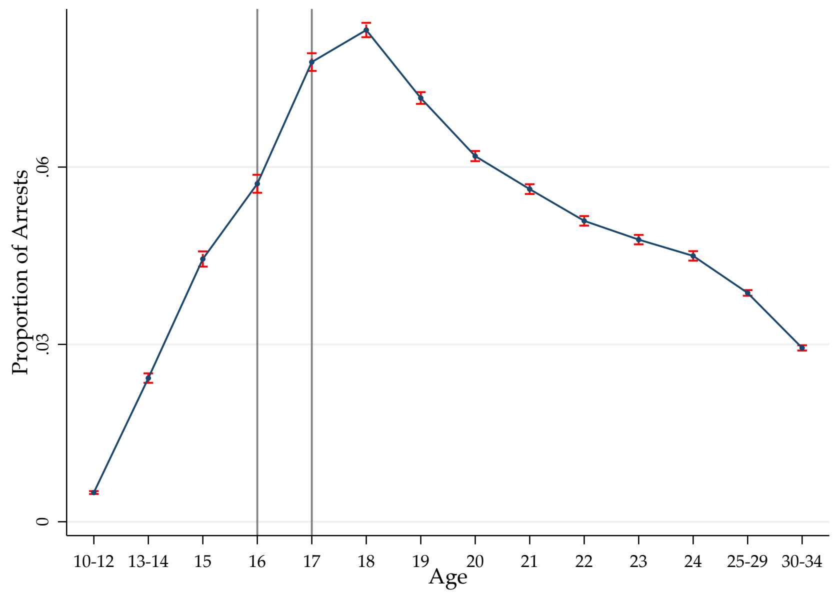
(b) Age of Criminal Majority = 18



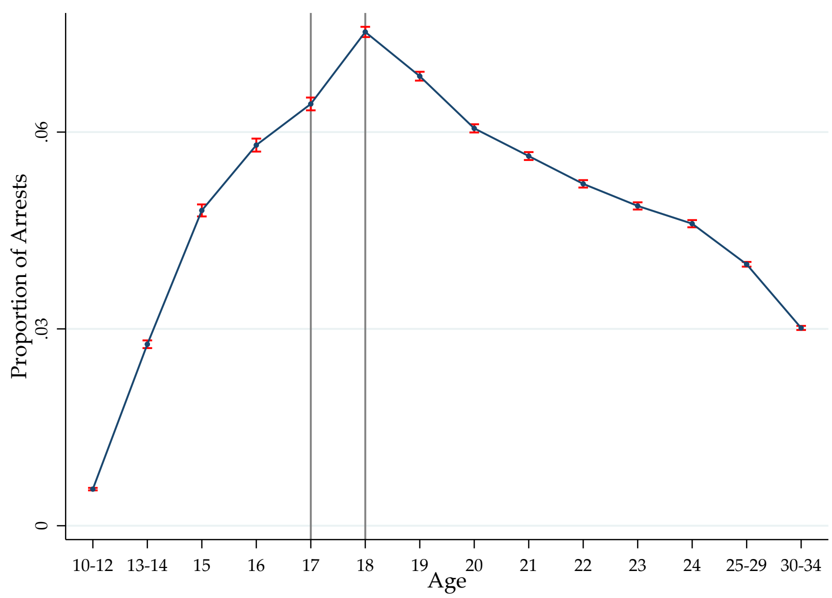
Notes: These graphs display results from OLS regressions of the proportion of offenses other than six Index crimes (homicide, assault, robbery, burglary, larceny, and motor vehicle theft) at the law enforcement agency level on age fixed effects. Standard errors are clustered at the agency level, and 95% confidence intervals are marked in red. Source: 2006-14 National Incident-Based Reporting System data.

Figure A.5. Arrests Recorded by Police Increase at the Age of Criminal Majority

(a) Age of Criminal Majority = 17



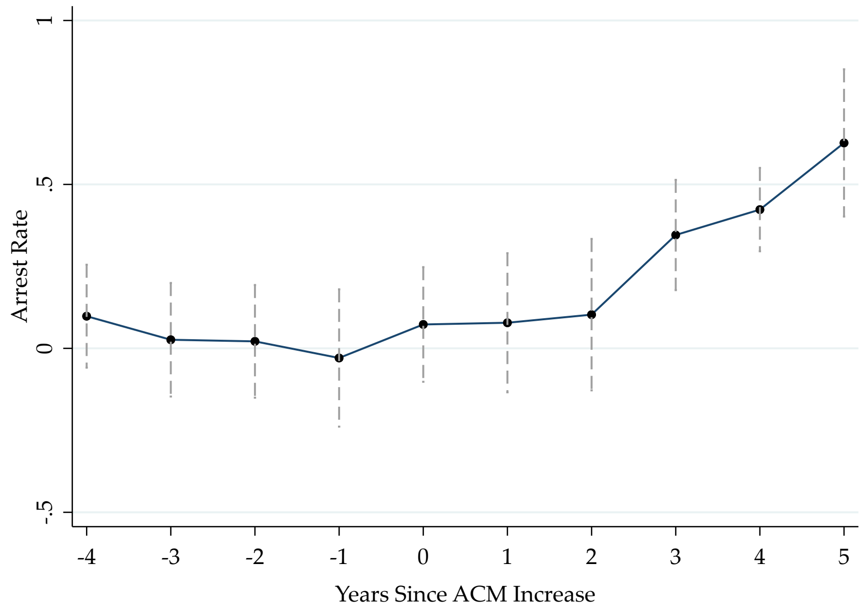
(b) Age of Criminal Majority = 18



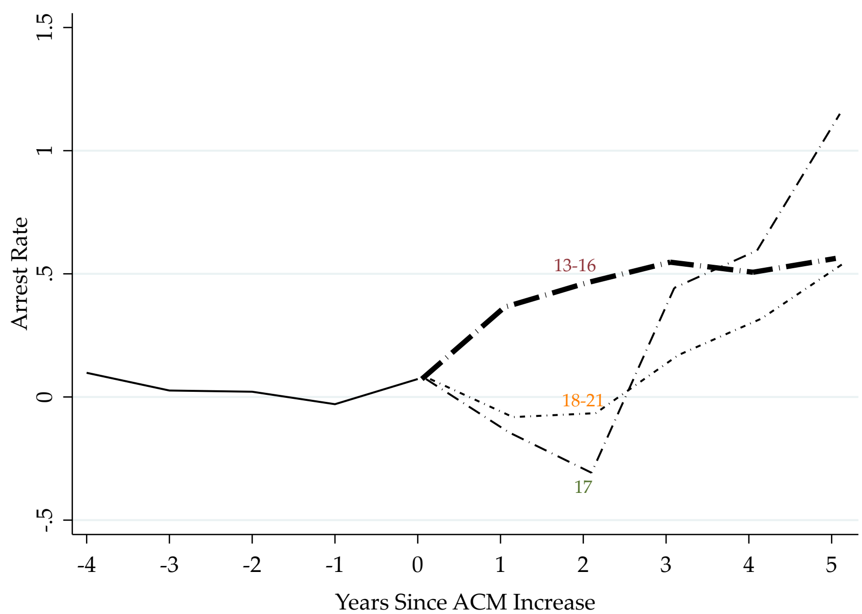
Notes: These graphs display results from OLS regressions of the proportion of arrests for six Index crimes (homicide, assault, robbery, burglary, larceny, and motor vehicle theft) at the law enforcement agency level on age fixed effects. Standard errors are clustered at the agency level, and 95% confidence intervals are marked in red. Figure 2 presents analogous results using National Incident Based Reporting System data. **Source: 2006-14 Uniform Crime Reports.**

Figure A.6. Impact of an Increase in the Age of Criminal Majority DDD Imputation Estimates

(a) Adolescent (Age 13-21) Arrest Rates



(b) Arrest Rates by Age Group



Notes: These figures display point estimates using the estimator developed by Borusyak *et al.* (2021) (and in panel (a), 95% confidence intervals) of the year-by-year impact of an increase in the age of criminal majority from seventeen to eighteen on arrest rates for all adolescents (i.e. those aged 13 to 21) in panel (a), and separately for those aged 13-16, 17, and 18-21 in panel (b). Source: 2005-16 FBI Uniform Crime Reports.

A.2 Tables

Table A.1. States' Age of Criminal Majority Over Time

State	ACM in 2017	Changes
Alabama	18	16 until 1975, 17 until 1976
Connecticut	18	16 until 12/31/2009, 17 until 6/30/2012
Illinois	18	17 for misdemeanors until 12/31/2009 17 for felonies until 12/31/2013
Louisiana	18	17 until 2016
Massachusetts	18	17 until 9/18/2013
Mississippi	18	17 for misdemeanors until 6/30/2011+ Still 17 for some felonies
Missouri	17	Will change to 18 on 1/1/2021
New Hampshire	18	18 until 1996, 17 until 6/20/2015
New York	16	17 on 10/1/2018; 18 since 10/1/2019
North Carolina	16	Will change to 18 on 12/1/2019 for misdemeanors, low-level felonies
Rhode Island	18	18 until 30/6/2007, 17 until 11/7/2007
South Carolina	18	17 until 2016
Vermont	18	22 for nonviolent crimes since 7/1/2018
Wisconsin*	17	18 until 1996
Wyoming	18	19 until 1993
Alaska, Arizona, Arkansas, California, Colorado, Delaware, District of Columbia, Florida, Hawaii, Idaho, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Minnesota, Montana, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Dakota, Tennessee, Utah, Virginia, Washington, West Virginia	18	-
Georgia, Michigan*, Texas*	17	-

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

Table A.2. Impact of an Increase in the Age of Criminal Majority Sample Excluding Outliers

Age Group	Adolescents	Juveniles		Young Adults
	13-21	13-16	17	18-21
		Arrest Rates		
DDD Estimate	0.263	0.371	0.226	0.191
	(0.058)	(0.074)	(0.223)	(0.069)
Mean	1.913	1.317	2.516	2.209
		Violent Crime Index		
DDD Estimate	0.007	0.011	0.008	0.004
	(0.004)	(0.005)	(0.009)	(0.005)
Mean	-0.0180	-0.017	-0.021	-0.018
		Property Crime Index		
DDD Estimate	0.036	0.047	0.032	0.029
	(0.005)	(0.007)	(0.013)	(0.006)
Mean	-0.037	-0.041	-0.032	-0.035
Observations	1,249,212	920,472	788,976	986,220
Clusters	114	84	72	90

Notes: This table displays DDD estimates of the impact of an increase in the age of criminal majority from seventeen to eighteen after dropping agencies that are outliers in terms of recorded crime; more details on sample construction can be found in Section V. The dependent variable in the first panel is the age-specific monthly arrest rate, defined as the number of arrests by age per 100,000 residents; each crime index is the average of the z-scores of its components, which are calculated by subtracting the comparison group mean and dividing by the comparison group standard deviation. The sample includes a balanced panel of 487 law enforcement agencies in the six contiguous states of Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont, each of which introduced legislation to raise the age of criminal majority during the study period. Standard errors are clustered at the age-state level. Source: 2005-16 data from the FBI Uniform Crime Reports.

Table A.3. Impact of an Increase in the Age of Criminal Majority
DDD Imputation Estimates

Age Group	Adolescents	Juveniles		Young Adults
	13-21	13-16	17	18-21
		Arrest Rates		
DDD Imputation Estimate	0.259 (0.068)	0.430 (0.071)	0.165 (0.091)	0.154 (0.082)
Mean	1.900	1.294	2.524	2.198
		Violent Crime Index		
DDD Imputation Estimate	0.006 (0.003)	0.012 (0.003)	0.009 (0.007)	0.002 (0.004)
Mean	-0.021	-0.020	-0.024	-0.021
		Property Crime Index		
DDD Imputation Estimate	0.041 (0.006)	0.054 (0.007)	0.037 (0.008)	0.033 (0.007)
Mean	-0.038	-0.042	-0.031	-0.036
Observations	1,332,432	981,792	841,536	1,051,920
Clusters	114	84	72	90

Notes: This table displays DDD estimates of the impact of an increase in the age of criminal majority from seventeen to eighteen using the estimator developed by Borusyak *et al.* (2021). The dependent variable in the first panel is the age-specific monthly arrest rate, defined as the number of arrests by age per 100,000 residents; each crime index is the average of the z-scores of its components, which are calculated by subtracting the comparison group mean and dividing by the comparison group standard deviation. The sample includes a balanced panel of 487 law enforcement agencies in the six contiguous states of Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont, each of which introduced legislation to raise the age of criminal majority during the study period. Standard errors are clustered at the age-state level. Source: 2005-16 data from the FBI Uniform Crime Reports.

Table A.4. Jurisdictions Bordering Treatment and comparison States

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

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

Table A.5. Impact of an Increase in the Age of Criminal Majority on the Social Cost of Arrests

Age Group	Adolescents	Juveniles		Young Adults
	13-21	13-16	17	18-21
DDD Estimate	1,420.198	2,221.663	1,783.091	728.375
	(822.208)	(928.398)	(3,157.279)	(1,277.838)
Mean	25,451.82	17,180.174	30,999.589	30,268.612
Observations	1,332,432	981,792	841,536	1,051,920
Clusters	114	84	72	90

Notes: This table displays DDD estimates of the impact of an increase in the age of criminal majority from seventeen to eighteen. The dependent variable is the monthly social cost (= victim + criminal justice costs) of crime per 100,000 residents; this exercise relies on Autor *et al.* (2017)'s estimates of $67,986 and $3,626 as the costs of violent and property crimes respectively (in 2015 USD). The sample includes a balanced panel of 487 law enforcement agencies in the six contiguous states of Connecticut, Massachusetts, New Hampshire, New York, Rhode Island and Vermont, each of which introduced legislation to raise the age of criminal majority during the study period. Standard errors are clustered at the age-state level. Source: 2005-16 data from the FBI Uniform Crime Reports.

Table A.6. Costs of Incarcerating 17-year-olds in Juvenile Facilities

Offense	Monthly Arrest Rate	% Referred to Court	% Placed/ Incarcerated	Annual Incarcerations	Duration (Months)	Cost Adult Facilities	Cost Juvenile Facilities
Homicide	0.003	1.000	0.28	0.003	8.18	146	400
Robbery	0.100	1.000	0.28	0.101	8.18	4908	13483
Aggravated Assault	0.237	0.897	0.28	0.215	8.18	10447	28702
Burglary	0.355	1.000	0.25	0.320	5.72	10873	29872
Larceny	1.747	0.927	0.25	1.460	5.72	49606	136292
Motor Vehicle Theft	0.082	0.907	0.25	0.067	5.72	2276	6254
Other Assaults	1.239	1.000	0.28	1.251	8.18	60785	167005
Arson	0.016	1.000	0.25	0.014	5.72	476	1307
Stolen Property	0.193	0.859	0.25	0.150	5.72	5097	14003
Other Property	0.126	1.000	0.25	0.114	5.72	3873	10642
Vandalism	0.668	1.000	0.25	0.602	5.72	20454	56197
Weapon Laws	0.093	0.979	0.29	0.095	4.38	2472	6791
Prostitution	0.002	1.000	0.29	0.002	4.38	52	143
Drug	1.730	1.000	0.16	0.998	4.78	28336	77854
Other Public Order	2.655	0.092	0.29	0.255	4.38	6634	18228
Other Person	0.039	1.000	0.28	0.040	8.18	1944	5340
Liquor Laws	1.623	0.126	0.29	0.214	4.38	5568	15297
Disorderly Conduct	0.702	0.497	0.29	0.365	4.38	9496	26091
Total				**6.266**		223,443	613,901
Additional Cost							**390,458**

Notes: The monthly arrest rate column is based on UCR 2005-16 data for the six Northeastern states. % referred to court uses the ratio of offense-specific juvenile arrests to juvenile court cases in 2015, based on the UCR and National Center for Juvenile Justice (2015), and is capped at 100%. % incarcerated also relies on National Center for Juvenile Justice (2015). The annual number of incarcerations is evaluated at a population of 30,051, the mean for the study sample. Daily cost estimates are in 2015 $ – $198 for adult facilities and $544 for juvenile facilities – and are based on estimates from Vera Institute of Justice (2017) and Justice Policy Institute (2014). Other Property Crimes include Forgery, Counterfeiting, Fraud and Embezzlement; Prostitution includes Commercialized Vice; Other Public Order Offenses include Gambling, Driving Under the Influence, Suspicion, and All Other Non-Traffic Offenses; Other Person Offenses include Offenses against the Family and Children; Liquor Laws include Drunkenness; Disorderly Conduct includes Vagrancy Offenses. Offenses omitted include manslaughter by negligence, for which the arrest rate is 0; curfew/loitering law violation and runaways, status offenses that only apply to juveniles; rape and sex offenses, since the UCR definition for these offenses changed in 2013.

A.3 Theoretical Framework

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

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

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

$$c_t \geq 0$$

The probability of facing criminal sanctions $p(.)$ is assumed to be an increasing convex function of criminal activity c_t.[50]

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

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

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

$$0 < \delta < 1$$

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

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

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

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

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

At each age t, individuals choose how much crime to commit c_t to maximize lifetime utility, subject to the criminal capital accumulation equation and an initial level of criminal capital k_0.[51]

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

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

Dynamics Under Fixed Sanctions

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

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

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):

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

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

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

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

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

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

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

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

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

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

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

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

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

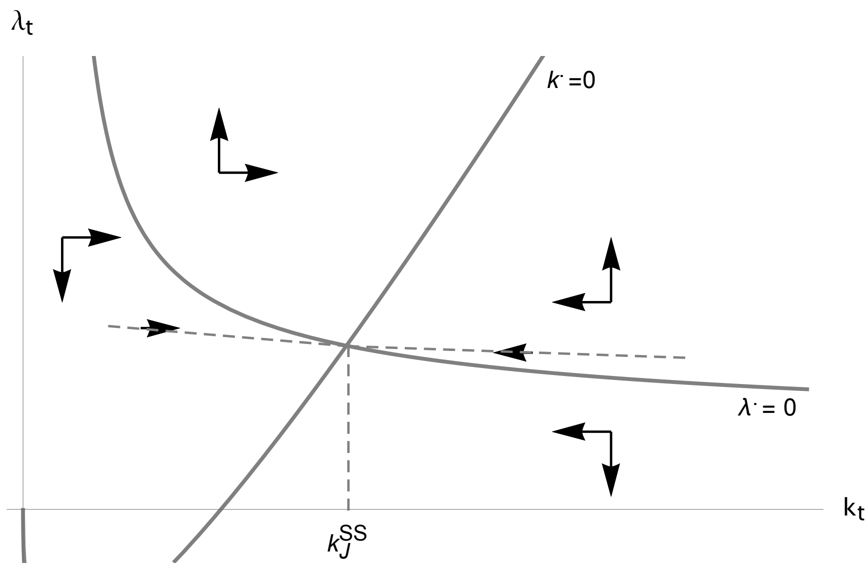
$$\dot{\lambda_t} = (\rho+\delta)\lambda_t - \alpha c_t k_t^{\alpha-1} = (\rho + \delta - \frac{\alpha}{2S_J}k_t^{\alpha-1})\lambda_t - \frac{\alpha}{2S_J}k_t^{2\alpha-1}$$

Figure A.7 displays the $\dot{k_t} = 0$ and $\dot{\lambda_t} = 0$ loci graphically.[52] The arrows show how k_t and λ_t must evolve in order to satisfy conditions $(2a)$ and $(2b)$, given their initial values. The $\dot{k_t} = 0$ and $\dot{\lambda_t} = 0$ loci intersect at the steady state level of capital of criminal capital k_J^{SS} - optimizing individuals will not increase or decrease their stock of criminal capital beyond

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

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

Figure A.7. Saddle Path under Age-Independent Sanctions



This system of differential equations exhibits saddle path stability for a wide range of parameter values, as detailed in Section A.3.2.[53] Recall that the initial value of capital k_0 is assumed to be given, while the shadow value of capital λ_0 is free to adjust. Saddle path stability indicates that there is a unique value of λ_0 (on the saddle path, shown as the dashed line) such that k_t and λ_t converge to the steady state. If λ_0 starts below the saddle path, the individual eventually crosses

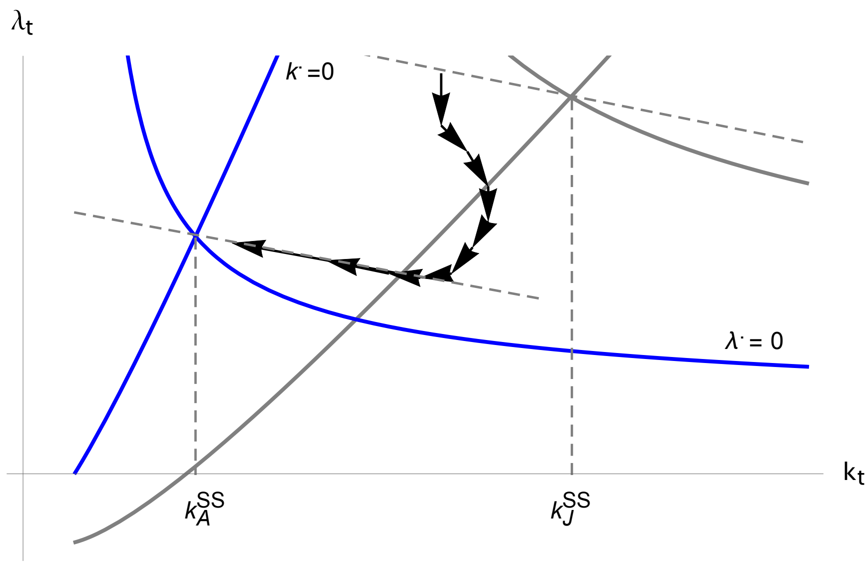
[52]This figure is drawn using the following parameter values: $\alpha = 0.4, \delta = 0.3, \rho = .05, s = 10$.
[53]For instance, $0 < \alpha \leq 0.5$ is a sufficient condition for saddle path stability.

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 $(2c)$.[54]

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 A.8. Saddle Path under Age-Dependent Sanctions



The dashed lines in Figure A.9 represent this evolution graphically. In the absence of adult sanctions, both criminal activity and criminal capital increase as individuals age, and converge towards their respective steady states.

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

Dynamics Under Anticipated Adult Sanctions

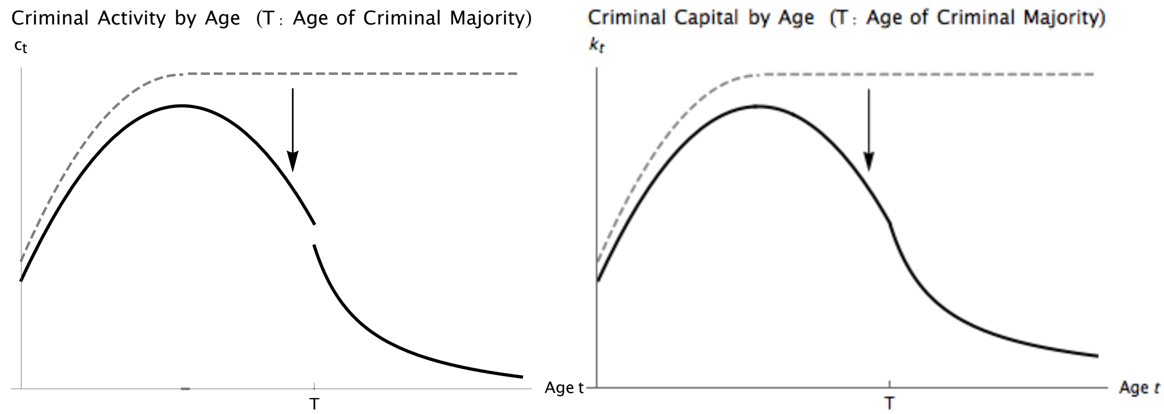
In this section, I describe the optimal response to the anticipation of higher sanctions S_A for $t \geq T$. Graphically, individuals anticipate that both the $\dot{k_t} = 0$ and $\dot{\lambda_t} = 0$ loci will shift to the left for $t \geq T$, as shown in Figure A.8. The $\dot{k_t} = 0$ locus shifts up and to the left because the increase in sanctions makes it more expensive to replenish depreciated capital. The $\dot{\lambda_t} = 0$ locus shifts down because c_t is expected to fall in the future (due to higher costs) and this lowers the future return to criminal capital. Figure A.8 also shows that the new steady state level of criminal capital k_A^{SS} will be lower than k_J^{SS}:

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

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

Figure A.9 shows how this has implications for criminal activity and criminal capital as individuals age into adulthood. While individuals are below the ACM T, they will first add to their stock of criminal capital k_t, and later begin to decumulate k_t as they approach T. Since the change in k_t depends on c_t net of depreciation, this also tells us about the behavior of c_t, which first increases and then decreases as individuals approach T. Optimal c_t drops discontinuously when individuals surpass T and face higher sanctions, and continues to decline as k_t declines (since k_t determines the return to crime). We can see that deterrence shows up as a discontinuous drop in c_t at T, but

Figure A.9. c_t **and** k_t **under Anticipated Adult Sanctions**



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

deterrence effects also generate lower c_t and k_t prior to reaching the threshold T. This is a deterrence effect because in the absence of adult sanctions, c_t and k_t would have converged towards their original steady state levels (represented by the dashed grey lines).

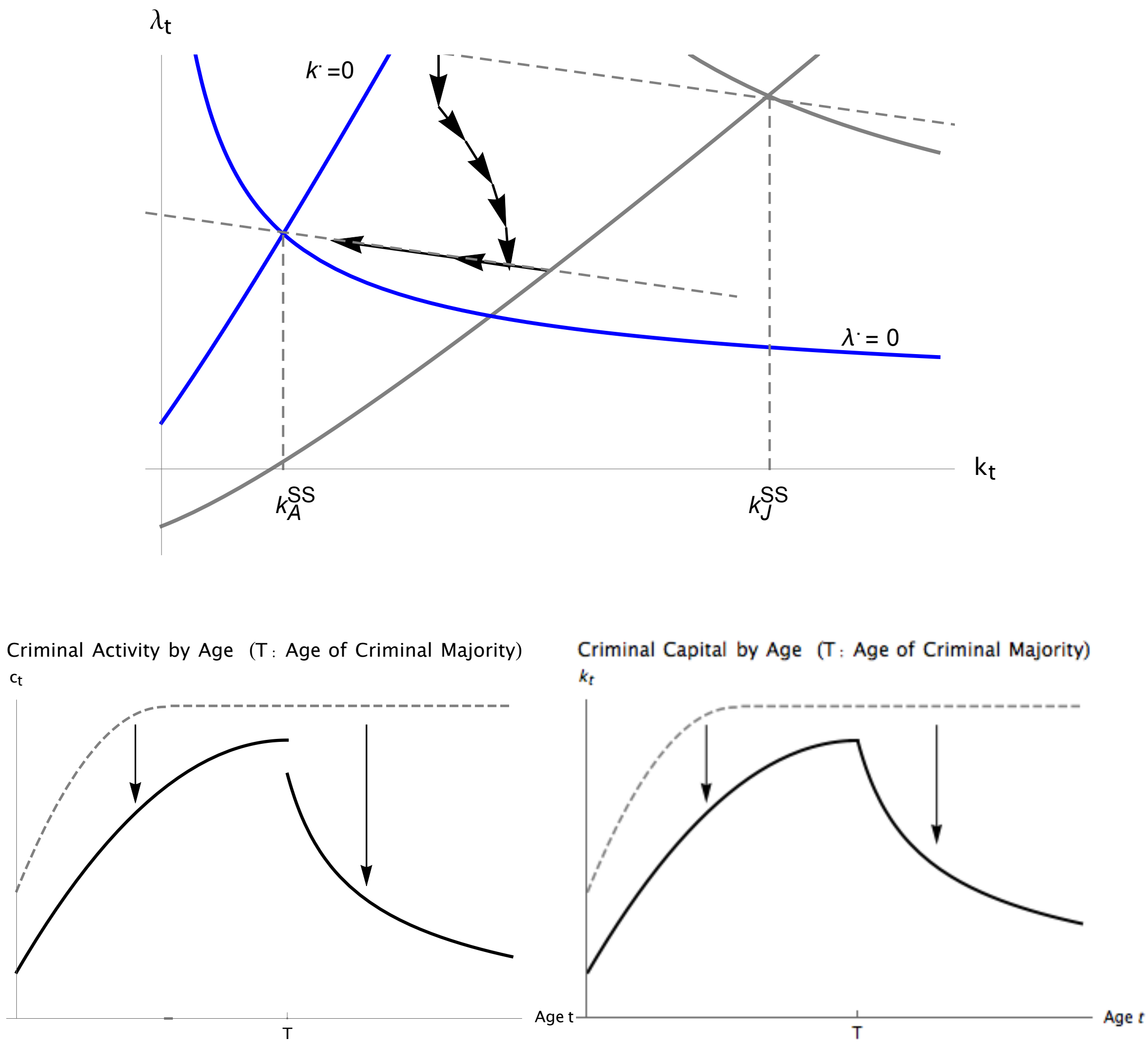
Figure A.10 presents an alternate saddle path for k_t that is consistent with optimizing behavior. In this situation, k_t and c_t continue to increase until age T, but are lower than they would be in the absence of adult sanctions. As individuals cross the threshold T and begin to face harsher sanctions, c_t decreases discontinuously. From this point onwards, k_t begins to converge to the lower steady state k_A^{SS}, and c_t follows suit. The predicted responses to an increase in the age of criminal majority T, discussed in Section A.3 below, remain similar under both of these scenarios.

Increasing the Age of Criminal Majority

This section focuses on the subset of adolescents who are both informed of the age threshold, and forward looking ($\rho < \infty$).[55] The model predicts that that when the ACM is raised from T to T',

[55] 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

Figure A.10. Alternate Paths for c_t, k_t and λ_t under Anticipated Adult Sanctions



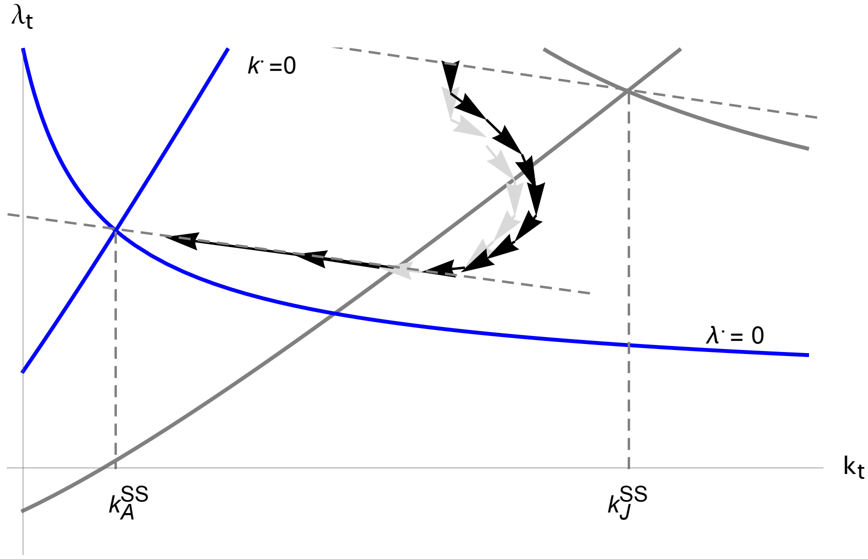
Notes: This figure displays paths for c_t, k_t and λ_t that are also consistent with optimizing behavior. The dashed lines mark optimal paths for c_t and k_t if sanctions stayed fixed at S_J. Importantly, k_t and c_t are lower than they would be in the absence of adult sanctions, even **before** the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

groups close to T should increase criminal activity.

When the age threshold is raised from T to T', the optimal response must continue to satisfy two requirements, shown graphically in Figure A.11. First, while the lower sanctions S_J are in effect the original $\dot{k_t}$ and $\dot{\lambda_t}$ functions still dictate the evolution of k_t and λ_t. Second, the shadow

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'.

Figure A.11. Response to an Increase in T



value of criminal capital λ_t must decrease *less* to ensure that the individual is on the new saddle path at age T', i.e. one year later. The individual moves toward the new saddle path during $t < T'$, and is on the new saddle path at age T'. Once past T', the individual moves up along the new saddle path, decumulating criminal capital until they reach the new steady state k_A^{SS}. For the case in which criminal capital decumulation only begins at T, the same argument applies - λ_t will decrease by less to ensure that the individual is on the new saddle path at age T' instead of T.

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

A.3.1 Steady State k_t and λ_t

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

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

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

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

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

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

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

Substituting in $c_t = \delta k_t$

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

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

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

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

A.3.2 Saddle Path Stability

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

This system can be written in matrix form:

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

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

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

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

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

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

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

A.3.3 k_{min}

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