Online Appendix
for Juvenile Crime and Anticipated Punishment
Ashna Arora

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

(a) Individuals Surveyed at Age 12
\(n = 1,713\)

(b) Individuals Surveyed at Age 13
\(n = 2,562\)

(c) Individuals Surveyed at Age 14
\(n = 4,279\)

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.
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

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

<table>
<thead>
<tr>
<th>State</th>
<th>ACM in 2017</th>
<th>Changes</th>
</tr>
</thead>
<tbody>
<tr>
<td>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</td>
<td>18</td>
<td>-</td>
</tr>
<tr>
<td>Georgia, Michigan*, Texas*</td>
<td>17</td>
<td>-</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Adolescents</th>
<th>Juveniles</th>
<th>Young Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>13-21</td>
<td>13-16</td>
<td>17</td>
</tr>
</tbody>
</table>

**Arrest Rates**

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDD</td>
<td>0.263</td>
<td>0.058</td>
<td>0.371</td>
<td>0.074</td>
<td>0.226</td>
<td>0.223</td>
<td>0.191</td>
<td>0.069</td>
</tr>
<tr>
<td>Mean</td>
<td>1.913</td>
<td></td>
<td>1.317</td>
<td></td>
<td>2.516</td>
<td></td>
<td>2.209</td>
<td></td>
</tr>
</tbody>
</table>

**Violent Crime Index**

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDD</td>
<td>0.007</td>
<td>0.004</td>
<td>0.011</td>
<td>0.005</td>
<td>0.008</td>
<td>0.009</td>
<td>0.004</td>
<td>0.005</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.0180</td>
<td></td>
<td>-0.017</td>
<td></td>
<td>-0.021</td>
<td></td>
<td>-0.018</td>
<td></td>
</tr>
</tbody>
</table>

**Property Crime Index**

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
<th>Estimate</th>
<th>(SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDD</td>
<td>0.036</td>
<td>0.005</td>
<td>0.047</td>
<td>0.007</td>
<td>0.032</td>
<td>0.013</td>
<td>0.029</td>
<td>0.006</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.037</td>
<td></td>
<td>-0.041</td>
<td></td>
<td>-0.032</td>
<td></td>
<td>-0.035</td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Adolescents</th>
<th>Juveniles</th>
<th>Young Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>13-21</td>
<td>13-16</td>
<td>17</td>
</tr>
<tr>
<td><strong>Arrest Rates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DDD Imputation Estimate</td>
<td>0.259 (0.068)</td>
<td>0.430 (0.071)</td>
<td>0.165 (0.091)</td>
</tr>
<tr>
<td>Mean</td>
<td>1.900</td>
<td>1.294</td>
<td>2.524</td>
</tr>
<tr>
<td><strong>Violent Crime Index</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DDD Imputation Estimate</td>
<td>0.006 (0.003)</td>
<td>0.012 (0.003)</td>
<td>0.009 (0.007)</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.021</td>
<td>-0.020</td>
<td>-0.024</td>
</tr>
<tr>
<td><strong>Property Crime Index</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DDD Imputation Estimate</td>
<td>0.041 (0.006)</td>
<td>0.054 (0.007)</td>
<td>0.037 (0.008)</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.038</td>
<td>-0.042</td>
<td>-0.031</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>State</th>
<th>Border Municipalities</th>
<th>Police Agencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Massachusetts</td>
<td>Williamstown, Hancock, Richmond, West Stockbridge, Alford, Edgemont, Mount Washington, Clarksburg, Monroe, Florida, Rowe, Heath, Colrain, Leyden, Bernardston, Northfield</td>
<td>Williamstown, Egremont, State Police: Berkshire County, State Police: Franklin County, Bernardston</td>
</tr>
<tr>
<td>New York</td>
<td>Petersburg, Berlin, Stephentown, Northeast (Millerton), Amenia, Dover, Pawling, Patterson, Southeast (Brewster), North Salem, Lewisboro, Pound Ridge, North Castle, Harrison, Rye Brook, Port Chester</td>
<td>Millerton, Rensselaer, Brewster, Lewisboro, Pound Ridge, North Castle, Harrison, Rye Brook, Port Chester</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Adolescents</th>
<th>Juveniles</th>
<th>Young Adults</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>13-21</td>
<td>13-16</td>
<td>17</td>
</tr>
<tr>
<td>DDD Estimate</td>
<td>1,420.198</td>
<td>2,221.663</td>
<td>1,783.091</td>
</tr>
<tr>
<td></td>
<td>(822.208)</td>
<td>(928.398)</td>
<td>(3,157.279)</td>
</tr>
<tr>
<td>Mean</td>
<td>25,451.82</td>
<td>17,180.174</td>
<td>30,999.589</td>
</tr>
<tr>
<td>Observations</td>
<td>1,332,432</td>
<td>981,792</td>
<td>841,536</td>
</tr>
<tr>
<td>Clusters</td>
<td>114</td>
<td>84</td>
<td>72</td>
</tr>
</tbody>
</table>

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

**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 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 $k_t$.

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

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

$$c_t \geq 0$$

The probability of facing criminal sanctions $p(\cdot)$ is assumed to be an increasing convex function of criminal activity $c_t$.\(^{50}\)

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

Criminal activity adds to an individual’s stock of criminal capital, which depreciates at the rate $\delta$. 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 $T$.

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

\(^{50}\)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 $k_0$.$^{51}$

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

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

### 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.

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

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

$$H_c = 0 \quad \implies \quad R(k_t) - p_c(c_t)S_J + \lambda_t = 0 \quad (2a)$$

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

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

$k_0$ 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 \( \lambda_t \). 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 \( \lambda_t \) can decrease \( c_t \) today even if immediate returns \( R(k_t) \) remain high.

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

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

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

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

\[ \lambda_t = (\rho + \delta)\lambda_t - \alpha c_t k_t^{\alpha-1} = (\rho + \delta - \frac{\alpha}{2S_J}k_t^{\alpha-1})\lambda_t - \frac{\alpha}{2S_J}k_t^{2\alpha-1} \]
Figure A.7 displays the $\dot{k}_t = 0$ and $\dot{\lambda}_t = 0$ loci graphically.\footnote{This figure is drawn using the following parameter values: $\alpha = 0.4$, $\delta = 0.3$, $\rho = .05$, $s = 10.$} The arrows show how $k_t$ and $\lambda_t$ 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 $k_{JSS}^J$ - optimizing individuals will not increase or decrease their stock of criminal capital beyond

$$k_{JSS}^J = \left[\frac{1}{2sJ}\left\{\frac{\alpha}{(\rho+\delta)} + 1\right\}\right]^{-\frac{1}{\alpha}}$$

The steady state value of criminal capital decreases in criminal sanctions $S_J$, depreciation rate $\delta$ and the rate at which future utility is discounted $\rho$; $k_{JSS}^J$ increases with the returns to additional criminal capital $\alpha$. This is explicitly calculated in Section A.3.1.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{FigureA7}
\caption{Saddle Path under Age-Independent Sanctions}
\end{figure}

This system of differential equations exhibits saddle path stability for a wide range of parameter values, as detailed in Section A.3.2.\footnote{For instance, $0 < \alpha \leq 0.5$ is a sufficient condition for saddle path stability.} Recall that the initial value of capital $k_0$ is assumed to be given, while the shadow value of capital $\lambda_0$ is free to adjust. Saddle path stability indicates that there is a unique value of $\lambda_0$ (on the saddle path, shown as the dashed line) such that $k_t$ and $\lambda_t$ converge to the steady state. If $\lambda_0$ starts below the saddle path, the individual eventually crosses
into the region where both $k_t$ and $\lambda_t$ are falling indefinitely. If $\lambda_0$ starts above the saddle path, the individual eventually crosses into the region where both $k_t$ and $\lambda_t$ 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 $k^{SS}_J$. If an individual’s initial $k_0$ is lower than the steady state $k^{SS}_J$, $c_t$ and $k_t$ will increase until $k_t = k^{SS}_J$, and criminal activity will stabilize at

$$c^{SS}_J = \frac{1}{2S_J} [(k^{SS}_J)^\alpha + \lambda^{SS}_J]$$

**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 $k_{min} < k_0 < k^{SS}_J$ and describe $c_t$ and $k_t$ as they move along the saddle path towards $k^{SS}_J$. 

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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 $\lambda_t = 0$ 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 $\lambda_t = 0$ 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 $k_{SS}^{A}$ will be lower than $k_{SS}^{J}$:

$$k_{SS}^{A} = \left[ \frac{1}{2S_A \delta} \left( \frac{\alpha}{(\rho+\delta)} + 1 \right) \right]^{\frac{1}{1-\alpha}} < k_{SS}^{J}$$

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 $\lambda_t$ functions still dictate the evolution of $k_t$ and $\lambda_t$ - graphically, the original arrows indicate how $\dot{k}_t$ and $\lambda_t$ evolve while $t < T$. Second, the shadow value of criminal capital $\lambda_t$ cannot jump (decrease discontinuously) at time $T$, since no new information about sanctions is learned at time $T$. Instead, $\lambda_t$ 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 $k_{SS}^{A}$.

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 $k_t^{SS_A}$, 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 ($\rho < \infty$).\textsuperscript{55} The model predicts that that when the ACM is raised from $T$ to $T'$,
Figure A.10. Alternate Paths for $c_t$, $k_t$ and $\lambda_t$ under Anticipated Adult Sanctions

Notes: This figure displays paths for $c_t$, $k_t$ and $\lambda_t$ 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 $\lambda_t$ functions still dictate the evolution of $k_t$ and $\lambda_t$. 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 $T'$.

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Figure A.11. Response to an Increase in $T$

value of criminal capital $\lambda_t$ 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 - $\lambda_t$ 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 $\lambda_t$. 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 $\lambda_t$

This section calculates the the steady state values of $k_t$ and $\lambda_t$. Dynamics in the model can be summarized by the following equations:
\[
\dot{k}_t = c_t - \delta k_t = \frac{k_t^{\alpha} + \lambda_t}{2s_t} - \delta k_t
\]

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

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

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

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 \( \delta \) and the rate at which future utility is discounted \( \delta \). However, \( k_A^{SS} \) increases with the returns to additional criminal capital, represented by \( \alpha \).

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

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

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

\[
\frac{1}{2S_{\text{J}}} > 0
\]

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

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

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

A.3.3 \( k_{\text{min}} \)

\[
\dot{\lambda}_t = 0
\]

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

\[
\implies \lambda_t = \frac{\alpha k_t^\rho}{2S_{\text{J}}(\rho+\delta) k_t^{1-\alpha} - \alpha}
\]

\[
\rightarrow \infty
\]

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