Did Connecticut’s “Raise the Age” Increase Motor Vehicle Thefts?

Giovanni Circo1 and Alexander Scranton1

Abstract
In 2010, Connecticut followed the pattern of most other U.S. states by raising the age of juvenile jurisdiction from 15 to 16. This was further raised from 16 to 17 years, 2 years later in July 2012. This sweeping change meant youth were no longer automatically prosecuted as adults in the criminal justice system. Following the change, crimes in Connecticut steadily decreased in line with nationwide trends—However, a subsequent increase in motor vehicle thefts prompted concern among critics of the “raise the age” (RTA) legislation. This study examines the change in Uniform Crime Reports (UCR) county-level index crimes before and after Connecticut changed the maximum age of juvenile jurisdiction from 16 to 17 in 2012, focusing specifically on motor vehicle thefts. Using a weighted difference-in-differences design, we estimate that RTA played a minimal role on the increase in Connecticut auto thefts between 2012 and 2017.

Keywords
criminal justice policy, juvenile justice, juvenile waivers, program evaluation, juvenile justice reform

Introduction
Prior to 2007, Connecticut was one of three states nationwide that prosecuted all 16- and 17-year-olds as adults (Mendel, 2012). Changing attitudes toward punishment, along with a robust body of research on juvenile offending, led to most states diverting juveniles away from the adult criminal justice system (Connecticut Juvenile Justice Alliance [CJJA], 2019). Proponents for raising the age highlight evidence suggesting

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juveniles do not possess mature decision-making capabilities, and the often (long-term) negative impacts of incarceration (Aizer & Doyle, 2015). Connecticut responded to a series of lawsuits and investigations during the mid-1990s and early 2000s by passing legislation to broaden the jurisdiction of the juvenile court. Specifically, the age of juvenile jurisdiction in the state was increased from age 16 to age 18 as part of a gradual rollout. The law gave state agencies approximately 3 years to plan for the transfer of the 16-year-old population, effective January 1, 2010, and an additional 2.5 years for the transfer of the 17-year-old population, effective July 1, 2012 (CJJA, 2019). In addition to increasing the age of juvenile jurisdiction, other reforms were implemented in the state to divert youth from the adult justice system and, instead, direct them toward rehabilitative and community-based services.

The effects of this legislation appeared positive, with the number of juveniles under correctional supervision dropping substantially. By 2016, the number of juveniles admitted to youth prison was down 69% compared with 2004, and only 11% of incarcerated youth were committed to adult institutions (Love et al., 2017). Concerns about increased offending and arrests among juveniles also appeared unfounded. A 2015 analysis of Connecticut’s “raise the age” (RTA) policy by Loeffler and Chalfin (2017) found little evidence that broad measures of juvenile offending were affected by changing the age of juvenile jurisdiction to 18. Indeed, Connecticut’s property and violent crime rates continued to decrease consistently year-over-year (see Table 1). At the same time, however, motor vehicle thefts (MVTs) began to increase precipitously between 2014 and 2017. In general, the clearance rate for MVTs in Connecticut was between 9% and 12% from as far back as 1990. Of the total number of cleared cases, offenders under age 18 comprised between 30% and 12%. In 2008, offenders under

<table>
<thead>
<tr>
<th>Year</th>
<th>Assault</th>
<th>Burglary</th>
<th>Larceny theft</th>
<th>Motor vehicle theft</th>
<th>Murder</th>
<th>Rape</th>
<th>Robbery</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>163.7</td>
<td>420.5</td>
<td>1,759.6</td>
<td>247.5</td>
<td>3.7</td>
<td>18.9</td>
<td>112.5</td>
</tr>
<tr>
<td>2009</td>
<td>161.3</td>
<td>420.3</td>
<td>1,661.6</td>
<td>206.7</td>
<td>2.9</td>
<td>18.2</td>
<td>110.8</td>
</tr>
<tr>
<td>2010</td>
<td>158.3</td>
<td>413.1</td>
<td>1,538.8</td>
<td>182.8</td>
<td>3.6</td>
<td>16.2</td>
<td>96.90</td>
</tr>
<tr>
<td>2011</td>
<td>146.5</td>
<td>421.2</td>
<td>1,499.4</td>
<td>181.6</td>
<td>3.5</td>
<td>18.8</td>
<td>100.4</td>
</tr>
<tr>
<td>2012</td>
<td>147.3</td>
<td>401.6</td>
<td>1,518.2</td>
<td>175.9</td>
<td>3.9</td>
<td>25.3</td>
<td>100.7</td>
</tr>
<tr>
<td>2013</td>
<td>133.0</td>
<td>350.7</td>
<td>1,412.7</td>
<td>169.2</td>
<td>2.5</td>
<td>21.4</td>
<td>96.30</td>
</tr>
<tr>
<td>2014</td>
<td>122.5</td>
<td>325.8</td>
<td>1,387.9</td>
<td>165.8</td>
<td>2.4</td>
<td>21.5</td>
<td>86.00</td>
</tr>
<tr>
<td>2015</td>
<td>111.3</td>
<td>279.3</td>
<td>1,327.7</td>
<td>174.5</td>
<td>3.1</td>
<td>21.7</td>
<td>79.40</td>
</tr>
<tr>
<td>2016</td>
<td>125.2</td>
<td>274.4</td>
<td>1,297.8</td>
<td>194.1</td>
<td>2.1</td>
<td>20.9</td>
<td>74.00</td>
</tr>
<tr>
<td>2017</td>
<td>121.4</td>
<td>243.7</td>
<td>1,296.9</td>
<td>200.4</td>
<td>2.8</td>
<td>22.8</td>
<td>77.20</td>
</tr>
</tbody>
</table>

% Chg (2017 vs. 2008)

-25.8% -42.0% -26.3% -19.0% -24.3% 20.6% -31.4%

Note. UCR = Uniform Crime Reports.
age 18 made up about 20% of cleared MVT cases. By 2012, offenders under age 18 made up only 12% of cleared cases. However, between 2015 and 2017, the percentage of cleared cases with offenders under age 18 increased from 23% to 28%—reflecting a 10-year high (see Table 2).

Statewide concern grew over this increase, which manifested disproportionately in several Connecticut suburbs (Kramer, 2019). Among the causes for this increase, several state officials—including the chief state’s attorney and chiefs of police for Wethersfield and Westport—placed blame on changes to the juvenile justice system. Specifically, chief state’s attorney Kevin Kane lamented “. . . the gaps in our juvenile justice system that have emboldened young people to violate our laws with no fear of repercussions” (McWilliams, 2018). This prompted discussion on whether new bills were needed to increase the available criminal penalties against juvenile offenders (Dichello, 2019).

Despite these arguments, there is currently little evidence to support or reject the assertion that Connecticut’s RTA legislation played any part in the increase in MVTs. In our article, we first compare changes in Connecticut’s crime rate to nationwide trends, focusing specifically on MVTs. We then employ a quasi-experimental design using a weighted difference-in-differences (DiD) regression to estimate the county-level impact of Connecticut’s 2012 RTA change in juvenile jurisdiction from 16 to 17. In our results, we find little evidence that RTA had an impact on Connecticut’s subsequent increase in MVTs. In contrast, we find evidence that this increase was likely part of nationwide trends in MVT and unrelated to the RTA policy. Below, we review the literature regarding juvenile offending and the effects of diverting youth away from the adult criminal justice system. We then describe the history and implementation of the RTA legislation in Connecticut. Finally, we discuss our analytical methods and present our results. In our “Discussion” section, we note, more broadly, the efficacy of raising the age of juvenile jurisdiction and its implications for other states and cities.

Table 2. Connecticut UCR, Total and Cleared MVTs.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total reported MVTs</th>
<th>% total cleared MVTs</th>
<th>% total cleared MVTs &gt;18</th>
<th>% cleared MVTs &gt;18</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>8,891</td>
<td>0.09</td>
<td>0.02</td>
<td>0.20</td>
</tr>
<tr>
<td>2009</td>
<td>7,461</td>
<td>0.10</td>
<td>0.02</td>
<td>0.19</td>
</tr>
<tr>
<td>2010</td>
<td>6,701</td>
<td>0.10</td>
<td>0.02</td>
<td>0.17</td>
</tr>
<tr>
<td>2011</td>
<td>6,670</td>
<td>0.09</td>
<td>0.02</td>
<td>0.17</td>
</tr>
<tr>
<td>2012</td>
<td>6,478</td>
<td>0.10</td>
<td>0.02</td>
<td>0.12</td>
</tr>
<tr>
<td>2013</td>
<td>6,241</td>
<td>0.11</td>
<td>0.02</td>
<td>0.17</td>
</tr>
<tr>
<td>2014</td>
<td>6,114</td>
<td>0.11</td>
<td>0.02</td>
<td>0.16</td>
</tr>
<tr>
<td>2015</td>
<td>6,426</td>
<td>0.10</td>
<td>0.02</td>
<td>0.23</td>
</tr>
<tr>
<td>2016</td>
<td>7,090</td>
<td>0.12</td>
<td>0.03</td>
<td>0.25</td>
</tr>
<tr>
<td>2017</td>
<td>7,306</td>
<td>0.12</td>
<td>0.03</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Note. UCR = Uniform Crime Reports; MVTs = motor vehicle thefts.
Adolescence, Deterrence, and Juvenile Offending

The period of adolescence is marked by changes in psychosocial maturity—manifesting as the ability to manage impulsive behavior, to take long-term account of personal actions, and to take responsibility for one's behavior (Dmitrieva et al., 2012). Development of psychosocial maturity is seen as a crucial step in desistence from delinquent behavior (Moffitt, 2003; Monahan et al., 2009). Indeed, a major factor in desistence from delinquency is the development of these cognitive skills and the adult conceptualization of one's self (Paternoster & Bushway, 2008). While developmental trajectories vary between youth, it is generally accepted that adolescents do not reach full maturity until their early to mid-20s (Monahan et al., 2013; Sowell et al., 1999).

One of the primary goals of prosecuting juveniles as adults is to increase the perceived severity of punishment—consistent with deterrence theory. This logic supposes that juveniles who perceive the threat or severity of sanctions may be less likely to commit a crime (Nagin & Pogarsky, 2001). A concern, therefore, is that raising the age of adult responsibility may indirectly incentivize crime through a reduction in the perceived severity of punishment (Nagin, 2013; Redding, 2008). This deterrence-based perspective has only marginal support in the criminological literature. Longer prison sentences and “three-strikes” laws have marginal effects, at best, on overall crime rates (Kovandzic et al., 2004; Nagin, 2013; Stolzenberg & D’Alessio, 1997). These findings have been bolstered by other tests of general deterrence, finding no strong effects (Kleck et al., 2005). Rather, consistent research points toward the certainty of punishment, not severity, being a more effective deterrent (Nagin & Pogarsky, 2001). Among juveniles, there is similarly scant evidence that more severe punishments, or transfer to the adult criminal court system, deter criminal or delinquent behavior (Fagan, 1996; Jensen & Metsger, 1994; Paternoster, 1989). In the most optimistic case, the effects are of a small magnitude for a select number of offenses (Loeffler & Grunwald, 2015).

While little consistent evidence exists that harsher punishments (such as referral to the adult criminal justice system) are effective measures of reducing crime, there remains a question of whether increasing the age of juvenile jurisdiction incentivizes crime (Deitch et al., 2012). The logic of this argument is that a decrease in general deterrence will embolden offenders on one end of the juvenile-adult discontinuity (Lee & McCrary, 2005; Loeffler & Grunwald, 2015). However, several studies have examined this exact question and have found little evidence that policies diverting youth away from the adult criminal justice system incentivizes youth offending (Butts & Roman, 2014; Lee & McCrary, 2005). Several prior studies have examined the effects of diversion strategies and raising the age of adult responsibility. For instance, Lee and McCrary’s (2005) study of Uniform Crime Reports (UCR) arrest data found no evidence that young offenders changed their offending behaviors around the age discontinuity from juvenile (under 18) to adult (18 and older). A review of multiple states that had experimented with changing the age of juvenile jurisdiction also found little evidence on the effect of violent crimes (Butts & Roman, 2014). Perhaps most pertinent to the current study is prior research by Loeffler and Chalfin (2017), which examined
broad crime trends and youth arrest rates in Connecticut following the implementation of RTA in 2010 through 2015. They found arrests of 15- to 18-year-olds decreased between 2010 and 2013, and changes in both violent and property crimes followed general nationwide trends. There was little evidence to suggest that the changes in Connecticut’s age of juvenile jurisdiction caused increased juvenile offending. This finding was largely consistent with other nationwide studies finding that juvenile offending largely does not depend on age-based jurisdictional boundaries (Hjalmarsson, 2009).

Although these policies rely on a seemingly simple concept—namely, that applying harsher adult penalties to juveniles will deter crime—there does not exist robust evidence indicating that it decreases crime. Similarly, there is no clear evidence that abandoning these policies incentivizes crime either. While in the aggregate these policies may appear somewhat neutral (i.e., providing generally null effects), the negative individual-level effects of incarceration on youth are substantially more evident. Indeed, juvenile incarceration is linked to lower high school completion rates and increased likelihood of future adult incarceration (Aizer & Doyle, 2015; Lanza-Kaduce et al., 2005). With this in mind, we explore the changes to Connecticut’s age of juvenile jurisdiction below and frame the context for our evaluation of the impact of this policy on MVTs.

**RTA in Connecticut**

Prior to changes in the early 2000s, the age of juvenile jurisdiction in Connecticut had remained a contentious issue in the state. Critics pointed to a number of flaws in the system, which culminated in a class action lawsuit brought against the state in 1993 (Mendel, 2012). The lawsuit described unsanitary conditions, a lack of mental health care, inadequate education facilities, and overall punitive punishments in juvenile justice facilities (Emily J. v. Weicker, 1993). Because Connecticut’s maximum age of juvenile jurisdiction was 15, all 16- and 17-year-olds were prosecuted as adults regardless of the severity of the offense and were processed in the adult system. In adult settings, youth were subjected to extensive isolation, use of chemical agents, limited educational programming, and minimal family visits (Mendel, 2012). Mental health services were limited due to only a handful of licensed professionals.

In an effort started by the CJJA, a massive, multiyear RTA campaign was initiated in 2005. This effort was bolstered by numerous reports between 2000 and 2005 highlighting severe deficiencies in the way Connecticut handled juvenile offenders. At the time, Connecticut lagged behind most of the country as just one of three states that still prosecuted 16- and 17-year-olds as adults—including New York and North Carolina (National Center for Juvenile Justice, 2019). The outcome of this educational and advocacy campaign was legislation that passed in 2007. Concerns over the fiscal crisis led to the staggered implementation of RTA. All 16-year-olds were deferred to juvenile court by January 1, 2010, and all 17-year-olds were deferred by July of 2012. RTA also led to reforms in the juvenile justice system, by transferring
juveniles to facilities focusing on rehabilitation and education, rather than warehousing (Mendel, 2012).

As part of the RTA statute passed in 2007, only Class A felonies, consisting of crimes such as murder, and certain Class B felonies, such as robbery or burglary in the first degree, required automatic transfer to the adult criminal docket. For all other offenses, 16- and 17-year-old offenders were retained in the juvenile justice system. The charge for MVT in Connecticut varies based on the dollar value of the car. As it currently stands, the most serious charge resulting for theft of a motor vehicle is a Class B felony. To receive a Class B felony, the car stolen must be valued in excess of $20,000. Even so, this is not one of the Class B felonies that is automatically transferred to the adult system under law. However, these cases are eligible for transfer following a discretionary hearing in the juvenile court.

**Study Description**

We collected data from the Federal Bureau of Investigation’s (FBI) UCR for the 10-year period of 2008–2017. These data included annual county-level rates per 100,000 for Part I index crimes. We utilized all U.S. counties with sufficient data, which included 3,012 counties spanning all 50 states and the District of Columbia. As our dependent variable, we chose to analyze all reported MVT offenses. Although it would have been preferable to estimate age-specific MVT arrest rates, the exceptionally low clearance rate for MVT (approximately 14%) makes this estimation strategy difficult. However, while MVTs have low clearance rates, they are among the most consistently reported—making overall counts a valid indicator of general offending (Langton et al., 2012). Therefore, in contrast with other studies that have examined age-specific offending rates across a wide category of offenses (i.e., violent crimes and property crimes), we apply an approach that examines a single crime category of interest as a broader outcome. An assumption of our evaluation strategy is that changes in offending rates among young offenders (those aged 15–17) would manifest as an overall change in statewide crime rates. However, the general weakness of this strategy (in contrast with Loeffler & Chalfin, 2017) is that we are unable to determine age-specific offending rates. We first examined changes in violent and property crimes in Connecticut from 2008 to 2017. Figure 1 shows that the overall rate of both violent and property crimes consistently decreased during this 10-year period. In particular, property crimes such as burglary and larceny were down nearly 42% and 26.3% from their 2008 rates, respectively. Connecticut’s MVT rate followed this downward trend until it began to reverse by 2014. Despite these increases, Connecticut’s MVT rate in 2017 was still 19% lower than its 2008 rate.

Comparing this change with nationwide trends shows that Connecticut’s increase was large, but still followed larger nationwide trends in MVT. As a whole, MVT rates had decreased by about 19.4% from 2008 to 2017 throughout the United States. A small reversal of this trend began when MVT rates increased by 10.4% from 2013 to 2017 (Crime in the United States, 2017). Figure 2 displays a comparison of MVT rates in Connecticut compared with all other U.S. states—highlighting the similar trends
pre- and post-2012 (the year when Connecticut changed the jurisdiction of the juvenile court from 16 to 17). The bottom panel displays the same data as the top, except with each U.S. state plotted separately to highlight variation in state-level MVT rates. We continued to the next step, which was estimating how much of this change in Connecticut’s MVTs was attributable to the RTA legislation. We chose to focus on the 2012 shift due to its proximity in time to the subsequent increase in MVTs.

**Quasi-Experimental Design**

Estimating the effect of Connecticut’s RTA legislation is made more complicated because the policy took effect immediately and was implemented statewide. The implicit question of this study is what would have happened to Connecticut’s MVT rates had the policy not been implemented. In randomized experiments, this question is more easily answered because the effect of an intervention can be compared with an observational unit that was not affected. Through random assignment of treatment, all observable and unobservable covariates are balanced in expectation, removing potential sources of confounding (Imbens & Rubin, 2015). Therefore, estimates of a treatment effect can be calculated as simple differences between the treatment and control
groups. In this case, we utilized a method to account for residual differences between states and counties, recognizing that many factors unique to Connecticut’s counties might also account for the change in MVT. In observational studies like this, a popular method is known as DiD estimation. The strength of DiD estimation is its ability to isolate the impact of a treatment effect net of pretreatment differences and observable covariates. The two-way DiD model can be conceptualized as

\[ Y_{it} = \alpha_i + \lambda_t + \rho D_{it} + X_{it} \beta + \epsilon_{it} \]

where the outcome variable \( Y_{it} \) is the expected value for unit \( i \) at time \( t \), \( \alpha_i \) are individual fixed effects, \( \lambda_t \) is a time variable with \( n \) levels corresponding to each time point, \( X_{it} \) are time varying covariates, and \( \epsilon_{it} \) is a random error term. The coefficient of interest is the treatment indicator \( \rho D_{it} \), which takes on the value 1 for each treated unit in the posttreatment period and takes on 0 for the remaining comparison units. Estimating the value for \( \rho D_{it} \) consists of differencing out the mean outcomes in the treatment and comparison groups pre- and posttreatment, then taking the difference of those values (Angrist & Pischke, 2008; Athey & Imbens, 2006). An underlying, untestable assumption of DiD models is that both the treated unit(s) and control unit(s) change over time is relatively constant—known as the parallel trends assumption (Angrist & Pischke, 2008). This assumes that the treatment group’s trend would have changed at the same rate as the control group, absent treatment. An inspection of the

**Figure 2.** MVT rate per 100,000, Connecticut versus all other states.  
*Note.* The top panel shows the change in MVTs in Connecticut compared with all other U.S. states combined. The bottom panel shows the same data with all other U.S. states disaggregated. MVT = motor vehicle theft.
trends, pre-2012 in Figure 2, suggests that both Connecticut and the remaining U.S. states were generally following parallel trends.

Applying a DiD model in a regression is useful because it allows the researcher to control for covariates and to obtain standard errors and related test statistics (Gelman & Hill, 2012). A weakness with this estimation strategy is that it relies on the assumption that for every treated unit where $D_t = 1$, there exists a comparable untreated unit where $D_t = 0$. Violations of the common support assumption occur when there are no comparison units with similar observed covariates (Imbens & Rubin, 2015). In the modeling stage, this leads to estimates that are highly sensitive to the model specification. To address this, we employed a weighting technique known as inverse probability weighting (IPW). Given a set of treated units and untreated units, IPW reduces covariate imbalance between the two groups by assigning weights based on the value of pretreatment covariates. In the most general case, weights are estimated using a logistic regression that returns a propensity score—reflecting the conditional probability that a unit would have received or been exposed to treatment. When properly specified, weighting, matching, or subclassifying on the propensity score can recover unbiased estimates of a treatment effect (Imbens & Rubin, 2015).

While other methods such as propensity score matching remain immensely popular, we chose to utilize weighting due to a number of advantages for this study. First, rather than matching Connecticut counties to a subset of all U.S. counties (or counties in adjacent states), we chose to weight all counties based on their pre-RTA similarity to Connecticut counties. Therefore, rather than just generating matches on a subset of counties (which entails the discarding of information), we consider the full distribution of states and weight their counties proportionally. Because our weights are based on census-level variables, by nature, many states near Connecticut are also good candidates for the comparison group and, thus, are weighted higher than other, less similar states. Both New Jersey and Pennsylvania have the highest county-level weights (along with Georgia, Colorado, Virginia, and California). In this way, counties that are very dissimilar to Connecticut are weighted much lower in the analysis (Ridgeway et al., 2017). Furthermore, methods such as IPW and synthetic controls are increasingly being advocated over propensity score matching due to substantial limitations of the latter method (King & Nielsen, 2019). We used the “twang” (Toolkit for Weighting and Analysis of Nonequivalent Groups) package in R to estimate the propensity score using a generalized boosted regression (Ridgeway et al., 2017). This method requires the user to select relevant covariates to balance on, which are then passed to the program. Using a generalized boosted model, the optimal number of variables, interactions, and higher order functions are selected using an iterative process. Through repeated analyses, the weighting algorithm identifies the propensity score model that minimizes imbalance between the treated and comparison units. For our analysis, we estimated weights reflecting the average treatment effect on the treated (ATT). The covariates we chose included a limited number of important variables that were the (percentage of) male population, Black population, Hispanic population, population not working, population unemployed, low-income households, households in poverty, high-rent households (households where $>30\%$ of income is spent on rent), households on Supplemental Nutritional Assistance
Table 3. County-Level Covariates, Mean Value, Treated Versus Comparison.

<table>
<thead>
<tr>
<th></th>
<th>Treated counties</th>
<th>Comparison counties</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( N = 8 )</td>
<td>( N = 3,004 )</td>
</tr>
<tr>
<td>Connecticut Weighted</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Male</td>
<td>0.491</td>
<td>0.496</td>
</tr>
<tr>
<td>% Black</td>
<td>0.066</td>
<td>0.087</td>
</tr>
<tr>
<td>% Hispanic</td>
<td>0.099</td>
<td>0.107</td>
</tr>
<tr>
<td>% Not working</td>
<td>0.254</td>
<td>0.257</td>
</tr>
<tr>
<td>% Unemployed</td>
<td>0.085</td>
<td>0.080</td>
</tr>
<tr>
<td>% Low income</td>
<td>0.204</td>
<td>0.221</td>
</tr>
<tr>
<td>% Poverty</td>
<td>0.085</td>
<td>0.094</td>
</tr>
<tr>
<td>% High rent</td>
<td>0.477</td>
<td>0.437</td>
</tr>
<tr>
<td>% SNAP</td>
<td>0.084</td>
<td>0.083</td>
</tr>
<tr>
<td>% Renting</td>
<td>0.254</td>
<td>0.253</td>
</tr>
<tr>
<td>% Vacant</td>
<td>0.093</td>
<td>0.122</td>
</tr>
</tbody>
</table>

Note. KS = Kolmogorov–Smirnov; SNAP = Supplemental Nutritional Assistance Program.

Program (SNAP), and households renting. Table 3 shows the balance statistics, post-weighting, for the eight Connecticut counties and the 3,004 comparison counties. The mean of all Connecticut counties, the mean of the weighted counties, and the mean of the unweighted counties are displayed side-by-side. Covariate balance was assessed using the Kolmogorov–Smirnov (KS) statistic and related nonparametric KS \( p \) values (Ridgeway et al., 2017). In general, the weighting procedure was effective in reducing covariate imbalance between the two groups, with the diagnostic tests indicating no statistically significant differences. The weights calculated from this step were then used in the regression model.

Analysis Strategy

We employed a weighted DiD regression using the Bayesian modeling package “brms” (Bürkner, 2017). Because our outcome variable was distributed as a discrete number of events, we modeled MVT rates as a negative-binomial distribution with the county-level population applied as an offset. We employed a two-level hierarchical linear model (HLM) where we clustered observations at the county level and included time as a fixed and random effect for each county. HLM is uniquely appropriate in this case because it accounts for within-county correlations and allows the estimation of unit-level time trends. Regression methods that do not take into account within-unit correlations (such as ordinary least squares) generate estimates with downwardly biased standard errors (Gelman & Hill, 2012). In contrast, methods such as HLM allow the direct estimation of both group-level and unit-level time trends. These are reflected as unique county-level time trends—often referred to as “growth slopes” or “growth curves” (Bryk & Raudenbush, 1987). HLM also partially pools model
coefficients toward the group-level means, which often improves predictive inferences (Gelman et al., 2013). We indexed time relative to the year 2012, where 2008 was equal to −4, 2012 was equal to 0, and 2017 was equal to 5. To estimate the effect of RTA on MVT, we employed a dummy variable that took on the value of 1 in Connecticut counties at time 0. We then interacted this variable with the time variable to estimate the change in MVT post-RTA, relative to the weighted comparison states. Our regression equation was written as

\[ \text{MVT}_{it} = \alpha_i + \text{Time} + \text{Time}^2 + \text{RTA}_i + \text{RTA}_i \times \text{Times}, \]

where \( \text{MVT}_{it} \) is the expected MVT rate for county \( i \) at time \( t \), \( \text{Time} \) and \( \text{Time}^2 \) are the linear and quadratic year effects, \( \text{RTA}_i \) is a dummy variable taking on 1 for Connecticut counties in 2012 (where \( t = 0 \)), and \( \text{RTA}_i \times \text{Time} \) reflects the time trend for Connecticut counties post-2012 (where \( t > 0 \)). The coefficient of interest is the interaction of the treatment indicator (RTA) on the time variable (time). This method accounts for a common time trend and intercept shared by all counties (reflecting nationwide changes in MVT over time and baseline rates, respectively), as well as individual time trends and intercepts unique to each county. The effect of RTA is fixed for all Connecticut counties, with the assumption that it had equal effects across the state.² Using this method with IP weights estimated in the first step makes the causal estimate of RTA conditionally ignorable. The inclusion of time and unit fixed effects accounts for potentially unobserved differences between treatment and comparison counties (Angrist & Pischke, 2008).

**Results**

Table 4 displays the results from the weighted regression model, highlighting the estimates, standard errors, and 80% and 95% credible intervals (CIs). Because the analysis method utilized a Bayesian methodology, no \( p \) values are generated. Rather, the direction, size, and variability of the effect are considered. The chosen prior distribution for the model parameters were designed to be “weakly informative”—that is, they regularized the estimates without influencing the posterior distribution substantially (Bürkner, 2017; Gelman et al., 2013). A considerable advantage of Bayesian methods is the ability to explore the full posterior distribution of the data and generate point estimates and uncertainty intervals that reflect real-world probabilities (Gelman et al., 2013). Postweighting, we estimated that Connecticut’s 2012 shift in the age of juvenile jurisdiction was responsible for a near-zero increase in overall MVT rates (\( \beta = -0.018, 95\% \text{ CI} = [-0.14, 0.99] \)). At an 80% level of probability, the effect of RTA could have been responsible for between a 9% decrease and a 6% increase. At a 95% level of probability, this effect could have plausibly varied between −13% and 10%. Examining the model random effects showed that most of the between-county variation was attributable to baseline differences in MVT rates, while the county-level time trends varied relatively little.
Given the point estimates were small with CIs roughly symmetrical around zero, this provides very limited evidence in favor of the hypothesis that raising the age of juvenile jurisdiction caused an increase in MVT rates. Figure 3 shows the estimated difference (in green) between Connecticut and the weighted comparison counties, highlighting the point estimates and 50% and 95% probability intervals compared with the years relative to 2012. The differences between Connecticut and the comparison counties are extremely minor and contain a large deal of residual variability, highlighting the lack of any clear direction of an effect attributable to Connecticut’s 2012 shift in age of juvenile jurisdiction.

**Discussion**

This study focused specifically on the concern that RTA legislation was partly, or entirely, responsible for the sudden reversal of MVT trends between 2014 and 2017. Consistent with other studies, we found little evidence that changing the age of juvenile jurisdiction from 17 to 18 had no consistent effect on MVT rates in Connecticut (Loeffler & Chalfin, 2017). Using a weighted DiD regression design, we estimated that Connecticut’s RTA was likely responsible for a near-zero increase in MVT with a wide range of residual variation. Given the variability in these estimates, it is likely that several other factors have played a more significant role in the uptick in thefts. Given that Connecticut’s increase in MVT mirrored nationwide trends, it is likely that other factors may be responsible. For instance, the introduction of keyless entry has made vehicle theft easier to commit when owners inadvertently leave their key fobs within proximity or within the vehicle itself. Between 2013 and 2015, there was a 31% increase in the number of vehicle thefts where the key was left inside of the vehicle (National Insurance Crime Bureau, 2019). Regardless of the underlying reasons, the

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate</th>
<th>SE</th>
<th>2.5%</th>
<th>10%</th>
<th>80%</th>
<th>97.5%</th>
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</thead>
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<tr>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>RTA</td>
<td>0.110</td>
<td>0.108</td>
<td>−0.094</td>
<td>−0.033</td>
<td>0.253</td>
<td>0.320</td>
</tr>
<tr>
<td>RTA × Time</td>
<td>−0.018</td>
<td>0.061</td>
<td>−0.138</td>
<td>−0.094</td>
<td>0.062</td>
<td>0.099</td>
</tr>
<tr>
<td>Time</td>
<td>−0.032</td>
<td>0.031</td>
<td>−0.093</td>
<td>−0.072</td>
<td>0.008</td>
<td>0.028</td>
</tr>
<tr>
<td>Time²</td>
<td>0.013</td>
<td>0.007</td>
<td>−0.002</td>
<td>0.004</td>
<td>0.022</td>
<td>0.027</td>
</tr>
<tr>
<td>Intercept</td>
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<td>0.121</td>
<td>4.582</td>
<td>4.672</td>
<td>4.977</td>
<td>5.059</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(SD) Intercept</td>
<td>0.415</td>
<td>0.077</td>
<td>0.287</td>
<td>0.322</td>
<td>0.512</td>
<td>0.582</td>
</tr>
<tr>
<td>(SD) Time</td>
<td>0.015</td>
<td>0.012</td>
<td>0.001</td>
<td>0.003</td>
<td>0.031</td>
<td>0.044</td>
</tr>
<tr>
<td>(SD) Time²</td>
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<td>0.004</td>
<td>0.000</td>
<td>0.001</td>
<td>0.011</td>
<td>0.016</td>
</tr>
</tbody>
</table>

*Note. HLM = hierarchical linear model; MVT = motor vehicle theft; RTA = raise the age.*
data here do not support the assertion that changes to the age of juvenile jurisdiction played any role in the increase of Connecticut MVTs.

While carefully constructed to maximize causal inferences, this study does have some notable limitations. Our primary limitation is a lack of reliable information on age-specific arrest rates of MVT offenders. In general, MVT has among the lowest clearance rates (approximately 14%), which makes it difficult to determine which groups of individuals are most responsible for these thefts (Crime in the United States, 2017). While the UCR does report cleared cases for individuals under age 18, these were not consistent enough across counties to utilize in this study. In many cases, cleared MVT cases were not reported for 1 or more years in some counties and large municipalities. This is not a problem unique to our study—indeed, it is a general weakness of all research relying on reported crimes. While National Incident-Based Reporting System (NIBRS) data provide a greater breakdown of age-specific arrest statistics, to date only about 50% of agencies currently provide data (Crime Data Explorer, 2019). Because this study was more broadly concerned with the county-level impact of RTA, we opted for UCR data, which are more widely reported. An advantage of this approach is that it allows a more widely representative sample of crimes reported to police, with the notable trade-off of a lack of incident-level crime data. Clearly, this limitation speaks to the need for more comprehensive and consistent data collection on cleared cases—of which the switch to NIBRS as the default reporting system should alleviate. These results should not be entirely surprising. A large body of prior research points to the marginal effectiveness of severity-based deterrent

Figure 3. Predicted difference in motor vehicle thefts (per 100,000), in Connecticut versus comparison counties.

Note. Point estimates and 95% and 80% probability intervals are highlighted as points and shaded bars. Time is indexed relative to 2012, with year 0 being the intervention date.
measures (Nagin, 2013). Research on the psychosocial development of juveniles suggests they lack much of the foresight and maturity required to make decisions. Therefore, policies that emphasize punitive punishments as a deterrent measure are not likely to succeed (Nagin, 2013). Rather, the treatment of juveniles in the criminal justice system requires a treatment-based focus with concern for the youths’ reentry into society (Farrington et al., 2012). Abandoning policies that automatically treat juveniles as adults is also not likely to increase crime (Lee & McCrary, 2005; Loeffler & Grunwald, 2015). In contrast, there is a substantial evidence that points to juvenile incarceration as a negative turning point in youths’ lives (Aizer & Doyle, 2015). Exposure to the adult criminal justice system has long-term negative effects on youth reoffending and is associated with additional costs to a state’s criminal justice system (Butts & Roman, 2014). More evidence indicates that youth have better postrelease outcomes when adjudicated in the juvenile justice system (Bishop et al., 1996; Fagan, 1996; Kurlychek & Johnson, 2004). Taken together, this provides compelling evidence that policies diverting youth away from the adult criminal justice system be maintained.

While MVT thefts committed by teens and young adults continue to be a concern for many states and municipalities, our research finds that laws targeting the age of juvenile jurisdiction are unlikely to have any lasting or meaningful impact on general MVT trends. More effective strategies may focus on increasing guardianship (Copes, 1999; Gonzalez-Navarro, 2013) or targeting known repeat offenders (Tillyer & Kennedy, 2008). In contrast, applying adult penalties to juveniles is likely to have more negative long-term impacts (Bishop et al., 1996). As other cities and states wrestle with emerging crime issues, authorities should focus on strategies that are supported by a broad base of evidence. In this case, a reversion of the change the age legislation would likely not provide the intended benefits.

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Notes
2. We also considered the possibility that “raise the age” (RTA) had an unequal impact between Connecticut counties. Estimating the same model but allowing the effect to vary by county did not substantially change the estimates of RTA.
References


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