Estimating the Impact of the Age of Criminal Majority: Decomposing Multiple Treatments in a Regression Discontinuity Framework*

Michael Mueller-Smith, University of Michigan
Benjamin Pyle, University of Michigan
Caroline Walker, U.S. Census Bureau

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Abstract

This paper studies the impact of adult prosecution on recidivism and employment trajectories for adolescent, first-time felony defendants. We use extensive linked Criminal Justice Administrative Record System and socio-economic data from Wayne County, Michigan (Detroit). Using the discrete age of majority rule and a regression discontinuity design, we find that adult prosecution reduces future criminal charges over 5 years by 0.48 felony cases (↓ 20%) while also worsening labor market outcomes: 0.76 fewer employers (↓ 19%) and \$674 fewer earnings (↓ 21%) per year. We develop a novel econometric framework that combines standard regression discontinuity methods with predictive machine learning models to identify mechanism-specific treatment effects that underpin the overall impact of adult prosecution. We leverage these estimates to consider four policy counterfactuals: (1) raising the age of majority, (2) increasing adult dismissals to match the juvenile disposition rates, (3) eliminating adult incarceration, and (4) expanding juvenile record sealing opportunities to teenage adult defendants. All four scenarios generate positive returns for government budgets. When accounting for impacts to defendants as well as victim costs borne by society stemming from increases in recidivism, we find positive social returns for juvenile record sealing expansions and dismissing marginal adult charges; raising the age of majority breaks even. Eliminating prison for first-time adult felony defendants, however, increases net social costs. Policymakers may still find this attractive if they are willing to value beneficiaries (taxpayers and defendants) slightly higher (124%) than potential victims.

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JEL classification codes: C36, C45, K14, K42, J24

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1 Introduction

In the United States, the criminal justice system prosecutes and sentences "juvenile" and "adult" defendants in different ways based on a dual principle of evolving culpability over the age profile and a desire to protect children from the potential long-term harms stemming from justice involvement. Whether a defendant is treated as a juvenile or adult is largely defined according to a discrete function of their age at the time of the offense. Many states today define the cut-off between juvenile and adult, the age of majority, as 18 years old. An offense that occurs one day before the defendant's birthday is likely to be handled in an entirely different system (judges, prosecutors, physical location, possible sanctioning options, etc.) than one that occurs one day after. While many of the factors that are associated with culpability and the effectiveness of punishments and supervision evolve gradually over adolescence, the risks defendants face transforms overnight based on a statutorily specified age of criminal majority. Considering that a large majority of justice-involved individuals have their first contact with the justice system as a teenager (Figure 1),[1] a potentially life-altering experience, it is critical that we better understand how these different approaches shape the lives of their caseloads.

In this paper, we leverage a regression discontinuity (RD) design to study a range of impacts stemming from such a sharp change in the criminal justice system generated by the age of criminal majority. Using novel data containing adult and juvenile adjudication records from Wayne County (Detroit), Michigan between 2011 and 2020 developed through work described in Finlay, Mueller-Smith, and Papp (2022), we exploit variation generated by whether the alleged criminal conduct occurred just before or just after a defendant's 17th birthday, which was the defined age of criminal majority during our study period. We examine changes to future criminal activities, employment, and earnings and we find

[1]This fact would be missed when looking at a cross-section of the justice caseload in a given year, the typical format of data collection and reporting by federal agencies. While researchers have long recognized an age-crime curve (see Quetelet (1984) and Sampson and Laub (1995)), the typical composition of the justice caseload involves individuals mainly in their 20's and 30's. It is only through the innovation of multiple decades of longitudinally linked microdata from the justice system in CJARS that this nuanced and detailed perspective on justice-involvement over the life course is possible.

that a felony case in the adult system results in about a 20% reduction (0.48 fewer cases) in subsequent felony cases, but that the adult system also generates worse labor market outcomes, lowering annual earnings over the next 5-years by almost 30% (over $600 per year) and increasing poverty rates by about 33%. Examining a range of outcomes is particularly important in this context since differential rates of incarceration across the threshold can generate both good (↓ recidivism) and bad (↓ wages) outcomes as a result of incapacitation, an issue that has been acknowledged but previously unaddressed in prior work which primarily focused on recidivism due to data limitations.

To understand what specific mechanisms generate these overall changes at the discontinuity, we develop a new empirical methodology to estimate the specific treatment effects of a range of disposition and sentencing options that change at the threshold. For instance, both conviction and incarceration rates change depending on whether a defendant is prosecuted through the juvenile or adult criminal justice system. And, given factors like the greater availability of record sealing for juvenile defendants, the long-term implications of a conviction vary depending on which side of the threshold a case falls on. As a result, standard RD strategies cannot differentiate whether changes in outcomes in the overall caseload are attributable to differences in convictions rates, the legal implications of convictions for criminal records, incarceration, or something else entirely.

Previous research has speculated that differential incapacitation time driven by prison sentences might explain the higher recidivism rates for juveniles relative to adults (D. S. Lee & McCrary, 2017). We develop a methodology to address this directly. We apply a new regression discontinuity procedure to disentangle the impact not only of the reduced form effect of a case being handled in juvenile versus adult court but also what specific features of the juvenile and adult systems generate the impacts to future recidivism and employment outcomes. Using a machine learning approach and a rich set of covariates, we create predicted juvenile and adult case dispositions and sentencing outcomes to decompose and identify multiple changes in treatment across the discontinuity. The interaction of the predictions with the cutoff rule instrument for actual program take-up, while the uninteracted prediction terms partial out potential sources of omitted variables bias. Intuitively, the procedure allows us to isolate the subset of the analysis sample who would have received intervention X if prosecuted as juveniles and intervention Y if prosecuted as adults, thereby avoiding the problem of multiple interventions changing simultaneously at the threshold.

This decomposition allows us to learn not only about the impact of moving between the juvenile and adult criminal justice systems but also about marginal changes in punishments within the juvenile and adult systems (e.g. the marginal impact of incarceration compared to a non-carceral adult punishment). The decomposition exercise provides several important lessons. First, adult prosecution may generate a specific deterrence effect as we observe a causal decrease in recidivism for adult case dismissals relative to juvenile case dismissals. In addition, adult convictions significantly increase the risk of future justice involvement, but empirically this is often offset by being paired with incarceration which prevents crime through incapacitation. This latter point is amplified by our observation that both adult convictions and incarceration lead to decreases in earnings.

Using this framework, we consider 4 policy counterfactuals: (1) raising the age of criminal majority, (2) shifting the proportion of adult defendants receiving case dismissals to match the juvenile system (which is more lenient), (3) eliminating prison sentences for young defendants in the adult criminal justice system, and (4) making adult convictions operate like juvenile convictions (e.g. enhanced access to short-run expungement). We find that all policy options generate net revenue for the government's budget constraint and are attractive to defendants. Because several of these programs generate savings through reducing program costs at the risk of increasing recidivism, the net impact on society after accounting for potential victim costs becomes more ambiguous. Option 3 (eliminating adult incarceration) worsens societal outcomes; option 1 (raising the age of majority) roughly breaks even. However, these conclusions depend on equal weighting of taxpayers, defendants, and future victims in the social welfare calculation, an assumption that policymakers may forego in favor of alternatives that instead seek to address specific distributional inequalities in society. Options 2 and 4 unambiguously benefit all perspectives in our analysis, yielding the most social value through addressing the underlying mechanism that appears to generate the most harm: quasi-permanent adult conviction records.

Our analysis has immediate theoretical and policy relevance. Prompted by a growing body of neuroscience research showing that the brain continues to develop mature decision-making functions past the age of 18 (Center for Law, Brain and Behavior, 2018), eleven states have raised the age of criminal majority to the age of 18 in the last 15 years (including Michigan in 2021). Several states have considered raising the age of majority beyond 18. These reforms highlight the fact that the age of criminal majority is a policy choice.

Our analysis helps demonstrate that changes in how adolescent charges are resolved can help improve long-term public safety and productivity if appropriate justice programs are matched to the appropriate set of charged youths.

Additionally, our paper makes a broader methodological contribution which can be used to estimate the relative contribution of distinct underlying mechanisms in regression discontinuity designs with multiple policy levers that jointly change across a discontinuity threshold. This method has potential applications in a number of different fields, including income thresholds that trigger a range of safety net interventions, test score cutoffs that determine enrollment to differently ranked educational institutions with potentially different course and major offerings, or adjusted gross income thresholds that vary multiple tax incentives simultaneously.

2 Related literature

A considerable literature documents the important developmental and cognitive differences between children, developing adolescents, and adults, and the out-sized impact of interventions during early, formative years (Gruber, 2001; Heckman & Mosso, 2014). Neuroscientists have shown that youth brains continue to mature well into early adulthood, leaving them highly susceptible to reward- and peer-influence during their teenage years (Center for Law, Brain and Behavior, 2018). This period of physiological development likely plays an important role in the sensitivity of adolescents to their environment and also leaves them vulnerable to impulsive decisions (Monahan et al., 2015). There is evidence, for instance, that providing cognitive behavioral therapy to economically disadvantaged youths reduced arrest rates by about one-third, violent arrest rates by up to one-half, and increased school engagement and graduation rates (Heller et al., 2017). While brain maturation plateaus on average by age 25 (Arain et al., 2013), choices that lead to contact with the justice system at earlier ages could have life-long implications, especially as human capital develops dynamically over time, reinforcing earlier choices (Arora, 2019).

Aside from culpability, there is an additional reason to want to protect youth from traditional justice interventions. The National Prison Rape Elimination Commission Report (2018) found that juveniles were at a higher risk of being sexually assaulted while in prison than the average prisoner. Similarly, Justice Policy Institute (2017) provides evidence that juveniles in prison (as opposed to juvenile detention) face a higher risk of being beaten by guards and committing suicide. Such extreme outcomes lay bare the differential cost of justice involvement for youth compared to adults and provide strong motivation for a separate system of punishment and rehabilitation specifically designed for youth.

Economists have studied the age-of-majority threshold as part of two distinct but related literatures. First, researchers have sought to examine offending rates around the discrete jump in punishment severity to test the theory of general deterrence in the population (Arora, 2019; Hjalmarsson, 2009; D. S. Lee & McCrary, 2017; Loeffler & Chalfin, 2017; Lovett & Xue, 2018).[2] Findings in this literature have often been quite modest; for instance, D. S. Lee and McCrary (2017) finds that the odds of committing a crime decrease by only 2% when an individual turns 18 and are subject to adult criminal sanctions, a relatively small decline considering the serious increase in expected punishment. This small degree of behavioral response, however, comports with psychological research showing the developing teenage brain is less focused on long-term consequences of their actions (Blakemore & Choudhury, 2006).

A second line of research examines whether the bundle of interventions that comprise the juvenile justice system discourages future criminal activity compared to the adult criminal justice system. While causal identification has been challenging in this setting, a systematic meta-analysis conducted in 2016 suggests that marginal transfers of individuals under the age of majority into the adult court system ("waiver" in Michigan) have no statically significant impact on future recidivism. However, there is evidence of heterogeneous effect

[2]Levitt (1998) explores related themes, although without exploiting the variation stemming from the age-of-majority discontinuity. Our project helps us understand how Levitt (1998), that shows drops in crime in the overall population at or after the age of majority in states that especially rely on incarceration, might relate to D. S. Lee and McCrary (2017), that finds minimal evidence of general deterrence when looking at first-time felony defendants across the age of majority. We find evidence consistent with both of these narratives. First, there isn't a meaningful change in first time offending levels at the age of majority (that is, there is no real evidence of general deterrence in this population). At the same time, we see large declines in future crime associated with the application of incarceration to the adult caseload. The incapacitation here is substantially longer and more meaningful compared to the juvenile system.

depending on the specific nature of the transfer and the defendant involved (Zane et al., 2016). Additional studies support this summary and find mixed results and generally suggest that being processed as an adult decreases recidivism rates or fails to reject the null of no effect (Bishop et al., 1996; Fagan, 1990, 1996; Fagan et al., 2003; McNulty, 1996; Winner et al., 1997).

Several recent studies have exploited changes in several states' age of majority law in a difference-in-differences framework to understand the impact of moving between juvenile and adult systems (Fowler & Kurlychek, 2018; Loeffler & Braga, 2022; Loeffler & Grunwald, 2015a; Robinson & Kurlychek, 2019).[3] By expanding the treated sample beyond transfers to an entire population, this approach potentially improves both the external and internal validity.[4] This research has largely found that adult prosecutions have either no impact on recidivism (Loeffler & Grunwald, 2015a) or decrease the risk of recidivism (Loeffler & Braga, 2022; Robinson & Kurlychek, 2019).

The most promising work in this literature examines defendants just above and below the age-of-majority cutoff and follows their recidivism trends over time (D. S. Lee & McCrary, 2017; Loeffler & Grunwald, 2015b). By examining just the subsample of defendants with offenses around the discontinuity, the research design minimizes the risk of omitted variables bias, strengthening the credibility of the research findings. These studies consistently find that those prosecuted through the adult system exhibit modestly lower rearrest rates in the future. A range of theoretical factors may contribute to these findings, however, including differences in specific deterrence, rehabilitation, or incapacitation. Whether the lower rearrest rates are driven by incarceration (costly) versus deterrence (less costly) has not yet been established in the literature, though, which is crucial due to their fundamentally different implications for public policy.

3 Criminal justice systems for adult and juvenile defendants

We study the impact of the age of criminal majority in Wayne County, Michigan. During our sample period, the age of majority was 17 (it has since been raised to 18 as of October

[3]These states include Connecticut, Illinois, and Massachusetts.

[4]Although, as Arora (2019) points out, potential differences in policing and arrest behavior complicate interpreting these results.

2021). This means that an alleged criminal act committed by a person under the age of 17 will be processed in the juvenile system, while criminal behavior alleged to have been committed by someone over 17 will be in the adult criminal courts. Michigan, like many other states, transfers certain severe crimes into the adult system.[5]

The hearing is similar in many ways across the two systems (for instance, both systems can have a jury, judge, defense, and prosecution). Likewise, both the juvenile and adult systems require the state to make its case beyond a reasonable doubt and have similar rules regarding admissible evidence.

There are, however, a number of important differences, beginning with the average cost of prosecution; Wayne county reports an average juvenile case processing cost (in 2016) of $1,927 compared to $1,154 for an adult case. These costs are driven by different staffing needs and economies of scale. Similarly, the menu of available interventions (dispositions and sentences) and the implications of these assignments (availability of record sealing, location, and composition of institutional facilities, etc.) differ dramatically. These differences are detailed below with empirical evidence from our setting discussed in Section 6.

3.1 Youth criminal justice

In Wayne County, the juvenile system is administered by the Circuit Court Family Division, a specialized division of the legal system with more focus on treatment and rehabilitation. Although many of the same legal standards and procedures apply, Michigan courts have a great deal of discretion in assessing fines, fees, and assigning program participation in juvenile cases. Juvenile cases can be dismissed by the judge, and the judge may also issue a warning to the juvenile and the parents along with this dismissal. Alternatively, a juvenile may be found responsible for their actions, and these judgments may include fines, restitution, community service, imposition of curfews, behavioral/drug assessments and treatment, probation, and supervised residential placements out of the home. The county contracts with five Care Management Organizations (CMOs) that are responsible for adjudicated

[5]Waiver into the adult system is relatively rare. In our sample, under 2% of juvenile cases were transferred. The two most emphasized factors in a waiver hearing are the defendant's previous criminal record and the seriousness of the charged offense. Our analysis sample is restricted to first-charged felonies, putting downward pressure on the first factor.

juveniles within a zip code cluster and provide case management, residential placements, and other services (some of which are subcontracted).[6] Juveniles on probation may be offered mental health services such as cognitive behavioral therapy, regularly screened for substance use, provided academic tutoring, electronically monitored, and/or provided job readiness programming, among other services.

In our sample period, Wayne County reported just over half of those assigned to some sort of probation were assigned to out-of-home supervision.[7] In 2013, the overall length of stay in residential placement was 5.8 months with an average of 7.5 months for secure and 4.3 months for non-secure facilities (Chaney & Reed, 2018). The family court no longer has jurisdiction over a defendant 2 years beyond the maximum age of original jurisdiction (17 in our sample), which places a cap on how long incapacitation can be.

Juvenile defendants and their families face several fees and potential fines. These include mandatory fees such as victim rights assessments, DNA testing, and the cost of care and services such as daily detention fees for youth in out-of-home placements. There are also discretionary fees including fines generated by the statute violation, in-home cost of care services, and fees for court-appointed counsel (Uppal, 2020).

A final critical feature of the juvenile justice system is the greater availability of expungement opportunities.[8] Record sealing limits public access to criminal records and may have important long-term implications given that criminal records have been shown to causally impact outcomes like recidivism, employment, and wages (Mueller-Smith & Schnepel, 2021; Pager, 2003). Even though Michigan is less generous towards juvenile defendants than many states (Shah & Strout, 2016),[9] several key features make juvenile expungement more common than adult expungement. Most importantly, juveniles are eligible within one year after case disposition, exiting detention, or turning 18. This stands in

[6]The juvenile justice system is funded with a 50/50 cost-sharing plan between the county and state.

[7]Unfortunately, we do not have access to micro data on punishments or services associated with a juvenile case resolution, but annual caseload-wide statistics are publicly available from Wayne County.

[8]In the state of Michigan, record sealing is achieved via a procedure known as a set aside.

[9]Subsequent legislation has expanded record sealing in Michigan. See Public Acts 361 and 362 of 2020 for juveniles and Public Act 193 of 2020 for adults.

contrast to a 5-year waiting period for adult expungement, which only starts once a sentence is fully served effectively adding years to the clock. So, while a juvenile defendant might have their record sealed by age 19, a 17-year-old adult defendant might have to wait almost a full decade longer until their late 20's if their sentence came with a 5-year probation sentence. With such a long waiting period, adult defendants may be permanently harmed from diminished labor market experience or additional criminal activity, thereby making them ineligible for an expungment in the first place.[10]

3.2 Adult criminal justice

The criminal division of the Circuit Court handles adult felonies (the district court handles misdemeanors). While services for juveniles are provided by CMOs, the state directly oversees the supervision of the vast majority of adults, regardless of community-based or institutional correctional status.

About 16% of adult charges in our sample (regardless of disposition outcome) were sentenced to some incarceration. The average minimum sentence for new adult entrants to prison in Michigan was 3.6 years in 2012, and the average term of those in prison was 8.9 years (Michigan Department of Corrections, 2012). This figure may be significantly higher for Wayne, as Hornby Zeller Associates (2018) estimate an average prison stay of 23.1 years for Wayne. The adult incarceration system places less emphasis on community supervision and resources targeted at young inmates as the system is designed to accommodate a typically older population. In our sample, 70% of adult defendants were sentenced to some non-carceral punishment. Sentences in this category include probation, restitution or fines, and community service.

[10]In addition, three additional factors may benefit juvenile defendants with regard to criminal histories. First, juvenile expungement allows for more total cases to be sealed compared to adult expungement, which might also impact take-up. Second, a juvenile adjudication for delinquency is in family court and thus is legally not a prior conviction in Michigan, and such individuals do not need to report said criminal histories to employers if solely asked about prior convictions. For ease of exposition however, we refer to delinquency adjudications as juvenile convictions in this paper. Finally, juvenile records are generally differentiated on Law Enforcement Information Network (LEIN) background check reports requested by employers and may be viewed differently as a result.

In the adult system, a person convicted of no more than one felony offense (or two or fewer misdemeanors) may apply for a record sealing five years after imposition of sentence, completion of probation or parole, or release from prison, whichever is later. The accumulation of additional criminal records during this waiting period will make the defendant permanently ineligible for any expungement for all cases on their criminal history.

4 Data, econometric specification, and identification assumptions

4.1 Data sources

We use novel microdata linked through the Census Bureau data linkage infrastructure and accessed through the Federal Statistical Research Data Centers (FSRDCs) to observe individual socio-economic information as well as individual criminal and employment histories for adult and juvenile defendants in Wayne County, Michigan. Criminal records are measured using the Criminal Justice Administrative Records System (CJARS), which compiles criminal justice records from many jurisdictions and agencies (Finlay & Mueller-Smith, 2021). The CJARS data is supplemented with additional administrative data on juvenile cases provided by the Michigan State Court Administrative Office. CJARS uses a probabilistic matching algorithm (see Gross and Mueller-Smith (2020)) to track individual involvement in the justice system over time and across jurisdictions. In this paper, we use two primary types of records: criminal court charges, which are classified by type (e.g., property, drug, violent) and gravity (e.g., misdemeanor, felony); and correctional data, including incarceration, probation, and parole.

We make use of the detailed information available through the Census Bureau in order to expand the set of outcomes we can study (e.g. employment) as well as to broaden the range of covariates we can leverage in our machine learning model. In the latter case, we use information on the defendant's age from court records, their race and sex from the Census Bureau's Best Race and Ethnicity and Numident files, their household's historic earnings and employment from IRS 1040 and W-2 forms, household composition (based on Finlay, Mueller-Smith, and Street (2022)'s work) and previous charges, convictions, and incarcerations of the adolescent and their family members, and information (e.g. youth poverty rates and median income) about the census tract the youth is living in based on the public ACS 2010 5-year estimates. All data is merged using the Protected Identification

Key (PIK)[11] or a geographic identifier, which allows integration of anonymized datasets at the person level.

4.2 Sample construction

Following D. S. Lee and McCrary (2017), our sample is restricted to first-time felony defendants between the ages of 15 to 18 (i.e. two years on either side of the age of majority threshold).[12] If these defendants had previous charges, they are restricted to misdemeanor charges. The restriction on first-time felony defendants allows us to avoid having repeated observations for the same individual in our regression discontinuity analysis. We focus on the sample of defendants charged between 2011 and 2014 in Wayne County to balance the overall sample size and have a consistent follow-up period.

4.3 Empirical specification

To evaluate the reduced form impact of being charged as an adult defendant (relative to a juvenile defendant), we utilize a standard local linear fuzzy regression discontinuity framework:

$$\begin{aligned} Y_i = \alpha + \delta \text{Adult Defendant}_i + \gamma \text{Age at Offense}_i \\ + \beta [\text{Age at Offense}_i > 17] \times \text{Age at Offense}_i + \phi X_i + \epsilon_i \end{aligned}$$

where Y_i is a youth outcome, Adult Defendant$_i$ indicates the youth was charged through the adult criminal justice system, Age at Offense$_i$ is the continuous running variable measured based on exact date of birth and exact date of offense, and X_i is a vector of observable

[11]PIKs are a de-identified person identifier which is assigned to individual records through the Census Bureau's Person Identification Validation System (PVS). The PIK allows linkage across administrative and survey records within the Census Bureau data infrastructure, specifically matching individuals in the justice system to their tax records and demographic characteristics. Additional detail about PIK rates in the CJARS data can be found in Finlay and Mueller-Smith (2021), but is above 85% provided an individual appears in CJARS at least twice. Additional information about PVS is detailed in Wagner, Lane, et al. (2014).

[12]In Table A7 we show the robustness of our results to varying bandwidth windows between 1 and 3 years on either side of the cutoff.

characteristics. Whether the youth is charged as an adult is instrumented using the following equation:

$$\begin{aligned}\text{Adult Defendant}_i = \alpha_1 + \delta_1[\text{Age at Offense}_i > 17] + \gamma_1\text{Age at Offense}_i \\ + \beta_1[\text{Age at Offense}_i > 17] \times \text{Age at Offense}_i + \phi_1 X_i + \nu_i\end{aligned}$$

where crossing the age of majority threshold (i.e. $[\text{Age at Offense}_i > 17]$) functions as our excluded instrument for Adult Defendant_i.[13] Coefficients in this equation have "1" subscripts to denote being in the first stage equation.

The vector of control variables includes a range of defendant characteristics: the time since the defendant's first criminal charge, binned categories for time since last charge (within the last month, between a month and 6 months, more than 6 months and less than a year, greater than a year), whether the defendant has a previous misdemeanor of each crime types (violent, property), the category of charges present in the current case (violent, property, drug, or other), whether the defendant was Black, or male, the number (by crime type) of criminal offenses charged to people living in the defendant's zip code in 2010, household structure, census tract demographic information from the 2010 ACS (age structure, the percent of the tract that is male, Black, White, and Hispanic), tract child poverty rates and income distribution.

4.4 Identification assumptions

Our reduced form regression discontinuity evidence requires two critical assumptions. First, the discontinuity has a material impact on case processing and outcomes, and second, whether a defendant ended up on one side of the discontinuity or the other is as good as randomly assigned in order for our estimates to be interpreted causally. Failure to satisfy either of these requirements should raise serious questions about how to interpret our findings.

To address the first concern, which is not mechanically satisfied since defendants below

[13] In our empirical implementation, we normalize Age at Offense_i to be centered at zero such that having a positive value indicates crossing the age of majority threshold and negative values indicate being under the threshold. For expositional purposes, we abstract from this detail in the main text.

the age of majority can be prosecuted as adults if the nature of their offense is sufficiently severe, we study whether there is a sharp change in the probability of a case being processed in the adult system around the age of criminal majority (Figure 2 panel A). In our data, a few defendants are waived into the adult system prior to 17, but this is rare. After the age of 17, criminal defendants are automatically processed in the adult system.[14] Ultimately, we observe a jump of 86 percentage points at the cutoff, indicating significant relevance of the age of majority cut-off.

The second concern, often referred to as potential sample imbalance, is whether differences in outcomes are the product of changes in interventions at the threshold or changes in (observed or unobserved) characteristics. There are many theoretical reasons why this key assumption may not hold in our application. First, evidence has shown that in some settings, there is a non-trivial general deterrence effect of the increase in expected punishment at the age of majority threshold. Similarly, it is possible that actors in the justice system (police, prosecutors, etc.) alter their behavior depending on the would-be defendant's age at the offense. These hypothesized behavioral responses to the age of majority threshold would predict that we might expect to see discrete changes in the size of the criminal justice caseload and the composition of the caseload just before and after the discontinuity.

While there are hypothesized reasons why we might see sample imbalance, in our setting the caseload density is smooth through the age of majority (Figure 2 panel B). The blue bars represent cases in the juvenile system and the red bars cases in the adult system. In this case, we see a similar number of cases filed just before and after age 17.

Although it is reassuring that caseload is smooth through the discontinuity,[15] for a causal interpretation to be valid, it is important to also asses whether the composition of cases and defendants on either side of discontinuity are similar. We provide additional evidence whether cases filed just before and just after the age of criminal majority are comparable

[14]We do not have consistent data coverage for the date an alleged offense occurs, so we use the defendant's age at the time the charge was filed in the court. While charges are typically filed near to the date of the alleged offense (for the cases that have both offense and filing date the average gap was about a week), this is not always the case and leads to a small number of instances with defendants who have recorded ages over 17 being processed in the juvenile system.

[15]See Table 1 for statistical tests.

in Figure 3 and A1, which show the evolution of a range of socioeconomic characteristics over the support of the running variable, with corresponding statistical tests evaluating a discrete jump at the cutoff reported in Table 1. We find that defendants just before and just after 17 are of similar race, sex, have similar household composition, and have similar childhood exposure to the criminal justice system.[16] In addition, the evidence indicates that family income and neighborhood wealth are similar across the discontinuity, as are the types of charges bringing the defendant into the criminal justice system. Overall, we find statistical balance on 44 of the 46 characteristics considered, spanning demographic background, neighborhood characteristics, family resources, and criminal histories.[17]

5 The impact of adult prosecution for justice-involved youth

Being charged as an adult defendant creates both positive and negative outcomes for youth during the 5-year follow-up period tracked in our study sample. As shown in Figure 4 and Table 2,[18] prosecution through the adult criminal justice system significantly lowers a range of recidivism outcomes on both the extensive and intensive margins. We find a statistically significant decrease of 7.6 percentage points of facing any criminal proceedings over the next five years (↓ 9%)[19] and 1.02 fewer criminal cases overall (↓ 19%). Total felony level activity drops by a striking 0.48 cases (↓ 20%) and 0.32 convictions (↓ 16%). Declines in

[16]Note that parents of the adolescents in our sample are far more likely to have felony charges and convictions than the average child; in our sample almost 40% of parents have a felony charge, while Finlay, Mueller-Smith, and Street (2022) estimate this number at about 10% in the general population.

[17]Among the 46 observable traits we evaluate, two exhibit modest but statistically significant differences at the discontinuity. These are: whether the defendant is facing a drug charge (β=0.036; p-value = 0.087), and whether anyone in the house had a previous felony conviction while co-residing (β=-0.068; p-value = 0.039). While we believe some imbalance is inevitable given the number of traits we consider, we will control for all observable traits in our regressions to minimize any resulting bias.

[18]Additional results can be found in Figure A2.

[19]While this decline might seem modest given the high degree of future justice involvement in this population, another way of viewing this is that adult prosecution increases 5-year total desistance by 54% [0.07593/(1-0.8538)].

total criminal activity are observed for all major offense types: 0.42 fewer violent charges (↓ 23%), 0.37 fewer property charges (↓ 21%), 0.31 fewer drug charges (↓ 33%), and 0.81 fewer other charges (↓ 23%).[20]

At the same time, the reduction in future charges and convictions comes at the expense of a drop in future labor market activity over the same 5 year follow up period. We observe statistically significant and economically meaningful reductions in annual wage income (↓ $674 or 21%), average number of employers – proxied by the number of distinct W-2 information returns with over $1,500 – per year (↓ 0.08 returns or 19%), and whether the defendant earns sufficient wages to exceed the poverty threshold for a single adult (↓ 2.7 percentage points or 31%). As shown in Table A7, these regression discontinuity results are robust to varying local weighting, bandwidths, and estimation techniques.

This pattern of results is potentially surprising given that crime and employment outcomes are typically negatively correlated with each other absent incapacitation (e.g., Mueller-Smith and Schnepel (2021)), and creates a tension over the trade-offs for policy makers who might decide whether to raise or lower the age of majority. While raising the cutoff threshold (as many states have done in recent decades) might improve the employment trajectories of justice-involved youth, we should also expect an increase in prevailing crime rates. Whether there might be policy alternatives through which society can reap the benefits without the costs requires a careful examination of the underlying mechanisms, which is the focus of our next section.

6 Understanding the mechanisms that drive the impacts of adult prosecution

Multiple levers change at the age of majority cutoff and together generate our previously described estimates on the impact of adult prosecution. These include differences in the likelihood of conviction, the distribution of sentencing outcomes, and the ability to expunge or seal one's criminal record which can be seen in Figure 2 panels C through F. While prior research has speculated that changes in incarceration are what drive the estimated treatment

[20]Note that criminal "cases" can be composed of multiple distinct "charges" and so summing across the effects by offense type should not be expected to add up to the total effect discussed earlier.

effects, data and methodological limitations have prevented more concrete conclusions regarding mechanisms in this literature.

In this section, we develop a novel estimation strategy to disentangle the relative contribution of the multiple underlying treatments. Intuitively, we leverage a rich set of defendant characteristics combined with machine learning prediction methods to identify distinct subsets of our analysis sample who would have experienced disposition and sentencing outcome X if prosecuted as a juvenile but disposition and sentencing outcome Y if prosecuted as an adult. Combined with a non-trivial homogeneity assumption on the distribution of treatment effects conditional on observed covariates, we are able to recover mechanism-specific treatment effect estimates, which deepen our understanding of the impacts observed at the age of majority cutoff and enable us to consider a range of hypothetical policy counterfactuals that aim to maximize the benefits while minimizing the costs of adult prosecution.

6.1 Identifying mechanism-specific treatment effects using a regression discontinuity and predicted case outcomes

We build on the multi-valued RD treatment methodology from Caetano et al. (2022) to study identification and estimation in the regression discontinuity setting with a multi-valued treatment variable and unknown counterfactual treatment across the discontinuity. Our identification strategy returns the marginal effects for a range of potential interventions relative to an omitted treatment category.

Our work and econometric methodology also relates to the broader literature analyzing instrumental variable models with multiple potential treatments (Caetano & Escanciano, 2021; Feller et al., 2016; Heckman & Pinto, 2018; Hull, 2018; Kirkeboen et al., 2016; S. Lee & Salanié, 2018; Mountjoy, 2022). From this literature, we know that it can be difficult to interpret multivariate instrumental variable estimands since they combine comparisons across many treatment margins and compliers. This literature highlights the usefulness of interacting an instrument with covariates and the required constant treatment effects assumption. In our setting, we leverage defendant characteristics in a machine learning model to generate predictions of disposition outcomes. We then interact said probabilities with the exogenous age-of-majority cutoff to instrument for take-up of mutually exclusive disposition outcomes. This requires only a weaker homogeneity assumption within our marginal population of compliers (see Caetano et al. (2022)).

Model.[21] Let $\mathcal{N}$ represent a population, that is divided into two subgroups $\mathcal{N}^j$ (defendants charged as juveniles) and $\mathcal{N}^a$ (defendants charged as adults). Let D_i define the allocation of individual i to one of the two mutually exclusive subgroups, such that $D_i = 1$ if $i \in \mathcal{N}^a$ and $D_i = 0$ if $i \in \mathcal{N}^j$.

Individuals in $\mathcal{N}^j$ receive one of a finite set of K interventions $d_i^j \in D^j$ while individuals in $\mathcal{N}^a$ receive one of a finite set of L interventions $d_i^a \in D^a$.[22] There is no restriction on the degree of overlap between the elements of D^j and D^a; they could be mutually exclusive, have partial overlap, or have complete overlap. Every individual receives one and only one intervention: $\left(\sum_{k=1}^{K} d_i^{j,k} + \sum_{l=1}^{L} d_i^{a,l}\right) = 1 \ \forall i \in \mathcal{N}$, and we approach this as an unordered choice model akin to (Heckman & Pinto, 2018).

Outcome vector Y_i is a function of both individual characteristics (X_i), interventions (d_i^a, d_i^j), and a linear random shock (ϵ_i):

$$Y_i = \beta X_i + \sum_{k=1}^{K} \delta_{j,k} \underbrace{\left(d_i^{j,k} \times (1 - D_i)\right)}_{\text{Juv. treat among Juv. Def.}} + \sum_{l=1}^{L} \delta_{a,l} \underbrace{\left(d_i^{a,l} \times D_i\right)}_{\text{Adult treat among Adult Def.}} + \epsilon_i$$

For simplicity, we define D_i to be exogenous and uncorrelated with ϵ_i (achieved in our empirical application through the exogenous discontinuous cutoff rule). Treatment allocation within subgroups, however, may not be exogenous (i.e. $E[\iota_i^j \epsilon_i] \neq 0$ and $E[\iota_i^a \epsilon_i] \neq 0$).[23]

With this setup, the typical empirical approach (abstracting again from the RD) is to estimate a regression as follows:

$$Y_i = \beta^* X_i + \delta^* D_i + \epsilon_i^*$$

where, δ^* measures the net difference in outcome Y_i between $\mathcal{N}^a$ and $\mathcal{N}^j$. It can also be stated

[21]The model in this section is intentionally described at a high level for accessibility. For a more complete econometric treatment of this exercise, see Caetano et al. (2022) or Appendix Online Appendix D:, which applies their framework to our specific approach.

[22]To help make this more concrete, in our setting we consider $K = 2$ {juvenile non-conviction, juvenile conviction plus services} and $L = 3$ {adult non-conviction, adult conviction without incarceration sentence, adult conviction with incarceration sentence}.

[23]Note that the specification above imposes a conditional homogeneous treatment effects assumption, which we will rely on later.

as a difference in two weighted sums of treatment effects: $\delta^* = \sum_{l=1}^{L} \rho^l \delta_{a,l} - \sum_{k=1}^{K} \rho^k \delta_{j,k}$, where ρ captures the share of the relevant population receiving a given subgroup-specific treatment. The problem of treatment assignment endogeneity within subgroups is avoided by abstracting to a higher level (from d_i to D_i) where group status is in fact exogenous.

Recall that since D_i is exogenous, the $\mathcal{N}^j$ and $\mathcal{N}^a$ populations are statistically equivalent in expectation, and $E[Y_i]$ for the two groups would be equal in the absence of any d^j or d^a interventions. If it were possible to know the counterfactual treatment assignment for a given i, we could recover unbiased treatment effect estimates (δ's) by estimating the following regression:

$$Y_i = \beta X_i + \sum_{k=1}^{K} \delta_{j,k} \left(d_i^{j,k} \times (1 - D_i) \right) + \sum_{l=1}^{L} \delta_{a,l} \left(d_i^{a,l} \times D_i \right) + \gamma_{j,a} + \epsilon_i$$

where conditioning on the hypothetical treatment assignment regardless of subgroup allocation through a fully saturated set of fixed effects $\gamma_{j,a}$ absorbs the bias.

For example, suppose we could isolate the set of youth for whom we knew with complete certainty that they would receive a case dismissal if prosecuted as a juvenile and receive a case dismissal if prosecuted as an adult. If we estimated a separate RD regression on this hypothetical subsample of youth, we would be able to recover a causal estimate of the impact of being charged as an adult as opposed to being charged as a juvenile. This logic can be extended to all possible combinations of juvenile and adult case outcomes, and if we stacked these regressions, we would end up with the fixed effects regression specified above.

Unfortunately, this cannot be estimated since it is unknown and unmeasured what intervention would have been assigned to a given person if, instead of falling on one side of the discontinuity, they ended up on the other. Stated alternatively, we do not know the value of d_i^j if $D_i = 1$ and conversely we do not know the value of d_i^a if $D_i = 0$.

An alternative strategy is to focus on an unbiased prediction of the likelihood of receiving a given intervention. Using this, in conjunction with D_i, to instrument for actual take-up can yield unbiased treatment effect estimates.

$$
\begin{aligned}
Y_i &= \beta X_i + \sum_{k=1}^{K} \delta_{j,k} \left(d_i^{j,k} \times (1 - D_i) \right) + \sum_{l=1}^{L} \delta_{a,l} \left(d_i^{a,l} \times D_i \right) \\
&\quad + \sum_{k=1}^{K} \sum_{l=1}^{L} \phi^{k,l} Pr[d_i^{j,k} = 1] \times Pr[d_i^{a,l} = 1] + \epsilon_i
\end{aligned}
$$

$$
\begin{aligned}
\left(d_i^{j} \times (1 - D_i) \right) &= \theta_j X_i + \sum_{k=1}^{K} \sum_{l=1}^{L} \rho_j^{k,l}\, Pr[d_i^{j,k} = 1] \times Pr[d_i^{a,l} = 1] \times D_i \\
&\quad + \sum_{k=1}^{K} \sum_{l=1}^{L} \psi_j^{k,l}\, Pr[d_i^{j,k} = 1] \times Pr[d_i^{a,l} = 1] + \nu_i^{j}
\end{aligned}
$$

$$
\begin{aligned}
\left(d_i^{a} \times D_i \right) &= \theta_a X_i + \sum_{k=1}^{K} \sum_{l=1}^{L} \rho_a^{k,l}\, Pr[d_i^{j,k} = 1] \times Pr[d_i^{a,l} = 1] \times D_i \\
&\quad + \sum_{k=1}^{K} \sum_{l=1}^{L} \psi_a^{k,l}\, Pr[d_i^{j,k} = 1] \times Pr[d_i^{a,l} = 1] + \nu_i^{a}
\end{aligned}
$$

In the above system of equations, the interactions of the unbiased predictions with the exogenous group indicator variable D_i act as our excluded instruments. These instruments satisfy the exclusion restriction since both the outcome and first stage equations partial out the uninteracted effect of the predicted probabilities for the entire sample.[24,25]

6.2 Predicting treatment status with machine learning

To surmount the identification problem described in the previous section, we turn to machine learning methods to generate predicted probabilities of juvenile and adult treatment status. We use random forest models to estimate the expected case outcome for each obser-

[24]An interesting special case of this system of equations is when the prediction function has perfect accuracy. In this case, the probability of a given d_i will be either 0 or 1, which will lead this setup to collapse back to the fixed effects model previously described.

[25]For further information, Appendix Online Appendix C: provides a series of empirical simulations of the performance of this model under a variety of scenarios, including violations of our modeling assumptions.

vation.[26] This is a pure prediction exercise in which we allow the model to use a rich set of covariates and allow for complex interactions across criminal histories, current charges, and socioeconomic histories to find patterns in how cases are disposed.

We use the same set of controls that we used in the regression analysis as our random forest predictors, but also add information about year-month of case filing. Controls include the time since the defendant's first criminal charge, binned categories for time since last charge (within the last month, between a month and 6 months, more than 6 months and less than a year, greater than a year), whether the defendant has previous misdemeanor of each crime types (violent, property), the category of charges present in the current case (violent, property, drug, or other), whether the defendant was Black, or male, the number (by crime type) of criminal offenses charged to people living in the defendant's zip code in 2010, household structure and criminal exposure from Finlay, Mueller-Smith, and Street (2022), census tract demographic information from the 2010 ACS (age structure, the percent of the tract that is male, Black, White, and Hispanic), tract child poverty and income distribution.

Using the same set of covariates, we separately estimate two random forest prediction models. First, using the sample of juvenile cases, we estimate the probability that a case ends in (1) no punishment or (2) conviction (delinquency adjudication) and services/punishment in the juvenile system.[27] After estimating this model, we use the model to generate predictions for every case (both juvenile and adult) in our full sample. While the model has only been trained on juvenile cases, we can use this model to create a prediction for juvenile disposition for every juvenile and adult defendant in our sample since the covariates are common across the full analytic sample. We then perform the analogous exercise for the adult system by estimating a second model based on the adult cases across three sets of outcomes: (1) no conviction, (2) conviction with non-incarceration sentence, or (3) conviction with incarceration sentence.[28] As before, we then use this model, trained on the adult

[26]In random forest models, an ensemble of individual decision trees is used to generate predictions for each tree. Then, a vote is performed across the predicted results and the model selects the final prediction value using a majority vote rule.

[27]While it would be of both theoretical and policy interest to subdivide the second category into the different kinds of sentencing outcomes that can occur in the juvenile caseload, this information was unfortunately unavailable from the data provider.

[28]For each model we use 100 estimators and hidden layers with a maximum depth of 15. We set the maximum number of features as the square root of the number of features in

sample, to generate predictions of adult disposition over the full sample (juvenile and adult defendants alike).

This prediction exercise generates five probabilities for every defendant, regardless of whether they were actually prosecuted through the juvenile or adult system: that their case would resolve as (1) no conviction conditional on juvenile prosecution,(2) conviction and services/punishment conditional on juvenile prosecution, (3) no conviction conditional on adult prosecution, (4) conviction and only non-incarceration punishment conditional on adult prosecution, and (5) conviction with incarceration punishment conditional on adult prosecution. In order to evaluate how well our predictions are sorting cases, we produce a confusion matrix of our predicted values compared to realized values, as shown in Table A1. The "predicted juvenile outcome" for each case is the larger predicted probability between the two potential juvenile outcomes for each juvenile defendant and the "predicted adult outcome" is the largest probability of three potential adult case outcomes for each adult defendant. We see strong performance of the prediction models, with the vast majority of observations appearing along the diagonals (showing that our model is correctly categorizing many of the cases).

Table A2 demonstrates the importance of non-linearities and interaction terms for our predictions. We show that regressing each prediction on the set of covariates used by the random forest only explains between a quarter and half of our overall predictions. In the linear setting, certain features appear to be more important in explaining our predictions. These include race, sex, criminal history, family income, and census tract poverty and crime rates. Other features, like criminal exposure of others in the household, seem less predictive (at least linearly).

As in the traditional RD setting, it is important that our predictions are smooth through the discontinuity. While the predictions are based on the covariates assessed above, it is possible that the random forest introduced some non-linearities that are not smooth. To verify that the random forest did not introduce any non-linearities in the covariates when transforming them into the estimated probabilities, we show that predicted case outcomes are smooth through the discontinuity. As shown in Figure A3, the random forest did not

the model. We use the Gini impurity criteria to measure the quality of a split. We have a constant learning rate initialized at .0001, an alpha pruning parameter of .0001, and use the Adam solver. We re-weight the prediction sample to equally weight each case outcome.

introduce any evidence of a discontinuity across the discontinuity. That is, similar shares of the populations on either side of the discontinuity are predicted to receive each case outcome, which aligns with the earlier observation that caseload characteristics are balanced across the cutoff threshold.

Table 3 shows the first stage of the decomposition exercise. Each column shows the loadings of each treatment onto the set of potential instruments. Each row shows an individual instrument defined as the random-forest-generated probability of an adult case outcome interacted with the probability of a juvenile case outcome times a dummy variable which takes the value of 1 if the case was filed after the defendant was age 17. As one might expect the instruments with adult conviction (adult conviction x juvenile conviction and adult conviction) have large and statistically significant loadings on the endogenous adult conviction case outcome. This means that moving across the age discontinuity from juvenile to adult for defendants predicted to likely have an adult conviction explains much of the variation in who actually receives an adult conviction. Moving to column 2, we see that the coefficients on the instruments with adult conviction are now near 0 or negative. Similarly, the coefficients with adult no conviction are negative. For juvenile no conviction, we see the instruments that include the probability of juvenile no conviction interacted with the defendant being older than 17 (rows 1 and 5 especially) have large negative loadings. What this represents is that moving from the juvenile to the adult system moves these defendants from receiving no conviction in the juvenile system to some adult case resolution.

6.3 Findings of mechanisms analysis

We apply this decomposition methodology to better understand which case resolutions (and thus what mechanisms) drive the changes in recidivism and employment seen in the traditional RD exercise in the previous section. Figure 5 presents a subset of our results graphically; the full set of findings are presented in Table A5.[29,30] Our evidence highlights

[29]In this table, each column represents a different estimated treatment effect relative to an adult defendant with a case dismissal. Each row within the extensive and intensive supercolumns represents a single regression.

[30]As a confirmatory exercise, we also conduct separate RD estimates by predicted adult and juvenile subgroup, which can be found in Table A3. These results support the conclusions described in our IV results. The first three columns show subgroups that are

the complex interplay of policy levers and impacts on outcomes that otherwise would be missed using standard regression discontinuity techniques.

Our excluded category are youth who are charged as adult defendants but whose cases are ultimately dismissed. While the choice of excluded category is admittedly subjective, we believe this option provides several interesting and policy-relevant empirical tests: (1) the impact of adult convictions and sentencing outcomes relative to dismissals, and (2) the impact of juvenile charges relative to adult charges.

Relative to an adult case dismissal, adult convictions significantly increase future felony charges and convictions over the next 5 years by 1.6 and 1.8 cases, respectively, and increases the chance of any felony charge by 19 percentage points and any felony conviction by 29 percentage points.[31] For many defendants, however, these increases are neutralized through incarceration, which entirely cancels out the increase in felony recidivism risk stemming from adult convictions.

For labor market outcomes, we observe the opposite dynamic: convictions appear to diminish earnings, which is then reinforced with further declines for those who are also incarcerated. We find especially large impacts for incarceration, with statistically significant and economically meaningful reductions in annual wage income (↓ \$1,968 or 66%), average number of employers – proxied by the number of distinct W-2 information returns – per year (↓ 0.26 returns), and whether the defendant earns sufficient wages to exceed the poverty threshold for a single adult (↓ 6.6 percentage points). Together these results provide further

predicted to have no conviction in the juvenile system and either no conviction in the adult system (column 1), incarceration in the adult system (column 2), or a non-incarceration punishment in the adult system (column 3). Not every combination of juvenile and adult outcome is equally likely; there are only 110 individuals predicted to have their case dismissed in the juvenile system but be incarcerated in the adult system, while there are 2600 who are predicted to be punished in the juvenile system and receive some adult non-carceral punishment. We also provide a simpler subsample analysis in Table A4, which splits the subsample along various covariates. In Table A8, we show that our results are robust to the choice of bandwidth used.

[31] This reduction can be seen in declines in total criminal activity for violent, property, and other major offense types: 1.5 fewer violent charges (about 0.7 after restriction to just convictions), 1.6 fewer property charges (1.2), and 1.6 fewer other charges (1.0). See Table A5.

evidence on the potential individual harm generated from adult criminal records (Agan et al., 2021; Mueller-Smith & Schnepel, 2021).

Charging adolescents as juvenile defendants also appears to increase their risk of future felony activity. We observe juvenile prosecution increasing future felony charges and convictions by 1.6 and 1.8 cases respectively and increasing the chance of any felony charge and conviction by 17 and 26 percentage points. Part of what might drive this relationship is that the experience of adult prosecution acts as a form of specific deterrence, which is missing when youth are charged as juvenile defendants. Alternatively stated, juvenile prosecution might impart a false impression of leniency in the adult criminal justice system for youth who are on the cusp of aging into the adult system. Although imprecise, the direction of the coefficients suggest that juvenile prosecution does improve employment trajectories, especially when charges are combined with juvenile convictions (and the corresponding services/interventions that accompany juvenile convictions).

It is remarkable that juvenile convictions, unlike adult convictions, do not appear to significantly worsen outcomes conditional on the impact of being charged. This provides suggestive evidence that convictions do generate differential impacts depending on whether the conviction was made in the juvenile or adult criminal justice system. As previously discussed in Section 3, there are many legal factors that make these distinct interventions, especially with regard to their long-term implications for holding a criminal record that would show up on a background check and additional rehabilitative services offered to juveniles.

To better understand these dynamics, we plot the evolution of outcomes year-by-year over our five-year follow-up period in Figure 6. In this figure, we introduce follow-up impacts on being incarcerated in adult prison (measured from actual institutional confinement records) and observe an immediate and sustained impact of being convicted as an adult defendant and sentenced to incarceration on actual time served in prison. Five years after the initial case filing, adult defendants sentenced to prison spend approximately 140 additional days in prison relative to adult defendants who received case dismissals. There is no meaningful decline in the impact on time confined over time, indicating that our five-year follow-up period is insufficient in duration to fully capture the long-term implications of being charged as an adult defendant as many appear to still be imprisoned at the end of our follow-up period. In contrast, the sizeable gains to crime prevention arising from incarceration previously discussed are mostly concentrated in the first two years after initial case filing.

We find that juvenile prosecution creates an initial protective effect for defendants from ending up in prison, although this wanes within three years following initial case filing. Given that the modest increase in felony convictions appears sustained throughout the follow-up period, something other than just incapacitation likely drives the increase in felony activity observed for juvenile defendants. There is a modest short-run increase in earnings above the poverty line, a result that is echoed with less precision in later years, which suggests some positive outcomes are achieved in spite of the increase in illicit activity for this group.

6.4 Robustness exercises

To ensure that our conclusions are not driven by arbitrary functional form or sample construction decisions, we explore a variety of robustness checks in Table A8. Our findings are qualitatively unchanged when adjusting the bandwidth from 1.5 years to 2.5 years as well as incorporating triangular weights with our main bandwidth of 2 years.

In addition, as described in Caetano et al. (2022), identification in this setting requires assuming treatment effect homogeneity conditional on the complier population generated from our vector of interacted probabilities. For example, we assume that those tried in juvenile court and not convicted are expected to have the same treatment effect, regardless of whether some may be more likely to be convicted in an adult court than others. This is a strong assumption which warrants careful consideration.

We explore the viability of this assumption through three complementary exercises. First, we rotate through dropping one of each of our six instruments and re-estimate our model, an exercise that is only possible because our main results are overidentified (6 instruments for 4 interventions). Dropping instruments will change the composition of the complier population, allowing us to test the null hypothesis of treatment effect homogeneity across the six different leave-one-out exercises. Columns 2 through 7 of Table A9 shows our findings. The estimated coefficients are all qualitatively quite similar, and a formal test of their joint equality fails to reject the null hypothesis (column 8), which supports our homogeneity assumption.

The second exercise removes defendant characteristics from the random forest prediction algorithms. Recall that we only require homogeneity conditional on the information contained in the probability scores. The thought behind this exercise is to eliminate traits that might be most likely to generate to treatment effect heterogeneity (e.g., defendant race, defendant sex, defendant criminal history, defendant offense type, etc.). While this will weaken the strength of the prediction models and our first stage estimates, the resulting findings might have weaker homogeneity assumptions given that our identification only relies on differences in defendant disposition outcomes stemming from household and neighborhood characteristics. Column 9 of Table A9 shows our results, which largely replicate our findings from the full model. In fact, we are unable to reject the null hypothesis that the estimated effects are the same between the full and "slim" models (column 10), consistent again with the required homogeneity assumption.

As a final test, we can consider the p-values from Sargan-Hansen J-test for over-identification in our core results. As discussed in Caetano et al. (2022), a rejection of the null is a sign of potential violations of the homogeneity assumption. In Table A5 (see notes), we fail to reject the null in the Sargan-Hansen J-test, which provides our last piece of evidence in support of our homogeneity assumption.[32]

7 Cost-benefit analysis of policy counterfactuals

We conduct a cost-benefit analysis to evaluate a range of policy counterfactuals that echo recent debates in criminal justice reform efforts.[33] A strength of the decomposition presented in Section 6 is that we can use our estimates from that exercise to go beyond simply identifying the net impact of the shift from juvenile to adult prosecution to also considering policy interventions that might isolate specific components of the full array of changes that

[32]In spite of these empirical tests, some may remain unconvinced. Caetano et al. (2022) derive and bound the bias if the homogeneity assumption is violated. When homogeneity fails, it is possible to misattribute changes in outcomes to incorrect interventions. While the overall RD remains valid, the mechanism decomposition may be cross-contaminated. The degree of bias depends importantly on the variance of the treatment effect heterogeneity in the marginal population, which in our setting appears to be relatively small given the empirical tests described in this subsection.

[33]Given our research design, these exercises are most relevant for first time felony offenders. Whether these findings extend to those with repeated contact the justice system remains a question for future research.

occur at the age of majority threshold. We evaluate four scenarios: (1) raising the age of criminal majority, (2) altering the dismissal rate for adult defendants to match that of juvenile defendants, (3) eliminating the use of incarceration for adult defendants, and (4) making adult criminal records have the same expungement options as juvenile criminal records. Across all of these scenarios, the evidence speaks to the net cost for changing policies for youth (i.e. teenagers) charged in the adult system; extrapolating these exercises to the entire adult caseload requires stronger assumptions that we do not believe are satisfied given our research design.

The first policy counterfactual we consider was implemented in Michigan in 2021 and our analysis will inform whether the state can expect this to yield positive social returns. The second exercise allows us to consider whether reforms to how much leniency is granted to young defendants and thus changes to the procedures that might generate this leniency might be socially beneficial. The third exercise addresses calls to reduce the carceral system's reach for adolescents and highlights a major difference between the juvenile and adult systems. The final counterfactual explores the implications of differential access to more immediate record sealing in the juvenile system and reflects recent reforms in Michigan (and elsewhere) to limit the impact of criminal records on other outcomes and provide work readiness training.[34]

We consider the following cost and benefit components: the direct costs of implementing the program, savings from tax revenue from earnings, government savings from changes in recidivism behavior, benefits for the defendants themselves, and savings for future victims. We sum over the first three components to provide an estimate of the net impact per defendant to the government budget constraint.

All four of these scenarios create savings for the government's balance sheet and taxpayers. Immediate savings in program costs are observed, especially for policy options that reduce the reliance on prison. Some of these gains have to be weighed against other government costs associated with increasing future illicit behavior, which tax payers must

[34]Treating adult criminal records like juvenile records for expungement purposes, however, is a significantly more substantial change than has been considered in recent legislation on clearing criminal records. Whether similar gains could be achieved with a more modest approach (e.g. leaving in place longer waiting periods for expungement) is a question for future research.

cover through additional expenses in law enforcement, courts, and correctional supervision.

The largest total budgetary gains ($5,098 per defendant) are observed for the eliminating prison sentences for teenage adult defendants policy option, although this would only impact 18% of the caseload. Raising the age of criminal majority also appears attractive, creating government savings of $4,966 per defendant, especially considering it would have a substantially wider reach in the justice-involved caseload. In both of these policy counterfactuals, the net gains are largely achieved by eliminating costly spending in the justice system on prison.

Similarly, defendants exclusively gain from each of the four policies considered, although some more than others. We include two components in this estimate: (1) the freedom costs of incarceration,[35] and the after-tax wages received by a defendant.[36] Increasing the age of majority creates the largest gains for defendants ($7,117), followed by expanding juvenile record-sealing ($3,899) and eliminating adult incarceration for teenage defendants ($3,674). Interestingly, among these latter two options, the gains in the first are largely driven by improvements in personal income, while in the second scenario defendants largely benefit from avoiding significant time in prison.

While so far all of these policies appear exclusively beneficial for society, the challenge comes when incorporating impacts to future potential victims. Two of the scenarios, raising the age of majority and eliminating adult incarceration, increase total future crime albeit through different hypothesized mechanisms (i.e., $\downarrow$ specific deterrence versus $\downarrow$ incapacitation). There are non-trivial increases in both property and violent crime, but given existing estimates on the social costs of crime,[37] the changes in violent crime dominate this exercise. Raising the age of majority creates $12,053 additional costs per defendant shouldered by future victims, and eliminating adult incarceration for teenagers similarly generates $11,566 in victim costs per defendant.

How to value these trade-offs, especially when beneficiaries and victims might be drawn from different socio-economic backgrounds, is a normative question best left to

[35]We utilize willingness-to-pay estimates from Abrams and Rohlfs (2011) for the value of a day in prison.

[36]Consistent with our treatment of the government balance sheet, we assume a 10% tax rate for our sample.

[37]We rely on (Cohen & Piquero, 2009) for our victim cost estimates.

policymakers. For completeness, we provide a simple summation totaling across the three considered perspectives (taxpayers, defendants, and future victims) but recognize that other weighting schemes may be preferable in practice due to their distributional implications.

Overall, we find that expanding juvenile record sealing options to teenage defendants in the adult criminal justice system has the largest net social impact. While not the most beneficial option for either tax-payers or defendants, it manages to substantively improve their outcomes while also reducing future crime for potential victims. A similar but less effective "everyone wins" scenario is observed for the increasing dismissal rates for marginal adult defendants option considered.

Raising the age of criminal majority presents the largest gains for defendants but also the largest losses for future potential victims. With equal weighting, this counterfactual comes out as roughly neutral in social welfare. In contrast, eliminating incarceration for teenage adult defendants generates similar losses for future victims but worsens social welfare due to relatively smaller defendant benefits. In this setting, even without incarceration, adult conviction records negatively impact the future trajectories of defendants. However, if policymakers are willing to value taxpayers and defendants at a rate of at least 124% that of future potential victims, this still would be attractive to invest in.

The interplay of costs and benefits highlights the complexity of running a criminal justice system. For example, conditional on how adult criminal histories operate in this setting, incarceration could be viewed as a productive investment to limit the criminogenic effect of conviction records. However, if society was able alter the impact of the conviction record itself (e.g. removing the scarring mark of a criminal record), incarceration may no longer appear to be as valuable to society.

8 Conclusion

Adolescence is a critical period. For first-time felony defendants, their treatment at the hands of the criminal justice system may set an individual on starkly different life-long paths. Both the age at which defendants are treated as adults and what punishments and services they receive from the resolution of their case impact their future earnings and criminal behavior.

This paper makes use of a detailed decomposition of different treatments across the juvenile and adult criminal justice systems relying on previously unavailable rich administrative data. While data limitations in previous work only allowed for speculation regarding the underlying mechanisms, we are able to provide direct evidence on this matter. Incapacitation does play a significant role in reducing aggregate crime rates across the age of majority threshold. In fact, it also compensates for the increased risk of recidivism that comes with a permanent adult criminal record, a fact that has been missed by prior work. But, at the same time, accomplishing this reduction in recidivism is quite expensive due to both the significant program costs and the negative consequences for labor market outcomes in the population.

Our data allows us to provide previously missing measures of the consequences and prevalence of different case outcomes between the juvenile and adult criminal justice systems and the characteristics of those who are charged in either system. In addition, linking juvenile and adult records to a variety of other information allows us to show that adolescents facing different treatment in the criminal justice system are set on starkly different life paths in terms of employment and future time incarcerated. Understanding these hard-to-reach populations would not have been possible without access to the Census data linkage infrastructure.

The methodology we develop to answer these questions has broad applicability beyond our specific research question. The combination of machine learning and regression discontinuity could be leveraged in a variety of interesting settings where decomposing multiple simultaneously changing mechanisms at a single discontinuity could provide a deeper understanding of the question or policy being studied.

Our findings have immediate policy relevance. In October 2021, Michigan raised their age of majority from 17 to 18 years old, and our analysis suggests the overall impact will largely be neutral. That said, the policy change should create concentrated benefits for young defendants who will be prosecuted as juveniles under the new policy environment, with distributed victim costs shared across the rest of the population. Our analysis of policy counterfactuals provides guidance on future directions for policy reform in the justice system. In particular, it suggests that limiting adult convictions and increasing opportunities for expedited record sealing for young defendants prosecuted as adults might generate substantial gains shared throughout society.

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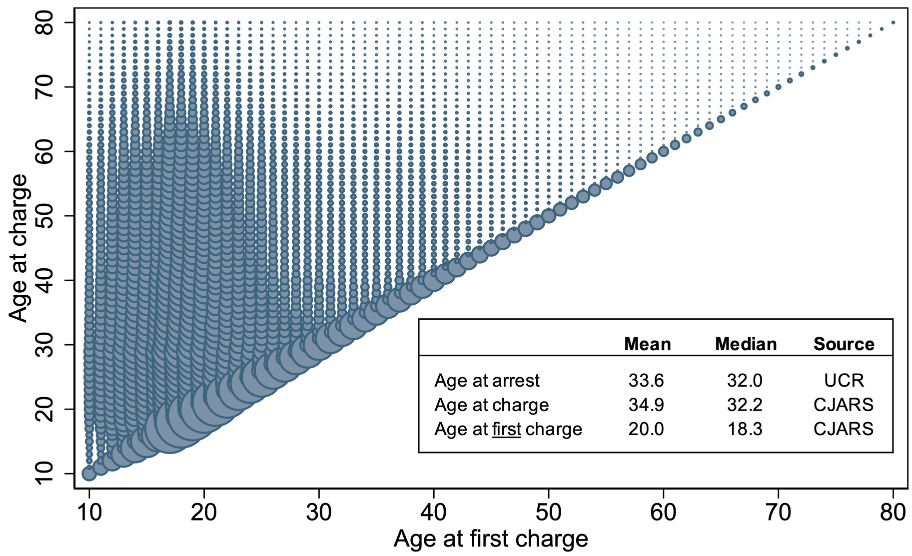
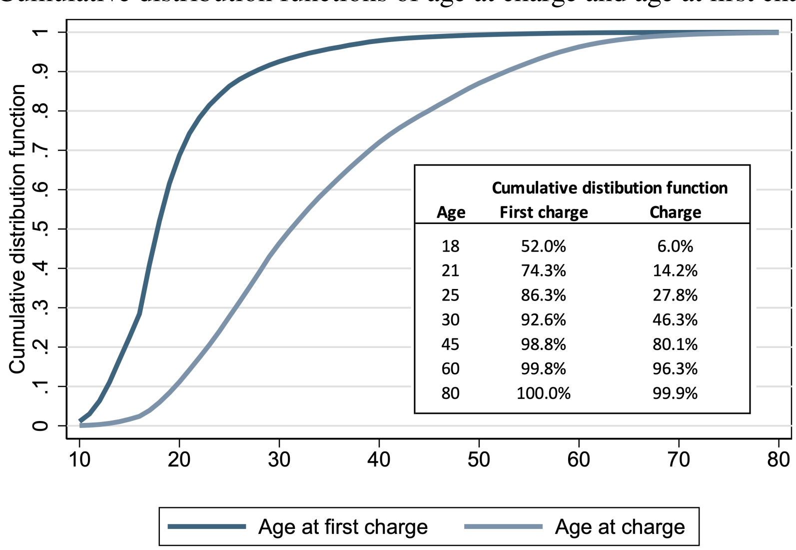
Figures and Tables

Figure 1: Age at (first) criminal justice involvement

A: Comparing age at charge and age at first charge



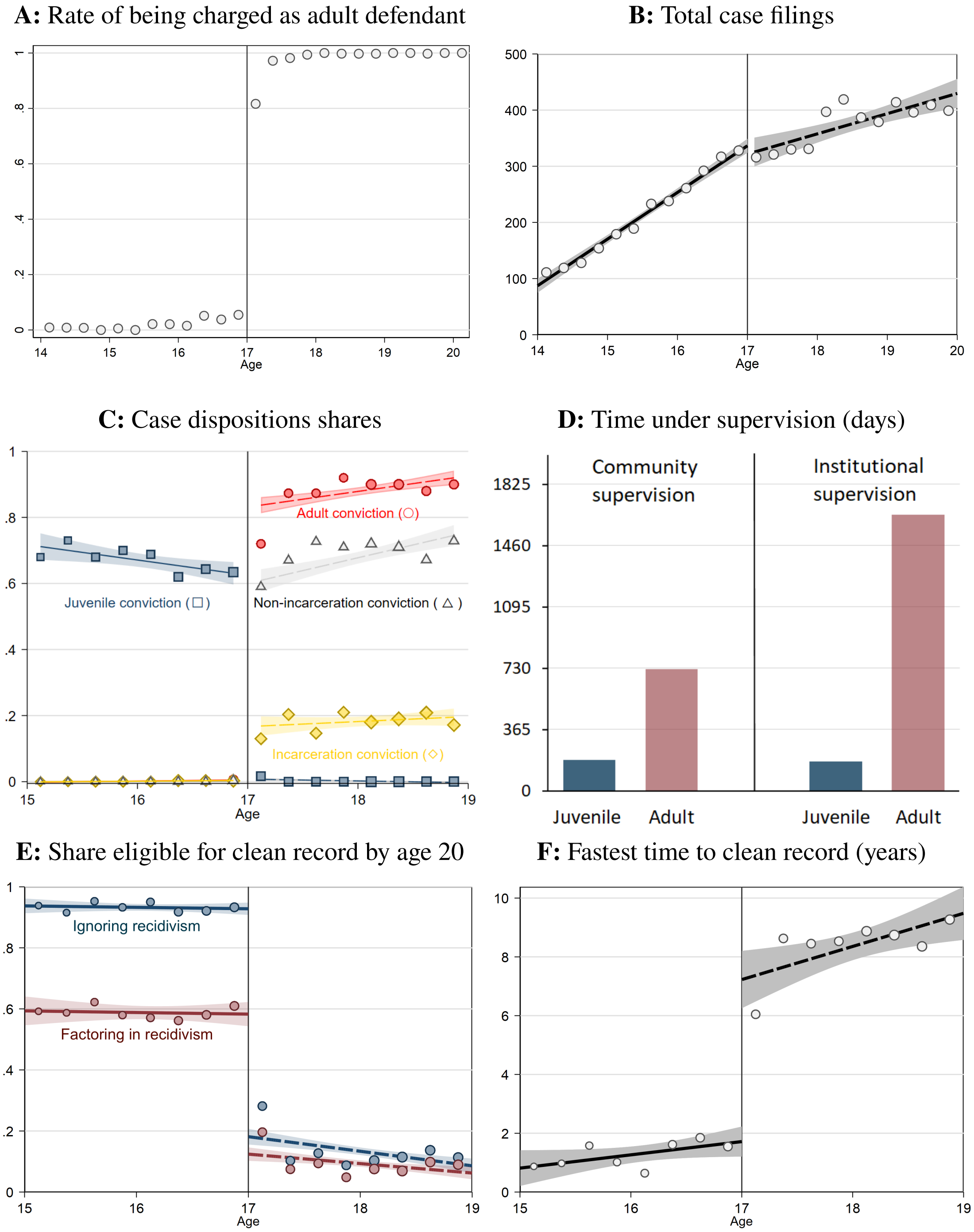
B: Cumulative distribution functions of age at charge and age at first charge



Source: 2019 Uniform Crime Report. CJARS data and juvenile supplement held at the University of Michigan.

Notes: The UCR reports binned ages for age at arrest. The median and mean age of offense are based on a kernel density (bandwidth of 1.5 years) fit across this binned distribution. CJARS data is constructed based on the cross-section of individuals charged with juvenile and adult, misdemeanor and felony criminal offenses in Michigan in calendar year 2019 and their corresponding observed criminal histories. Our juvenile justice records in Michigan only extend back to 2010, and the adult criminal justice records often start in the 1990's (start dates vary by county and circuit/district courts). Due to these coverage limitations, we assume a stable age/crime profile and use the observed distribution for non-censored populations to fill in censored data. For those over age 21 in 2019 (potentially impacted by the juvenile justice record censoring), we reallocate the observed density below 20 to fit the observed non-censored distribution from younger cohorts between ages 10 to 20 years old. For those over 41 (potentially impacted by the adult justice record censoring), we iteratively reallocate the full observed distribution to fit non-censored adult age/crime profiles from younger cohorts, with an additional lagged dependent variable model to estimate the decay in the density for previously unobserved first ages in the distribution.

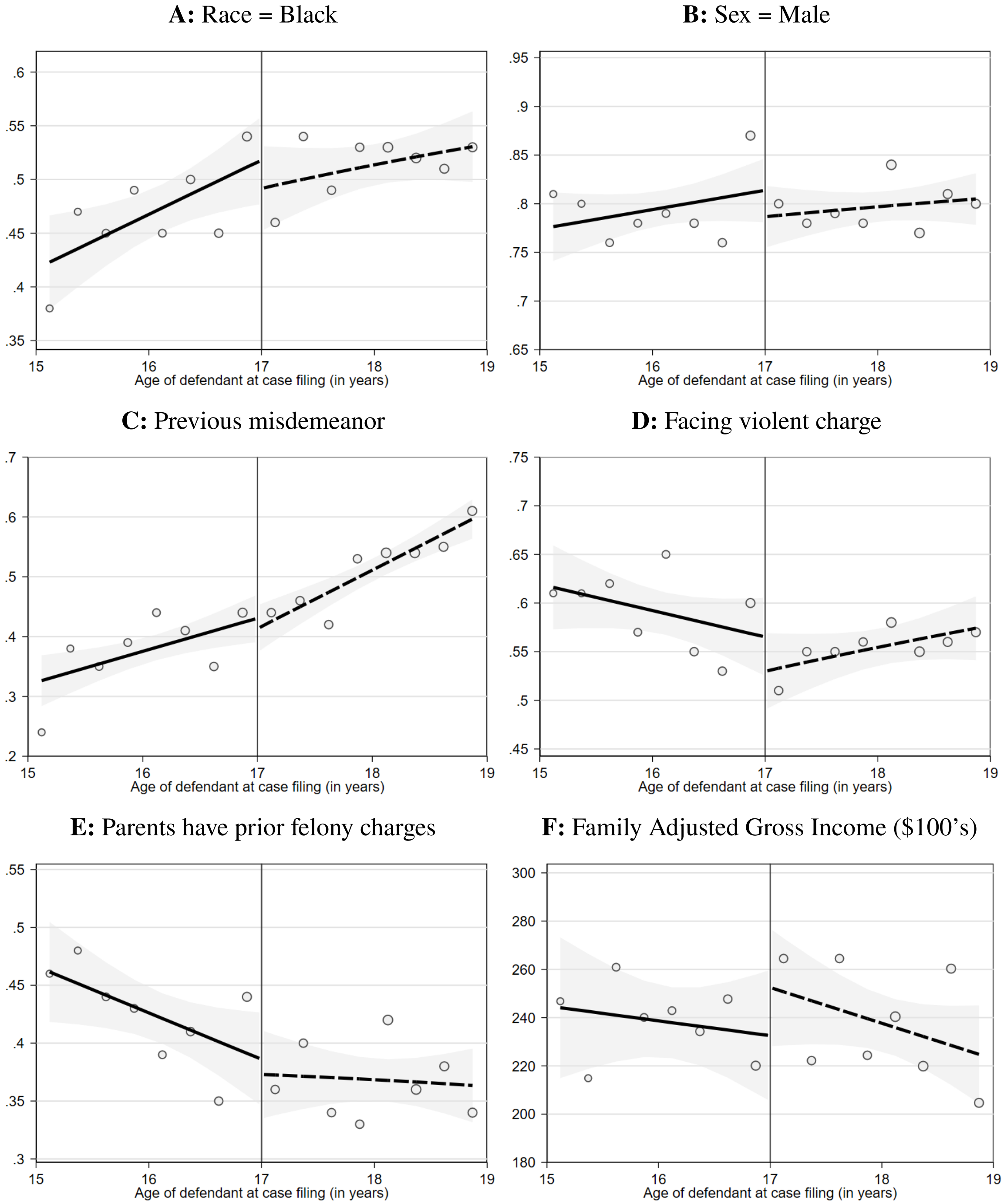
Figure 2: First stage, caseload density, and other differences in the treatment of juvenile and adult defendants



Source: CJARS data and juvenile supplement held at the University of Michigan.

Notes: The estimates are based off of a sample of all individuals whose first observed felony charge was between 2011 and 2014 in Wayne County Michigan. In panel D, adult results are calculated from the adult observations used elsewhere in the analysis and are calculated conditional on receiving either probation or detention. Juvenile results are based on reported 2013 values from Chaney and Reed (2018), for the full population of juveniles receiving either probation or detention. In order to best match the reported juvenile statistics, the median is shown for probation and the mean for detention.

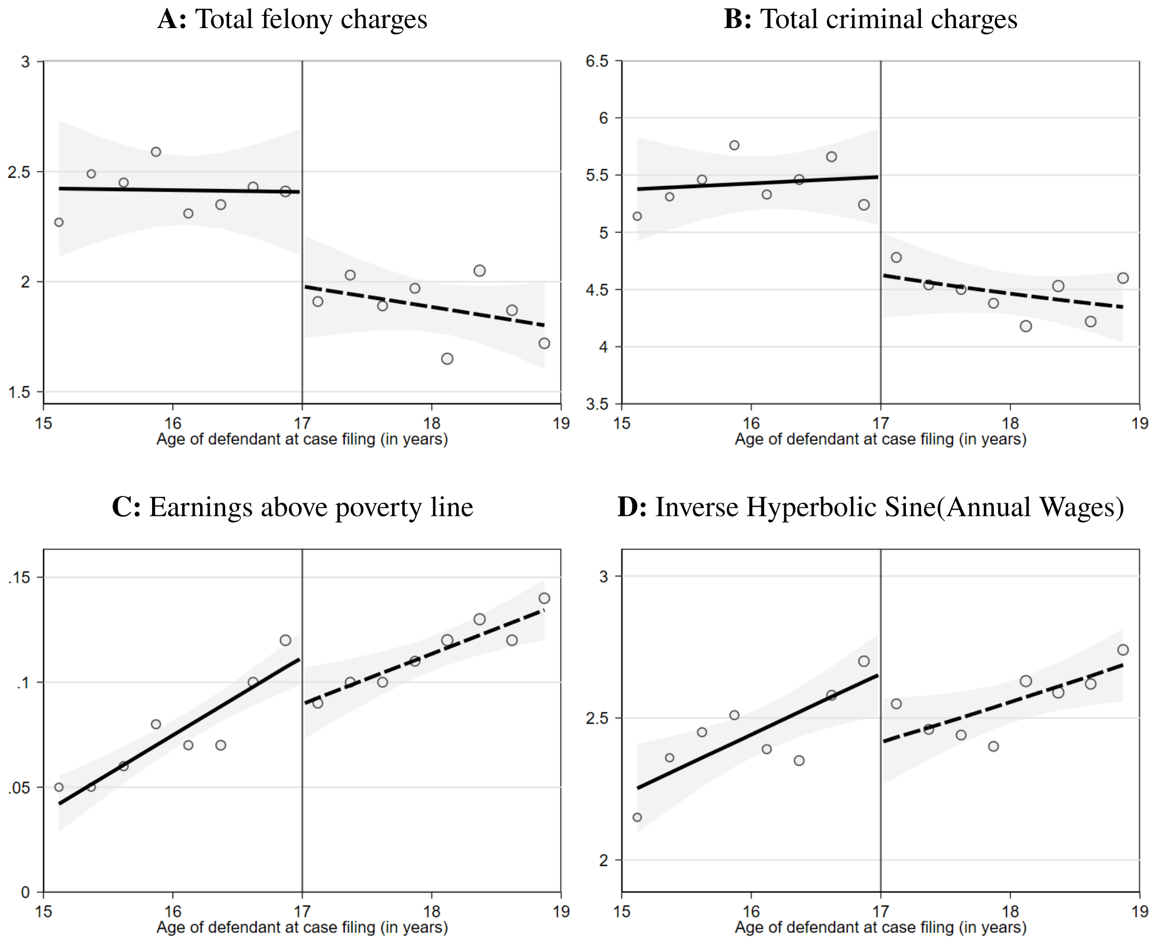
Figure 3: Evaluating balance in caseload composition



Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Previous misdemeanor is an indicator if the defendant had a previous misdemeanor charge. Facing violent charge is an indicator if the defendant is facing a charge for a violent crime within the set of current charges. We construct a measure of parents' exposure to a felony charge in the child's 2010 residence (including biochild-parent; adoptedchild-parent; stepchild-parent; fosterchild-parent; and; unclassified child-parent). We also use information from the 1040 filing to generate the income of the person claiming the defendant as a dependent (coded as 0 if no one claimed the defendant) in 2010.

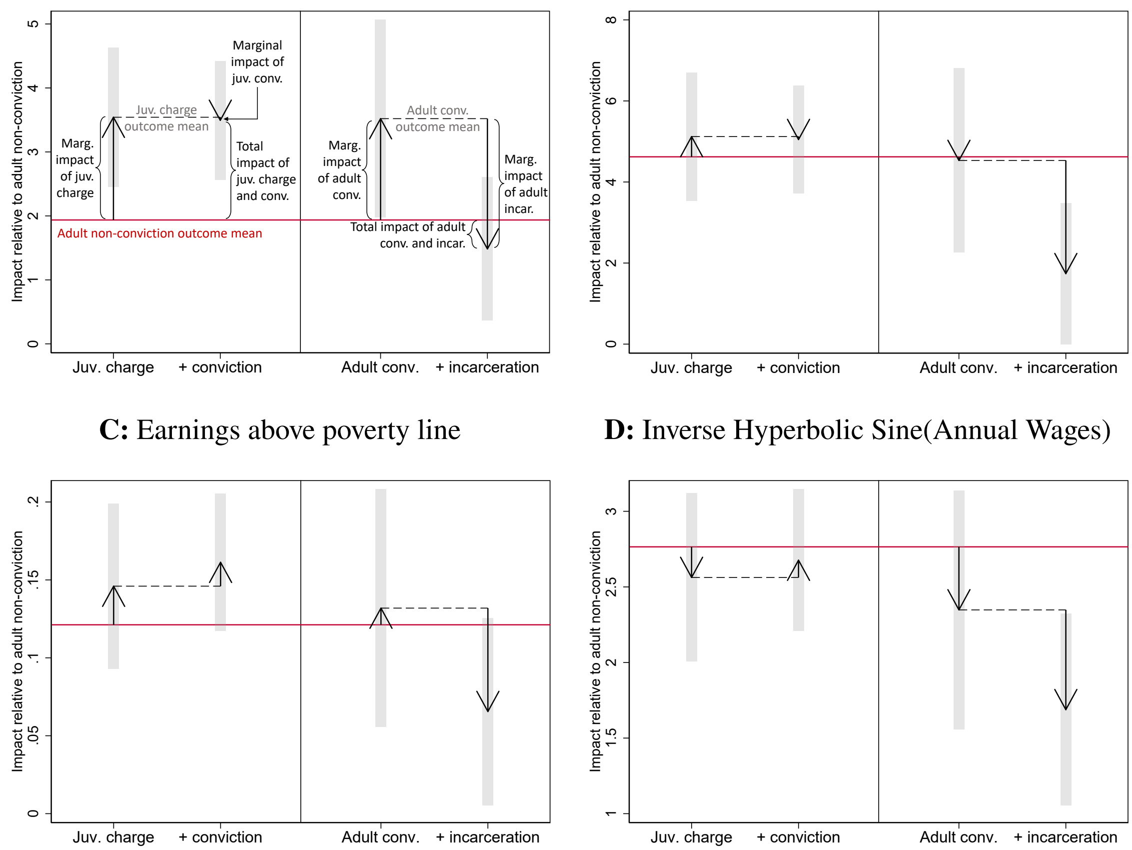
Figure 4: Reduced form: recidivism and employment outcomes across the cutoff



Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors. Regression also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Figure 5: Mechanism-specific recidivism and employment treatment effect estimates

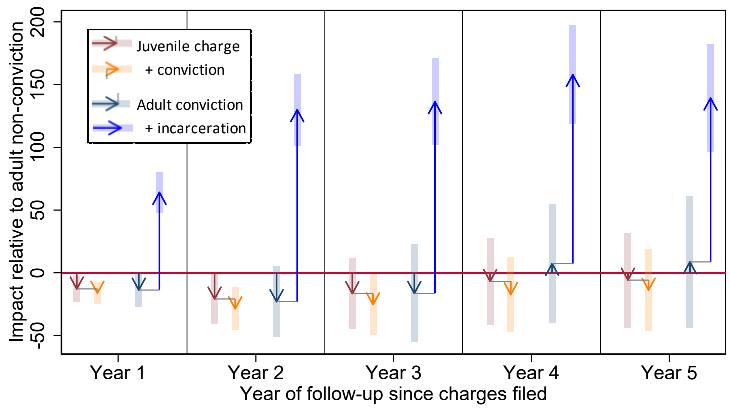
A: Total felony charges **B:** Total criminal charges



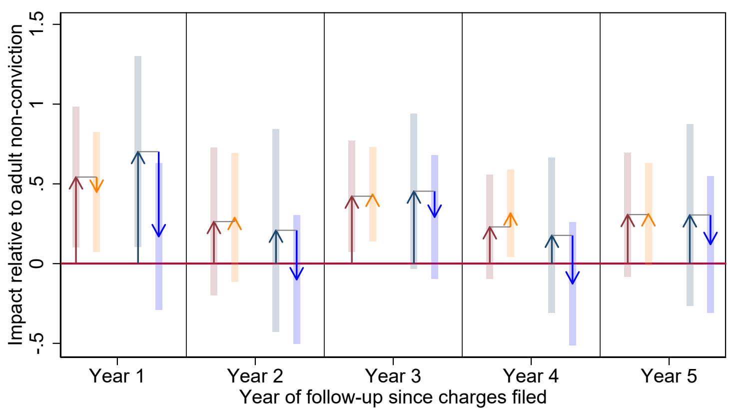
Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). Sargan-Hansen J for 5-year felony conviction recidivism (intensive) is 3.737, p-value 0.154 and for IHS(Average yearly income over next 5-years), 1.923 p-value 0.382). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022) and #CBDRB-FY23-088 (approved 12/12/2022). Estimates are from an RD decomposition (instrument age 17+ interacted with probabilities) with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Figure 6: Evolution of mechanism-specific impacts over the follow-up period

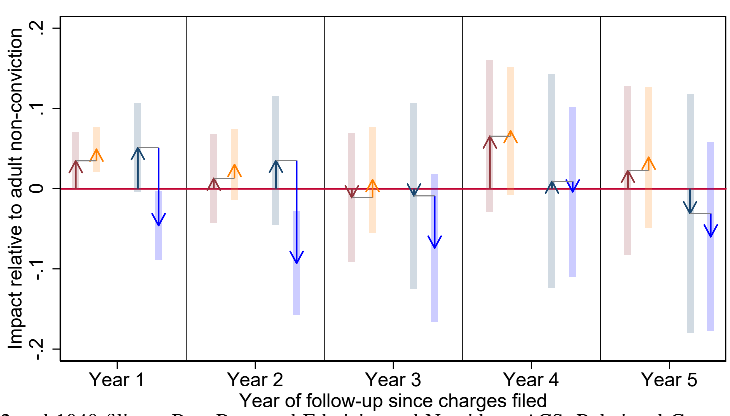
A: Total days in prison



B: Total felony convictions



C: Earnings above poverty line



Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates are from an RD decomposition (instrument age 17+ interacted with probabilities) with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Table 1: Balance of individual, household, neighborhood, and predicted characteristics

Dependent variable	RD Pt Est (Std Error)	Dependent variable	RD Pt Est (Std Error)
Caseload Density Test			
Total caseload size	-0.007	Census tract percent youth poverty	-2.515
	(0.053)		(1.751)
Youth Characteristics		Census tract median household earnings	1779
Black	-0.029		(1408)
	(0.034)	Census tract mean household earnings	2293
Male	-0.031		(1523)
	(0.027)	Census tract percent white	-2.295
Any misdemeanor history	-0.02		(2.953)
	(0.033)	Census tract percent black	2.117
Number of violent misdemeanors history	-0.025		(3.149)
	(0.03)	Census tract percent hispanic	-0.288
Number of property misdemeanors history	0.00		(0.736)
	(0.038)	Census tract percent male	0.292
Days since first charge	-0.077		(0.337)
	(0.05)	Census tract percent age 15 to 19	-0.325
Facing violent felony charge	-0.04		(0.259)
	(0.033)	Census tract percent age 20 to 24	0.019
Facing property felony charge	0.017		(0.213)
	(0.033)	2009-10 violent charges in zip	-0.007
Facing drug felony charge	0.036*		(0.052)
	(0.021)	2009-10 property charges in zip	-0.003
Household Characteristics			(0.035)
Total parents in 2010 house	0.004	2009-10 drug charges in zip	-0.002
	(0.05)		(0.024)
Total other adults in 2010 house	-0.073	2009-10 public order charges in zip	-0.004
	(0.057)		(0.006)
Family 2010 Adjusted Gross Income ($100's)	23.27	**Predicted Indices**	
	(21.91)	Prob adult no conviction	-0.008
Household 2010 Adjusted Gross Income ($100's)	14.27		(0.01)
	(35.21)	Probability adult conviction	0.008
Previous charge in house	-0.031		(0.01)
	(0.026)	Probability adult incarceration	-0.01
Parent previous charge in house	-0.042		(0.013)
	(0.029)	Estimated probability of no juvenile punishment	0.018
Previous felony charge in house	-0.032		(0.014)
	(0.032)	Estimated probability of juvenile punishment	-0.018
Parent previous felony charge in house	-0.014		(0.014)
	(0.033)	P(Adult conv.) x P(Juv no punish)	0.016
Previous felony conviction in house	-0.068**		(0.012)
	(0.033)	P(Adult conv.) x P(Juv punish)	-0.009
Parent previous felony conviction in house	-0.009		(0.013)
	(0.024)	P(Adult incarc.) x P(Juv no punish)	0.003
Previous incarceration in house	-0.019		(0.006)
	(0.024)	P(Adult incarc.) x P(Juv punish)	-0.013
Parent previous incarceration in house	-0.004		(0.009)
	(0.014)	P(Adult no conv.) x P(Juv no punish)	0.002
Neighborhood Characteristics			(0.005)
Census tract percent poverty	-0.846	P(Adult no conv.) x P(Juv punish)	-0.01
	(1.267)		(0.008)

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Coefficients are estimated using a linear IV approach with robust standard errors restricted to sample cases with defendants between the ages of 15 and 19. Whether a case occurs prior to or after age 17 is used as an instrument for whether the case is in the adult system. The IV estimate of the case being in the adult system is displayed. Case load density is tested using a McCrary test with default parameters.

Table 2: Impact of adult prosecution on 5 year recidivism and employment outcomes

	Extensive			Intensive		
	RD Pt Est (SE)	IV Pt Est (SE)	Juv. Mean	RD Pt Est (SE)	IV Pt Est (SE)	Juv. Mean
First stage:						
Charged as adult defendant	0.860***		.017			
	(0.002)					
Recidivism:						
Any charge	-0.0655***	-0.07593***	0.8538	-0.8847***	-1.019***	5.368
	(0.0219)	(0.02546)		(.2855)	(0.3288)	
Any conviction	-0.0426*	-0.04937*	0.7498	-0.5205**	-0.5759**	3.998
	(0.0253)	(0.02945)		(.2539)	(0.2809)	
Felony charge	-0.0333	-0.0386	0.5058	-.4359**	-.4840**	2.393
	(0.0278)	(0.03223)		(0.1968)	(0.2185)	
Felony conviction	-0.0255	-0.0296	0.4646	-0.2963*	-0.3188*	1.954
	(0.0278)	(0.03223)		(0.1757)	(0.1891)	
Recidivism by type of offense:						
Violent charges	-0.0087	-0.01016	0.4395	-0.3644**	-0.4237**	1.877
	(0.0278)	(0.03227)		(0.1668)	(0.1939)	
Property charges	-0.0360	-0.0419	0.4224	-0.3161*	-0.3675*	1.746
	(0.0279)	(0.0324)		(0.1657)	(0.1927)	
Drug charges	-0.0488*	-0.0568*	0.2897	-0.2674**	-0.3109**	0.9426
	(0.0253)	(0.02939)		(0.1161)	(0.135)	
Other charges	-0.0888	-0.1032	0.7525	-0.7003***	-0.8143***	3.604
	(0.0258)	(0.02997)		(0.2236)	(0.26)	
Employment:						
Average # of W-2s per year	-0.0545**	-0.07597**	0.3919			
	(0.0238)	(0.03322)				
Earnings above poverty line	-0.0251**	-0.02666**	0.08072			
	(0.0117)	(0.01248)				
IHS(Annual Wages)				-0.2349**	-0.2856**	2.475
				(0.1026)	(0.1248)	
Annual W-2 Wages ($100's)				-5.711*	-6.738*	32.27
				(3.289)	(3.881)	

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). Earnings in 2020 dollars. All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Table 3: First stage estimates of RD decomposition

Interaction of 17+ dummy and:	(1) Adult conviction	(2) Adult incarceration	(3) Juvenile no conviction	(4) Juvenile conviction
	First stage on outcome:			
P(Adult conv.) x P(Juv no conv.)	0.8321***	0.04727	-1.069***	0.2397***
	(0.0496)	(0.03167)	(0.04932)	(0.03104)
P(Adult conv.) x P(Juv conv.)	1.034***	-0.1516***	0.0732***	-1.007***
	(0.02949)	(0.02199)	(0.02081)	(0.0269)
P(Adult incarc.) x P(Juv no conv.)	0.4357***	0.6775***	-0.01151	0.2224**
	(0.1596)	(0.151)	(0.1438)	(0.1053)
P(Adult incarc.) x P(Juv conv.)	0.2083***	1.278***	0.1961***	-0.1352*
	(0.07961)	(0.07928)	(0.05066)	(0.07025)
P(Adult no conv.) x P(Juv no conv.)	0.1181	-0.4428***	-1.499***	0.4818***
	(0.1529)	(0.1187)	(0.1399)	(0.1191)
P(Adult no conv.) x P(Juv conv.)	-0.226***	-0.5915***	0.4853***	-1.32***
	(0.07161)	(0.06029)	(0.05105)	(0.05988)
F-Stat	720	110	320	680
Observations	4700	4700	4700	4700

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Coefficients are the first stages of decomposition exercise with robust standard errors restricted to sample cases with defendants between the ages of 15 and 19. Whether a case occurs prior to or after age 17 interacted with each variable indicated in the first column is used as an instrument for whether the case is in the adult system. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Table 4: Cost-benefit of policy counterfactuals per impacted defendant (2020 dollars)

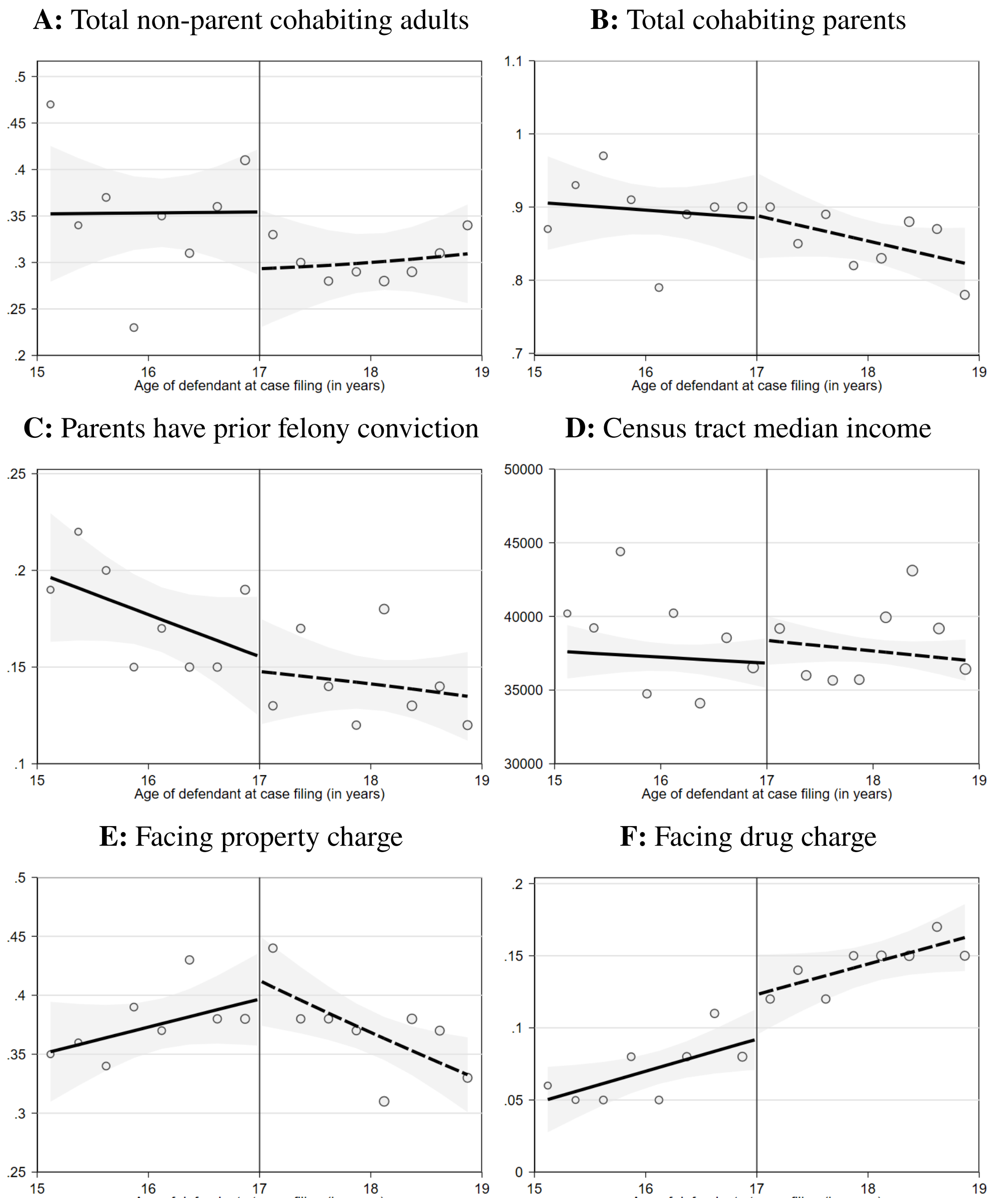
	Policy Counterfactuals			
	Raise the age of criminal majority	Increase adult dismissal rate to match juvenile rate	Eliminate adult incarceration for young adults	Make juvenile record sealing available to young adults
Share of young adult caseload affected:	100%	19%	18%	88%
A) Net impact to government budget:	$4,966	$2,523	$5,098	$4,245
Average program savings for government	$9,102	$1,427	$14,879	$0
Tax revenue from earnings	$326	$9	$188	$345
Government savings from changes to future crime:				
– Law enforcement	-$9,178	$1,679	-$5,742	-$1,107
– Court resources	-$1,396	$153	-$839	-$207
– Correctional supervision	$6,112	-$744	-$3,388	$5,214
B) Savings for potential victims:	-$12,053	$1,240	-$11,566	$4,689
Property crime reduction (negative for gain)	-$547	$15	-$275	-$141
Violent crime reduction (negative for gain)	-$11,506	$1,224	-$11,291	$4,830
C) Benefits for defendants:	$7,117	$116	$3,674	$3,899
Non-wage benefits of non-incarceration freedom	$4,185	$37	$1,981	$798
Post-tax personal income	$2,932	$79	$1,694	$3,101
TOTAL (A + B + C)	**$31**	**$3,878**	**-$2,794**	**$12,834**

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relations and exposure from Finlay, Mueller-Smith, and Street (2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022).

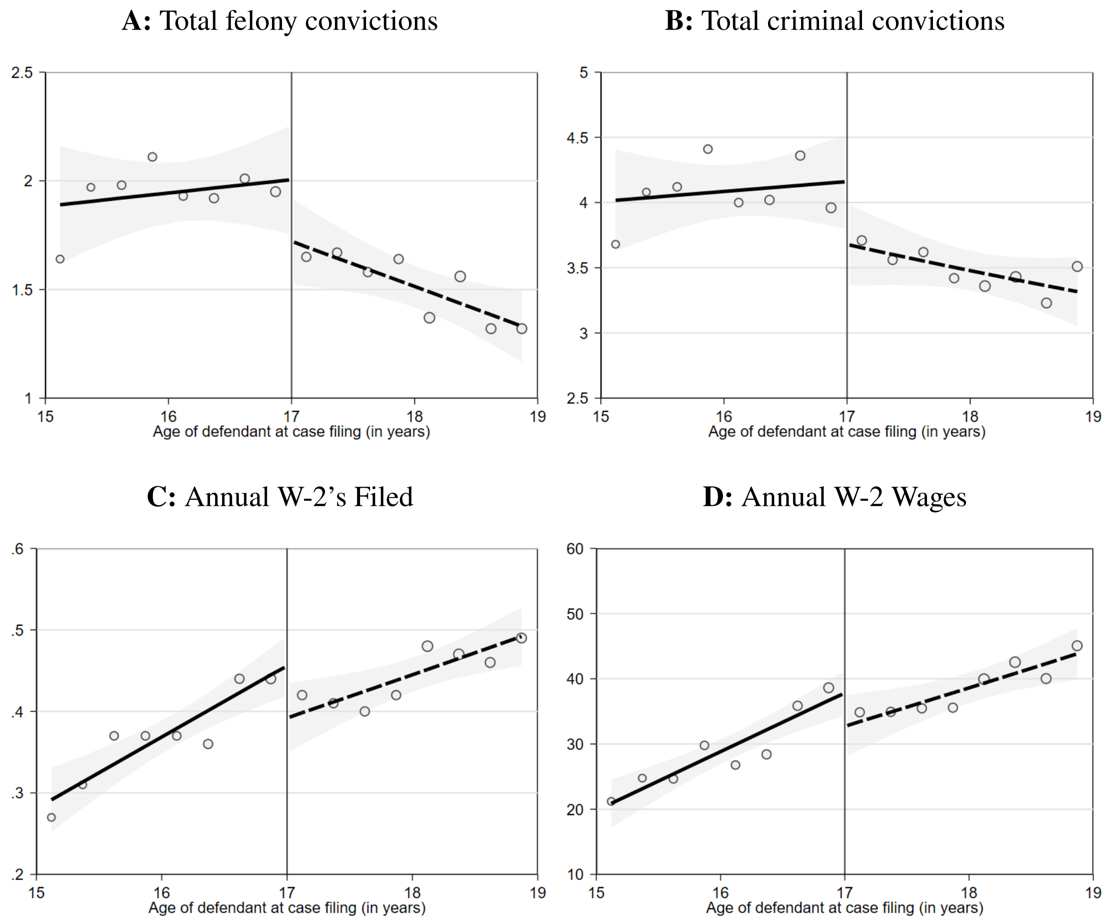
Online Appendix A: Supplementary Results

Figure A1: Additional evidence on caseload balance



Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022).

Figure A2: Additional crime and employment outcomes across the cutoff

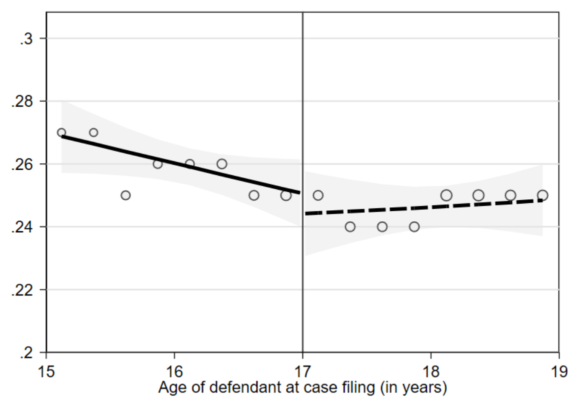


Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

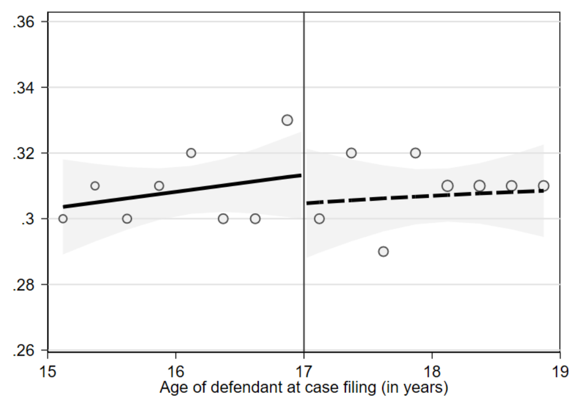
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors restricted. Regression also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Figure A3: Reduced form: predicted dispositions across the discontinuity

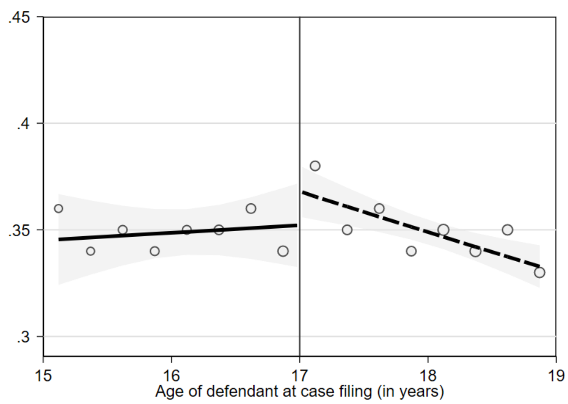
A: Probability of adult dismissal



B: Probability of adult incarceration



C: Probability of juvenile dismissal



Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022).

Table A1: Confusion matrices and distribution of out-of-sample predictions

Number of realized (rows)	Number predicted (columns)		
Panel A: Confusion matrix among adult defendants			
	No Conviction	Conviction + incarceration	Conviction + other punish.
Adult no conviction	**250**	20	D
Adult conv. + incar.	D	**500**	30
Adult conv. + other punish.	D	150	**1,800**
Panel B: Confusion matrix among juvenile defendants			
	No conviction	Conviction + services	
Juvenile no conviction	**600**	60	
Juvenile conv. + services	30	**1,400**	
Panel C: Out-of-sample predictions among adult defendants			
	No conviction	Conviction + services	
Adult no conviction	40	250	
Adult conv. + incar.	50	450	
Adult conv. + other punish.	350	1,600	
Panel D: Out-of-sample predictions among juvenile defendants			
	No Conviction	Conviction + incarceration	Conviction + other punish.
Juvenile no conviction	D	80	550
Juvenile conv. + services	40	200	1,200

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases).All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). D indicates a cell is small and suppressed to preserve confidentiality.

Table A2: Regression of random forest generated probabilities on explanatory variables

	(1)	(2)	(3)
	P(Adult conviction)	P(Adult incarceration)	P(Juvenile conviction)
Black	-0.792*	1.81***	-0.205
	(0.426)	(0.466)	(0.602)
Male	2.907***	12.33***	3.333***
	(0.643)	(0.546)	(0.821)
Any misdemeanor history	5.547***	6.418	-0.394
	(2.15)	(5.022)	(5.693)
Days since first charge	0.267	-0.015	0.723
	(0.404)	(0.508)	(0.512)
Charged in past month	-3.91*	-4.925	6.121
	(2.274)	(5.081)	(5.781)
Charged between one month and last half year	-3.654*	-3.885	8.556
	(2.189)	(5.049)	(5.707)
Charged between half year and last year	-2.889	-4.938	8.46
	(2.214)	(5.065)	(5.726)
Employed in 2010	0.05	0.345	-2.164*
	(1.203)	(1.23)	(1.153)
Number of violent misdemeanors history	1.412***	-0.016	-0.76
	(0.389)	(0.48)	(0.615)
Number of property misdemeanors history	0.551**	0.688	-0.645*
	(0.269)	(0.472)	(0.378)
Facing violent felony charge	-1.515***	15.34***	6.703***
	(0.554)	(0.7)	(0.713)
Facing property felony charge	3.039***	2.566***	3.827***
	(0.535)	(0.699)	(0.698)
Facing drug felony charge	13.26***	-11.52***	-1.552
	(0.776)	(0.872)	(0.972)
Previous charge in house	1.684*	0.604	-0.266
	(1.02)	(1.079)	(1.377)
Parent previous charge in house	-1.09	1.078	1.013
	(0.755)	(0.836)	(1.012)
Previous felony charge in house	-0.894	-0.479	1.436
	(0.648)	(0.741)	(0.91)
Parent previous felony charge in house	0.642	0.589	0.427
	(0.543)	(0.597)	(0.735)
Previous felony conviction in house	-0.256	0.586	-0.171
	(0.537)	(0.575)	(0.722)
Parent previous felony conviction in house	0.928	-0.702	0.306
	(0.636)	(0.722)	(0.94)
Previous incarceration in house	0.978	-1.176*	0.05
	(0.596)	(0.631)	(0.86)
Parent previous incarceration in house	0.769	-0.429	0.468
	(0.931)	(1.053)	(1.371)
Family 2010 AGI	0.002**	-0.007***	-0.004***
	(0.001)	(0.001)	(0.001)
Household 2010 AGI	0.001	0.00	-0.002**
	(0.00)	(0.00)	(0.001)
Parents in 2010 house	-0.166	-1.324***	-1.565***
	(0.309)	(0.334)	(0.438)
Other adults in 2010 house	0.987***	-0.406	0.299
	(0.196)	(0.259)	(0.31)
2009-10 violent charges in zip	-3.657***	1.424	-0.717
	(1.064)	(1.154)	(1.587)
2009-10 property charges in zip	-0.205	-1.025	-0.186
	(1.592)	(1.691)	(2.312)
2009-10 drug charges in zip	3.248*	-0.062	0.29
	(1.752)	(1.958)	(2.415)
2009-10 public order charges in zip	-26.86	-89.62***	-71.95
	(29.68)	(30.41)	(46.02)
2009-10 public order charges in zip	8.456	7.349	38.79***
	(5.23)	(5.519)	(7.008)
Unable to identify zip	-2.342***	10.63***	8.373***
	(0.728)	(0.736)	(0.978)
Unable to identify tract	-14.33***	16.04***	-11.2***
	(0.389)	(0.447)	(0.567)
Tract percent poverty	0.236***	-0.012	-0.086
	(0.058)	(0.067)	(0.089)
Tract percent youth poverty	-0.091***	0.006	-0.011
	(0.031)	(0.037)	(0.05)
R-squared	0.422	0.552	0.273
Obs	4700	4700	4700

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022).

Table A3: Simple RD estimated on samples defined by predicted case dispositions

	5-year employment from RD over subsample:					
	Predicted juvenile no conviction and adult:			Predicted juvenile conviction and adult:		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	No conviction	Incarceration	Non-Incar. punishment	No conviction	Incarceration	Non-Incar. punishment
Recidivism:						
Felony Charge	3.924**	-1.277	-0.691	-2.231	-1.216*	-0.278
	(1.552)	(1.946)	(0.495)	(1.589)	(0.671)	(0.284)
Felony Conviction	2.56*	-1.62	-0.07	-2.103	-1.155*	-0.223
	(1.496)	(1.735)	(0.435)	(1.489)	(0.618)	(0.244)
Charge	-0.167	-5.103	-1.191	-2.264	-2.252**	-0.577
	(2.646)	(3.536)	(0.801)	(1.786)	(0.894)	(0.429)
Conviction	-2.88	-4.808	-0.439	-2.101	-1.679**	-0.282
	2.067	2.763	0.696	1.667	0.788	(0.367)
Employment:						
IHS (Annual Wages)	1.167	-1.025	0.07	0.342	-0.236	-0.274
	(1.016)	(1.34)	(0.301)	(0.697)	(0.336)	(0.162)
5-year income (1000s)	-19.95	9.118	-0.737	-17.41	-4.43	-4.357
	(17.75)	(32.15)	(11.58)	(21.17)	(5.846)	(4.387)
W2 worked w/in 5yr	-0.187	-0.045	0.005	-0.121	-0.125	-0.054
	(0.229)	(0.286)	(0.093)	(0.198)	(0.069)	(0.044)
Earnings above poverty line	-0.124	-0.013	-0.007	-0.06	-0.008	-0.026
	(0.08)	(0.115)	(0.037)	(0.076)	(0.02)	(0.016)
Left obs	<30	60	500	50	250	1100
Right obs	40	50	350	200	550	1500

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Table A4: Simple RD estimated on samples defined by covariates

		Race		Sex		Facing felony type:			Family AGI vs median	
	Full sample	Black	Not black	Male	Female	Violent	Property	Drug	Above	Below
Recidivism (intensive):										
Felony conviction	-0.361*	-0.543**	-0.224	-0.469**	-0.042	-0.838***	0.18	0.383	-0.199	-0.568*
	(0.188)	(0.272)	(0.258)	(0.214)	(0.381)	(0.251)	(0.294)	(0.529)	(0.252)	(0.281)
Charge	-1.022***	-1.493***	-0.618	-1.272***	-0.376	-1.618***	-0.415	-1.089	-0.903**	-1.198**
	(0.326)	(0.461)	(0.459)	(0.364)	(0.715)	(0.423)	(0.496)	(1.113)	(0.433)	(0.492)
Employment:										
IHS (Annual Wages)	-0.275**	-0.123	-0.33**	-0.206	-0.395**	-0.055	-0.598***	-1.012**	-0.144	-0.329*
	(0.124)	(0.178)	(0.168)	(0.144)	(0.181)	(0.164)	(0.192)	(0.417)	(0.17)	(0.175)
Earnings above poverty line	-0.027**	-0.016	-0.03	-0.023	-0.039*	-0.009	-0.053***	-0.065	-0.01	-0.04**
	(0.012)	(0.015)	(0.019)	(0.014)	(0.021)	(0.015)	(0.02)	(0.047)	(0.018)	(0.016)
Incarceration:										
Prison days	125***	161.9***	81.78**	124.4***	111.7**	149.1***	141.9***	64.68	106.5***	148***
	(27.92)	(42.1)	(36.38)	(32.13)	(55.45)	(40.33)	(40.14)	(64.47)	(35.82)	(43.49)
Jail days	26.67***	20.98**	32.01***	25.4***	32.02***	12.67	40.92***	31.04	24.94***	27.46***
	(6.8)	(10.08)	(9.172)	(7.943)	(11.83)	(9.112)	(10.39)	(20.41)	(8.871)	(10.35)
Disposition:										
Juvenile conviction	-0.682***	-0.726***	-0.638***	-0.691***	-0.656***	-0.749***	-0.704***	-0.597***	-0.639***	-0.73***
	(0.023)	(0.03)	(0.034)	(0.025)	(0.055)	(0.027)	(0.037)	(0.081)	(0.031)	(0.033)
Adult no conviction	0.081***	0.075***	0.087***	0.062***	0.159***	0.085***	0.099***	0.026	0.092***	0.069***
	(0.014)	(0.02)	(0.019)	(0.015)	(0.035)	(0.019)	(0.02)	(0.036)	(0.018)	(0.021)
Adult incareration	0.171***	0.201***	0.142***	0.179***	0.135***	0.185***	0.191***	0.112***	0.126***	0.225***
	(0.017)	(0.026)	(0.024)	(0.02)	(0.035)	(0.025)	(0.027)	(0.035)	(0.022)	(0.028)
Adult conv. non-incareration	0.748***	0.725***	0.771***	0.759***	0.706***	0.73***	0.71***	0.862***	0.782***	0.706***
	(0.02)	(0.029)	(0.028)	(0.023)	(0.044)	(0.029)	(0.032)	(0.048)	(0.026)	(0.031)
Left obs:	2000	1000	1100	1600	400	1200	700	100	1100	900
Right obs:	2700	1400	1300	2200	600	1500	1000	400	1400	1300

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Table A5: Mechanism-specific treatment effect estimates (IV decomposition)

	Extensive					Intensive				
	Juvenile Charge	Juvenile Conv.	Adult Conv.	Adult Incar.	Adult No. Conv. Ave.	Juvenile Charge	Juvenile Conv.	Adult Conv.	Adult Incar.	Adult No. Conv. Ave.
Recidivism:										
Charge	-0.016	0.013	-0.049	-0.292***	0.761	0.499	-0.073	-0.09	-2.793***	4.621
	(0.062)	(0.052)	(0.086)	(0.068)		(0.807)	(0.678)	(1.161)	(0.888)	
Conviction	0.027	-0.001	0.016	-0.228***	0.674	0.896	-0.067	0.69	-1.994***	3.371
	(0.071)	(0.060)	(0.101)	(0.08)		(0.686)	(0.574)	(0.989)	(0.766)	
Felony charge	0.173**	-0.008	0.193*	-0.257***	0.455	1.606***	-0.048	1.584**	-2.037***	1.936
	(0.077)	(0.065)	(0.11)	(0.088)		(0.555)	(0.4739)	(0.788)	(0.572)	
Felony conviction	0.257***	-0.003	0.29***	-0.226***	0.379	1.767***	0.032	1.847***	-1.491***	1.356
	(0.078)	(0.065)	(0.11)	(0.087)		(0.489)	(0.414)	(0.693)	(0.505)	
Recidivism by type of offense:										
Violent charges	0.120	-0.002	0.164	-0.236***	0.402	0.961*	-0.065	0.859	-1.546***	1.648
	(0.077)	(0.065)	(0.11)	(0.087)		(0.485)	(0.411)	(0.692)	(0.515)	
Property charges	0.037	-0.012	0.045	-0.286***	0.318	0.423	-0.188	0.345	-1.632***	1.28
	(0.078)	(0.066)	(0.111)	(0.086)		(0.463)	(0.387)	(0.675)	(0.516)	
Drug charges	0.105	0.004	0.073	-0.125	0.277	0.093	0.014	-0.2	-0.242	0.883
	(0.070)	(0.059)	(0.101)	(0.079)		(0.331)	(0.285)	(0.475)	(0.38)	
Other charges	-0.017	0.032	-0.067	-0.371***	0.64	0.023	0.018	-0.593	-1.612**	3.03
	(0.072)	(0.060)	(0.101)	(0.08)		(0.638)	(0.538)	(0.913)	(0.71)	
Employment:										
Average # of W-2s per year	0.076	0.035	0.04688	-0.2567***	0.4924					
	(0.075)	(0.063)	(0.1057)	(0.0813)						
Earnings above poverty line	0.025	0.015	0.0107	-0.06637**	0.1212					
	(0.027)	(0.022)	(0.03889)	(0.03065)						
Annual W-2 wages						1.96	4.54	-0.87	-19.68**	42.42
						(7.42)	(6.16)	(10.89)	(8.61)	
IHS(Annual wages)						-0.202	0.114	-0.4169	-0.6602**	2.765
						(0.284)	(0.239)	(0.4025)	(0.3237)	

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). Sargan-Hansen J for 5-year felony conviction recidivism (intensive) is 3.737, p-value 0.154 and for IHS(Average yearly income over next 5-years), 1.923 p-value 0.382). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022) and #CBDRB-FY23-088 (approved 12/12/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Table A6: Impact of case outcomes on crime and employment outcomes by follow-up year (IV decomposition estimates)

	Juvenile No Conv.	Juvenile Conv.	Adult Conv.	Adult Incar.	Adult No. Conv. Ave.		Juvenile No Conv.	Juvenile Conv.	Adult Conv.	Adult Incar.	Adult No. Conv. Ave.
						Recidivism (intensive):					
Felony Conviction						Charge					
Year 1	0.744**	0.449	0.702**	-0.532**	0.341	Year 1	0.447	0.145	0.186	-0.635**	1.008
	(0.316)	(0.296)	(0.305)	(0.235)			(0.429)	(0.398)	(0.421)	(0.313)	
Year 2	0.211	0.288	0.209	-0.309	0.371	Year 2	0.461	0.394	0.141	-0.566*	1.072
	(0.317)	(0.313)	(0.324)	(0.206)			(0.429)	(0.406)	(0.433)	(0.306)	
Year 3	0.398	0.434*	0.454*	-0.162	0.261	Year 3	-0.059	-0.214	-0.171	-0.358	0.864
	(0.251)	(0.233)	(0.248)	(0.198)			(0.417)	(0.378)	(0.422)	(0.33)	
Year 4	0.046	0.316	0.177	-0.303	0.189	Year 4	-0.155	-0.031	-0.254	-0.989***	0.875
	(0.239)	(0.217)	(0.248)	(0.197)			(0.397)	(0.375)	(0.414)	(0.333)	
Year 5	0.3	0.311	0.305	-0.184	0.193	Year 5	-0.037	0.132	0.008	-0.246	0.803
	(0.293)	(0.257)	(0.291)	(0.219)			(0.446)	(0.402)	(0.453)	(0.356)	
						Employment:					
Average # of W-2s per year						Earnings above poverty line					
Year 1	0.012	0.192**	0.248***	-0.511***	0.337	Year 1	0.004	0.049**	0.051*	-0.097***	0.027
	(0.095)	(0.083)	(0.093)	(0.073)			(0.028)	(0.023)	(0.028)	(0.022)	
Year 2	-0.067	0.108	-0.021	-0.072	0.644	Year 2	-0.024	0.03	0.035	-0.128***	0.095
	(0.193)	(0.177)	(0.189)	(0.142)			(0.043)	(0.036)	(0.041)	(0.033)	
Year 3	-0.086	0.065	-0.085	-0.224*	0.485	Year 3	-0.059	0.011	-0.009	-0.065	0.125
	(0.156)	(0.137)	(0.151)	(0.118)			(0.06)	(0.053)	(0.059)	(0.047)	
Year 4	0.178	0.15	0.078	-0.055	0.538	Year 4	0.051	0.072	0.009	-0.013	0.163
	(0.172)	(0.157)	(0.168)	(0.129)			(0.068)	(0.063)	(0.068)	(0.054)	
Year 5	-0.067	0.108	-0.021	-0.072	0.644	Year 5	-0.013	0.039	-0.031	-0.029	0.197
	(0.193)	(0.177)	(0.189)	(0.142)			(0.077)	(0.07)	(0.076)	(0.06)	
						Incarceration:					
Prison days						Jail days					
Year 1	-5.664	-16.17**	-13.75**	77.81***	12.03	Year 1	0.241***	-4.333**	19.39	-12.24	6.196
	(7.163)	(6.706)	(7.004)	(8.399)			(6.738)	(5.676)	(6.429)	(5.379)	
Year 2	-4.101	-28.64**	-23	152.9***	29.17	Year 2	1.299	-3.233	9.138	-6.183	7.603
	(14.13)	(13.25)	(14.29)	(14.47)			(8.704)	(7.174)	(8.237)	(7.73)	
Year 3	2.257	-25.34	-16.34	152.6***	38.69	Year 3	0.202	1.474	5.363	-13.89	3.114
	(19.58)	(19)	(19.92)	(17.62)			(7.88)	(7.293)	(8.121)	(7.61)	
Year 4	15.91	-17.4	7.338	150.5***	46.48	Year 4	22.68**	19.51**	21.51**	-8.367	7.722
	(23.85)	(23.26)	(24.18)	(20.03)			(9.467)	(8.464)	(9.192)	(6.747)	
Year 5	11.32	-13.77	8.697	130.5***	49.88	Year 5	-16.48	-3.897	-6.758	-10.03	4.29
	(26.33)	(25.48)	(26.71)	(21.82)			(8.57)	(7.687)	(9.133)	(8.854)	

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relations and exposure from Finlay, Mueller-Smith, and Street (2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Coefficients are estimated using a linear IV approach with robust standard errors restricted to sample cases with defendants between the ages of 15 and 19. Regressions also control for the full set of variables.

Table A7: Regression Discontinuity Bandwidths and Controls (IV estimates)

	Bandwidth in years around age 17:					2 yr. bw &		Triangular
	1	1.5	2 (main)	2.5	3	No controls	RD robust	weights
Recidivism (intensive):								
Felony conviction	-0.359	-0.346	-0.361*	-0.251	-0.347**	-0.406**	-0.42	-0.343
	(0.288)	(0.222)	(0.188)	(0.168)	(0.152)	(0.193)	(0.3)	(0.222)
Charge	-0.68	-0.811**	-1.022***	-0.783***	-0.939***	-1.05***	-0.564	-0.777**
	(0.49)	(0.384)	(0.326)	(0.289)	(0.261)	(0.335)	(0.516)	(0.382)
Employment:								
IHS (Annual Wages)	-0.238	-0.208	-0.275**	-0.306***	-0.267***	-0.271*	-0.196	-0.240
	(0.185)	(0.144)	(0.124)	(0.11)	(0.099)	(0.141)	(0.214)	(0.162)
Earnings above poverty line	-0.043**	-0.034**	-0.027**	-0.023**	-0.014	-0.024*	-0.042**	-0.030**
	(0.019)	(0.015)	(0.012)	(0.011)	(0.01)	(0.013)	(0.021)	(0.015)
Incarceration:								
Prison days	76.58*	105.2***	125***	136.7***	135***	108.1***	58.57	93.05***
	(41.77)	(33.08)	(27.92)	(24.74)	(22.32)	(28.55)	(41.31)	(31.86)
Jail days	15.01	25.27***	26.67***	25.39***	22.2***	25.97***	17.27*	22.89***
	(10.38)	(7.994)	(6.8)	(6.068)	(5.468)	(6.841)	(10.08)	(7.826)
Left obs:	1200	1600	2000	2300	2500	2000	2400	2000
Right obs:	1200	2000	2700	3500	4200	2700	3900	2700

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022). Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022) and #CBDRB-FY23-088 (approved 12/12/2022). Coefficients are estimated using a linear IV approach with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; the time since last charged category; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offense character of the zip code of the defendant's residence (measured between 2008-2010); an indicator for whether the defendants residence is matched into a Wayne County tract or zip code.

Table A8: Regression Discontinuity Decomposition Bandwidths

	Bandwidth (years) around 17:			Triangular
	1.5	2 (main)	2.5	weights
Felony conviction recidivism (intensive)				
Juvenile No Conv.	1.968**	1.709**	1.355**	1.879**
	(0.84)	(0.773)	(0.612)	(0.871)
Juvenile Conv.	1.888**	1.558**	1.318**	1.991**
	(0.778)	(0.729)	(0.579)	(0.82)
Adult Conv.	2.036**	1.584**	1.495**	2.134**
	(0.85)	(0.788)	(0.62)	(0.881)
Adult Incar.	-1.485**	-2.037***	-1.419***	-1.754***
	(0.599)	(0.572)	(0.463)	(0.624)
IHS (Annual Wages)				
Juvenile No Conv.	-0.701	-0.4476	-0.427	-0.826*
	(0.486)	(0.4054)	(0.363)	(0.5)
Juvenile Conv.	-0.333	-0.08815	-0.108	-0.481
	(0.444)	(0.3715)	(0.335)	(0.46)
Adult Conv.	-0.629	-0.4169	-0.433	-0.865*
	(0.489)	(0.4025)	(0.363)	(0.505)
Adult Incar.	-0.681*	-0.6602**	-0.69**	-0.321
	(0.381)	(0.3237)	(0.296)	(0.397)
Left obs:	1600	2000	2300	2000
Right obs:	2000	2700	3500	2700

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022) and #CBDRB-FY23-088 (approved 12/12/2022). Coefficients are estimated using a linear IV approach with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; the time since last charged category; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offense character of the zip code of the defendant's residence (measured between 2008-2010); an indicator for whether the defendants residence is matched into a Wayne County tract or zip code.

Table A9: Regression Discontinuity Treatment Homogeneity

	Main Results	*Leave-one-instrument-out Results*						Joint test of coeff. equal. (2) - (7)	*"Slim" pred. model*	Joint test of coeff. equal. (1) & (9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Felony conviction recidivism (intensive)										
Juvenile No Conv.	1.709**	1.803***	1.997***	1.595**	1.69**	1.277*	2.308***	0.951	1.851**	0.629
	(0.773)	(0.696)	(0.749)	(0.699)	(0.69)	(0.733)	(0.753)		(0.864)	
Juvenile Conv.	1.558**	1.771***	1.949***	1.688***	1.798***	1.513**	2.575***	0.935	1.867**	0.674
	(0.729)	(0.645)	(0.645)	(0.644)	(0.639)	(0.662)	(0.749)		(0.798)	
Adult Conv.	1.584**	1.805***	2.23***	1.743**	1.783**	1.535**	2.541***	0.941	1.971**	0.593
	(0.788)	(0.699)	(0.756)	(0.697)	(0.693)	(0.721)	(0.767)		(0.883)	
Adult Incar.	-2.037***	-1.474***	-1.832***	-1.556***	-1.132*	-1.516***	-1.317**	0.977	-1.668**	0.471
	(0.572)	(0.507)	(0.584)	(0.508)	(0.616)	(0.504)	(0.521)		(0.682)	
IHS (Annual Wages)										
Juvenile No Conv.	-0.448	-0.348	-0.155	-0.382	-0.441	-0.478	-0.406	0.997	-0.466	0.709
	(0.405)	(0.408)	(0.451)	(0.411)	(0.405)	(0.435)	(0.442)		(0.586)	
Juvenile Conv.	-0.088	-0.115	0.058	-0.018	-0.087	-0.108	-0.0354	1.000	-0.207	0.546
	(0.372)	(0.372)	(0.384)	(0.377)	(0.371)	(0.385)	(0.445)		(0.532)	
Adult Conv.	-0.417	-0.457	-0.041	-0.351	-0.371	-0.439	-0.370	0.991	-0.363	0.735
	(0.403)	(0.404)	(0.484)	(0.407)	(0.404)	(0.418)	(0.457)		(0.597)	
Adult Incar.	-0.660**	-0.644**	-0.994**	-0.619*	-0.919**	-0.662**	-0.648**	0.968	-1.513***	0.154
	(0.323)	(0.324)	(0.409)	(0.326)	(0.401)	(0.324)	(0.328)		(0.463)	
Instrument dropped:	–	P(Ad. conv.) ×P(Ju. no conv.)	P(Ad. conv.) ×P(Ju. conv.)	P(Ad. incar.) ×P(Ju. no conv.)	P(Ad. incar.) ×P(Ju. conv.)	P(Ad. no conv.) ×P(Ju. no conv.)	P(Ad. no conv.) ×P(Ju. conv.)		–	
Covariates used in prediction models:										
Defendant traits	x	x	x	x	x	x	x			
Household characteristics	x	x	x	x	x	x	x		x	
Neighborhood information	x	x	x	x	x	x	x		x	

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from Finlay, Mueller-Smith, and Street (2022).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022) and #CBDRB-FY23-088 (approved 12/12/2022). A joint test of all coefficient equality in the leave-one-out robustness yields a p-value of 1. A joint test of the coefficients from the slim random forest model and the full random forest model is .961 for recidivism and .553 for IHS(Annual Wages). Coefficients are estimated using a linear IV approach with robust standard errors. Regressions also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; the time since last charged category; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offense character of the zip code of the defendant's residence (measured between 2008-2010); an indicator for whether the defendants residence is matched into a Wayne County tract or zip code.

Online Appendix B: Details of Cost Benefit Calculations

The first row of Table 4 details the share of the relevant population impacted by the reform. This represents the share of the adult caseload who would be impacted by the reform and is used as a scaling factor throughout the remaining rows. For instance, 100% of the adult population considered would be impacted by raising the age of majority, while only those incarcerated (19%) would be impacted in order to achieve parity in conviction rates. 18% would be impacted by eliminating prison, and 88% (everyone with a conviction) would be impacted by expanding juvenile record sealing.

The next row shows the average program savings. All values are displayed in 2020 dollars. These are calculated by multiplying the relevant coefficients from our causal estimates with the corresponding costs associated with the interventions (detailed below). The calculation varies by scenario. In order to calculate the first scenario, raising the age of majority, we multiply the reduced form coefficients on the number of days of initial prison/probation/jail/parole times by their daily marginal cost from various sources. The unit cost is high for prison ($107) and jail ($119) and much lower for probation ($3) and parole ($8) (Henrichson and Galgano (2013); Henrichson et al. (2015); Bureau (2019)). We add to this the full cost of juvenile probationary ($6,118) and additional court processing costs $805 Hornby Zeller Associates (2018). For scenario 2, program costs are decreased by the marginal change (the coefficient on adult conviction in the decomposition) in initial jail and probation days. For scenario 3, program costs are changed by the marginal decrease (the coefficient on adult incarceration in the decomposition) in prison and parole time and scaled up by the commensurate marginal change in initial probation and jail costs. We define program costs as zero in scenario 4, where the intervention being considered is simply adjusting the legal rules authorizing who is eligible to apply for an expungement of one's criminal record and when.

The next row shows the amount of tax revenue that the reform generates (10% of the earnings generated). For scenario 1 this is simply the reduced form estimate on earnings times 10%. For scenario 2, this is the share impacted times negative one times the coefficient on adult conviction. For scenario 3, the share is multiplied by negative one times the coefficient on incarceration. For scenario 4, the share impacted is multiplied by the difference between the coefficient on juvenile conviction and adult conviction.

We then calculate the costs due to changes in recidivism. We estimate the change in the number of offenses for each reform using our decomposed RD estimates to translate the increase or decrease in specific crime type recidivism (we include larceny, trespass, robbery, assault, sexual assault, drug dealing, and drug possession). Additional criminal behavior generates costs via enforcement (via investigation costs). For most charges, the price of investigation is around \$1,000-\$2,000, but costs are lower for drug possession (\$483) and much higher for violent crimes (e.g., \$12,211 for assault) (Caulkins (2010); P. E. Hunt et al. (2019)). To calculate court costs from each additional offense, we use the estimated change in the number of charges and multiply this by the price per prosecution for that charge type. The price per prosecution is less variable than the price of investigation: the price for most charges is within a few hundred dollars of \$1,000, reflecting the modest amount of time spent per case in the U.S. justice system (Schlueter et al. (2014); P. Hunt et al. (2017)). We calculate the estimated change in time for each correctional facility generated by recidivism using our RD decomposition with days over the next 5 years spent in each type of supervision.

We also include the costs of crime to victims as estimated using Cohen and Piquero (2009). Violent offenses include robbery, sexual assault, and other violent crimes. Property crimes include burglary, larceny, trespass, and other property crimes.Assaults include both aggravated and simple assault and are priced according to the proportion of the offense reduction for each type. Similarly, sexual assaults are composed of both rape as well as misdemeanor sexual assault and are priced according to each in proportion. Because we are unable to directly place a value on other uncategorized offenses, we use the value for simple assaults for other violent crimes and larceny for other property crimes.

Finally we include the value to defendants in two ways. First we assign the average willingness to pay for a day of freedom from Abrams and Rohlfs (2011) (\$17 per day). We also include the after tax wages a defendant generated by the policy change.

Table B1: Estimates underlying cost-benefit calculation

	RD estimate	Juv. no conv.	Juv. conviction	Adult conv.	Adult incar.
Larceny	-0.1222	0.596	0.05916	0.4037	-1.641
	(0.164)	(0.5805)	(0.5259)	(0.5887)	(0.4378)
Trespass	-0.1424	0.09244	0.08649	-0.02892	-0.179
	(0.06456)	(0.2344)	(0.2049)	(0.2317)	(0.1826)
Robbery	-0.1356	0.2701	0.3411	0.2428	-0.2794
	(0.06489)	(0.2254)	(0.2131)	(0.2309)	(0.1684)
Assault	-0.2603	0.7159	0.2588	0.3109	-0.891
	(0.1475)	(0.537)	(0.4905)	(0.5399)	(0.405)
Sexual assault	0.0137	-0.0734	-0.1257	-0.07823	-0.1588
	(0.02665)	(0.1032)	(0.0795)	(0.09064)	(0.08097)
Drug dealing	-0.004107	-0.0352	-0.08835	-0.0445	-0.2298
	(0.0601)	(0.1773)	(0.1564)	(0.1699)	(0.1545)
Drug use	-0.2999	0.0975	0.1343	-0.1693	-0.1542
	(0.1313)	(0.4449)	(0.4274)	(0.4618)	(0.3729)
Homicide	-0.0264	-0.03109	-0.02634	-0.04192	-0.1063
	(0.05162)	(0.1591)	(0.1734)	(0.2016)	(0.1156)
Other violent	-0.417	0.6407	0.7552	0.5093	-0.9953
	(0.1683)	(0.6003)	(0.5658)	(0.61)	(0.4432)
Other property	-0.1984	0.1742	-0.02277	-0.1334	-0.2277
	(0.114)	(0.3546)	(0.334)	(0.3785)	(0.3039)
Other	-0.7977	-0.2092	-0.07107	-0.7365	-1.54
	(0.252)	(0.8832)	(0.8141)	(0.8919)	(0.6893)
Prison days	135.6	19.72	-101.3	-37.06	664.3
	(27.74)	(77.74)	(74.76)	(78.85)	(71.14)
Jail days	27.58	7.943	9.524	48.64	-50.71
	(6.799)	(20.35)	(17.75)	(20.37)	(17.94)
Parole days	12.98	8.114	-0.6321	6.445	54.32
	(6.919)	(17.76)	(17.73)	(17.94)	(18.87)
Probation days	441.3	-51.58	-42.97	505.9	-436.7
	(32.8)	(101.5)	(92.13)	(99.32)	(81.89)
Earnings	-3258	-4132	3453	-463	-10450
	(1877)	(5743)	(5125)	(5786)	(4573)

Source: CJARS; IRS W2 and 1040 filings; Best Race and Ethnicity and Numident; ACS; Relational Crosswalk and family exposure measures from (Finlay, Mueller-Smith, & Street, 2022).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of 4700 observations between the ages of 15 and 19 (2000 juvenile cases and 2700 adult cases). All results were approved for release by the U.S. Census Bureau, Data Management System number: P-7512453 and approval number #CBDRB-FY22-291 (approved 6/24/2022). Estimates use a linear IV (instrument age 17+) with robust standard errors. Regression also control for the following variables: a linear age trend on either side of the discontinuity; whether the defendant was black; sex; time since first misdemeanor charge; time since last charged; whether the defendant worked in 2010; the number and crime type of previous crimes; the crime categories faced in the current charge; how many parents and other adults the defendant shares a mafid with; the number and type of offenses of the zip code of the defendant's residence (measured between 2008-2010); whether the defendant's residence is matched into a Wayne County tract or zip code.

Online Appendix C: Simulation exercise to test methodology

This appendix presents a number of simulation exercises to assess the performance of our methodological approach under a range of scenarios. We employ the following data generating process from Section 6:

$$Y_i = \sum_{m=1}^{10} \beta_m x_i^m + \sum_{k=1}^{K} \delta_{j,k}\, d_i^{j,k} + \sum_{l=1}^{L} \delta_{a,l}\, d_i^{a,l} + \epsilon_i$$

where $K = 2$ and $L = 2$ for simplicity. Each covariate x_i^m is drawn independently as $N(0, 1)$. Treatment assignment $\{d_i^{j,1}, d_i^{j,2}, d_i^{a,1}, d_i^{a,2}\}$ are defined as follows:

$$d_i^{j,1} = 1\,[\tau_i < 0] \times 1\left[\sum_{m=1}^{10} \beta_m^{j,1} x_i^m + \nu_i^{j,1} > 0\right]$$

$$d_i^{j,2} = 1\,[\tau_i < 0] \times 1\left[\sum_{m=1}^{10} \beta_m^{j,2} x_i^m + \nu_i^{j,2} \geq 0\right]$$

$$d_i^{a,1} = 1\,[\tau_i \geq 0] \times 1\left[\sum_{m=1}^{10} \beta_m^{a,1} x_i^m + \nu_i^{a,1} > 0\right]$$

$$d_i^{a,2} = 1\,[\tau_i \geq 0] \times 1\left[\sum_{m=1}^{10} \beta_m^{a,2} x_i^m + \nu_i^{a,2} \geq 0\right]$$

The parameterization of these questions (described below) should leave roughly 25% of the sample in each of the four possible treatment assignments. The goal of the empirical exercise is to estimate the δ coefficients from the outcome equation, or treatment effects.

We consider six scenarios that cover a range of potential empirical settings. In case 1, all β's and δ's are set equal to zero; essentially outcomes and treatment assignments are generated at random. It is a baseline exercise to ensure that our methodology does not over-reject the null hypothesis due to quirks of sample overfitting. In case 2, we maintain that δ's are set equal to zero (no true treatment effect), but allow the β's to be non-zero. This again helps verify that model overfitting does not arbitrarily lead to rejections of the null hypothesis.

For the remaining cases (3 through 6), we assign defined treatment effects as follows:

$\delta_{j,1} = 1$, $\delta_{j,2} = 2$, $\delta_{a,1} = 0$, and $\delta_{a,2} = -1$. In case 3, we set $\beta^{j,1}$, $\beta^{j,2}$, $\beta^{a,1}$, and $\beta^{a,2}$ all equal to zero, which will make the first stage purely a function of the forcing variable τ_i and the random shock ν_i. In effect, this should break the relevance assumption of our methodology since there are no subgroup characteristics that can help identify treatment counterfactuals. This scenario tests the performance of our model when one of our key assumptions does not hold, and should be expected to produce biased estimates.

In case 4, all of the β coefficients are non-zero, and we permit the empirical estimation to utilize all 10 covariates. Case 5 replicates case 4, except that the tenth covariate is withheld from the econometrician thereby creating omitted variables bias in naive ordinary least squares (OLS). Our methodology should return unbiased estimates of the true treatment effects. In the final scenario, we introduce treatment effect heterogeneity, allowing $\delta_{j,1}$ to vary with one of the ten covariates. This setup violates our homogeneity assumption, and should generate an unsigned bias in our methodological approach.

To conduct the simulations, we draw a sample of 10,000 observations according to the data generating process outlined above. Each iteration resamples the covariate values, the forcing variable, and the random shocks (ϵ and ν's). For any non-zero coefficient that is not explicitly assigned a value (e.g. β's), we draw values at random from $N(0, 1)$ with each iteration.

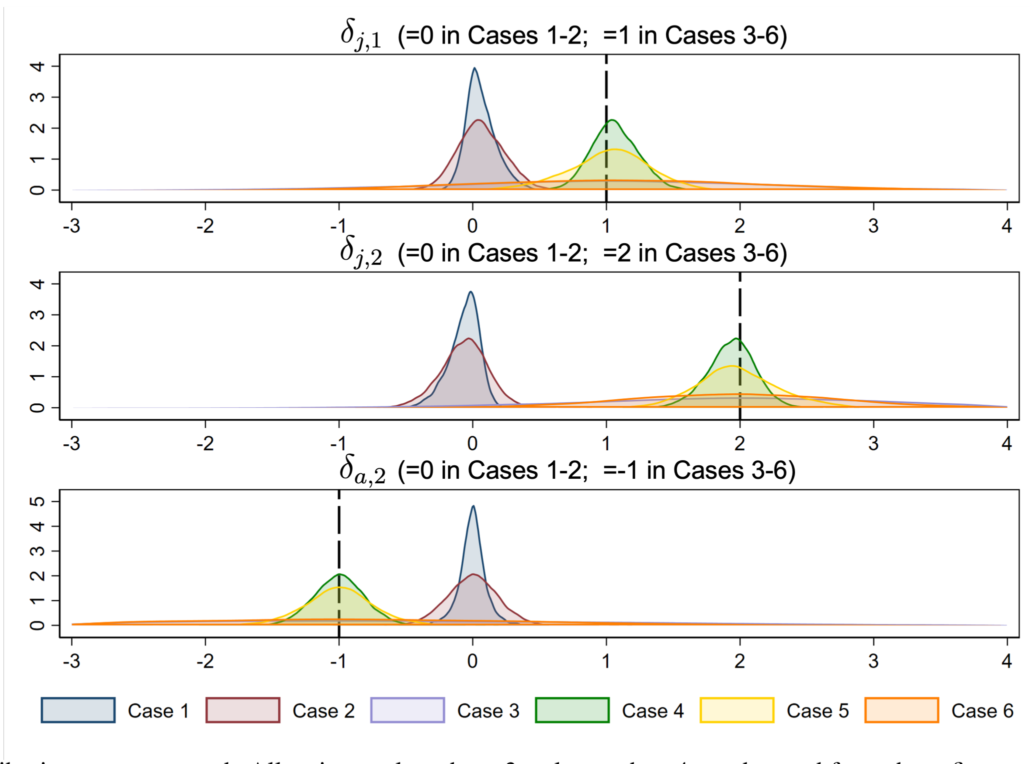
For speed and ease of simulation, we use the characteristics to predict treatment assignment in a simple OLS regression, although in practice a neural net or other predictive approach may be generally preferred. Using the sample to the left of the discontinuity, we estimate the probability of receiving each treatment available to observations on the left of the discontinuity. Similarly we estimate the likelihood of receiving treatments for observations to the right of the discontinuity. Using these models, each trained on 50% of the observations, we use the models to generate predictions for every case (both to the left and to the right of the discontinuity) in our full sample. We then interact these predictions to generate our set of four instruments (prediction of left treatment 1 times prediction of right treatment 1 ; prediction of left treatment 1 times prediction of right treatment 2 ; prediction of left treatment 2 times prediction of right treatment 1 ; prediction of left treatment 2 times prediction of right treatment 2). To estimate our treatment effects we regress the outcome on the running variable, our covariate predictions, and the treatments instrumented by the interaction of our predictions and the discontinuity indicator. Intervention $d_i^{a,1}$ is our excluded category, and since $\delta_{a,1} = 0$ (for cases 3 through 6) the resulting treatment effect estimates will comparable to the parameters in the defined data generating process without further normalization.

Figure C1 shows the results of these exercises. Cases 1 and 2 yield estimates for $\delta_{j,1}$, $\delta_{j,2}$, and $\delta_{a,2}$ that are tightly centered around zero, which is as expected. Our integration of machine learning into RD methods does not arbitrarily create non-zero treatment effect estimates that reject the null hypothesis when no such effect exists.

Cases 3 through 6 are each centered around the true treatment effects. Case 3 (weak IV) and case 6 (heterogeneous treatment effects) both show quite a wide dispersion around the true treatment effect, demonstrating two ways in which this method can break down and yield unreliable estimates when at least one of our fundamental assumptions are violated.

Cases 4 and 5 reassuring behave quite well. Whether the outcome and treatment assignment equations are or are not impacted by omitted variables bias in the empirical estimation, the estimation strategy reliably returns point estimates close to the true effect.

Figure C1: Simulation exercises to assess methodology for potential bias



Distributions are truncated. All estimates less than -3 or larger than 4 are dropped from these figures. In no estimate are more than 2.3% of estimates dropped by this truncation.

Online Appendix D: Mueller-Smith, Pyle, and Walker (2022) in the Caetano et al. (2022) framework

This section describes the econometric technique explicitly in the Caetano et al. (2022) framework. Formally, we are applying the method from this paper with a uniform kernel and bandwidth $h = 2$, and we are using instruments derived from our random forest approach.

In the Caetano et al. (2022) notation we describe our treatment vector of four potential treatments and one omitted category: $T_i = (T_{1i}, T_{2i}, T_{3i}, T_{4i})'$, where

$$
\begin{aligned}
T_{1i} =& 1(j, \not{c}) = 1(\text{tried in juvenile court, not convicted}) \\
T_{2i} =& 1(j, c) = 1(\text{tried in juvenile court, convicted}) \\
T_{3i} =& 1(a, c, \not{p}) = 1(\text{tried in adult court, convicted, no prison}) \\
T_{4i} =& 1(a, c, p) = 1(\text{tried in adult court, convicted, prison}) \\
T_{0i} =& 1(a, \not{c}) = 1(\text{tried in adult court, not convicted}). \quad \leftarrow \text{excluded category}
\end{aligned}
$$

We call Y_i the outcome (various measures of recidivism and employment); Z_i is the centered running variable (age) with $z_0 = 17$ as the RD cutoff, and we use controls W_i (our interacted probabilities of each potential treatment,

$$
\begin{aligned}
W_i = (&P_i(j, \not{c}) \times P_i(a, \not{c}), P_i(j, \not{c}) \times P_i(a, c, \not{p}), P_i(j, \not{c}) \times P_i(a, c, p), \\
&P_i(j, c) \times P_i(a, \not{c}), P_i(j, c) \times P_i(a, c, \not{p}), P_i(j, c) \times P_i(a, c, p))') ,
\end{aligned}
$$

and X_i (the other covariates entering linearly).

We estimate δ by 2SLS:

$$
\begin{aligned}
Y_i =& \delta' T_i + \phi' W_i + \beta' X_i + \epsilon_i \\
T_i =& \rho' W_i D_i + \psi' W_i + \theta' X_i + \nu_i
\end{aligned}
$$

In this framework we recover the treatment effects when the following assumptions are met. First, continuous selection at z_0: $\mathbb{E}[\beta_i X_i + \epsilon_i | W_i, Z_i = z]$ and $\mathbb{E}[\phi_i | W_i, Z_i = z]$ are continuous in z at z_0. $\delta_i, T_i(z) \perp\!\!\!\perp Z_i | W_i, Z_i \in (z_0 - \varepsilon, z_0 + \varepsilon)$ for some small $\varepsilon > 0$. Second, monotonicity: $T_{li}(z)$ is monotonic in z near z_0. We also need relevance, which in this setting means $E[\Delta_T(W_i)\Delta_T(W_i)']$ is invertible ($\delta = E[\Delta_T(W_i)\Delta_T(W_i)']^{-1}E[\Delta_T(W_i)\Delta_Y(W_i)]$). Finally, homogeneity in W_i of the expected treatment effects conditional on W_i and compliers for that treatment level: $\delta_l(W_i) := E[\delta_{li}|W_i, \lim_{e\downarrow 0}(T_{li}(z_0+e) - T_{li}(z_0-e)) \neq 0] = \delta_l$.

Caetano et al. (2022) shows how this identification strategy works under homogeneity:

$$\begin{aligned}\lim_{r\downarrow 0}(E[Y_i|W_i, Z_i = z_0 + r] - E[Y_i|W_i, Z_i = z_0 - r]) = \\ \delta' \lim_{r\downarrow 0}(E[T_i|W_i, Z_i = z_0 + r] - E[T_i|W_i, Z_i = z_0 - r]) + \\ \lim_{r\downarrow 0}(E[\beta' X_i + \epsilon_i|W_i, Z_i = z_0 + r] - E[\beta' X_i + \epsilon_i|W_i, Z_i = z_0 - r])\end{aligned}$$

Applying the classical RDD assumption of continuity in z at z_0 of $E[\beta' X_i + \epsilon_i|W_i, Z_i = z]$ yields $\Delta_Y(W_i) = \delta'\Delta_T(W_i)$ where $\Delta_Y(W_i) := \lim_{z\downarrow z_0} E[Y_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[Y_i|W_i, Z_i = z]$ and $\Delta_T(W_i) := \lim_{z\downarrow z_0} E[T_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[T_i|W_i, Z_i = z]$. The relevance assumption in this setting requires at least 4 linearly independent values of W_i, so that $E[\Delta_T(W_i)\Delta_T(W_i)']$ is invertible.

Caetano et al. (2022) also provides insight into what is recovered when the homogeneity assumption is not met.

$$\begin{aligned}\lim_{z\downarrow z_0} E[Y_i|W_i, Z_i = z] &= \lim_{z\downarrow z_0} E[\delta_i' T_i|W_i, Z_i = z] \\ &+ \lim_{z\downarrow z_0} E[\phi_i|W_i, Z_i = z]' W_i \\ &+ \lim_{z\downarrow z_0} E[\beta_i' X_i + \epsilon_i|W_i, Z_i = z]\end{aligned}$$

$$\begin{aligned}\lim_{z\uparrow z_0} E[Y_i|W_i, Z_i = z] &= \lim_{z\uparrow z_0} E[\delta_i' T_i|W_i, Z_i = z] \\ &+ \lim_{z\uparrow z_0} E[\phi_i|W_i, Z_i = z]' W_i \\ &+ \lim_{z\uparrow z_0} E[\beta_i' X_i + \epsilon_i|W_i, Z_i = z]\end{aligned}$$

Assuming $\mathbb{E}[\phi_i|W_i, Z_i = z]$ is continuous in z at z_0 (as in the classical RD setting) yields

$$\begin{aligned}\lim_{z\downarrow z_0} E[Y_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[Y_i|W_i, Z_i = z] = \\ \lim_{z\downarrow z_0} E[\delta_i' T_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[\delta_i' T_i|W_i, Z_i = z] \\ + \lim_{z\downarrow z_0} E[\beta_i' X_i + \epsilon_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[\beta_i' X_i + \epsilon_i|W_i, Z_i = z]\end{aligned}$$

Assuming the classic RD assumption of continuity in z at z_0 of $E[\beta' X_i + \epsilon_i|W_i, Z_i = z]$ removes the last term:

$$\begin{aligned}\lim_{z\downarrow z_0} E[Y_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[Y_i|W_i, Z_i = z] = \\ \lim_{z\downarrow z_0} E[\delta_i' T_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[\delta_i' T_i|W_i, Z_i = z]\end{aligned}$$

The additional classical RDD assumptions $\delta_i, T_i(z) \perp\!\!\!\perp Z_i$ near z_0 and $T_{li}(z)$ monotonic on z near z_0. This yields:

$$\begin{aligned}\lim_{z\downarrow z_0} E[Y_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[Y_i|W_i, Z_i = z] = \\ \delta(W_i) \lim_{z\downarrow z_0} E[\delta_i' T_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[\delta_i' T_i|W_i, Z_i = z]\end{aligned}$$

where $\delta_l(W_i) := \lim_{r\downarrow 0} E[\delta_i|W_i, T_{li}(z_0 + r) - T_{li}(z_0 - r) \neq 0]$.Thus we have

$$\begin{aligned}\Delta_Y(W_i) :=& \lim_{z\downarrow z_0} E[Y_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[Y_i|W_i, Z_i = z] \\ =& \delta(W_i)\delta' \Delta_T(W_i) \\ \Delta_T(W_i) :=& \lim_{z\downarrow z_0} E[T_i|W_i, Z_i = z] - \lim_{z\uparrow z_0} E[T_i|W_i, Z_i = z]\end{aligned}$$

When the homogeneity assumption *is* satisfied, $\delta(W_i) = \delta$.

$$\delta_l(W_i) = E[\delta_{li}|W_i, \lim_{e \downarrow 0}(T_{li}(z_0 + e) - T_{li}(z_0 - e)) \neq 0]$$

$$= \begin{cases} E[\delta_{1i}|W_i, Z_i = z_0, 1(j, \not{c}) = 1], \text{ for } l = 1 \\ E[\delta_{2i}|W_i, Z_i = z_0, 1(j, c) = 1], \text{ for } l = 2 \\ E[\delta_{3i}|W_i, Z_i = z_0, 1(a, c, \not{p}) = 1], \text{ for } l = 3 \\ E[\delta_{4i}|W_i, Z_i = z_0, 1(a, c, p) = 1], \text{ for } l = 4 \end{cases}$$

Thus when the homogeneity assumption is violated, we recover

$$\bar{\delta}_1 = E[\omega_1(W_i)\delta_1(W_i)] + \sum_{l=2}^{4} E[\omega_l(W_i)\delta_l(W_i)],$$

where $E[\omega_1(W_i)] = 1$ and $E[\omega_l(W_i)] = 0$, for $l = 2, 3, 4$ (and analogously for $\delta_{l=2,3,4}$). That is, we identify the treatment of interest which is contaminated by an average of the other LATEs with weights that average to zero.