Judicial Transparency and Criminal Justice

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Abstract

Elected officials at all levels of governance routinely make decisions that affect large populations, often without public scrutiny. This study examines the effect of increased transparency on judicial decision-making by leveraging a legislative reform that mandated public disclosure of court fee waivers. Using a regression discontinuity design, we find that the share of cases with court cost waivers increased by nearly 120%. The effects varied across political districts and re-election timing, indicating that electoral incentives play a significant role in judicial responsiveness. We also find that the effect size decreases with defendant income, suggesting potential targeting of waivers for those with lower ability to pay. Additionally, transparency-induced reductions in monetary obligations led to lower recidivism rates and improved timely compliance among defendants.

Keywords: Judicial transparency, legal financial obligations, judicial discretion, electoral accountability
JEL Codes: K4, D72, H73, H74.

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1 Introduction

Elected public officials routinely tailor their decisions to the preferences of their constituents (Besley and Coate, 2003). Public office candidates tailor their platforms to align with voter interests, and once elected, they steer clear of decisions that could risk future rejection at the polls. Extensive research in political economy underscores that accountability to voters often leads to more favorable policy outcomes. However, accountability is only effective when the electorate is well-informed and able to assess the actions of those in power.

The United States is one of the few countries where judges are elected.[1] In addition to determining criminal sentences, judges also preside over a wide array of legal financial obligations (LFOs) – with a high degree of discretion.[2] Over recent decades, the use of fines and fees has expanded, with many state and local governments relying on LFOs to fund courts and other services. Reliance on LFOs as a form of regressive taxation has drawn attention and controversy (Makowsky, 2019). Recent estimates suggest that 1 in 3 Americans have been directly impacted by fines or fees related to traffic, criminal, juvenile, or municipal court in the past ten years (Fines and Fees Justice Center and Wilson Center, 2023). These court-imposed financial burdens, including fees, fines, and surcharges, often accumulate to disproportionately affect low-income and marginalized communities (Harris, Evans, and Beckett, 2010).[3] Despite its ubiquity and impact, judicial decisions concerning LFOs remain largely hidden from public scrutiny.

This paper examines how increased transparency of judicial decisions regarding the imposition of legal financial obligations (LFOs) affects subsequent judicial behavior and its implications for defendants. It explores how judges modify their decisions in response to greater transparency, how these changes impact defendants, and the collection of LFOs. Finally, it investigates the mechanisms driving these judicial reactions, shedding light on how transparency influences decision-making.

It is challenging, however, to identify the causal effects of judicial transparency on judicial discretion in the imposition of monetary sanctions for two main reasons. First, the degree of transparency in the policy environment can shape how judges adjust their decisions, raising endogeneity concerns when assessing the link between transparency and judicial behavior, necessitating exogenous variation in transparency.[4] Second, high-quality data on total court fees and fines assessed to

[1]Aside from the U.S., only Japan and Switzerland hold some judicial elections. Recently, Mexico reformed its judicial system to introduce the election of judges. Even within the US, there is variation in judicial selection and retention rules. See Table 1 in Lim and Snyder Jr (2021) for variations across states in selection and retention rules for state trial court judges.

[2]LFOs comprise of three main components. Court fees: these are service-based "user fees" to cover the cost of trials; fines: these are sanction-based payments intended to punish convicted defendants and deter future criminal activity; restitutions are payments from convicted defendants to victims. See LaScala-Gruenewald and Paik (2023); Fernandes et al. (2019); Martin et al. (2018) for an overview of recent literature on LFOs.

[3]Gaebler et al. (2023) provides alarming evidence about debt imprisonment, where courts jail individuals for failing to pay LFOs. They estimate that between 2005 and 2018, around 38,000 residents in Texas and 8,000 in Wisconsin were jailed annually for failing to pay, often for minor offenses like traffic violations. These findings underscore the severe consequences LFOs have for low-income individuals.

[4]For instance, when decisions are not salient to the public, elected officials might feel less pressure to align with

defendants is difficult to obtain, and when available, it is often net of judicial discretion.

We leverage a policy change that provides exogenous variation in the transparency of judicial decisions. In 2014, North Carolina's legislature mandated the disclosure of judges' decisions regarding criminal court cost waivers, requiring the Administrative Office of Courts to produce reports on these decisions for all judges. Before this mandate, judges exercised discretion over waivers without their decisions being publicly visible. This policy change creates an ideal natural experiment to study the effects of increased transparency on judicial behavior.

To address the data challenge, we construct novel data on judges serving in North Carolina District courts, linking it to the universe of administrative court records from the state's Administrative Office of Courts. These records include detailed information on all criminal offenses, defendants' demographic characteristics, offense details, and the judges' initials presiding over each case. Importantly, this data allows us to observe judicial discretion in administering court fees, specifically whether a judge granted or waived court costs in a given case.[5]

We leverage this legislative change in a regression discontinuity (RD) design to estimate the causal effects of increased oversight on judicial decisions. This design allows us to compare individuals convicted before and after the law's effective date.[6] In RD designs, the key identifying assumption is the continuity of potential outcomes around the running variable; however, we find no evidence of manipulation or systematic sorting around the threshold.

It is unclear, a priori, whether increasing the salience of judicial decisions will lead to judges waiving court costs more or less frequently. On the one hand, judges may be inclined to increase the rate of waivers to project a more generous image or to align with the electorate's preferences. On the other hand, they may decrease the number or share of waivers to avoid being perceived as contributing to revenue loss or to cater to the electorate's preference. Moreover, judges might have limited responsiveness due to institutional constraints, legal precedent, or the need to maintain impartiality and adhere to sentencing guidelines.

Following the mandatory disclosure of criminal court cost waivers, the court cost waiver rate increased by about 8 percentage points – nearly a 120% increase from the baseline waiver rate of 7%. Since granting court cost waivers effectively amounts to a reduction in LFOs facing defendants, judges could potentially exercise their discretion to make adjustments on other financial obligations to counteract the increase in waivers. However, we do not find evidence of any such adjustments, either in the extensive margins–such as share of convictions resulting in any fines—or in the intensive margins, which would involve changing the amounts of fines levied against defendants. Additionally, we can rule out any adjustments in judges' non-monetary sentencing decisions, including the share of convictions resulting in incarceration or the length of incarceration spell.

public expectations. Conversely, they may be more inclined to align with the electorate's preferences when their actions are more transparent.

[5]We observe judicial discretion over court costs in even greater detail, as described in Section 2.

[6]In recent work, Giles (2023) and Finlay et al. (2024) adopt a similar RD in time design exploiting sentencing date cutoffs to examine the effects of statutory LFO increases.

Interestingly, despite a higher share of convicted defendants receiving waivers, the average assessed court cost per defendant increased. Since judges lack the statutory authority to set the amounts for assessed court costs, we attribute this modest increase to the judges' choices regarding which cases to waive costs. In the post-period, judges granted more waivers for cases at the lower end of the assessed cost distribution while reducing waivers for those at the higher end.

The average effects of mandatory disclosure on judicial court cost waivers mask significant heterogeneity. Judges in Democratic districts have a baseline waiver rate three times higher than those in Republican districts. However, both see an 8 percentage point increase in waiver rates following the mandatory disclosure mandate. Despite similar effect sizes, waiver rates in Democratic districts remain 7 percentage points higher than in Republican districts. Since the electorate only observes waiver rates from 2015 onward, this gap likely reflects differences in preferences and expectations of voters in these areas.

Our findings suggest that electoral incentives drive changes in judges' waiver decisions following mandatory disclosure of court cost waivers. Judges facing re-election sooner increased waivers by 10 percentage points, while those with more time before re-election showed a smaller effect. In competitive districts, mandatory disclosure led to an even larger increase in waivers, rising by 15 percentage points—nearly double the average effect size. Overall, these results highlight the influence of political context and electoral incentives on judicial behavior under transparency reforms.

To help understand mechanisms driving changes in cost waivers, we develop a conceptual framework wherein incumbent judges are driven by re-election incentives. In this framework, judges strategically decide the share of cases to grant waivers, based on the size of the vulnerable population, the transparency of their decisions, and their political support. The model predicts that judges will increase waivers with greater transparency, a larger vulnerable population, and lower political support. Political competition is key, as it drives judges to adjust their behavior to improve re-election prospects.

To understand the impact of mandatory disclosure on court cost waivers and lower LFOs, we examine the characteristics of defendants who benefited from the policy. Compliers—those who began receiving waivers post-disclosure—are more likely to be a minority and from lower-income areas. They are also more likely to have prior records and face serious charges like violent and property crimes, while traffic offenses are less common. Compliers are also more likely to have indigent defense and higher incarceration rates. These findings suggest that compliers face greater legal challenges and harsher outcomes than the general defendant population.

Next, we examine the impact of increased transparency in judicial waivers on recidivism, focusing on both criminal involvement and convictions over 1, 2, and 3-year horizons. The results indicate a consistent decline in overall criminal involvement, with the effects growing stronger over time. Defendants sentenced after the transparency mandate are 1.7 percentage points less likely to face new charges within 3 years, translating to a reduction in criminal involvement of around 10%. However, the impact on financially motivated crimes is minimal, suggesting that the reduction in recidivism is primarily driven by non-financial offenses, which show a 12% decrease over 3 years.

Our study contributes mainly to three different strands of literature. First, our study relates to the broader political economy question of the effect of electoral accountability on elected officials' behavior (Besley and Coate, 2003; Maskin and Tirole, 2004; Alesina and Tabellini, 2007, 2008). We provide some of the first causal evidence on the effects of transparency in the criminal justice system, specifically focusing on how disclosure influences judicial decision-making.[7] Within the criminal justice system, our work closely relates to Lim, Snyder Jr, and Strömberg (2015), which focuses on violent crimes and finds that greater media coverage increases sentence lengths for nonpartisan elected judges. Our research departs from theirs by examining the role of transparency through mandatory disclosure rather than media coverage. Whereas their study explores how media scrutiny leads to harsher sentencing for serious crimes, our paper investigates how public disclosure of judicial decisions on legal financial obligations (LFOs) affects waiver decisions across a broad range of crime types. Additionally, we leverage an exogenous policy change as a natural experiment, offering a novel contribution to understanding how broad-based transparency reforms, rather than media influence, shape judicial discretion.

Second, this paper adds to the literature on the influence of "extra-legal considerations" in judicial decision-making, demonstrating how factors beyond the law–such as judges' characteristics, political affiliations, and external pressures–can shape sentencing outcomes.[8] While judges are expected to be impartial, mounting evidence reveals that their decisions are often shaped by strategic behavior and external influences. For instance, Boston and Silveira (2023) show that judges in North Carolina adjust their sentencing based on changes in their electorate's ideology after a shift from statewide to district-level elections. Numerous studies have also documented the presence of electoral cycles in sentencing decisions, showing that elected judges impose longer sentences when facing re-election (Huber and Gordon, 2004; Gordon and Huber, 2007; Berdejó and Yuchtman, 2013; Abrams et al., 2023).[9] Dippel and Poyker (2019) find significant heterogeneity across states in the presence of electoral sentencing cycles, arguing that the strength of these cycles depends on the competitiveness of judicial elections. We provide new evidence on these "extra-legal factors" in judicial decisions by showing that judges serving in districts with differing political leaning ex-

[7]Outside of the judicial system, our work closely relates to Banerjee et al. (2024), who experimentally examine the effects of anticipated pre-election disclosures on political performance and electoral outcomes among the city councilors in New Delhi. They find that anticipation of public disclosures motivated councilors representing high-slum wards to better align spending priorities with their constituents.

[8]Studies have documented a wide range of factors influencing judges' sentencing decisions, including gender, ethnicity, ideology, and political affiliation (Lim, Silveira, and Snyder, 2016; Harris and Sen, 2019; Cohen and Yang, 2019; Beim, Clark, and Lauderdale, 2021). Abrams et al. (2022) provide evidence of local sentencing norms, showing that judges in new courts gradually converge toward these norms through learning.

[9]Other actors in the criminal justice system also exhibit electoral cycles in their decisions. Guillamón, Bastida, and Benito (2013) show that municipalities increase police spending in election years; Dyke (2007) and Okafor (2021) show that defendants face a higher probability of conviction in District Attorney's election year.

hibit different responses to anticipated transparency of their decisions. While prior research has documented electoral sentencing cycles for severe crimes, we show that such cycles also exist for a broader range of crime types.[10]

Lastly, this paper adds to a growing empirical literature on LFOs by examining judicial discretion in court cost waivers.[11] Prior studies on LFOs explore a range of outcomes, including fiscal incentive of LFOs for law enforcement behavior (Harvey, 2020; Makowsky and Stratmann, 2009, 2011), the deterrent effects of fines on recidivism (Traxler and Dušek, 2023; Gonçalves and Mello, 2023; Diaz, 2024), and the impact of fines on defendants' financial health and payment behavior (Kessler, 2020; Mello, 2023; Giles, 2023; Pager et al., 2022).[12] Finlay et al. (2024) study a broad range of statutory increases in fines and find null effects of higher fines on the future criminality of defendants and their labor market outcomes.

The role of judicial discretion in administering LFOs is relatively understudied.[13] Norris and Rose (2023) broadly examines the fiscal and deterrence implications of LFOs, showing that increasing LFOs can generate a "Laffer curve" effect, where higher fines eventually reduce net revenue due to defaults. They argue that targeting LFO reductions for disadvantaged defendants may not only increase revenue but also improve equity in outcomes. In our setting, judicial discretion in granting court cost waivers can potentially target exactly these defendants – those with limited ability to pay and a higher likelihood of default. We provide suggestive evidence that, following mandatory disclosure of judicial decisions on court waivers, judges increasingly granted waivers to defendants from high-poverty areas.

The remainder of the paper is structured as follows. Section 2 provides a brief overview of the criminal justice system in North Carolina, how court costs are assessed, and describes the policy that increased the salience of court cost waivers. Section 3 describes the data we use and provides some summary statistics. Section 4 describes our empirical strategy. Section 5 presents the results

[10] Research on judicial electoral sentencing cycles has primarily focused on severe crimes. Huber and Gordon (2004) restrict to cases of aggravated assault, rape, and robbery convictions in Pennsylvania; Berdejó and Yuchtman (2013) restrict to severe crimes like assault, murder, rape, and robbery in Washington. These severe cases only constitute a small share of cases in state courts (see Table 1 in Dippel and Poyker (2019)). These studies emphasize that electoral cycles should be expected primarily for more severe crimes because these are more visible to voters.

[11] Other studies investigate discretion in different contexts. For instance, Gonçalves and Mello (2023) studies police discretion in Florida traffic stops, showing that a \$125 increase in fines reduces the likelihood of reoffending by 1.6 percentage points. Research on prosecutorial discretion includes work by Agan, Doleac, and Harvey (2023), Fischer and Ludwig (2024), and Harrington and Shaffer (2024), all focusing on different aspects of discretion in the criminal justice system.

[12] Traxler and Dušek (2023) find strong deterrence effects of speeding tickets, finding that receiving a ticket (extensive margin) reduces speeding by one-third and re-offense rates by 70%, but limited additional deterrence effects of higher fines (intensive margin). Gonçalves and Mello (2023) utilize police discretion over fines and find that higher fines reduce the likelihood of future traffic offenses. Pager et al. (2022) conducted a randomized controlled trial in Oklahoma County, offering debt relief to misdemeanor defendants. They do not find any significant effect of debt relief on future criminal behavior, but it did lead to increased debt collection and court supervision for unpaid fines. However, they can't rule out a wide range of estimates resulting from a small sample size. Giles (2023) exploit sentencing date cutoff to examine the effects of statutory fine increases in Milwaukee, Wisconsin, and find that higher fines increase the likelihood of defendants carrying outstanding court debt and re-offending.

[13] Diaz (2024) is a notable exception, who uses a judge leniency design to study the impact of fine imposition and finds that fines reduce reoffending by 9 percentage points within two years.

on changes in judicial decision-making with increased transparency, and Section 6 discusses the downstream effects of lower LFOs on future defendant outcomes, and at last, Section 7 concludes.

2 Background and Conceptual Framework

North Carolina's criminal justice system follows a unified structure known as the General Court of Justice, divided into three main divisions: the District Court Division, the Superior Court Division, and the Appellate Division. District Courts handle lower-level offenses, such as misdemeanors, infractions, and family law matters like divorce, child custody, and support. Superior Courts serve as the highest trial courts, managing all felony cases, major civil matters, and appeals from District Court decisions. In the Appellate Division, the Court of Appeals and the Supreme Court review legal procedures and interpretations of law. The Supreme Court, as the highest court in the state, addresses significant legal and constitutional issues. Additional details on the structure of the judicial system in the state are provided in Appendix A. This paper focuses on district courts, which have primary jurisdiction over misdemeanor and infraction cases.

At the trial court level, the judicial system is divided into several districts for electoral and administrative purposes. District court districts are comprised of one or more counties. Some districts comprised only one county, while others comprised as many as 7 counties.[14] Appendix figure A.1 maps judicial districts and counties in 2014. In 2014, there were 42 District court districts, and the number of judges per district varied significantly, ranging from as few as 2 to as many as 21, depending on the district's population and geographic area. At a time, about 270 judges serve in District courts across the state.

Judges in the District Courts are elected for four-year terms under the non-partisan system. When vacancies arise, the governor appoints judges to serve until the next election, a common pathway to office for many judges.

2.1 Legal Financial Obligations

There are three broad components of legal financial obligations (LFOs): court fees, fines, and restitution. Fines and restitution are part of the criminal sentence and are at the judge's discretion. On the other hand, court fees are assessed to all convicted defendants and consist of several "user fees". These fees are assessed at the disposition and cover different aspects of the criminal and legal process.

Court fees, our primary focus in this paper, broadly fall into two categories: basic costs and contingent costs. Basic costs apply to all convicted defendants. Contingent costs constitute addi-

[14] We obtain the mapping of judicial districts for district courts from the North Carolina Judicial Branch and the historical and current composition of judicial districts in the states can be found here: https://www.nccourts.gov/documents/publications/prior-judicial-districts-maps

tional costs determined by the individual factors for each case (supervision fee, jail fee, etc.), or specific offenses (e.g., impaired driving, etc.) and are assessed in addition to the basic costs. A defendant convicted in the District Court can expect to pay a minimum of $173 upon conviction. The state legislature (General Assembly) determines court fee amounts, which apply uniformly across the state. Courts and judges do not have the discretion to change these fees. A more detailed breakdown of court costs for the types of cases under study in this paper is in Figure A.2.

Although judges do not have any discretion over the assessed court fee amounts, they do have discretion to waive or to allow a party to delay their payment.[15] However, judges must provide a written finding of "just cause" whenever they grant a full or partial waiver of criminal court costs.[16] These typically include defendant's ability to pay considerations. Appendix Figure A.3 shows an example of "just cause" considerations judges make before ordering relief from financial obligations.

Courts have two primary mechanisms to enforce the collection of LFOs, in case of a nonpayment.[17] First, through the criminal legal system, courts can penalize defendants for nonpayment by revoking their driver's licenses, imposing additional monetary sanctions, extending probation, or even ordering jail time. Second, courts can enforce the payment of LFOs through the civil legal system by issuing a civil order known as a judgment, which a court clerk then dockets to create a public record of debts. Once docketed, this judgment acts as a lien against any real estate owned by the defendant within that county, potentially leading to civil asset forfeiture and accruing interest (Sparko et al., 2023; Markham, 2017).

2.2 Monitoring of Criminal Court Cost Waivers

Following the Great Recession, the state and local governments' reliance on fines and fees revenue increased significantly. As local tax revenues dropped and tax increases became less politically viable, jurisdictions increased the amounts of fines and fees and imposed them more frequently to fund government services (Harris, Ash, and Fagan (2020); Harris et al. (2017); Singla, Kirschner, and Stone (2020)). In North Carolina, the General Court of Justice Fees in District courts increased by 37% from $126 in 2010 to $173 in 2011. Figure A.4 shows trends in General Court of Justice Fees in the state over the years. Notably, after 2011, there haven't been any increases in the basic costs component of court costs.

[15] Judges, however, have discretion over other components of monetary obligations. The fine amounts are at the complete discretion of the judge, except for Class 2 and 3 misdemeanors, whose maximum amount is capped. For Class 2 misdemeanors, fines cannot exceed $1,000; for Class 3 misdemeanors, the maximum is $200.

[16] S.L. 2011-145, § 15.10.(a)., S.L. 2012-142, § 16.6(b)

[17] Monetary obligations from criminal and infraction cases are due at the time of conviction. However, payment can be delayed to a later date or paid in installments over time for a one-time fee of $20 to cover the State's costs of processing these future payments. If the total amount is not paid within 40 days of conviction (or within 40 days of the date allowed by the court) this triggers what is referred to as a "failure to comply" (FTC), which carries an additional fee of $50 and requires the defendant to appear in court and "show cause", i.e., to explain why they should not be jailed or otherwise penalized for their failure to comply.

The increase in court costs in North Carolina was accompanied by heightened monitoring of court cost waivers. Judges in the state are required to make a written finding of "just cause" whenever they grant a waiver of criminal court costs. A 2011 legislation mandated the Administrative Office of Courts to maintain records of all cases in which the judge makes a finding of a "just cause" to grant a waiver of criminal court costs.[18] This mandate was largely a monitoring exercise that enabled state legislature to gauge the extent of criminal court cost waivers in the state (Bantz, 2014).

Mandatory Disclosure of Criminal Court Cost Waivers: In June 2014, the North Carolina State Legislature subsequently modified General Statue § 7A-304(a), mandating NCAOC to report on criminal cost waivers to 3 different Justice and Public Safety committees by February 1 of each year.[19] This legislative change specifically required the NCAOC to aggregate the waivers by the district in which the waiver or waivers were granted and by the name of each judge granting a waiver. Although the legislation was passed on June 30, 2014, it didn't become effective until January 1, 2015. The NCAOC has complied with this mandate and published reports on criminal cost waivers for each calendar year since 2015.[20] It released its first report on criminal court cost waivers in February 2016, covering the calendar year 2015. We discuss the implications of the gap between when the law was enacted and when it became effective in more detail in Section 4.

Although there are no stated official reasons for tracking court cost waivers, some legislators argue that it is fundamentally about accountability, emphasizing the need to hold courts accountable for recouping costs from criminal defendants. They assert that the monitoring of waivers is not intended to punish counties with high numbers of waivers; instead, waiver statistics serve an important role from a taxpayers' protection standpoint. Legislators believe that identifying areas with unusually high amounts of waivers can help local judicial officials recognize when they deviate from the norm. Conversely, some judges perceive the tracking requirement as intended to create a chilling effect, potentially deterring them from granting waivers (Bantz, 2014).

This legislative mandate received extensive coverage in several articles, including Markham (2014), Bantz (2014), and Musgrave and Hager (2017). In particular, Bantz (2014) reports on the prevalence of court cost waivers across counties, based on an interim NCAOC report. The report highlights significant differences in waiver rates among counties. Additionally, there is a marked difference between North Carolina and the rest of the United States in terms of search intensity for court costs. Appendix Figure A.5 shows the trends in search interest for the "court cost" topic

[18] S.L. 2011-145, § 15.10.(a); N.C. General Statue § 7A-304

[19] The exact verbatim of the legislation states: "The Administrative Office of the Courts shall make the necessary modifications to its information systems to maintain records of all cases in which the judge makes a finding of just cause to grant a waiver of criminal court costs under G.S. 7A-304(a) and shall report on those waivers to the Chairs of the Senate Appropriations Committee on Justice and Public Safety, the Chairs of the House Appropriations Subcommittee on Justice and Public Safety, and the Chairs of the Joint Legislative Oversight Committee on Justice and Public Safety by February 1 of each year. The report shall aggregate the waivers by the district in which the waiver or waivers were granted and by the name of each judge granting a waiver or waivers." – Source: https://www.ncleg.net/EnactedLegislation/SessionLaws/HTML/2013-2014/SL2014-100.html

[20] Link to waiver reports: here

between 2010 and 2019 for North Carolina and the rest of the United States. Notably, the search interest for court costs in the state is consistently higher than in the rest of the country. In addition, there is an uptick in search interest in last 2 quarters of 2014, and that coincides with the legislative change.

2.3 Conceptual Framework

In this section, we adapt the model from Besley and Burgess (2002) to develop a conceptual framework for analyzing the decision-making process of judges when determining whether to grant court cost waivers.

We consider a two-period model, wherein at the beginning of period 1, an incumbent has been voted or appointed to the office. Each incumbent decides on the share of cases to grant court cost waivers, denoted by s ($s \in [0, 1]$). There are three types of incumbents: 1) lenient judges who always grant waivers when litigants are in financial distress; 2) harsh judges who never grant waivers for financial obligations; and 3) strategic judges who grant court cost waivers if it increases their likelihood of re-election. Judges are driven by re-election incentives, and an incumbent judge derives a value of V from holding office.

There are two types of citizens. Citizens with direct contact with the criminal justice system constitute share $\theta < \frac{1}{2}$ of the population, and share without direct contact with the criminal justice system constitute $(1-\theta)$ of the population. We call these two groups of citizens vulnerable and non-vulnerable groups, respectively. Among the vulnerable group, a share γ faces financial hardships, and we call this group the needy group.

Incumbent judges' waiver of criminal court costs is not directly observable. However, the needy litigants ($\gamma\theta$) can acquire information in two ways – directly through their own experience with the incumbent and indirectly via the degree of transparency of judicial waivers. We denote it as $p(s, o)$.[21]. Non-needy, vulnerable litigants can only learn about the incumbent judge's propensity to waive court costs indirectly, i.e., through the degree of transparency of waivers. We denote this as $q(s, o)$. The total fraction of vulnerable litigants who become informed about the incumbent judge's propensity to waive court costs is:

$$\sigma(s, o, \theta) = \gamma\theta\, p(s, o) + (1 - \gamma)\theta\, q(s, o)$$

After the citizens have learned about the incumbent judges' court cost waivers, there is an election in which the incumbent faces a randomly selected challenger. In period 2, a random fraction of the vulnerable population may still be needy. All vulnerable citizens informed of non-zero s by judges weakly prefer to vote for the incumbent. The non-vulnerable share $(1 - \theta)$ of

[21] Probability that a needy litigant is informed about the incumbent waivers is $p(s, o) = s + (1 - s)f(o)$, where they receive a waiver with probability s, and with probability $1 - s$ they may still learn about incumbent judge's waivers through the degree of transparency of waivers. We assume that $f'(o) > 0$ and $f(0) = 0$

the population votes based on ideology, other features of judges' performance, competence, and/or criminal sentencing history unrelated to criminal court cost waivers. The support for incumbent among the non-vulnerable population, denoted as (λ), is uniformly distributed over $[a, 2b-a]$.[22] Assume that the uninformed, vulnerable voters do not vote.[23] The incumbent wins the election if

$$\sigma(s,o,\theta)+(1-\theta)\lambda>\frac{1}{2}$$

For a given support (b) for the incumbent, the probability that the incumbent wins if they waive court costs in s share of cases is given by:

$$P(s;o,\theta,\gamma,b,\phi)=\begin{cases}1, & \text{if } \lambda^*<a \quad \text{(Incumbent always wins)}\\ \frac{1}{2(b-a)}\left((2b-a)-\lambda^*\right), & \text{if } a<\lambda^*<2b-a \quad \text{(Probability between 0 and 1)}\\ 0, & \text{if } \lambda^*\geq 2b-a \quad \text{(Incumbent always loses)}\end{cases} \tag{1}$$

where:

$$\lambda^*=\frac{\frac{1}{2}-\sigma(s,o,\theta)}{1-\theta}, \quad \sigma(s,o,\theta)=\theta\left[\gamma\, p(s,o)+(1-\gamma)\, q(s,o)\right]. \tag{2}$$

An incumbent judge chooses the share of cases s to maximize,

$$P(s;o,\theta,\gamma,b,\phi)V-c(s)$$

where V is the value of holding office, $c(s)$ is the disutility cost of granting waivers, $P(.)$ is the probability of re-election.

First-order conditions imply:

$$\frac{\theta V}{2(b-a)(1-\theta)}[\gamma p_s(s^*,o)+(1-\gamma)q_s(s^*,o)]=c_s(s^*) \tag{3}$$

Judges will increase cost waivers if the marginal benefit (LHS in 3) of doing so outweighs the marginal cost (RHS in 3). This generates several testable predictions. First, greater transparency of their waiver decisions is expected to increase the share of waivers. Second, a larger vulnerable population (θ) will also lead to more waivers, as judges may respond to the greater need within this group. Third, incumbents with lower expected political support (lower b) are predicted to

[22] We restrict $1>a>b$ and $2b-a<1$ such that the support for the incumbent among the non-vulnerable population lies between 0 and 1.

[23] We impose this restriction for simplicity. We can allow uniformed vulnerable voters to vote randomly or similarly to the non-vulnerable population.

increase waivers as a strategic move to improve their standing. Lastly, a larger needy population (γ) amplifies this effect, leading to even more waivers. Importantly, political competition serves as a necessary condition for any responsiveness by strategic incumbent judges.

3 Data

This section provides an overview of the data sources, how they were collected and linked, the construction of key outcome variables, and concludes with descriptive statistics. Additional details of the data cleaning procedure are included in Appendix C.

3.1 Court Records

The main data for our analysis comes from the Active Criminal/Infraction System (ACIS), maintained by the North Carolina Administrative Office of the Courts (NCAOC), and encompasses the universe of criminal cases in North Carolina. Our data extract covers all criminal cases in the state whose last update was between January 1, 2013, and December 31, 2021. The data allow us to track the progress of individuals interacting with the criminal justice system from arrest to sentencing.

The ACIS data has two key components: 1) Case Records, and 2) Offense Records. The case records are at the *case-level* and have information on defendant demographics and case characteristics. Demographic information on defendants includes their date of birth, gender, race, and their exact address and ZIP code. Case characteristics include court type (district or superior court), county, and origination date. Importantly, for our empirical strategy, the case records data consists of the case trial date and case disposition dates, allowing us to observe the exact date when the decision on a case was made.

The offense records contain information on each charge for each criminal case. For each case, it includes the list of all charges and corresponding disposition outcomes. Each offense within a case contains the offense characteristics like offense date, offense type, offense class, offense description, and offense statute. Each offense charge includes information on the defendant's plea, verdict, and the type of disposition. Additionally, it contains the initials of the judges who make the disposition. Most importantly, it also contains detailed information on sentencing outcomes, including sentence length, fines/restitution, court costs, and whether the court costs were waived. Court cost waiver decisions and the assessed court costs are our outcomes of primary interest. Both case records and offense records contain unique case identifiers, allowing us to link them together. For each case, court costs are assessed at the case level, and we keep the most serious offense charge for each case. Descriptions of key variables and details of the data cleaning process are provided in Appendix C.1 and C.3, respectively.

3.2 Other Data

Political leaning of judicial districts: In North Carolina, judicial elections are held at the judicial district level. We construct the political leaning of a judicial district by using the party vote share in presidential elections. To do so, first, we obtain county-level level vote share by party in presidential elections from MIT Election Data and Science Lab (2018). Next, we map the counties to their judicial districts and classify a district as Republican-leaning or Democratic-leaning based on the vote shares of presidential candidates in the 2012 elections.

Judges' Profiles: We manually construct the profiles for all district court judges in North Carolina who served between 2013 and 2018 using various sources. We identify the universe of all *current* judges and the districts they serve in from the judicial directory of North Carolina and the list of past district court judges using `Ballotpedia.org`, along with other secondary sources.[24,25] For all district court judges who served between 2013 and 2018, we gather data on their name, race, gender, the year of their initial appointment, the years they were up for re-election and contested elections, and the year they left office. These detailed judge profiles complement the information on judges in court records, allowing us to characterize heterogeneity in judge responses to the increased salience of their judicial decisions.

American Community Survey (ACS): We use data from 2014-2018 5-year American Community Survey Census Block level tabulations to obtain neighborhood characteristics – and link it to the defendants' home addresses from court records – to construct proxies for defendants' economic characteristics.

3.3 Analytical Sample

Our analytical sample includes all cases in the District courts that were disposed between January 1, 2013, and November 30, 2017. Although our court records data extends until 2021, we restrict our analytical sample to only until November 2017 to avoid confounding from other legislation directly affecting court cost waivers.[26] We restrict our sample to only the cases where a final decision has been made. We drop cases with intermediate outcomes like pretrial proceedings, habitual felon offenses, offenses with superseding indictments, etc. Since only cases where a defendant is convicted are subject to court fees, we restrict our analytical sample to these convicted cases.[27]

[24] The judicial directory of North Carolina can be found here: https://www.nccourts.gov/judicial-directory

[25] For more information on the data collection process for judge's profiles, see Appendix C.3.

[26] Legislation enacted in 2017 mandated judges to give 15 days written notice to all affected agencies that stand to lose revenue from court fee waivers before issuing a waiver. This legislation, which went into effect on December 1, 2017, practically imposed additional bureaucratic costs on judges if they wish to waive court costs.

[27] In all subsequent analyses, we exclude acquitted defendants since they are not liable for any court costs, unless otherwise noted. Extremely low court fees may reflect data errors, since all convictions in District courts entailed a minimum court fee of at least $173 for convictions after July 2011.

3.4 Summary Statistics

In Table 1, we report the descriptive statistics of our analytical sample. After the data cleaning procedure, the main dataset includes about 6.1 million cases, with dispositions dated between January 2013 and November 2017 in North Carolina District courts. In column 1, we describe the characteristics of all cases in this sample. Since only cases where a defendant is found guilty are subject to court fees, in column 2, we restrict our focus to only convicted cases.Our analytical sample includes 1.5 million cases that resulted in a conviction.

Panel A describes the demographic characteristics of the defendants in our sample. The defendants in our sample are predominantly male (65%) and majority non-Hispanic white (49%) followed by African American (37%). Defendants in our sample live predominantly in low-middle-income neighborhoods with a median annual household income of $50,000. Details of the case characteristics are provided in Panel B. A disproportionately large share of cases have previous criminal charges (74%). A large share of cases have traffic-related offenses (66%).

Lastly, Panel C describes our primary outcomes of interest – court costs and court cost waivers. In column 1, which includes all cases in our analytical sample, court costs were waived for about 2% of cases. Among convicted cases, the court cost waiver rate is about 7%. waiver rates pre- and post-introduction of mandatory disclosure of judges' waiver decisions.

There is a large variation in court cost waivers across counties. In Figure 1, we show the spatial variation across counties in court cost waiver rate in the year right before and right after the introduction of the mandatory disclosure of court cost waivers by judges. In Panel A, we present the spatial variation across District courts in the year prior to the enactment of the legislation, while Panel B shows the variation across counties in the year right after the enactment of the mandatory disclosure law. Prior to the legislation, a large majority of the district courts in counties had very low criminal court cost waiver rates ($< 2\%$), with only a few counties with waiver rates higher than 5%. Judges in district courts in two counties, Cumberland and Robeson, waived court costs at a much higher rate ($> 20\%$) than the rest of the state. However, this changed dramatically in the year right after the legislation. District courts in several counties saw an increase in the court cost waiver rate, while a few counties saw a decline in the court cost waiver rates

4 Empirical Strategy

4.1 Regression Discontinuity Design

We exploit a legislative change in North Carolina that mandates the public disclosure of judges' decisions to waive criminal court costs to estimate 1) the causal effects of increased oversight on judicial decision-making and 2) the impact of reduced legal financial obligations (LFOs) on defendants. To estimate these effects, we use a regression discontinuity design, comparing individuals convicted before the law's effective date (untreated) with those convicted after (treated). Our regression model is as follows:

$$y_i = \alpha + \tau \times \text{Post}_i + \beta^{-}\text{ConvictionDate}_i + \beta^{+}\text{Post}_i \times \text{ConvictionDate}_i + u_i$$

where y_i is the outcome of interest for case i, Post_i is an indicator equal to one for cases disposed on or after January 1, 2015, and ConvictionDate_i is the running variable. τ is the causal parameter of interest, capturing the effect of the legislative change. We focus mainly on reduced form estimates, but provide fuzzy RDD/2SLS estimates for defendant outcomes in the Appendix.

There is a considerable gap between the enactment of the legislation in July 2014 and its effective date in December 2014. To prevent any potential confounding from anticipatory behavior by judges during this transition period, we exclude cases disposed of within this timeframe.[28] Consequently, our method aligns with the *donut* RDD design described by Barreca, Lindo, and Waddell (2016).

Our preferred specification for all outcomes is a local linear regression discontinuity design using a uniform kernel, with a bandwidth of approximately 400 days–depending on the outcome–on each side of the discontinuity (outside of the donut). We determine the bandwidth using the MSE-optimal selector proposed by Calonico, Cattaneo, and Titiunik (2014), allowing for different bandwidths on each side of the cutoff.[29] To test the robustness of our results, we also evaluate wider and narrower bandwidths (see Figure B.4). Additionally, we present results using a triangular kernel weighting function, a quadratic local regression, and specifications that exclude defendant and case covariates. We report both conventional standard errors and robust bias-corrected confidence intervals and p-values (Calonico, Cattaneo, and Titiunik, 2014).

4.2 Identifying Assumptions

The main identifying assumption in a continuity-based regression discontinuity design is that the average potential outcomes are continuous at the running variable's cutoff point (Hahn, Todd, and Van der Klaauw, 2001). In our context, this implies that there should be no systematic sorting of defendants around the threshold.

There are several ways this sorting could manifest. For instance, the anticipation of higher legal financial obligations (LFOs) might discourage poorer individuals from committing crimes, resulting in an imbalance in defendant characteristics on either side of the treatment threshold. Another concern is that certain parties might selectively delay or expedite sentencing to shift defendants across the cutoff in a way that correlates with the likelihood of receiving a waiver. For example, judges might rush sentencing for defendants they plan to grant waivers to, ensuring these waivers do not appear on next year's report on criminal cost waivers.

[28] This approach is similar to that used by Gerard and Gonzaga (2021) and Albanese, Cockx, and Dejemeppe (2024).

[29] We use the `R` package `rdrobust` (Calonico et al., 2017).

To address this, we first test for discontinuities in observable defendant characteristics at the cutoff by estimating the following equation:

$$x_i = \alpha + \tau \times \text{Post}_i + \beta^{-}\text{ConvictionDate}_i + \beta^{+}\text{Post}_i \times \text{ConvictionDate}_i + u_i$$

where x_i represents various defendant attributes for case i, including race (whether the defendant is Black), gender (whether male), age at arrest, type and severity of the crime, number of prior convictions, number of concurrent convictions, and neighborhood income. The results, displayed in Table **??**, show no evidence of sorting based on these observable characteristics.

Next, we examine whether there are discontinuities in the density of cases around the cutoff, as well as in the time from arrest to sentencing, which could indicate strategic scheduling. Additionally, we test for breaks in estimated "risk scores," which predict the likelihood of receiving total or partial waivers based on logistic regressions of defendant demographics and case details. The results of these tests, presented in Figure 2, also show no evidence of systematic sorting.

Finally, a common concern in regression discontinuity designs that use time as the running variable is the potential overlap between the policy cutoff date and seasonal patterns. For example, it is reasonable to question whether defendants sentenced at the start of a new year might systematically differ from those sentenced at the end of the previous year due to seasonal trends in offenses. Thus, there could be spurious seasonality around January 1. To address this concern, we present the distribution of RDD estimates in Figure B.3 across 273 placebo regressions, including all other January 1s in our data (2016, 2017, 2028, 2019, 2020, 2021). These results are discussed later in Section 5.3.2.

5 Results

In this section, we discuss the main findings on the effects of increasing the salience of judicial decisions through mandatory disclosure of court cost waivers by judges. In particular, we examine how judges adjust their court cost-waiving behavior in anticipation of increased salience of their decisions.

5.1 Effects on Judges' Behavior

Figure 3 shows our main results. We present the results in tabular form in Table 2 presents sharp regression discontinuity design (RDD) estimates evaluating the impact of a mandatory disclosure law on the likelihood of defendants receiving any court cost waiver at case disposition. Columns 1 and 2 use uniform and triangular weighting kernels, respectively. Column 3 controls for prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. In column 4, instead of a linear local polynomial, we report estimates with a local quadratic fit. Across all specifications, the mandatory reporting of criminal court cost waivers led to an increase in court cost waiver rate by about 8 percentage points. This change, albeit seemingly small, reflects a change of nearly 120% from a baseline waiver rate of about 6.6%. Given that, on average, there are nearly 300,000 convictions annually by District court judges in the state during our analysis period, court costs were waived for an additional 23,000 defendants every year following the mandatory disclosure requirement.[30] We present additional robustness and heterogeneity in waiver rates in Section 5.3.

In Tables B.1 and B.2, we present estimates by breaking them down by the type of waiver – full or partial waivers. In the case of total waivers, all court costs are entirely waived, while in the case of partial waivers, only a portion of the court fees is waived. After the mandatory disclosure law was enacted, total and partial waivers increased by 6.3 p.p. and 1.3 p.p., respectively.

An interesting pattern in waivers emerges between the law's passage date and its effective date, i.e., between July 2014 and December 2014. Notably, we observe a significant break in the waiver rate around July. Since the legislation did not specify an exact implementation date, judges may have had varying interpretations of when the law would become effective. Some judges might have assumed the law was immediately in force, prompting them to adjust their behavior in anticipation of heightened scrutiny preemptively. Additionally, the NCAOC released a statewide report on court fee waivers in September 2014, which may have played a role in shaping judicial behavior during this period (Bantz, 2014).

Other sentencing margins: Since granting court cost waivers effectively amounts to a reduction in LFOs facing a defendant, judges could potentially exercise their discretion to adjust other financial obligations to counteract the increase in waivers. In Table 3 (Figure 4), we present results on these other margins. However, we do not find evidence of any such adjustments, either on the extensive margins or on the intensive margin. In column 2, the point estimate on average fines (0.15 (s.e=0.42) can rule out fine increases of more than a dollar on average. Similarly, we can rule out any adjustments in judges' non-monetary sentencing decisions, including the share of convictions resulting in incarceration or the length of incarceration spell.

Interestingly, despite a higher share of convicted defendants receiving waivers, the average assessed court cost per defendant increased. Since judges lack the statutory authority to set the amounts for assessed court costs, we attribute this modest increase to the judges' choices regarding which cases to waive costs. In the post-period, judges granted more waivers for cases at the lower end of the assessed cost distribution while reducing waivers for those at the higher end.

[30] Note that there are more convictions than those decided by judges. These include convictions by magistrates and guilty pleas with waived court appearances. We restrict our sample to only the cases where a decision is made by a judge.

5.2 Determinants of Waiver Decisions

We analyze the characteristics of defendants and cases where mandatory disclosure increased the likelihood of receiving a court cost waiver, leading to reduced legal financial obligations (LFOs). To do this, we apply methods from the instrumental-variable (IV) literature to identify and profile the defendants whose court costs were waived–referred to as "compliers" in this context.

In an experimental framework, the population can be divided into four groups based on their response to treatment: compliers, always-takers, never-takers, and defiers. Always-takers receive the treatment regardless of assignment, never-takers consistently reject it, compliers accept the treatment when assigned, and defiers always do the opposite of their assigned treatment.

To characterize the compliers, we follow the methodology of Dahl, Kostøl, and Mogstad (2014) and Frandsen, Lefgren, and Leslie (2019). Specifically, we estimate complier means by regressing the treatment, interacting with the characteristic of interest, on the treatment instrumented using an indicator for cases disposed on or after January 1, 2015.

Table 4 compares covariate means of always-takers and compliers. In the RD-in-time setting, convicted cases that received court cost waivers before the mandatory disclosure are always-takers, while those that change treatment status discontinuously in January 1, 2015, correspond to compliers. Column 1 shows the demographic and case characteristics in our analysis sample. Column 2 shows the characteristics of the always-takers, and Column 3 shows the compiler group's characteristics.

Panel A examines the demographic characteristics of convicted defendants in our analytical sample. Two-thirds of the convicted defendants in our sample are male; however, this proportion increases among always-takers and compliers, where about three-fourths are male, respectively. Minorities are overrepresented among the always-takers and compliers (62% and 57%, respectively), relative to all convictions (51%). When it comes to income levels, a larger proportion of always-takers and compliers reside in zip codes with median annual income less than $42,000 - 34% and 40%, respectively – compared to 25% in the full sample. Conversely, fewer always-takers (20%) and compliers (14%) live in zip codes with a median annual income greater than $61,000, compared to 25% in the full sample. The age distribution remains relatively consistent across all groups.

Panel B details offense characteristics. Nearly a quarter of the convicted defendants have multiple charges, with a similar share among always-takers (19%) and compliers (22%). A significant difference emerges in prior records: 27% of the defendants in our analytical sample have a prior record, while this figure increases to 49% among always-takers and 64% among compliers. Regarding offense types, violent offenses account for 2% of the full sample but rise to 6% among both always-takers and compliers. Property offenses are more common among always-takers (19%) and compliers (21%) than in the full sample (8%). Traffic offenses are predominant in the full sample at 66%, but are significantly less likely to be among always-takers (25%) and compliers (22%). In terms of offense seriousness, more severe offenses are more prevalent among always-takers and compliers. Offense Class A1 represents 3% of the full sample but increases to 8% in both subgroups. Offense Class 1 is observed in 19% of the full sample, rising to 40% among always-takers and 32% among compliers. Conversely, Offense Class 3, which is less severe, is more common in the full sample (60%) than among always-takers (28%) and compliers (35%).

Panel C examines case and disposition characteristics. Indigent defense representation is more likely to be among always-takers and compliers relative to the full sample. About half of the always-takers and compliers have indigent defense representation, even though they only constitute about 20% in the full sample. The proportion of individuals representing themselves (pro se) is relatively consistent across groups, at about a third in the analytical sample, among always-takers and compliers. Nearly half of the convicted defendants had private attorneys, but fewer than a fifth of convictions constitute the always-takers and compliers. The likelihood of incarceration differs markedly across groups. In the analytical sample, about a third of convictions resulted in incarceration, whereas about three-fourths of convictions resulted in incarceration among always-takers and compliers.

Overall, the always-takers and compliers tend to have higher proportions of males, minorities, and individuals with lower income levels. They are more likely to have prior records, face more serious offenses, and experience incarceration. Additionally, they are less likely to have private attorneys and more likely to rely on indigent defense or represent themselves.

5.3 Heterogeneity and Mechanisms

In this section, we explore the mechanisms underlying changes in judges' waiver decisions following the mandatory disclosure of their court cost waiver decisions. First, we examine heterogeneity along several dimensions, as guided by the conceptual framework in Section 2.3, and discuss the role of electoral incentives. We also discuss alternative mechanisms. Lastly, we discuss potential threats to causal interpretations of our results and present robustness.

Heterogeneity by Defendant Characteristics: There is a growing concern that LFOs disproportionately affect low-income defendants. Low-income defendants are less likely to comply with court-imposed financial obligations, as shown in Figure B.7. This raises the question of whether judges, under increased transparency, are more likely to target defendants with a lower likelihood of payment when granting waivers

To examine this, we analyze heterogeneity in judges' responses using a proxy for defendants' economic characteristics. Since we do not directly observe individual defendant income, we construct two proxy measures using data from the defendant's residence ZIP code. First, we use the median income of the defendant's ZIP code as a proxy for their income level. Second, we utilize the poverty rate in the defendant's ZIP code as an alternative measure of economic context. Figure 8 presents the estimates for quintiles of each measure. Panel A shows the effects across five quintiles of median income. Although court waivers increase across all quintiles of defendant income, the effect size is nearly 3 times higher in the lowest quintile compared to the highest quintile, with a monotonically decreasing effect size across the income distribution. A similar pattern emerges in Panel B, which shows the RDD estimates for quintiles of poverty rates.

Heterogeneity by Political Leaning of Judicial Districts: District court judges in North Carolina are elected through non-partisan elections.[31] Although judges were not officially affiliated with political parties during elections in our study period, their behavior often reflects the preferences of their constituents (Boston and Silveira, 2023). Therefore, if judges are motivated by re-election incentives, increased transparency regarding their waiver decisions should encourage them to align more closely with the electorate's policy preferences.

Table 5 presents changes in waiver rates by judges in judicial districts with different political leanings. Notably, judges in Democratic districts (column 1) exhibit a substantially higher baseline waiver rate compared to their counterparts in Republican districts (column 2). Judges in Democratic districts are 3 times more likely to waive criminal court costs than those in Republican districts. However, the waiver rates for judges in both Democratic and Republican districts increase by about 8 percentage points following the mandatory disclosure mandate. Figure 5 illustrates these differences visually. Despite similar effect size across judges in Democratic and Republican judicial districts, the waiver rates in these districts differ by 7 percentage points. Given that the electorate only observes waiver rates from 2015 onward, this divergence likely reflects underlying differences in the political preferences and expectations of the electorate in these districts.

Re-election incentives and Electoral Competitiveness: We provide two additional pieces of evidence suggesting that changes in judges' waiver decisions are driven by electoral incentives. Judges in North Carolina District Courts are elected in biannual November elections and serve a four-year term in their district. They must seek re-election at the end of their current term. Judicial elections are, however, staggered such that only a portion of judges is up for re-election in any given election year. This creates an exogenous variation in time to re-election at the time when legislation mandating disclosure of court cost waivers becomes effective. Some judges are up for re-election sooner than others. Table 6 presents the effect of increased transparency on judicial waivers by time to re-election. Column 1 shows that judges facing re-election sooner (after 2 years in 2016) are 10 percentage points more likely to grant court cost waivers. On the other hand, judges up for re-election later (after 4 years in 2018) show a relatively smaller increase in waiver rates following the effective implementation of the mandatory disclosure law. Figure 6 shows these differences visually.

Next, we focus on judges' responses in competitive electoral districts. A defining feature of judicial elections in North Carolina, and more commonly across jurisdictions in the US, is that many incumbents seeking re-election do not face a challenger. Electoral incentives are stronger

[31] North Carolina District court judges were elected via non-partisan elections during our study period. However, this changed in 2018 when the state transitioned from non-partisan to partisan elections for judges.

in districts where incumbents face a challenger (Gordon and Huber, 2007).[32] Thus, we focus on districts where judges faced a challenger in the previous election cycle. Focusing on districts where incumbents faced a challenger in the previous election cycle is informative; however, it doesn't capture the likelihood of facing a challenger in the next election cycle or the nature of the political divisions within the district.[33] To this end, we use the vote shares of Presidential candidates in the preceding election and classify a district as "competitive" if the difference in vote shares in the district is less than 10 percentage points. Figure 7 presents the heterogeneity in waivers by the competitiveness of judicial districts. In competitive districts, we find that the mandatory disclosure of judicial waivers of court costs led to an increase in waivers by 15 percentage points, nearly double the effect size in Table 2.

Taken together, differences in waivers by judges in Democratic and Republican districts, differential responses by time to re-election, and substantially larger responses in competitive judicial districts highlight the role of political considerations in judicial decision-making pertaining to court cost waivers.

5.3.1 Alternative Mechanisms

Peer learning: A potential explanation for our finding can be the herding behavior by judges. In the absence of mandatory reporting of waivers, judges likely don't have a benchmark for how often other judges waive court costs. After the reporting requirement was introduced, judges may have become more aware of the court cost-waiving norms in their district and across the state, prompting them to align their behavior with their peers. However, the first report on waivers for 2015 was not released until February 1, 2016. Therefore, it is unlikely that the immediate changes we observe in waiver rates are driven by peer effects. Nevertheless, judges within the same courthouse may interact and learn about their peers' waiver behavior, becoming aware of where they stand compared to their peers. To explore this, we calculate the waiver rate for each judge and create a measure of dispersion in waiver rates among judges within the same district. In Figure B.2, we show that dispersion among judges in the same district increases following the mandatory disclosure requirement. If peer effects or learning were driving the observed changes, one would expect the dispersion in waiver rates within districts to decrease.[34] Thus, we can rule out the possibility that peer learning drives our finding of an increase in waiver rate.

Information Channel: Another potential explanation for the observed increase in fee waivers

[32] Serious challengers in competitive elections not only provide voters with alternatives at the ballot but also can scrutinize incumbents and inform voters about their qualifications and actions/performance in office. The mere prospect of having a challenger can significantly impact how incumbents behave. In our setting, waiver statistics can be used by challengers against their incumbent opponents, a possibility also echoed by Bantz (2014).

[33] As noted by, Gordon and Huber (2007), challenges to incumbents are endogenous to their behavior in office, rendering the existence of incumbents an imperfect measure of political competitiveness.

[34] Increase in dispersion in waiver rate among judges within a judicial district may partly reflect judges distinguishing themselves from their peers for electoral reasons. We are limited in our scope to test this formally.

is that judges were previously unaware of their ability to waive fees, and the policy change made them aware, driving the effects we observe. However, this is unlikely, as legislative changes in 2011 already required courts to record waivers. Therefore, judges were likely aware that waivers were an option well before the transparency mandate. Furthermore, as shown in Figure 9, we observe increased waivers across all quartiles of pre-period waiver rates, suggesting that the effect is not driven solely by a lack of information among judges about their ability to waive fees. Although we cannot completely rule out this possibility, this evidence indicates that our estimated effects are not entirely driven by the lack of information among judges.

Self-image concerns: Judges may also be influenced by self-image concerns, adjusting their behavior to appear more generous or fair when their decisions become publicly visible. However, this is unlikely to be the primary mechanism driving the results. The heterogeneity in judges' responses—based on factors like time to re-election, political leaning, and district competitiveness—suggests that external accountability and electoral incentives play a larger role. If self-image were the dominant factor, we would expect more uniform changes across all judges. Instead, the evidence points to transparency and electoral incentives as the key drivers, with self-image concerns likely playing a complementary role.

5.3.2 Robustness

A potential threat to the internal validity of our design is the existence of contemporaneous local or national shocks that may influence judicial decisions. For example, the Department of Justice (DOJ) Investigation in the Ferguson Police Department, Missouri, following the shooting of Michael Brown, brought attention to the local government's reliance on revenue from the criminal justice system.[35] This incident may have contributed to a nationwide shift toward providing relief from legal financial obligations. However, since the shooting occurred on August 9, 2014, and the DOJ report highlighting the widespread focus on revenue generation was released in March 2015, it is unlikely that this event directly affected judicial waiver decisions regarding court cost waivers in North Carolina before the report's publication. Nonetheless, to address the validity of our design, we conduct a battery of placebo/falsification tests around other highly publicized shocks related to criminal justice.[36] We report the distribution of these placebo RDD estimates in Figure B.3. Reassuringly, we do not observe any detectable changes in the judges' court cost waiver around

[35]On August 9, 2014, Michael Brown, an 18-year-old African American man, was fatally shot by police officer, in Ferguson, Missouri. The incident garnered national and international attention, sparking widespread protests. The Department of Justice opened its investigation on September 4, 2014, and its final report came out on March 4, 2015. The report found that the City of Ferguson budgets for sizeable increases in municipal fines and fees each year, encouraging police and court staff to deliver those revenue increases and closely monitoring whether those increases are achieved. The DOJ report on Ferguson can be found here: DOJ report on the investigation of the Ferguson Police Department

[36]In addition to the shooting of Michael Brown, we also estimate RDD examine the changes in judicial behavior in North Carolina around the shootings of Laquan McDonald(October 20, 2014, in Chicago, Illinois), Freddie Gray (April 19, 2015 in Baltimore, Maryland), George Floyd (May 25, 2020 in Minneapolis, Minnesota).

the time of protests following the shooting of Michael Brown, the release of the DOJ report on Ferguson, or other highly publicized police shootings.

Another concern with our empirical strategy is that the waiver reporting cutoff falls on New Year's Day 2015. Defendants sentenced at the start of the new year may differ from those sentenced at the end of the previous year due to seasonal offense patterns, potentially affecting court cost waivers and confounding the effect of increased transparency. Therefore, I provide the distribution of RDD estimates of the effects of being sentenced on or after every January 1st and July 1st between July 2013 and July 2018. These estimates are plotted in Figure B.3. We do not find effect sizes statistically different for these placebo cut-off dates, assuring that the changes in waiver rate following mandatory disclosure in Table 2 are not purely driven by seasonality.

Lastly, Figure B.4 shows the robustness of our estimates to bandwidth choice. We impose equal bandwidth on either side of the cutoff and systematically vary bandwidth in 20-day increments. The estimated effects are robust to the bandwidth choice.

6 Effect on Defendants' Outcomes

In this section, we present our findings on the effects of mandatory disclosure of court cost waivers by judges on subsequent defendant outcomes. As shown in Section 5.1, judges are more likely to grant court cost waivers when their waiver decisions become more transparent and salient. This increase in waivers results in a reduction of LFOs imposed on defendants. By lowering the financial burden of LFOs, these waivers may alleviate some of the economic strain faced by defendants, which can, in turn, influence their future behavior and involvement with the criminal justice system.

6.1 Recidivism

Table 7 presents the reduced form estimates of the impact of increased transparency of judicial waivers on criminal involvement and convictions over different time horizons (1, 2, and 3 years). We measure future recidivism using two primary indicators of criminal activity: the number of charges and the number of convictions. In columns 1-3, we examine the impact on criminal involvement, while columns 4-6 focus on convictions. The results are divided into three panels, each addressing a different category of criminal behavior. Panel A covers all crime types, Panel B focuses on financially motivated crimes, and Panel C examines non-financially motivated crimes.

In Panel A, the RDD estimates for any criminal involvement consistently show a negative effect across all time horizons, with the impact increasing over time. The estimates range from -0.003 at 1 year to -0.017 at 3 years, implying that defendants sentenced on or after January 1, 2015, are 1.3 percentage points and 1.7 percentage points less likely to face any new criminal charges within 2 and 3 years after conviction, respectively. This translates to a reduction in criminal involvement of approximately 4% at 1 year and around 10% by the third year. These reductions represent meaningful declines in recidivism, particularly over the longer term, suggesting that increased transparency in judicial waivers may help deter future criminal involvement.

Panel B focuses on financially motivated crimes, where the estimates are near zero across all time horizons, ranging from -0.001 to -0.002. We can not rule out null effects of increased court cost waivers These findings indicate that the recidivism effects are primarily driven by non-financial criminal involvement, as shown in Panel C. In Panel C, defendants are 1.3 p.p. less likely to face non-financially motivated charges within 2 years, and the effect increases to 1.8 p.p. within 3 years. This represents a 10% and 12% reduction in recidivism at 2 years and 3 years, respectively.

Taken together, these findings suggest that transparency-induced court cost relief plays a key role in deterring certain types of re-offense, particularly for non-financially motivated crimes.

6.2 Timely Payments and Collected Costs

When defendants fail to pay their court-imposed financial obligations on time, they incur additional fines and penalties. Increased transparency may influence both the frequency of court cost waivers and the amount of court costs collected. It could prompt judges to target defendants who are less likely to make timely payments (or more likely to "fail to comply"), granting waivers to those with genuine financial difficulties while ensuring costs are collected from those more likely to pay. This strategic targeting could reduce the incidence of late fees and penalties, while maintaining or even increasing the total amount of court costs collected. In this section, we examine the effects of increased transparency on timely payments and the total amount of costs collected by the courts.

Panel A in Figure 10 shows the reduced form effect of increased transparency on failure to comply (FTC) rates. Fewer defendants failed to meet their financial obligations after the reforms. This reduction in non-compliance suggests that transparency prompted judges to target waivers more effectively toward defendants less likely to comply. Despite the drop in FTC rates, the average collected cost per defendant (in Panel B) remained unchanged. Figure 11 shows heterogeneity in FTC rates by assessed court cost amounts. FTC rates decreased significantly for defendants with lower court costs (less than $200), indicating better compliance in this group. However, FTC rates increased for defendants facing higher court costs. This suggests that while judges granted more waivers to those with lower costs, improving compliance, defendants with higher court costs struggled more with payments, leading to increased non-compliance. In a subsequent version of the paper, we aim examine the optimal allocation of court cost waivers and whether judges could better target defendants with a low-likelihood of compliance.

7 Conclusion

Each year, over 17 million criminal cases enter court systems across the United States—at least one for every 15 American adults (Court Statistics Project 2020). A vast majority of these cases result in defendants owing legal financial obligations (LFOs), including various user fees for interacting with the criminal justice system. The Fines and Fees Justice Center estimates that the recent national court debt exceeds $27 billion (Hammons 2021). These LFOs are often adjudicated by elected judges, whose decisions directly impact defendants' financial burdens. Yet, these judicial decisions on LFOs, including the granting of waivers, have historically been opaque to the public.

In this paper, we study the effects of making judicial waiver decisions transparent and find that increased transparency leads to a significant rise in the number of court cost waivers granted, particularly for defendants from low-income areas. Our analysis shows that judges, under greater public scrutiny, are more likely to grant waivers to defendants who are less able to pay their legal obligations, reducing the financial strain on these individuals. Additionally, we find that transparency has important implications for future criminal involvement, with a notable reduction in non-financially motivated recidivism over time. While financially motivated crimes are less affected, the overall decline in criminal activity highlights the potential of transparency to improve both judicial outcomes and defendant behavior.

Our study has broad implications for policy discussions on judicial accountability and the design of institutions for the selection of judges. By shedding light on the impact of transparency, we contribute to the understanding of how public scrutiny can influence judicial decision-making. The findings suggest that transparency can serve as a tool to reduce socioeconomic disparities in the justice system, ensuring that court cost waivers are granted more equitably. Additionally, the reduction in recidivism points to the broader societal benefits of relieving financial burdens on defendants. Policymakers considering reforms to increase judicial transparency should take note of these findings, as they suggest that such reforms could not only improve fairness but also reduce long-term criminal justice costs.

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8 Tables

Table 1: Summary Statistics

	All cases	Analysis Sample
Panel A: Demographic Characteristics		
Male	0.652	0.666
Race/Ethnicity		
Non-Hispanic White	0.495	0.496
African-American	0.370	0.362
Hispanic	0.090	0.092
Other	0.045	0.050
Age	33.503	33.701
	(12.564)	(12.580)
Income ($1000s)	53.444	54.099
	(17.634)	(18.399)
Panel B: Offense Characteristics		
Number of Offenses	1.399	1.243
	(0.534)	(0.458)
Previous criminal charges	0.218	0.885
	(1.061)	(1.991)
Type of offense		
Violent Offense	0.034	0.024
Property Offense	0.061	0.076
Drug Offense	0.064	0.059
Public Safety Offense	0.063	0.103
Traffic Offense	0.668	0.657
Other Offense	0.105	0.078
Panel C: Case Outcomes		
Total Waiver	0.024	0.077
Assessed Court Costs ($)	94.756	220.844
	(151.591)	(174.656)
Cases	6,183,342	1,515,319

Notes: This table presents summary statistics of all criminal cases in the North Carolina District Courts, and the construction of the analysis sample is described in section 3.4. Panel A shows defendant characteristics, Panel B shows offense/case characteristics, and Panel C shows relevant case outcomes. Column 1 includes all cases disposed in North Carolina District Courts during our study period. Column 2 restricts to cases with guilty convictions that were disposed by judges before December, 2017. All defendant and case characteristics, except for defendant income are from ACIS data, described in section 3.1. Defendant incomes are proxied by the median household income (in 2019 dollars) in their ZIP code of residence, obtained from the American Community Survey's 2014-2018 five year median family income estimate.

Table 2: RDD estimates of Law Enactment on Court Cost Waivers

	(1) Any Waiver	(2) Any Waiver	(3) Any Waiver	(4) Any Waiver
RDD Estimate	0.071	0.070	0.061	0.063
	(0.003)	(0.003)	(0.003)	(0.004)
Control Mean	0.076	0.076	0.004	0.004
Robust BC CI	[0.066 0.076]	[0.064 0.076]	[0.055 0.067]	[0.056 0.070]
Kernel	Uniform	Triangular	Triangular	Triangular
Covariates	No	No	Yes	Yes
Robust BC p-value	0.000	0.000	0.000	0.000
Polynomial Order	1	1	1	2
Bandwidth (Left)	147	128	132	173
Bandwidth (Right)	141	126	115	209
Observations	853,371	853,371	853,371	853,371

Notes: This table presents sharp RDD estimates of the change in any court cost waivers upon case disposition following the enactment of the mandatory disclosure law. The analysis sample is described in section 3.4. Column (1) refers to the baseline specification described in Section 4. Column (2) uses a triangular kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff. See Tables B.1 and B.2 for results broken down by type of waiver.

Table 3: RDD estimates of Law Enactment on Other Margins

	(1) Assessed Court Costs	(2) Fines	(3) Sentence Length
RDD Estimate	19.461	-2.890	0.107
	(1.260)	(0.458)	(0.071)
Control Mean	214.563	34.507	0.715
Robust BC CI	[16.991 21.931]	[-3.787 -1.993]	[-0.032 0.246]
Kernel	Triangular	Triangular	Triangular
Covariates	No	No	No
Robust BC p-value	0.000	0.000	0.131
Polynomial Order	1	1	1
Bandwidth (Left)	150	131	171
Bandwidth (Right)	85	192	139
Observations	853,371	853,371	853,371

Notes: This table presents sharp RDD estimates of the change in assessed court costs, fine amounts, and sentence length upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. All columns refer to the baseline specification described in Section 4. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table 4: Covariate Means for Compliers and Always-Takers

	Full sample	Always-takers	Compliers
Panel A: Demographic Characteristics			
Male	0.67	0.74	0.77
Minority	0.51	0.62	0.57
Income			
$< \$42$k	0.25	0.34	0.40
\$42–50k	0.25	0.22	0.24
\$50–61k	0.25	0.24	0.22
$> \$61$k	0.25	0.20	0.14
Age			
Age ≤ 24	0.25	0.25	0.24
Age 25–34	0.30	0.28	0.29
Age 35–44	0.20	0.20	0.20
Age 45–54	0.13	0.17	0.16
Age ≥ 55	0.07	0.07	0.07
Panel B: Offense Characteristics			
Multiple charges	0.23	0.19	0.22
Any Prior Record	0.27	0.49	0.64
Offense Type			
Violent Offense	0.02	0.06	0.06
Property Offense	0.08	0.19	0.21
Drug Offense	0.06	0.10	0.11
Public Safety Offense	0.10	0.17	0.18
Traffic Offense	0.66	0.25	0.22
Other Offense	0.08	0.22	0.23
Offense Seriousness			
Offense Class A1	0.03	0.08	0.08
Offense Class 1	0.19	0.40	0.32
Offense Class 2	0.08	0.13	0.14
Offense Class 3	0.60	0.28	0.35
Panel C: Case/Disposition Characteristics			
Any Guilty Plea	0.97	0.95	0.96
Any Incarceration	0.36	0.71	0.76
Representation Type			
Private Attorney	0.49	0.12	0.18
Indigent Defense	0.20	0.52	0.46
Pro Se	0.31	0.36	0.36

Notes: This table describes the observable characteristics of the complier and always-taker samples, relative to the full sample. Column (1) shows the probability that an individual has a given characteristic in the full analysis sample, while columns (2) and (3) show the probability that someone in the always-taker and complier group has that characteristic. The estimates in Column (2) correspond to the proportion of individuals with a given characteristic in the period before the passage of the law. The estimates in Column (3) are constructed by calculating the shares of compliers within these various subsamples.

Table 5: RDD estimates of Law Enactment on Court Cost Waivers by Political Leaning of Judicial Districts

	Democratic District	Republican Districts
	(1) Any Waiver	(2) Any Waiver
RDD Estimate	0.071	0.078
	(0.006)	(0.003)
Control Mean	0.115	0.042
Robust BC CI	[0.060 0.082]	[0.071 0.084]
Kernel	Triangular	Triangular
Covariates	No	Yes
Robust BC p-value	0.000	0.000
Polynomial Order	1	1
Bandwidth (Left)	94	114
Bandwidth (Right)	141	138
Observations	370,791	482,580

Notes: This table presents sharp RDD estimates of the relationship between the cutoff date and waiver rates and court costs. Defendants in this sample are charged in a North Carolina District Courts. All columns refer to the baseline specification described in Section 4. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table 6: RDD estimates of Law Enactment on Court Cost Waivers by Closeness to Next Election

	Re-election in 4 years	Re-election in 2 years
	(1) Any Waiver	(2) Any Waiver
RDD Estimate	0.076	0.093
	(0.006)	(0.004)
Control Mean	0.068	0.079
Robust BC CI	[0.064 0.089]	[0.085 0.101]
Kernel	Triangular	Triangular
Covariates	No	No
Robust BC p-value	0.000	0.000
Polynomial Order	1	1
Bandwidth (Left)	70	178
Bandwidth (Right)	158	184
Observations	294,522	397,153

Notes: This table presents sharp RDD estimates of the relationship between the cutoff date and waiver rates and court costs. Defendants in this sample are charged in a North Carolina District Courts. All columns refer to the baseline specification described in Section 4. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table 7: RDD estimates of Law Enactment on New Charges and Convictions

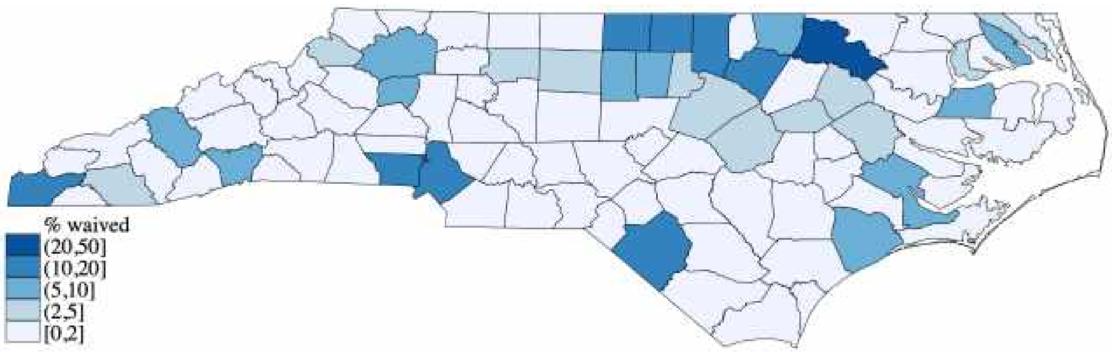
	Charges			Convictions		
	(1) 1 Year	(2) 2 Years	(3) 3 Years	(4) 1 Year	(5) 2 Years	(6) 3 Years
Panel A: Any criminal involvement within 2 years						
RDD Estimate	-0.003	-0.013	-0.017	-0.003	-0.012	-0.017
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Robust BC CI	[-0.009 0.002]	[-0.019 -0.006]	[-0.024 -0.010]	[-0.008 0.002]	[-0.018 -0.006]	[-0.024 -0.011]
Control Mean	0.079	0.132	0.165	0.068	0.112	0.139
Panel B: Financially motivated criminal involvement within 2 years						
RDD Estimate	-0.001	-0.002	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Robust BC CI	[-0.003 0.000]	[-0.004 0.000]	[-0.003 0.001]	[-0.003 0.000]	[-0.004 0.000]	[-0.003 0.001]
Control Mean	0.010	0.014	0.017	0.010	0.014	0.017
Panel C: Non-financially motivated criminal involvement within 2 years						
RDD Estimate	-0.004	-0.013	-0.018	-0.004	-0.013	-0.018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Robust BC CI	[-0.009 0.001]	[-0.019 -0.007]	[-0.025 -0.011]	[-0.009 0.001]	[-0.019 -0.007]	[-0.025 -0.011]
Control Mean	0.070	0.118	0.149	0.070	0.118	0.149
Observations	853,371	853,371	853,371	853,371	853,371	853,371

Notes: This table presents sharp RDD estimates of court cost waivers on future reoffending. The analysis sample is described in section 3.4. Columns (1), (2), and (3) refer to new charges, while columns (4), (5), and (6) refer to new convictions. “Control Mean” refers to the intercept from the local polynomial fit to the left of the cutoff.

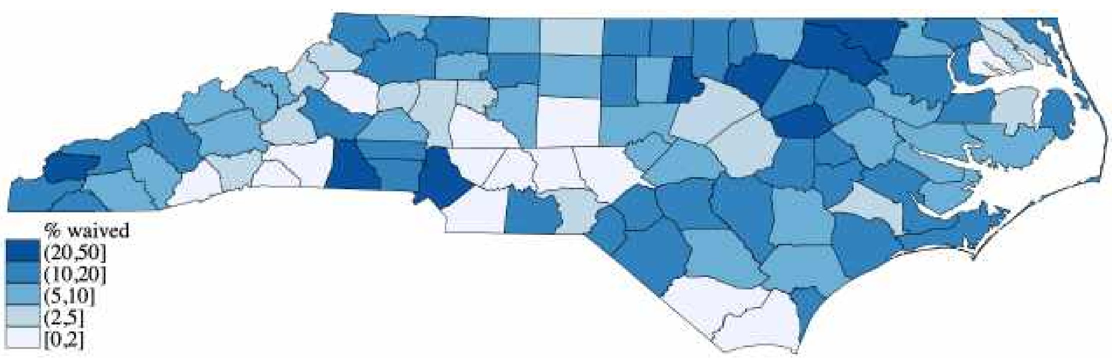
9 Figures

Figure 1: Spatial variation in waiver rates

(a) Waiver rate: 2013



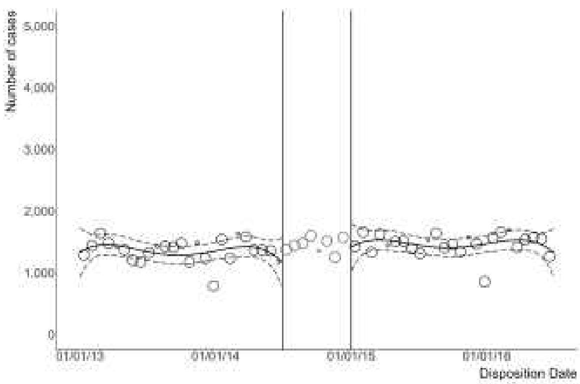
(b) Waiver rate: 2015



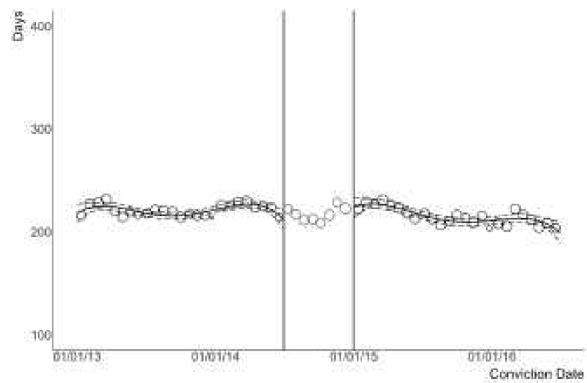
Notes: These figures show the distribution of criminal court cost waiver rates in different years. Panel A shows the distribution of waiver rates across counties in the District courts. Panel B presents the distribution of waiver rates across counties in the Superior courts. The dashed blue line shows the year in which legislation mandating disclosure of waivers by judges was introduced in North Carolina. The distributions highlight the flattening of the waiver rate distribution after the introduction of mandatory disclosure legislation.

Figure 2: Balance

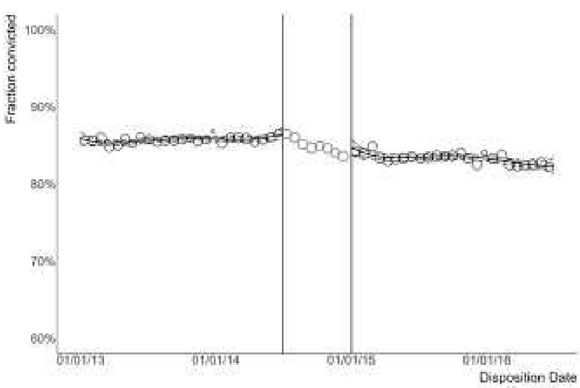
(a) Daily Caseload



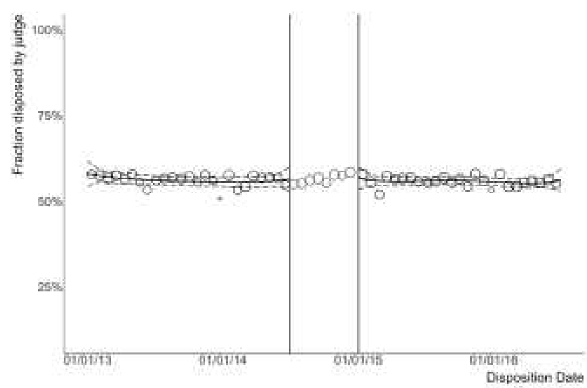
(b) Case Length



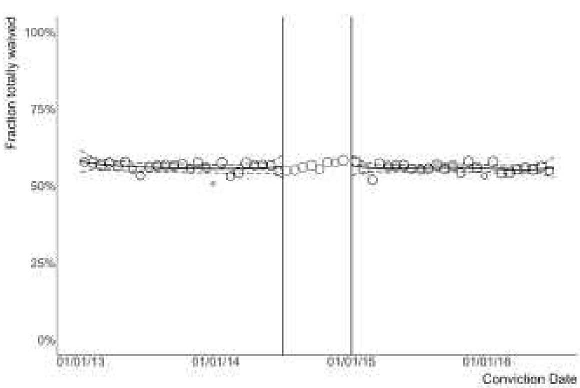
(c) Convictions



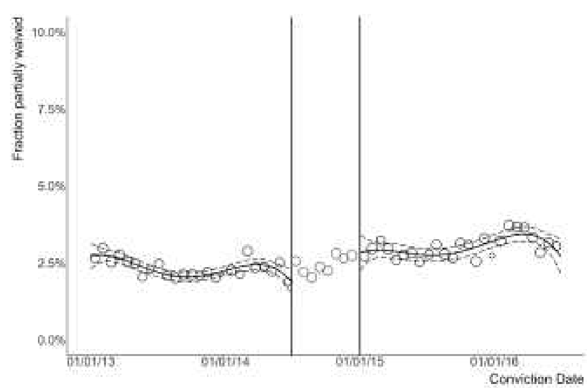
(d) Judge Dispositions



(e) Predicted Total Waivers

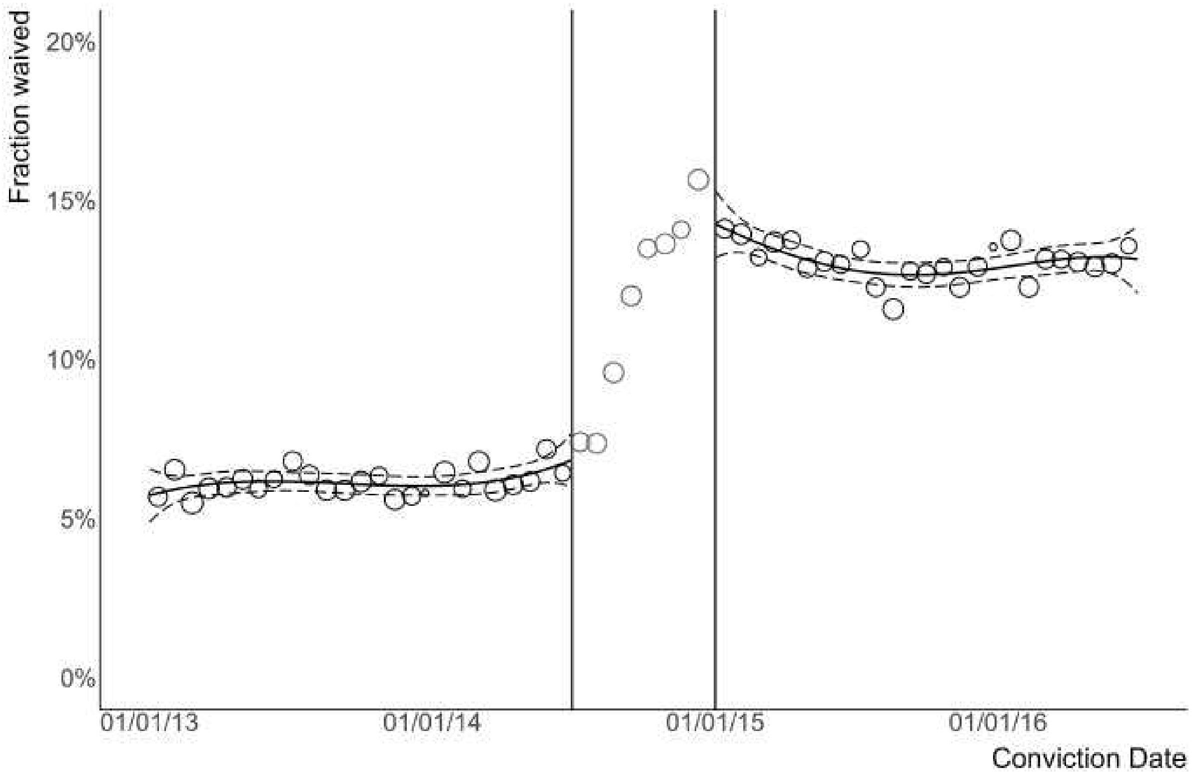


(f) Predicted Partial Waivers



Notes: This figure presents sharp RDD estimates for the effects of increased scrutiny on daily caseload density in panel (a), case length in panel (b), whether a defendant is convicted for any of offenses they are charged with in panel (c), whether the case is disposed of by a judge in panel (d), and predicted total and partial waiver rates in panels (e) and (f). See Section 4.2 for a description of the creation of the predicted indices. See Table **??** for results in tabular format. The analytical sample is the same as described in section 3.3, except for panels (a), (c), and (d) where it is all cases in district courts. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

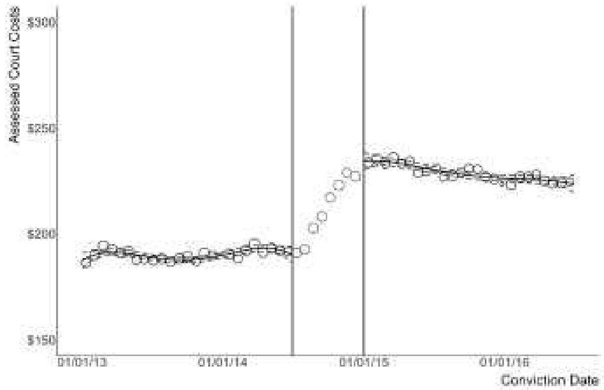
Figure 3: Change in Waiver Rates at Law Enactment Date



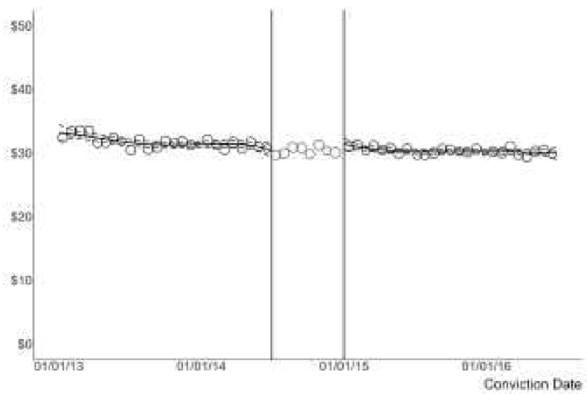
Notes: This figure displays sharp RDD estimates of the impact of increased judge monitoring on court cost waiver rates. See Table 2 for results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern and standard errors in dashed pattern.

Figure 4: Change in Other Margins at Law Enactment Date

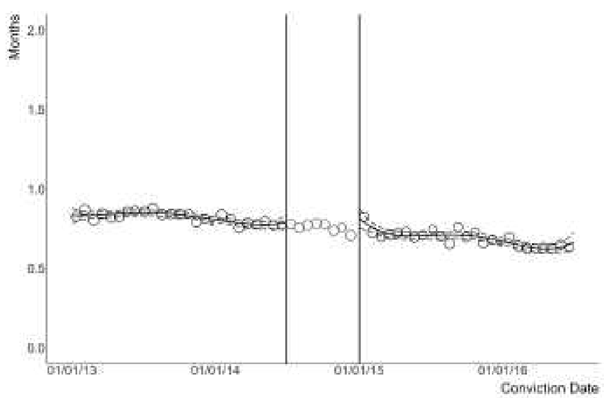
(a) Assessed Court Costs



(b) Fines



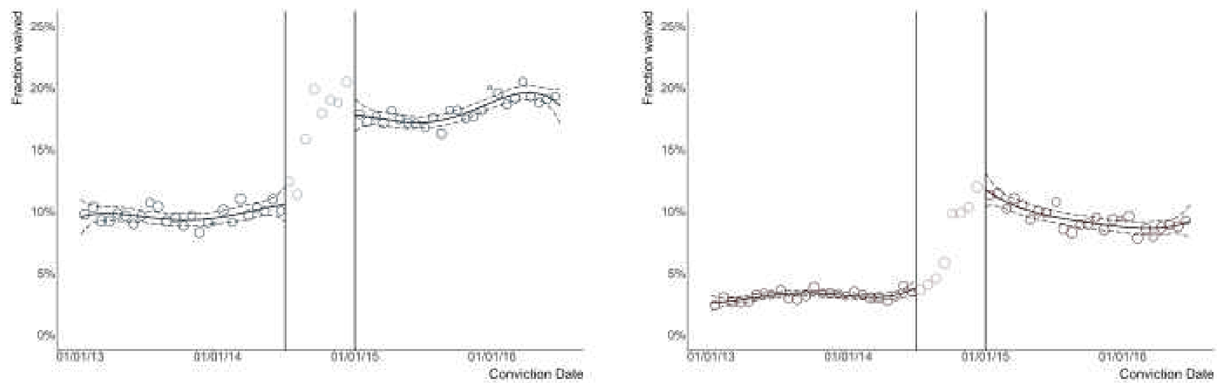
(c) Sentence Length



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on assessed court costs, fine amounts, and sentence length. See Table 3 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern and standard errors in dashed pattern.

Figure 5: Change in Waiver Rates by Political Leaning of Judicial Districts

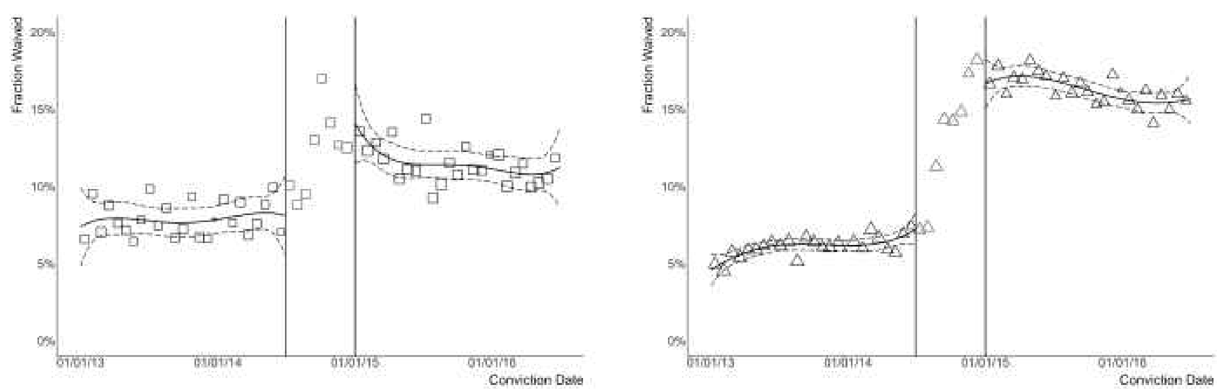
(a) Democratic Districts (b) Republican Districts



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates and court costs. Panel A shows the effects for Democratic-leaning judicial districts, while panel B shows the effects in Republican-leaning districts. See Table 5 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

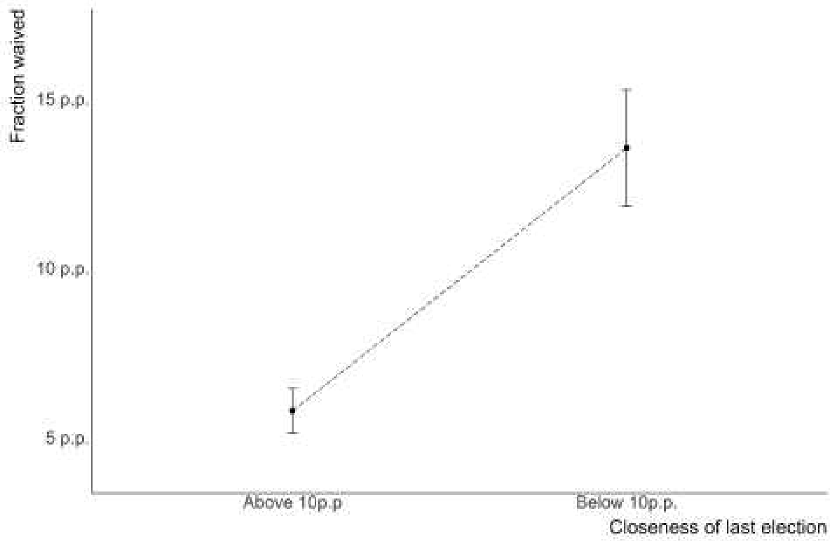
Figure 6: Change in Waiver Rates by Closeness to Next Election

(a) Re-election in 4 years (b) Re-election in 2 years



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates by how close the next election is. Panel A shows the effects for judges facing re-election in 4 years, while panel B shows the effects for judges facing re-election in 2 years. See Table 6 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

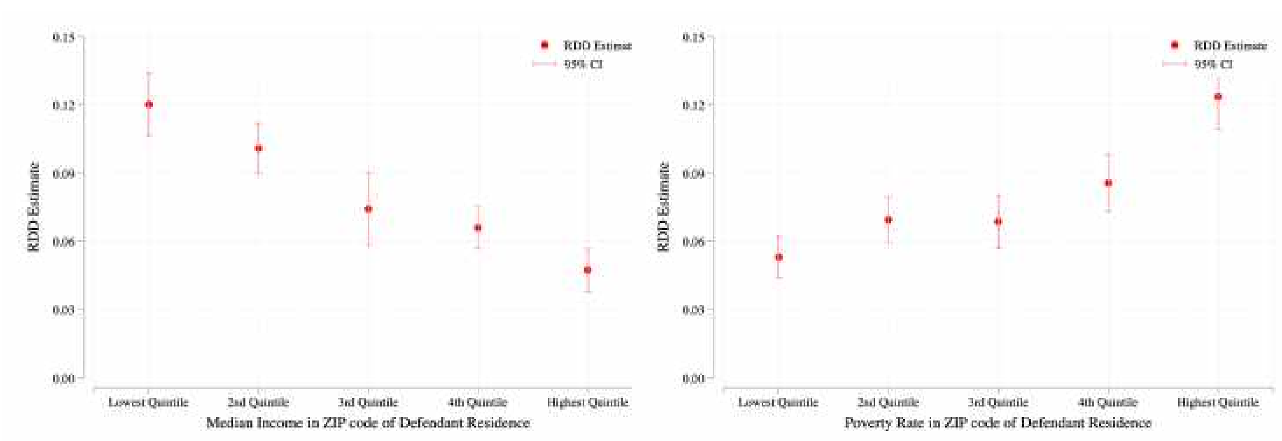
Figure 7: Change in Waiver Rates by Competitiveness of Judicial Districts



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates according to the competitiveness of the last presidential election.

Figure 8: Change in Waiver Rates by Defendants' Income and Poverty Quintiles

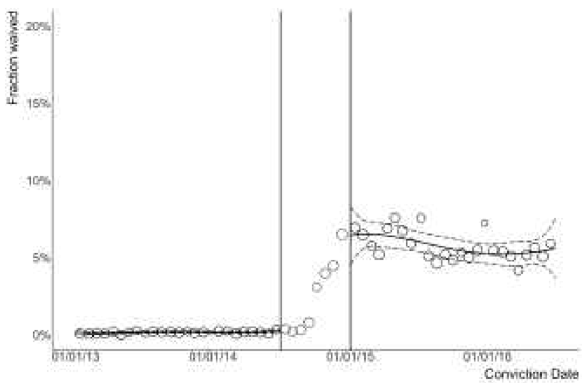
(a) Median Income (b) Poverty Rate



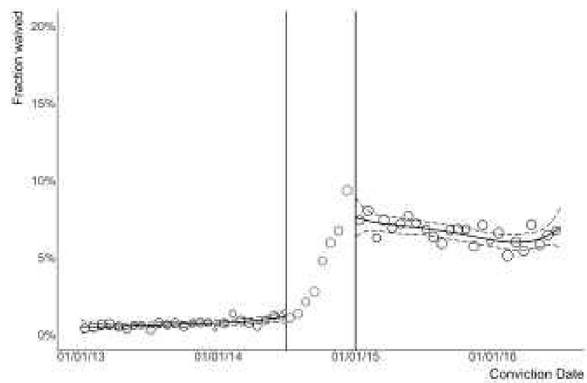
Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates by defendants' economic characteristics. Panel A shows the effects for five quintiles of median income in the defendant's ZIP code of residence, while panel B shows the RDD estimates by the quintiles of poverty rate in the defendant's ZIP code of residence. Point estimates for each quintile are estimated separately using the baseline specification described in 4. 95% confidence intervals show robust bias-corrected confidence interval.

Figure 9: Change in Waiver Rates by Pre-Legislation County Waiver Rates

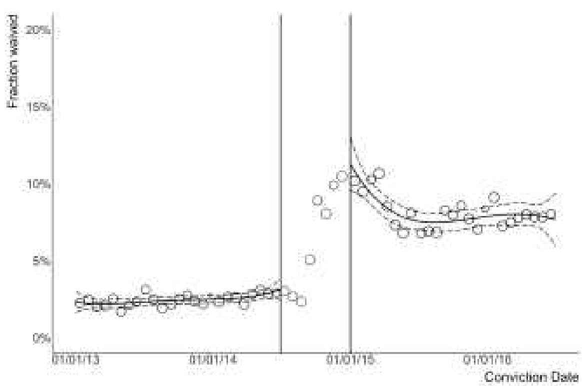
(a) First Quartile



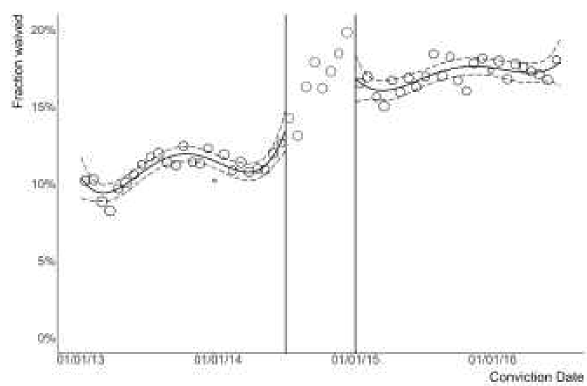
(b) Second quartile



(c) Third quartile



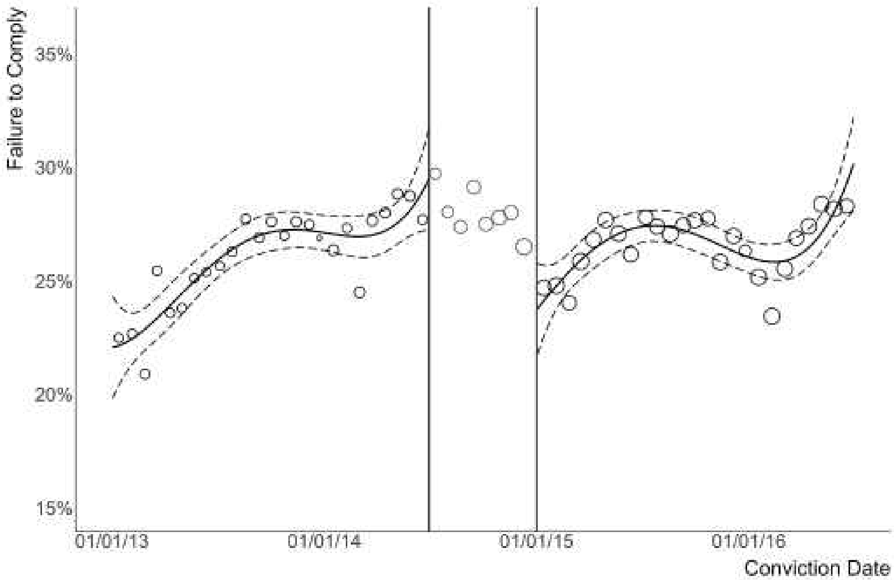
(d) Fourth quartile



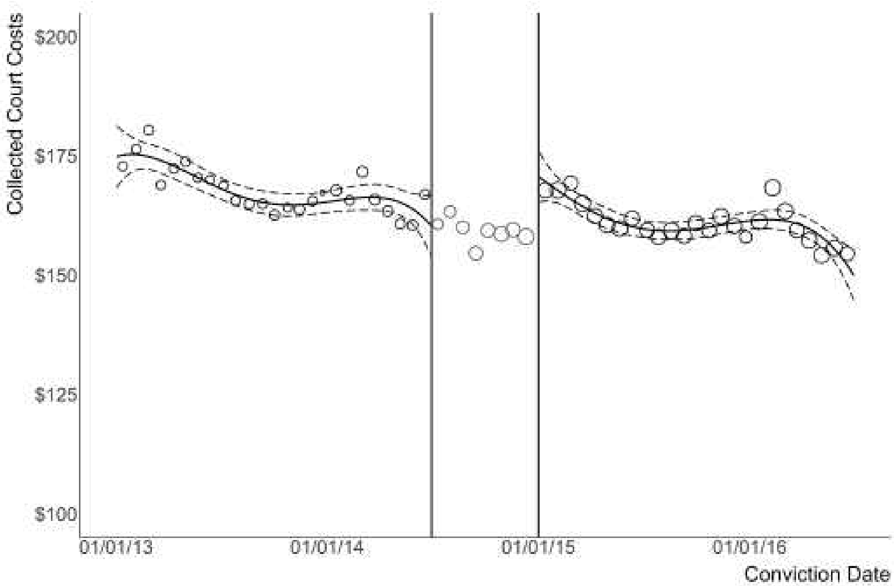
Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates by pre-legislation waiver rates in the county where the disposition takes place. See B.5 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure 10: Change in Timely Payments and Collected Court Costs

(a) Failure to Comply



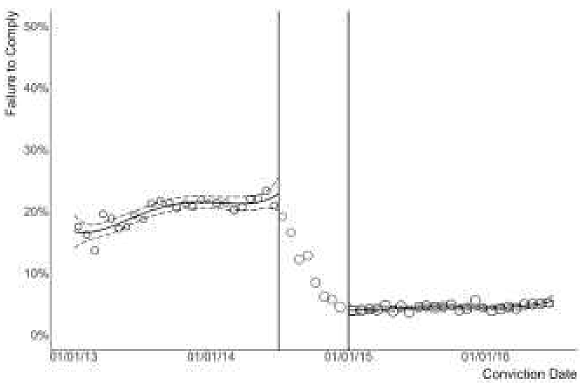
(b) Collected Court Costs



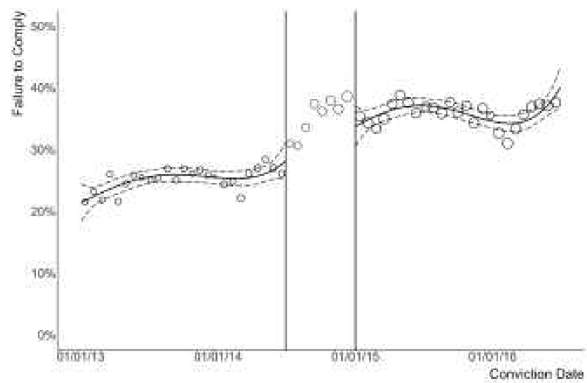
Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates and court costs. The black, solid vertical line denotes the time of enactment of the law. The black, dashed vertical line denotes the time of passage of the law. Predicted fit lines are generated using a sharp, linear RDD where time relative to the date of enactment of the law is the running variable. Sharp RDD estimated fit lines are in a solid pattern, and standard errors are in the dashed pattern.

Figure 11: Change in Timely Payments by Assessed Court Cost Amount

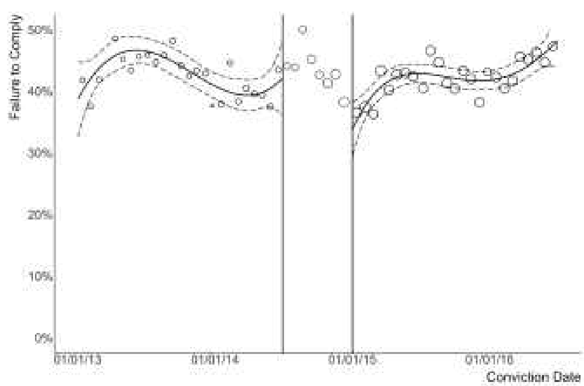
(a) \$0–\$200



(b) \$200–\$400



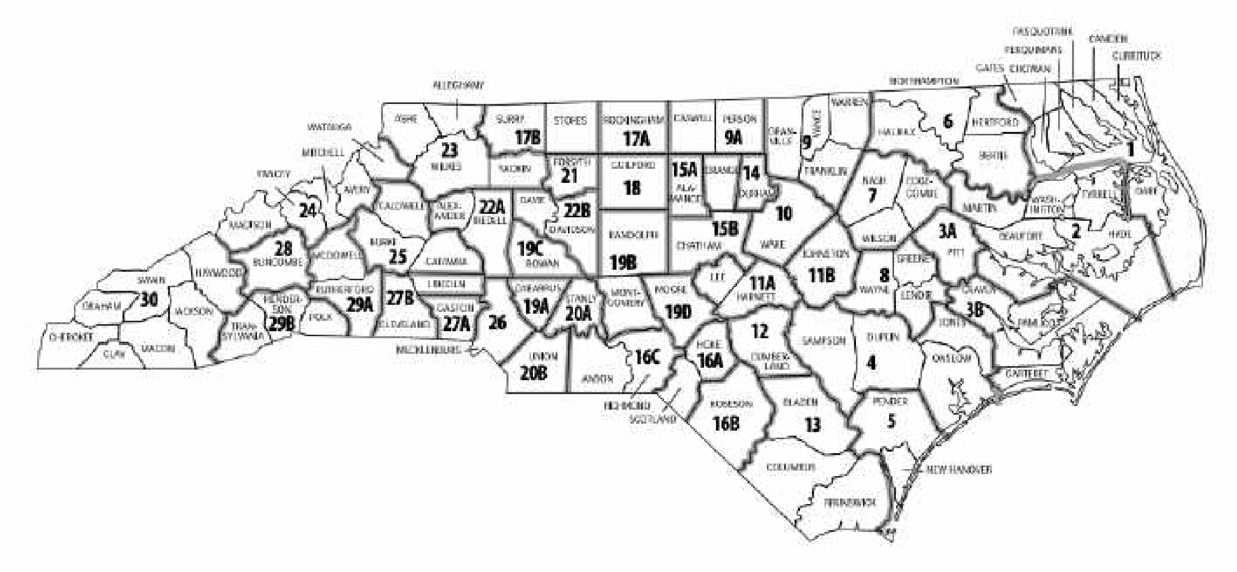
(c) \$400–\$600



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on sentence length and fine amounts. The black, solid vertical line denotes the time of enactment of the law. The black, dashed vertical line denotes the time of passage of the law. Predicted fit lines are generated using a sharp, linear RDD where time relative to the date of enactment of the law is the running variable. Sharp RDD estimated fit lines are in a solid pattern, and standard errors are in the dashed pattern.

A Institutional Details

Figure A.1: District Court Districts



Notes: This figure shows the composition of District Court districts in North Carolina in 2014. The entire state is divided into 42 District court districts for administrative and electoral purposes, each comprising one or more counties. Source: North Carolina Judicial Branch (https://www.nccourts.gov/documents/publications/judicial-districts-maps)

Figure A.2: Court Costs Breakdown

An additional summary chart of criminal costs has been attached to this cost chart as "Appendix - Criminal Costs Summary." The appendix summarizes the basic costs common to all dispositions in a particular trial division. It does **not** include additional cost items that must be assessed depending on individual factors for each case (*e.g.*, FTA fees, supervision fees, jail fees, etc.) or for specific offenses of conviction (*e.g.* improper equipment or impaired driving); those costs are assessed separately. Neither does it apply to offenses for which the relevant statute assesses specific costs or prohibits the imposition of costs.

CRIMINAL COURT COSTS G.S. 7A-304, unless otherwise specified			**AMOUNT**
DISTRICT COURT (including criminal cases before magistrates)			
General Court of Justice Fee. G.S. 7A-304(a)(4).	General Fund	127.05	129.50
	State Bar Legal Aid Account (LAA)	2.45	
Facilities Fee. G.S. 7A-304(a)(2).			12.00
Phone Systems Fee. G.S. 7A-304(a)(2a).			4.00
Misdemeanant Confinement Fund Fee. G.S. 7A-304(a)(2b).			18.00[1]
LEO Retirement/Insurance. G.S. 7A-304(a)(3) & (3a).			7.50
LEO Training and Certification Fee. G.S. 7A-304(a)(3b).			2.00
		TOTAL	173.00
Chapter 20 Fee. G.S. 7A-304(a)(4a) (for conviction of any Chapter 20 offense).			+10.00[2]
DNA Fee. G.S. 7A-304(a)(9) (criminal offenses, only; does not apply to infractions).			+2.00
Plus $5.00 service fee for each arrest or service of criminal process, including citations and subpoenas. G.S. 7A-304(a)(1).			+5.00

Notes: This figure shows the breakdown of criminal court costs in North Carolina. Source: North Carolina Judicial Branch (https://www.nccourts.gov/help-topics/fees-and-payments)

Figure A.3: Finding of Just Cause for Waivers

STATE OF NORTH CAROLINA
COUNTY OF DURHAM

IN THE GENERAL COURT OF JUSTICE
[ ] DISTRICT COURT DIVISION
[ ] SUPERIOR COURT DIVISION
FILE NO(S): ___________________________

STATE OF NORTH CAROLINA)
)
)
VS.) **ORDER OF RELIEF FROM FINES, FEES, AND**
) **OTHER MONETARY OBLIGATIONS**
____________________________)
DEFENDANT

THIS CAUSE coming on to be heard and before the undersigned Judge Presiding, after hearing the evidence from the prosecution and the defense,. The Court makes the following findings :

[ ] Defendant is unemployed.
[ ] Defendant's Primary source of Income is Welfare, Social Security, or Pensions.
[ ] Defendant has ______ Dependents.
[ ] Defendant's monthly expenses exceeds _______ per month.
[ ] Defendant has a child support obligation in the amount of ______ per month.
[ ] Defendant is not receiving child support..
[ ] Defendant is currently paying on another case of probation.
[ ] Defendant has medical/psychiatric issues that need to be addressed that causes great financial. obligations.
[ ] Defendant owes a substantial amount of restitution in the case,
[ ] Defendant is ordered to house arrest for _______ months
[ ] Defendant is ordered to complete ______ hours of community service.
[ ] Defendant is ordered to participate in substance an abuse assessment, monitoring or treatment.
[ ] Defendant is ordered to participate in an educational or vocational skills development program.
[ ] Other ____/

The Court concludes the Defendant's current financial condition makes paying certain court fees or fines an undue burden. THEREFORE, the Court finds there is good and just cause to grant relief and ORDERS the following remitted:

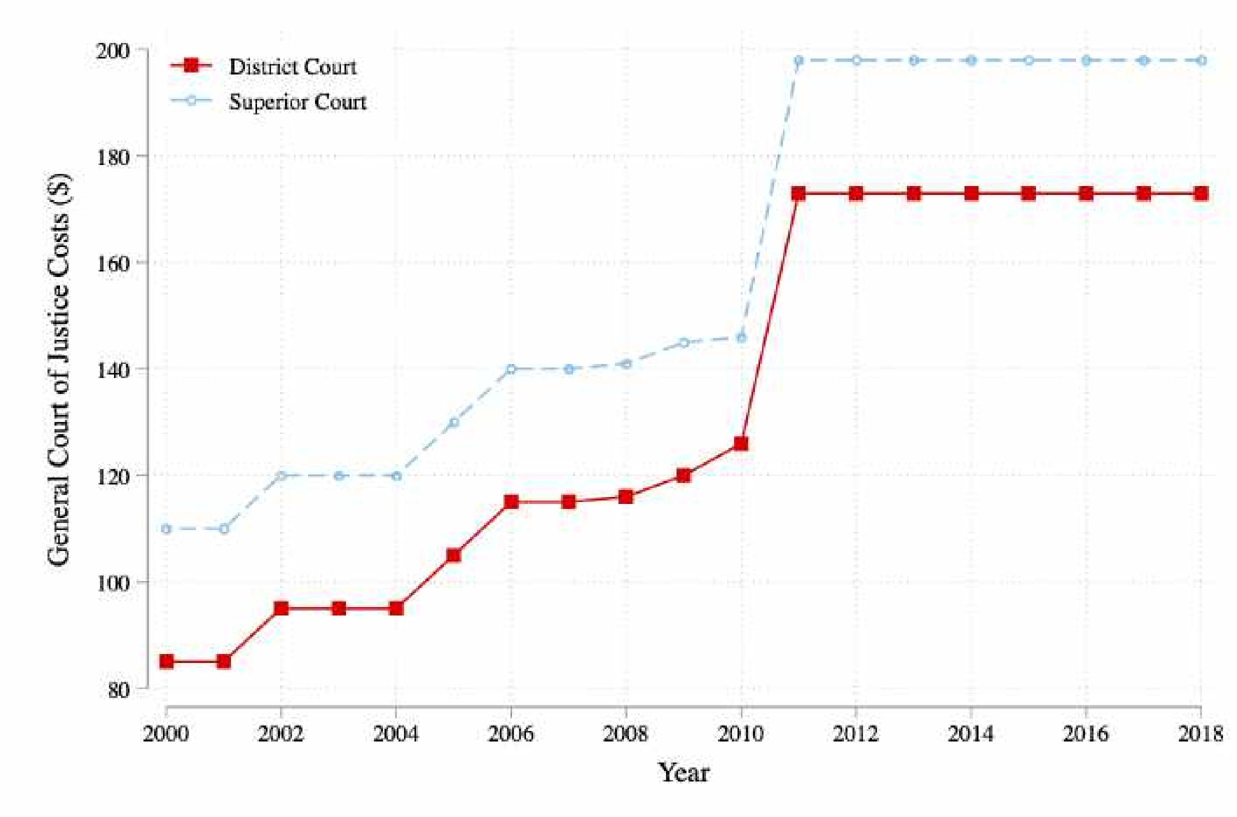
[ ] Cost of Court
[ ] Jail Fees.
[ ] SBI Lab/Witness Fee
[ ] Attorney's Fees (excluding the appointment fee)
[ ] Community Service Fee
[ ] Probation Supervision Fee..
[ ] FTA Fee
[ ] FTC Fee.
[ ] Fines
[ ] Other: ______________________________________

This the ___________ day of ___________, ___________ .

____
Judge Presiding

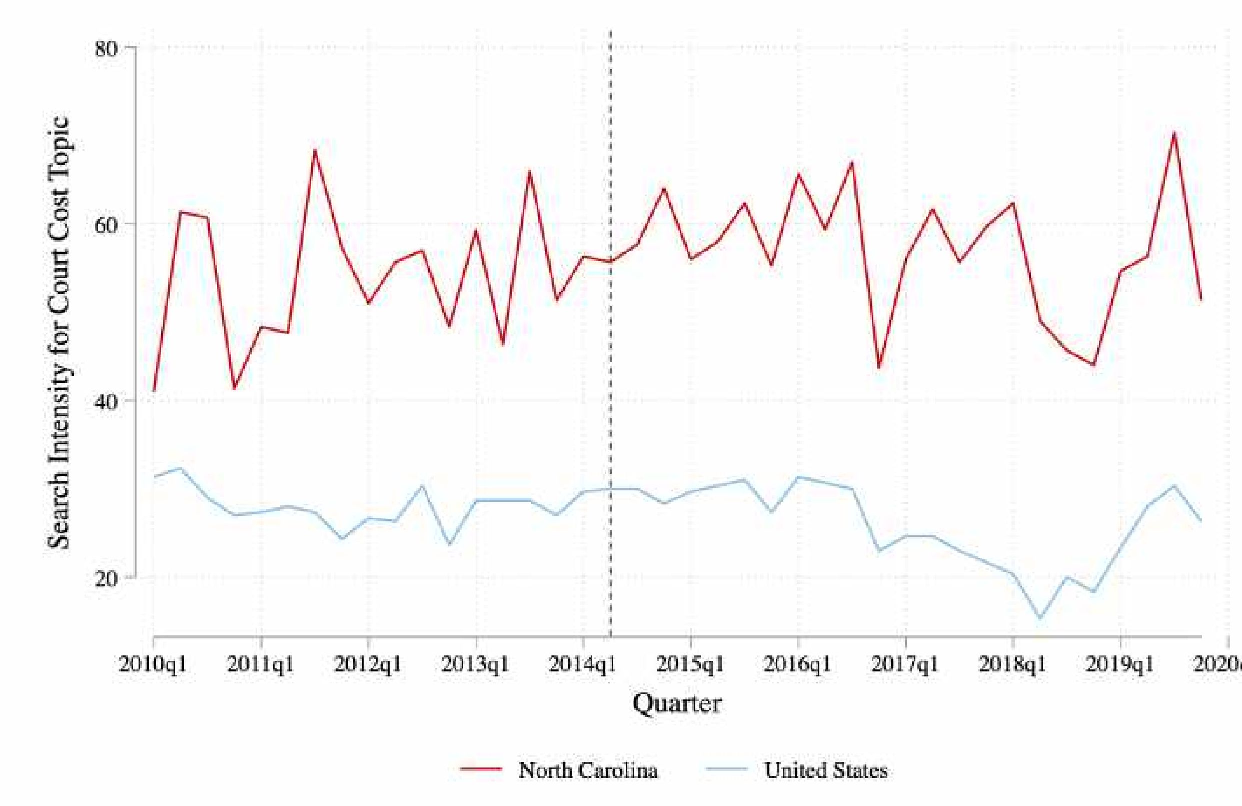
Notes: This figure shows an example form for considerations of Judical Court Cost Waivers

Figure A.4: Trends in court costs



Notes: This figure shows the trends in General Court of Justice Fees, the basic component of court costs applied to all convicted individuals. Source: North Carolina Judicial Branch

Figure A.5: Search interest for Court Cost



Notes: This figure shows the intensity of Google search trends for "Court Cost" topic in North Carolina and the United States. The data are aggregated at the quarterly level and obtained from https://trends.google.com/trends/

Figure A.6: Sentencing Guidelines for Misdemeanors

<table>
<tr><th rowspan="3">CLASS</th><th colspan="4">PRIOR CONVICTION LEVEL</th></tr>
<tr><th>I</th><th colspan="2">II</th><th>III</th></tr>
<tr><th>No Prior Convictions</th><th colspan="2">One to Four Prior Convictions</th><th>Five or More Prior Convictions</th></tr>
<tr><td>A1</td><td>C/I/A
1 - 60 days</td><td colspan="2">C/I/A
1 - 75 days</td><td>C/I/A
1 - 150 days</td></tr>
<tr><td>1</td><td>C
1 - 45 days</td><td colspan="2">C/I/A
1 - 45 days</td><td>C/I/A
1 - 120 days</td></tr>
<tr><td>2</td><td>C
1 - 30 days</td><td colspan="2">C/I
1 - 45 days</td><td>C/I/A
1 - 60 days</td></tr>
<tr><td rowspan="2">3</td><td rowspan="2">C
Fine Only*
1 - 10 days</td><th>One to Three Prior Convictions</th><th>Four Prior Convictions</th><td rowspan="2">C/I/A
1 - 20 days</td></tr>
<tr><td>C
Fine Only*
1 - 15 days</td><td>C/I
1 - 15 days</td></tr>
</table>

***Unless otherwise provided for a specific offense, the judgment for a person convicted of a Class 3 misdemeanor who has no more than three prior convictions shall consist only of a fine.**

A – Active Punishment   I – Intermediate Punishment   C – Community Punishment
Cells with slash allow either disposition at the discretion of the judge

Revised: 9/30/13

Sources: N.C. General Assembly and UNC Chapel Hill School of Government.

B Additional tables and figures

Table B.1: RDD estimates of Law Enactment on Total Court Cost Waivers

	(1) Total Waiver	(2) Total Waiver	(3) Total Waiver	(4) Total Waiver
RDD Estimate	0.059	0.059	0.050	0.050
	(0.003)	(0.003)	(0.003)	(0.003)
Control Mean	0.056	0.055	-0.022	-0.021
Robust BC CI	[0.052 0.065]	[0.054 0.064]	[0.045 0.056]	[0.044 0.056]
Kernel	Uniform	Triangular	Triangular	Triangular
Covariates	No	No	Yes	Yes
Robust BC p-value	0.000	0.000	0.000	0.000
Polynomial Order	1	1	1	2
Bandwidth (Left)	72	107	105	186
Bandwidth (Right)	76	144	130	228
Observations	853,371	853,371	853,371	853,371

Notes: This table presents sharp RDD estimates of the change in total court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. Column (2) refers to the baseline specification described in Section 4. Column (1) uses a uniform kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.2: RDD estimates of Law Enactment on Partial Court Cost Waivers

	(1) Partial Waiver	(2) Partial Waiver	(3) Partial Waiver	(4) Partial Waiver
RDD Estimate	0.012	0.013	0.012	0.012
	(0.002)	(0.002)	(0.002)	(0.002)
Control Mean	0.020	0.019	0.023	0.025
Robust BC CI	[0.007 0.016]	[0.009 0.017]	[0.008 0.020]	[0.008 0.020]
Kernel	Uniform	Triangular	Triangular	Triangular
Covariates	No	No	Yes	Yes
Robust BC p-value	0.000	0.000	0.000	0.000
Polynomial Order	1	1	1	2
Bandwidth (Left)	59	80	90	175
Bandwidth (Right)	58	90	88	196
Observations	853,371	853,371	853,371	853,371

Notes: This table presents sharp RDD estimates of the change in partial court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. Column (2) refers to the baseline specification described in Section 4. Column (1) uses a uniform kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.3: RDD estimates of Law Enactment on Total and Partial Court Cost Waivers by Political Leaning of Judicial Districts

	Democratic District		Republican Districts	
	(1) Total Waiver	(2) Partial Waiver	(3) Total Waiver	(4) Partial Waiver
RDD Estimate	0.057	0.017	0.062	0.014
	(0.004)	(0.004)	(0.003)	(0.002)
Control Mean	0.077	0.033	0.038	0.004
Robust BC CI	[0.048 0.065]	[0.010 0.025]	[0.056 0.068]	[0.011 0.018]
Kernel	Triangular	Triangular	Triangular	Triangular
Covariates	No	No	Yes	Yes
Robust BC p-value	0.000	0.000	0.000	0.000
Polynomial Order	1	1	1	1
Bandwidth (Left)	128	65	120	167
Bandwidth (Right)	133	101	178	92
Observations	370,791	370,791	482,580	482,580

Notes: This table presents sharp RDD estimates of the change in partial court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. Column (2) refers to the baseline specification described in Section 4. Column (1) uses a uniform kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.4: RDD estimates of Law Enactment on Total and Partial Court Cost Waivers by Closeness to Next Election

	Re-election in 4 years		Re-election in 2 years	
	(1) Total Waiver	(2) Partial Waiver	(3) Total Waiver	(4) Partial Waiver
RDD Estimate	0.050	0.010	0.065	0.023
	(0.005)	(0.004)	(0.004)	(0.003)
Control Mean	0.066	0.014	0.065	0.017
Robust BC CI	[0.040 0.060]	[0.002 0.019]	[0.057 0.073]	[0.018 0.028]
Kernel	Triangular	Triangular	Triangular	Triangular
Covariates	No	No	No	No
Robust BC p-value	0.000	0.018	0.000	0.000
Polynomial Order	1	1	1	1
Bandwidth (Left)	127	45	103	122
Bandwidth (Right)	103	81	177	113
Observations	294,522	294,522	397,153	397,153

Notes: This table presents sharp RDD estimates of the change in partial court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. Column (2) refers to the baseline specification described in Section 4. Column (1) uses a uniform kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. “Control Mean” refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.5: RDD estimates of Law Enactment on Waiver Rates by Pre-Legislation County Waiver Rates

	(1) First Quartile	(2) Second Quartile	(3) Third Quartile	(4) Fourth Quartile
RDD Estimate	0.078	0.078	0.098	0.035
	(0.005)	(0.004)	(0.004)	(0.008)
Control Mean	0.005	0.015	0.042	0.224
Robust BC CI	[0.068 0.087]	[0.070 0.086]	[0.090 0.110]	[0.019 0.050]
Kernel	Uniform	Uniform	Uniform	Uniform
Covariates	No	No	Yes	Yes
Robust BC p-value	0.000	0.000	0.000	0.000
Polynomial Order	1	1	1	1
Bandwidth (Left)	89	118	102	101
Bandwidth (Right)	101	148	128	150
Observations	141,751	174,541	324,868	212,211

Notes: This table presents sharp RDD estimates of the change in court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. All columns refer to the baseline specification described in Section 4. Each column refers to a specific quartile in pre-legislation county-level waiver rates. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. “Control Mean” refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.6: RDD estimates of Law Enactment on Court Cost Waivers by Judge Race

	White Judges	Minority Judges
	(1)	(2)
	Any Waiver	Any Waiver
RDD Estimate	0.042	0.126
	(0.006)	(0.015)
Control Mean	0.090	0.131
Robust BC CI	[0.030 0.055]	[0.098 0.155]
Kernel	Triangular	Triangular
Covariates	No	No
Robust BC p-value	0.000	0.000
Polynomial Order	1	1
Bandwidth (Left)	86	114
Bandwidth (Right)	125	80
Observations	262,608	75,897

Notes: This table presents sharp RDD estimates of the relationship between the cutoff date and waiver rates and court costs. Defendants in this sample are charged in a North Carolina District Courts. All columns refer to the baseline specification described in Section 4. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.7: RDD estimates of Law Enactment on Court Cost Waivers by Judge Gender

	Male Judges	Female Judges
	(1)	(2)
	Any Waiver	Any Waiver
RDD Estimate	0.068	0.091
	(0.004)	(0.007)
Control Mean	0.072	0.068
Robust BC CI	[0.059 0.077]	[0.078 0.105]
Kernel	Triangular	Triangular
Covariates	No	No
Robust BC p-value	0.000	0.000
Polynomial Order	1	1
Bandwidth (Left)	70	120
Bandwidth (Right)	140	77
Observations	545,794	233,557

Notes: This table presents sharp RDD estimates of the relationship between the cutoff date and waiver rates and court costs. Defendants in this sample are charged in a North Carolina District Courts. All columns refer to the baseline specification described in Section 4. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.8: RDD estimates of Law Enactment on Total and Partial Court Cost Waivers by Judge Race

	White Judges		Minority Judges	
	(1) Total Waiver	(2) Partial Waiver	(3) Total Waiver	(4) Partial Waiver
RDD Estimate	0.029	0.014	0.135	-0.002
	(0.006)	(0.003)	(0.011)	(0.009)
Control Mean	0.076	0.014	0.069	0.058
Robust BC CI	[0.018 0.040]	[0.008 0.020]	[0.114 0.157]	[-0.020 0.015]
Kernel	Triangular	Triangular	Triangular	Triangular
Covariates	No	No	No	No
Robust BC p-value	0.000	0.000	0.000	0.801
Polynomial Order	1	1	1	1
Bandwidth (Left)	99	73	190	100
Bandwidth (Right)	135	137	112	71
Observations	262,608	262,608	75,897	75,897

Notes: This table presents sharp RDD estimates of the change in partial court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. Column (2) refers to the baseline specification described in Section 4. Column (1) uses a uniform kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. “Control Mean” refers to the intercept from the local polynomial fit to the left of the cutoff.

Table B.9: RDD estimates of Law Enactment on Total and Partial Court Cost Waivers by Judge Gender

	Male Judges		Female Judges	
	(1) Total Waiver	(2) Partial Waiver	(3) Total Waiver	(4) Partial Waiver
RDD Estimate	0.056	0.011	0.069	0.031
	(0.004)	(0.003)	(0.005)	(0.003)
Control Mean	0.059	0.018	0.059	0.008
Robust BC CI	[0.048 0.064]	[0.006 0.016]	[0.058 0.079]	[0.025 0.037]
Kernel	Triangular	Triangular	Triangular	Triangular
Covariates	No	No	No	No
Robust BC p-value	0.000	0.000	0.000	0.000
Polynomial Order	1	1	1	1
Bandwidth (Left)	117	68	150	109
Bandwidth (Right)	76	90	118	94
Observations	545,794	545,794	233,557	233,557

Notes: This table presents sharp RDD estimates of the change in partial court cost waivers upon case disposition following the enactment of mandatory disclosure law. The analysis sample is described in section 3.4. Column (2) refers to the baseline specification described in Section 4. Column (1) uses a uniform kernel weighting function. Columns (3) adds controls: prior convictions; indicators for offense class and for whether the defendant faces charges for a violent, property, drug, public safety, or traffic offense; indicators for defendant race, gender, and age categories. Column (5) additionally uses a local quadratic fit instead of linear. Conventional standard errors calculated using a second order robust plug-in residuals variance estimator are given in parentheses. Robust bias-corrected confidence interval are reported in square brackets. "Control Mean" refers to the intercept from the local polynomial fit to the left of the cutoff.

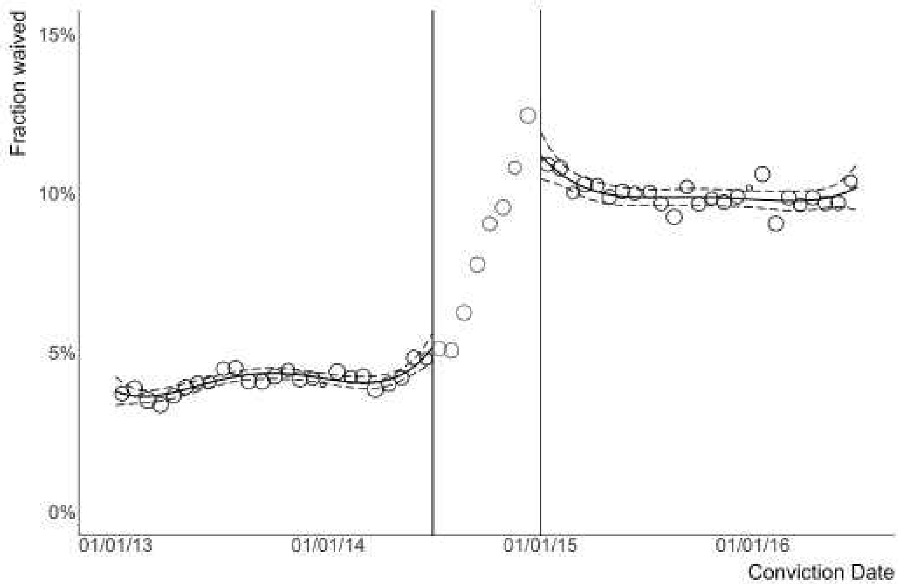
Table B.10: Covariate Means for Compliers and Always-Takers by Political Leaning of Judicial District

	Democratic Districts			Republican Districts		
	Full sample	Always-takers	Compliers	Full sample	Always-takers	Compliers
Panel A: Demographic Characteristics						
Male	0.67	0.76	0.78	0.66	0.71	0.76
Minority	0.63	0.74	0.71	0.41	0.42	0.41
Income						
$<$ \$42k	0.25	0.38	0.43	0.25	0.27	0.37
\$42–50k	0.19	0.15	0.20	0.29	0.34	0.28
\$50–61k	0.23	0.22	0.20	0.28	0.27	0.25
$>$ \$61k	0.33	0.25	0.18	0.19	0.12	0.10
Age						
Age $\leq$ 24	0.24	0.25	0.23	0.26	0.26	0.25
Age 25–34	0.31	0.26	0.27	0.30	0.30	0.32
Age 35–44	0.20	0.20	0.20	0.20	0.20	0.20
Age 45–54	0.13	0.18	0.18	0.13	0.15	0.14
Age $\geq$ 55	0.07	0.08	0.08	0.07	0.06	0.06
Panel B: Offense Characteristics						
Multiple charges	0.22	0.16	0.20	0.24	0.25	0.24
Any Prior Record	0.27	0.44	0.65	0.28	0.58	0.64
Offense Type						
Violent Offense	0.03	0.06	0.06	0.02	0.06	0.06
Property Offense	0.08	0.19	0.21	0.08	0.18	0.20
Drug Offense	0.06	0.11	0.10	0.06	0.10	0.11
Public Safety Offense	0.11	0.18	0.19	0.09	0.15	0.15
Traffic Offense	0.65	0.24	0.20	0.67	0.28	0.24
Other Offense	0.08	0.21	0.23	0.08	0.23	0.23
Offense Seriousness						
Offense Class A1	0.03	0.08	0.08	0.03	0.07	0.08
Offense Class 1	0.18	0.37	0.30	0.20	0.44	0.35
Offense Class 2	0.07	0.12	0.12	0.09	0.14	0.16
Offense Class 3	0.61	0.31	0.40	0.60	0.23	0.30
Panel C: Case/Disposition Characteristics						
Any Guilty Plea	0.96	0.95	0.96	0.98	0.96	0.96
Any Incarceration	0.34	0.66	0.72	0.37	0.80	0.80
Representation Type						
Private Attorney	0.45	0.09	0.18	0.53	0.17	0.18
Indigent Defense	0.21	0.55	0.47	0.19	0.47	0.44
Pro Se	0.35	0.36	0.35	0.28	0.36	0.39

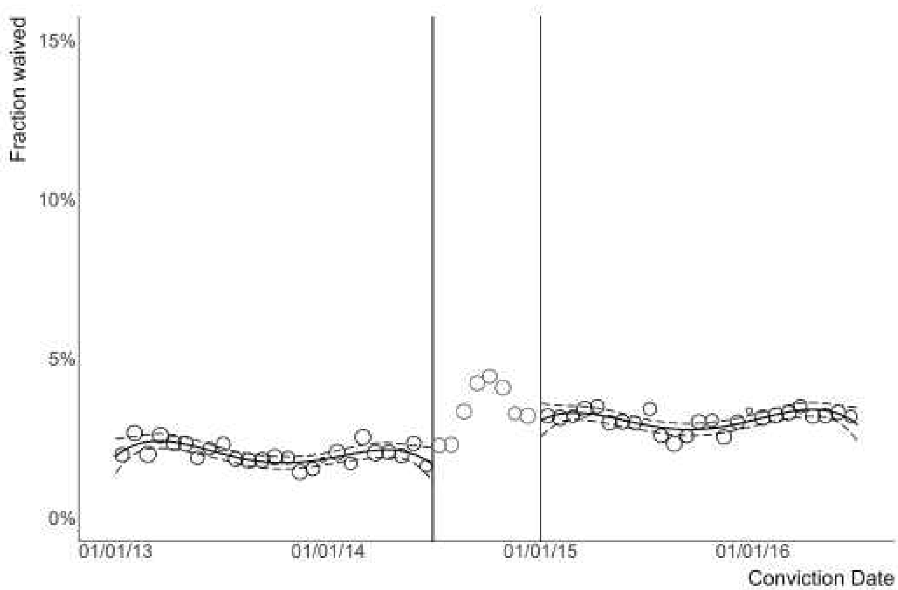
Notes: This table describes the observable characteristics of the complier sample, relative to the full sample. Column (1) shows the probability that an individual has a given characteristic in the full analysis sample. Column (2) shows the probability that someone in the complier group has that characteristic. Column (3) shows the ratio of the two (Column (2) divided by Column (1)). The estimates in Column (2) are constructed by calculating the shares of compliers within these various subsamples.

Figure B.1: Change in Total and Partial Waiver Rates at Law Enactment Date

(a) Total Waivers



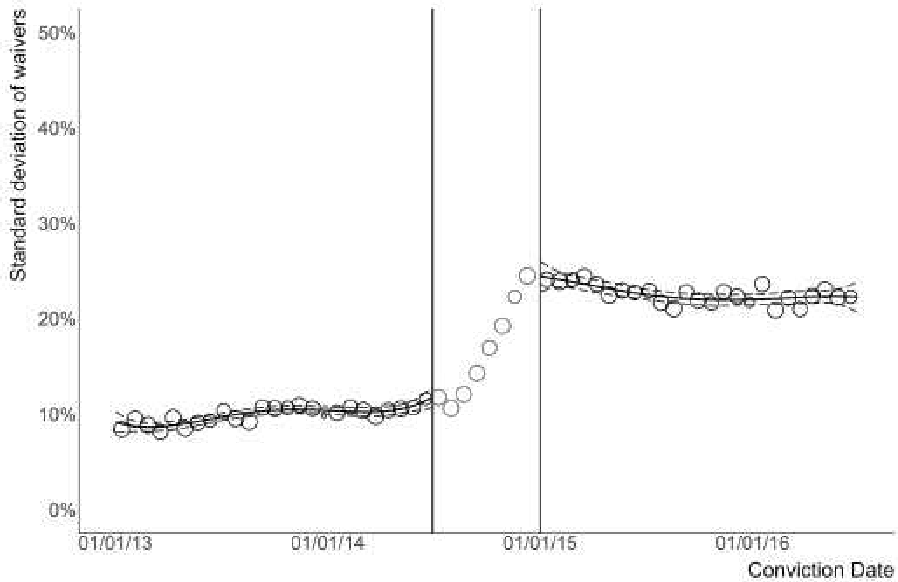
(b) Partial Waivers



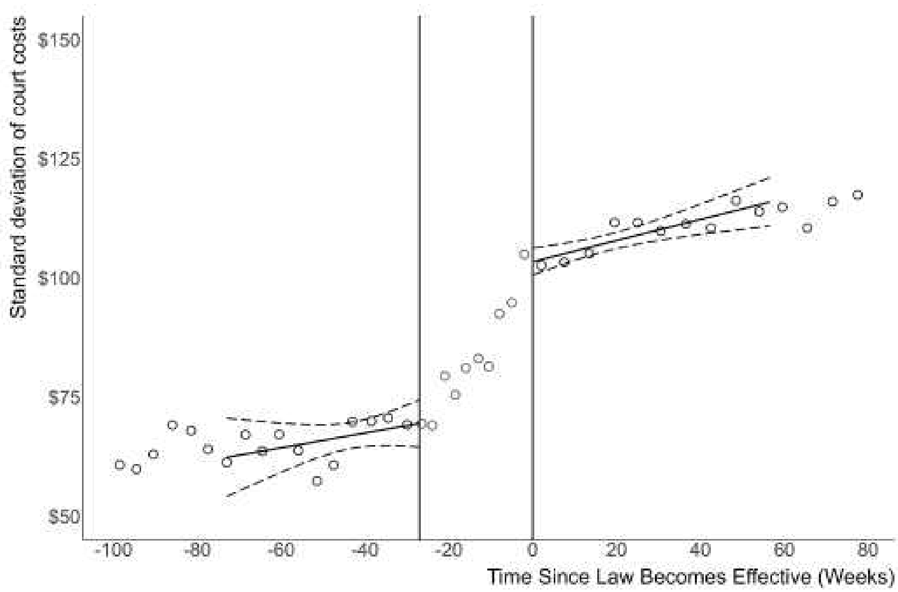
Notes: These figures display sharp RDD estimates of the impact of increased judge monitoring on court costs' waiver rates. See Table 2 for results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure B.2: Change in Variation in Waiver Rates and Court Costs Across Counties at Law Enactment Date

(a) Total Waivers

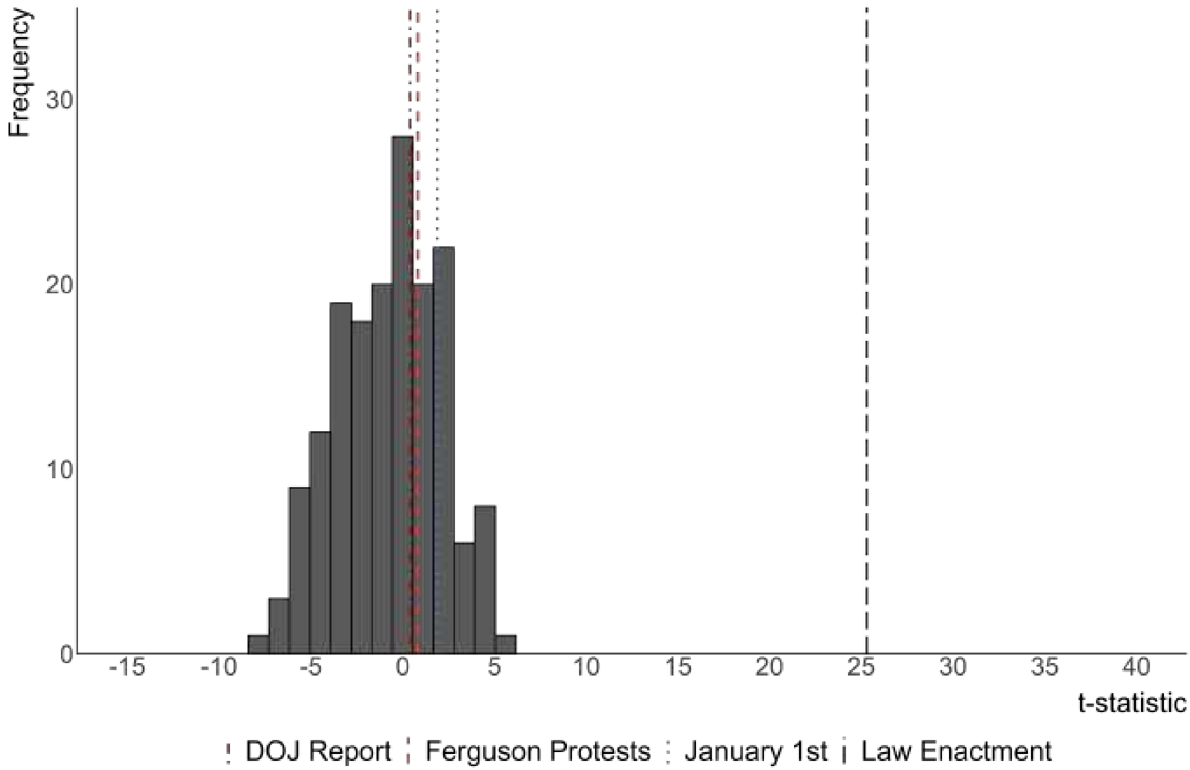


(b) Court Costs



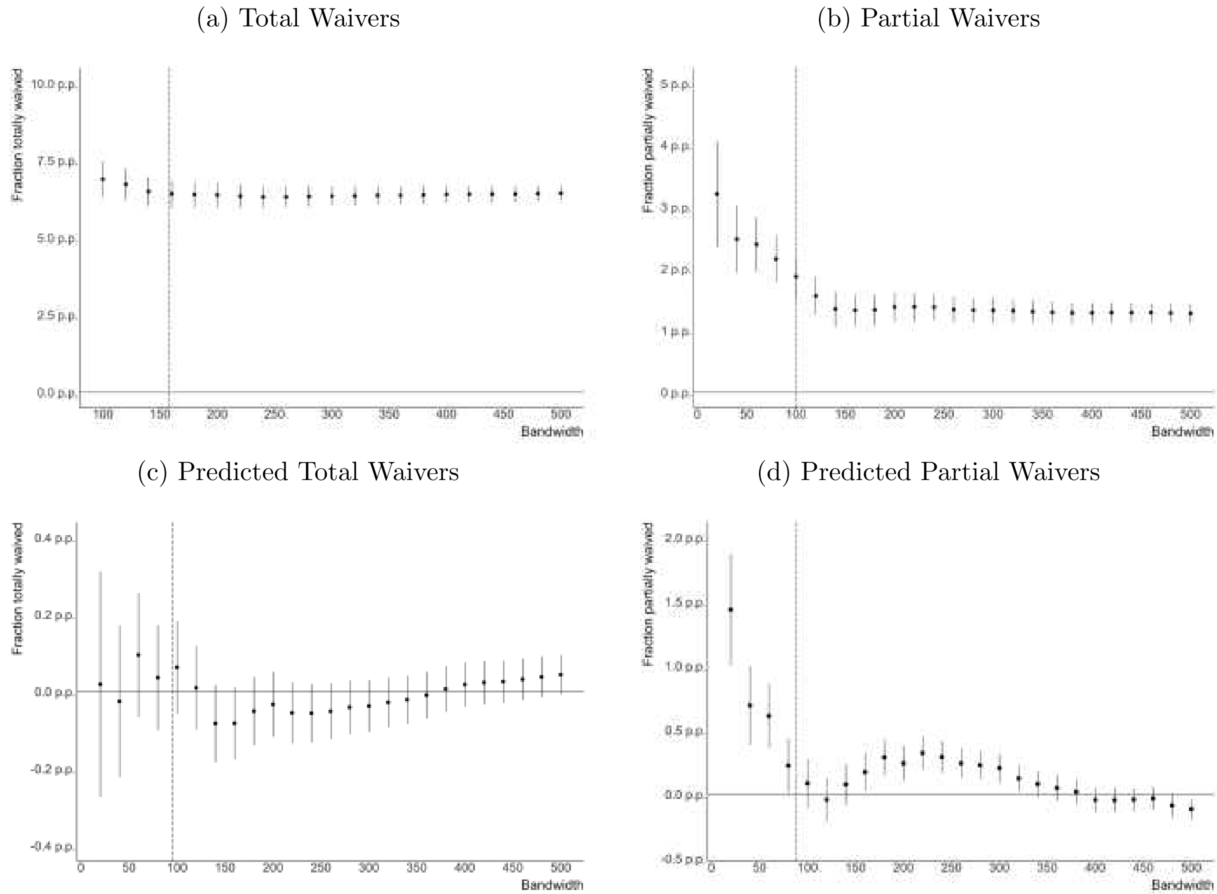
Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates and court costs. The black, solid vertical line denotes the time of enactment of the law. The black, dashed vertical line denotes the time of passage of the law. Predicted fit lines are generated using a sharp, linear RDD where time relative to the date of enactment of the law is the running variable. Sharp RDD estimated fit lines are in a solid pattern, and standard errors are in the dashed pattern.

Figure B.3: Change in Waiver Rates at Different Cutoff Dates



Notes: The figure above displays a histogram of t-statistics from 273 placebo regressions as well as the t-statistic associated with our main result (vertical dashed line). Estimates associated with the Ferguson protests, the release of the DOJ report, as well as the average of all January 1s are all also displayed.

Figure B.4: Robustness of balance in predicted indices and main results to varied bandwidths



(a) Total Waivers

(b) Partial Waivers

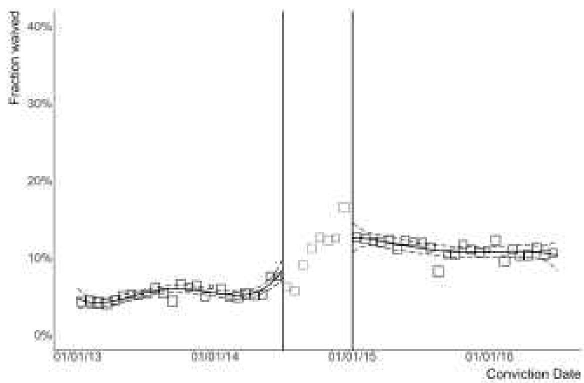
(c) Predicted Total Waivers

(d) Predicted Partial Waivers

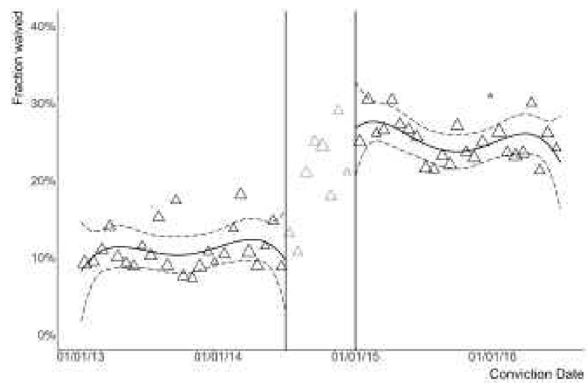
Notes: This figure plots the sharp RDD estimates measuring the effects of increased judge monitoring on predicted total and partial waivers (panels (a) and (b)) and actual total and partial waivers (panels (c) and (d)) for varying bandwidths (x-axis) ranging from 20 to 500 days in 20 day increments. Predicted outcomes are constructed using the following specification: indicators for sex, race, age at time of arrest, controls for type and seriousness of the charged offense, criminal record, and neighborhood income.

Figure B.5: Change in Waiver Rates by Judge Race

(a) White Judges



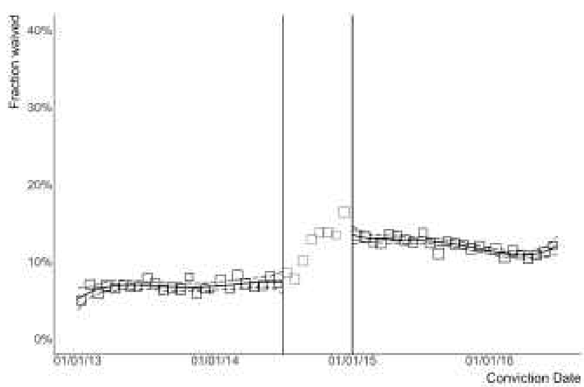
(b) Minority Judges



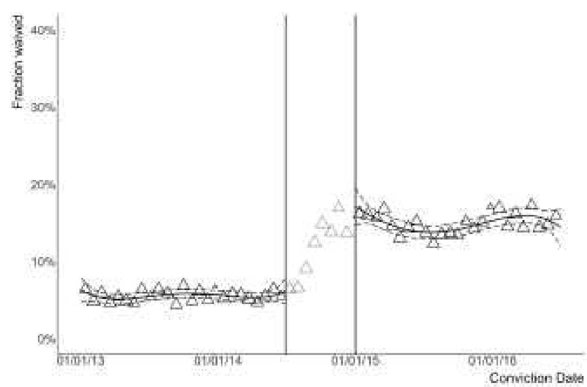
Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates and court costs. Panel A shows the effects for Democratic-leaning judicial districts, while panel B shows the effects in Republican-leaning districts. See Table B.6 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure B.6: Change in Waiver Rates by Judge Gender

(a) Male Judges

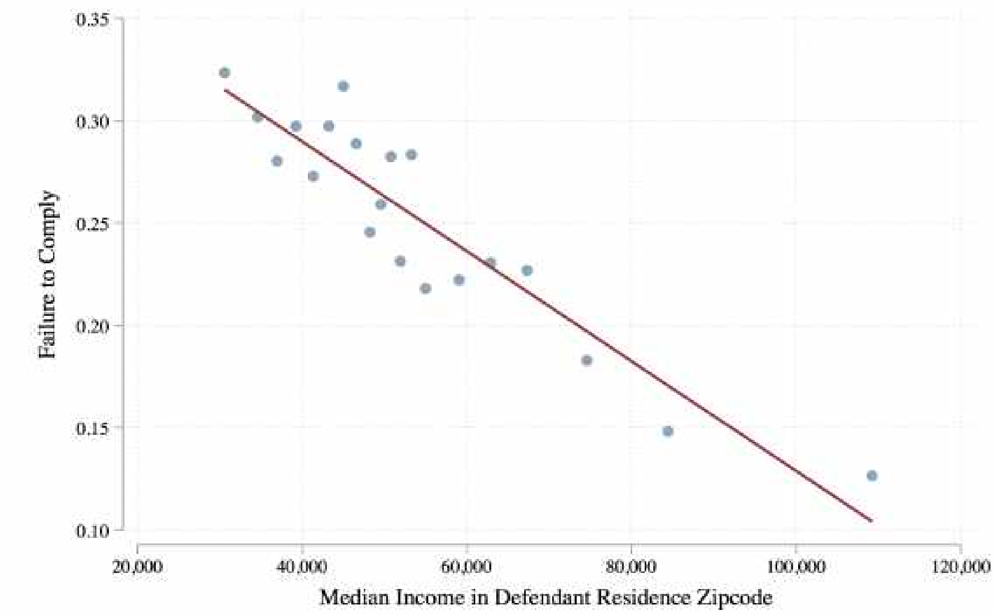


(b) Female Judges



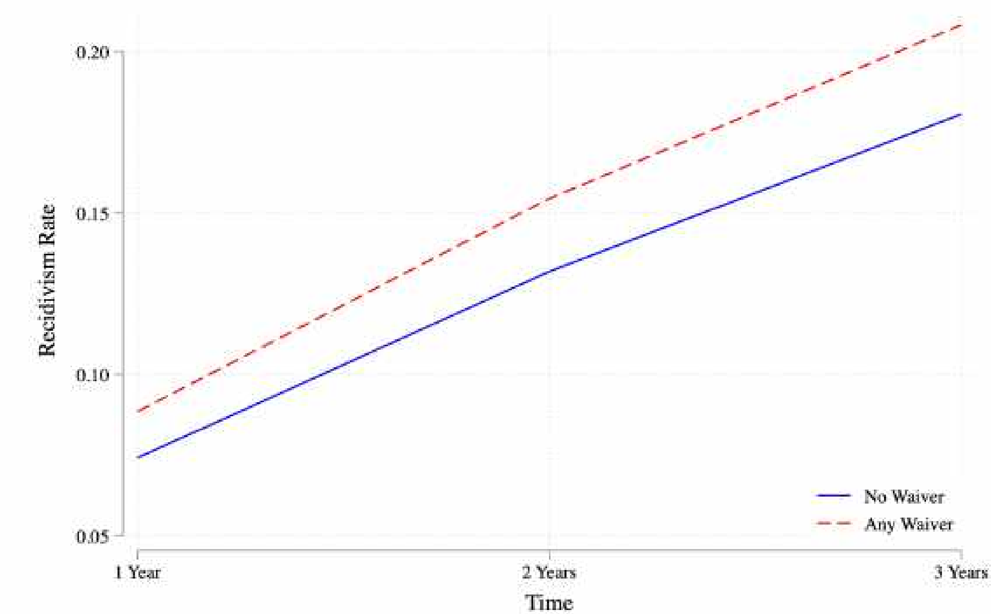
Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on waiver rates and court costs. Panel A shows the effects for Democratic-leaning judicial districts, while panel B shows the effects in Republican-leaning districts. See Table B.7 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure B.7: FTC and Defendant Income



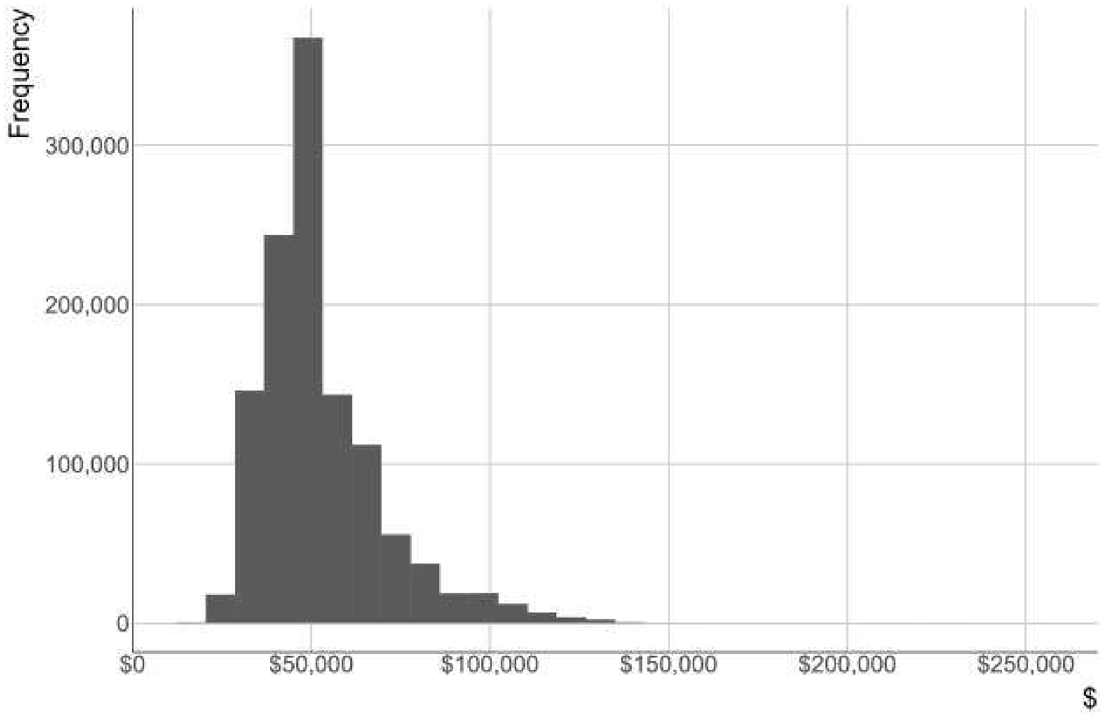
Notes:

Figure B.8: Recidivism by Court Cost Waiver Status



Notes:

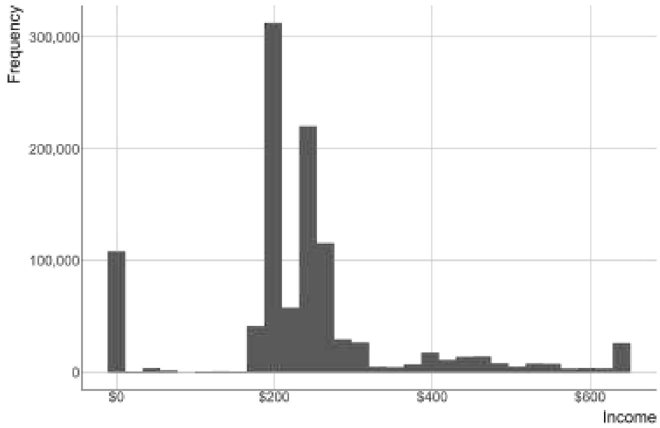
Figure B.9: Distribution of ZIP Code Median Income



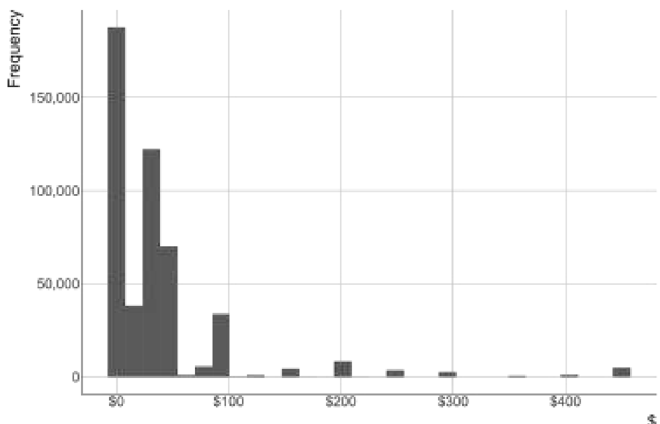
Notes: This figure displays the distribution of ZIP Code median income for North Carolina District Court Defendants for the period 2013–2021.

Figure B.10: Distribution of Court Costs, Fines, and Restitution

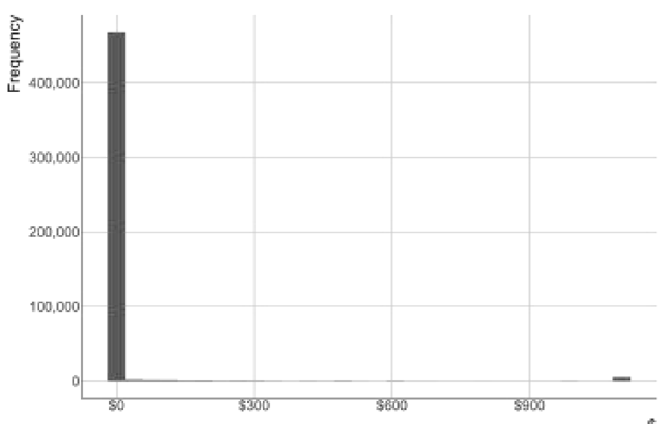
(a) Court Costs



(b) Fines



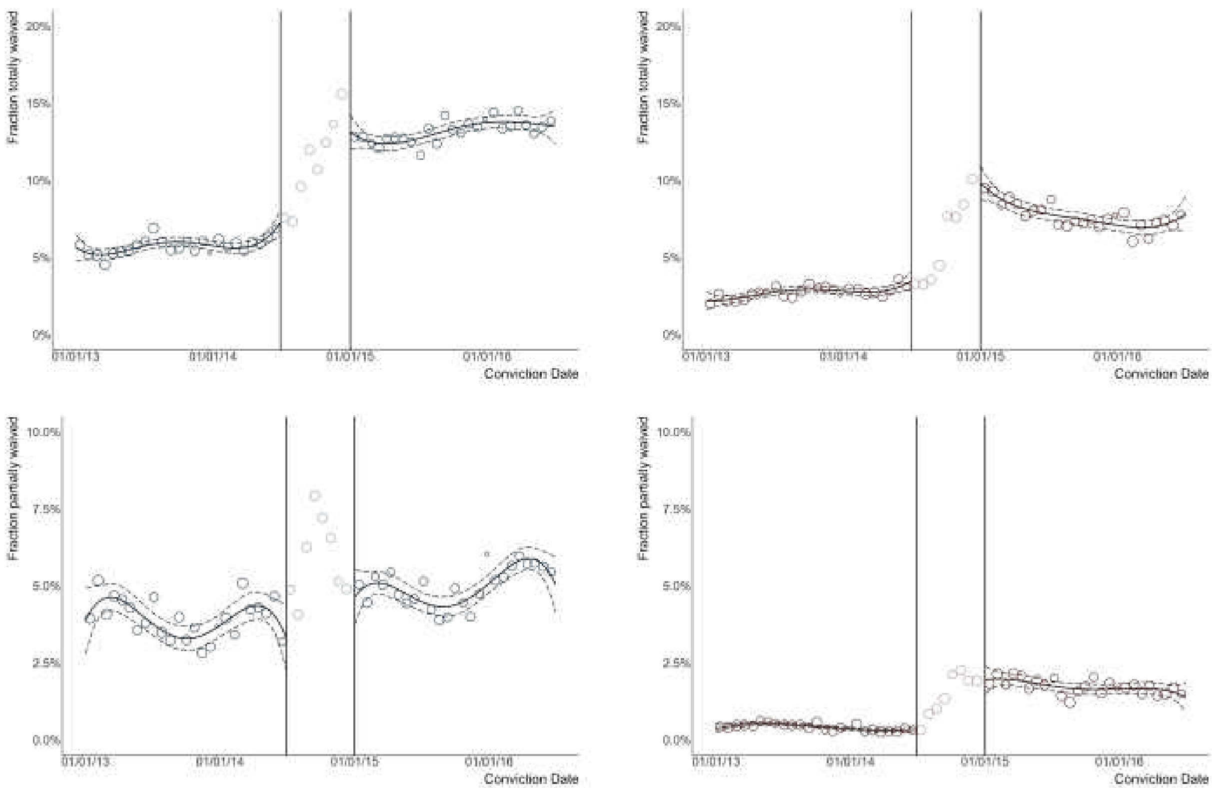
(c) Restitution



Notes: This figure displays the distribution of court costs, fines, and restitution for North Carolina District Court Defendants for the period 2013–2021. Values are winsorized at the 99th percentile.

Figure B.11: Change in Total and Partial Waiver Rates by Political Leaning of Judicial Districts

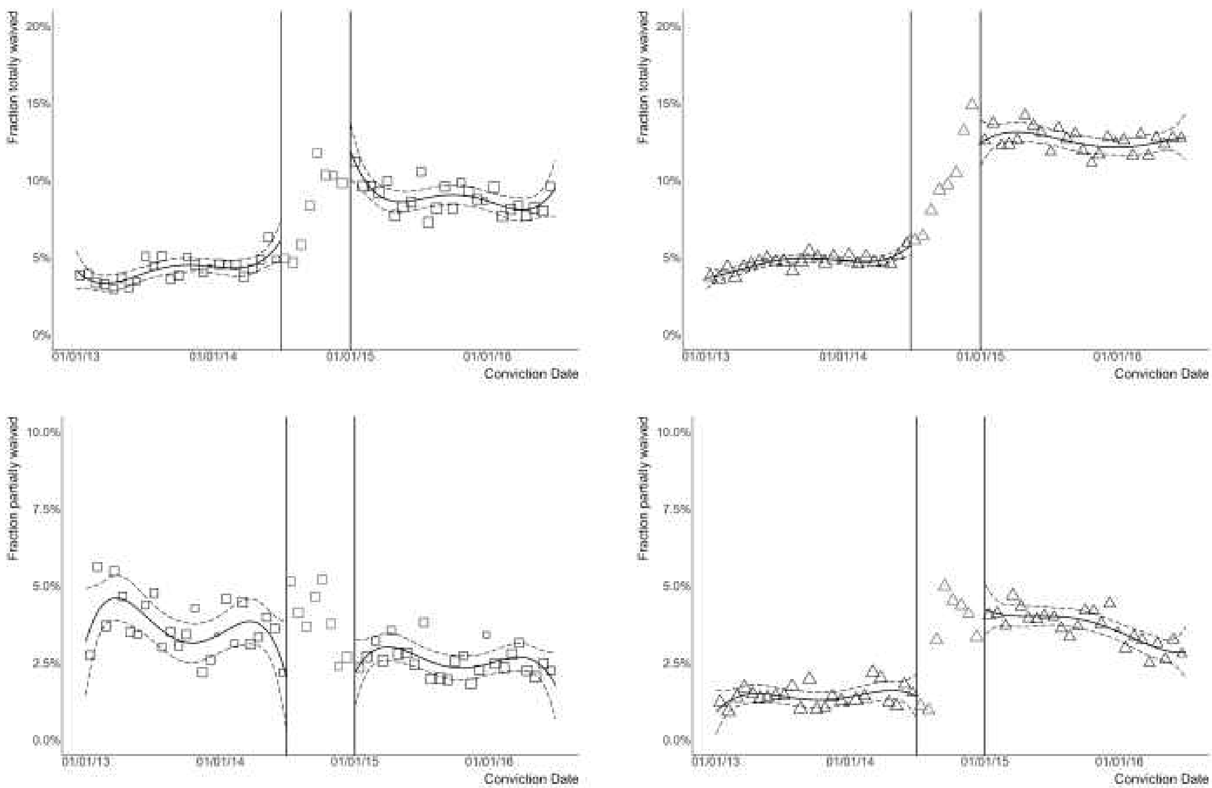
(a) Democratic Districts (b) Republican Districts



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on total and partial waiver rates. Panel A shows the effects for Democratic-leaning judicial districts, while panel B shows the effects in Republican-leaning districts. See Table B.3 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure B.12: Change in Total and Partial Waiver Rates by Closeness to Next Election

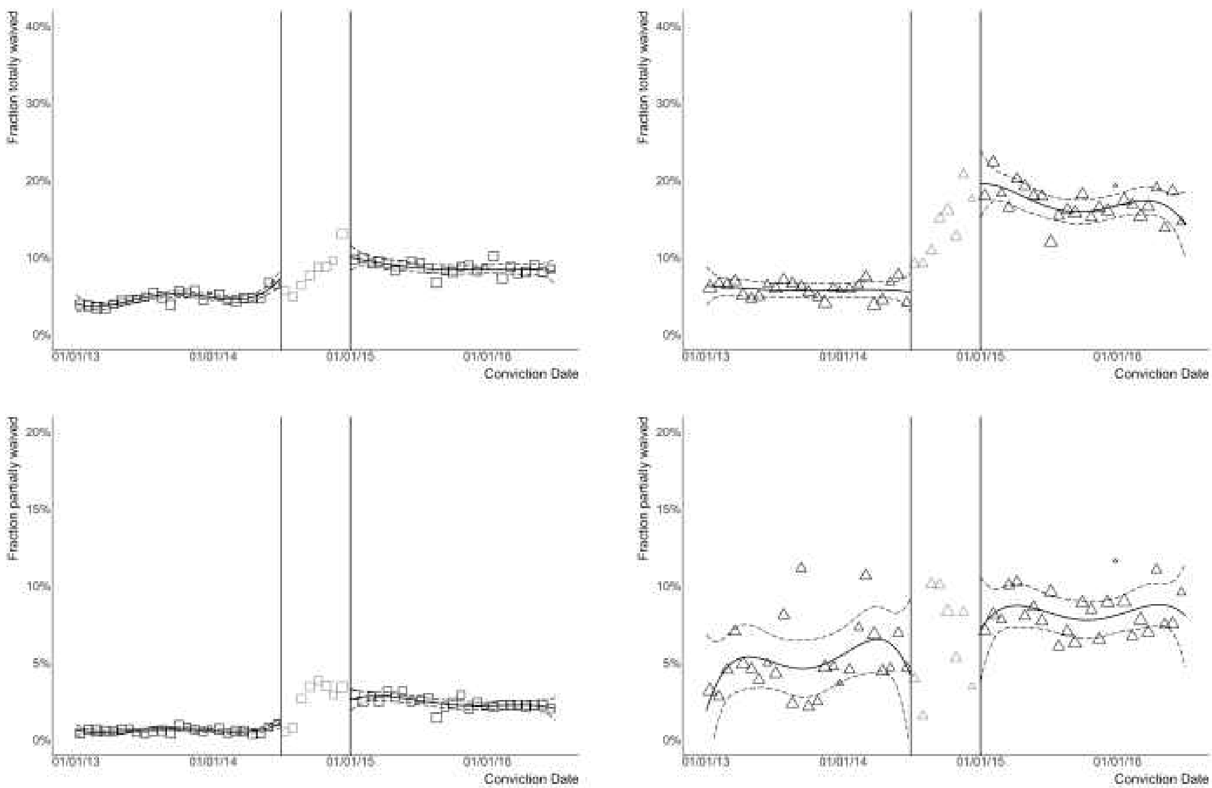
(a) Re-election in 4 years (b) Re-election in 2 years



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on total and partial waiver rates. Panel A shows the effects for judges who face re-election in 4 years, while panel B shows the effects for judges who face re-election in 2 years. See Table B.4 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure B.13: Change in Total and Partial Waiver Rates by Judge Race

(a) White Judges (b) Minority Judges

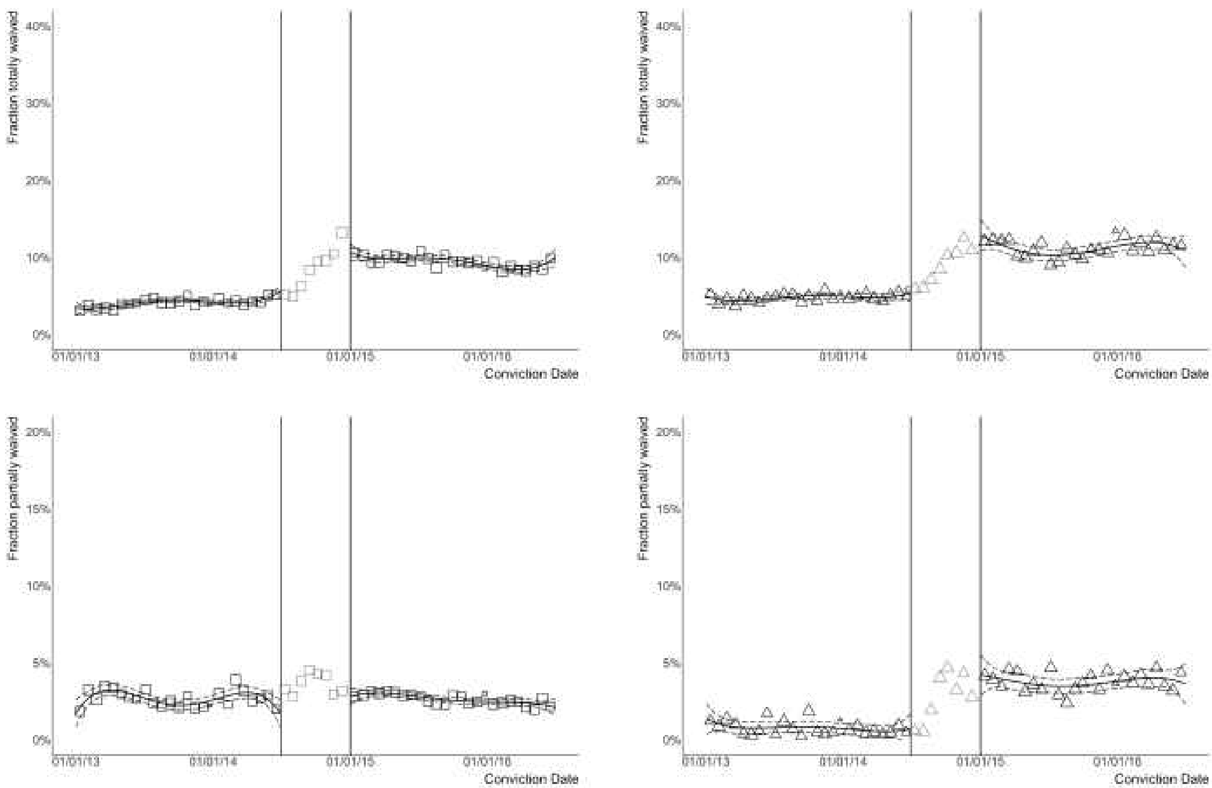


Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on total and partial waiver rates. Panel A shows the effects for White judges, while panel B shows the effects minority judges. See Table B.8 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

Figure B.14: Change in Total and Partial Waiver Rates by Judge Gender

(a) Male Judges

(b) Female Judges



Notes: These figures show the visual representation of the sharp RDD estimates of the impact of increased judge monitoring on total and partial waiver rates. Panel A shows the effects for Male judges, while panel B shows the effects for Female judges. See Table B.9 for the results in tabular form. Scatter points are binned using 21-day windows, with the size of the circle denoting the number of observations within each bin. The black, solid vertical lines denote the time of passage and enactment of the law, respectively. 4th degree polynomial fit lines are shown in solid pattern, and standard errors are in the dashed pattern.

C Data and Empirical Appendix

C.1 Definition of key variables

- **Court fees.** State laws allow courts to charge criminal defendants fees to recoup justice system costs. These may include charges for the use of a public defender, the cost of summoning expert witnesses, daily charges for incarceration, etc.
- **Fines.** Financial punishments assessed by a judge upon conviction for any level of offense, typically specified in state statutes as a fixed dollar amount or variable range.
- **Restitution.** Costs imposed by the court on the defendant to compensate victims who were either injured and/or suffered loss of or damage to property as a result of the defendant's offense.
- **Legal Financial Obligation (LFO).** Fines, court fees, and restitution imposed by the court on top of a criminal sentence upon conviction, i.e., LFOs = fines + court fees + restitution.

C.2 Data

C.2.1 Court data

The main data for our analysis comes from the Active Criminal/Infraction System (ACIS), maintained by the North Carolina Administrative Office of the Courts (NCAOC), and encompasses the universe of criminal cases in North Carolina. Our data extract covers all criminal cases in the state whose last update was between January 1, 2013, and December 31, 2021.

The ACIS data has two main components: Case Records and Offense Records.

- *Case Records* are at the *case-level* and have information on defendant demographics and case characteristics. Demographic information on defendants includes their date of birth, gender, race, and their exact address and ZIP code. Case characteristics include court type (district or superior court), court county, and origination date. Importantly, for our empirical strategy, the case records data consists of the case trial date and case disposition dates, allowing us to observe the exact date when the decision on a case was made.
- *Offense Records* contain information on each charge for each criminal case. For each case, it includes the list of all charges and corresponding disposition outcomes. Each offense within a case contains the offense characteristics like offense date, offense type, offense class, offense description, and offense statute. Each offense charge includes information on the defendant's plea, verdict, and the type of disposition. Additionally, it contains the initials of the judges who make the disposition. Most importantly, it also contains detailed information on sentencing outcomes, including sentence length, fines/restitution, court costs, and whether the court costs were waived. Court cost waiver decisions and the assessed court costs are our outcomes of primary interest.

Both case records and offense records contain unique case identifiers, allowing us to link them together.

C.2.2 Judges' Profiles

In addition to the ACIS court data, we manually constructed profiles for all district court judges who served between 2013 and 2018. The ACIS data provides the judge's initials that disposed the case, the district/county of the case, and the disposition year. Using various sources, we manually linked the judges' initials to their names, allowing us to identify which cases were assigned to each judge. This also enabled us to gather additional information about the judges for further analysis of heterogeneity in treatment effects. Specifically, we collected details on each judge's name, race, gender, first appointment year, re-election years, contest elections, and when they left office.

Here is the list of sources we used to identify the judges' names, along with the additional information they provided:

- Judicial directory of North Carolina (for *current* judges): name, district/county.[37]
- Ballotpedia.org: name, gender, race (when picture was provided), district/county, year they first got appointed (provided most of the time), when they leave office (provided most of the time).
- North Carolina State Board of Elections: years when they are up for re-election.[38]
- Waiver Reports: name, year of being active.
- Emergency Judges List: name, district/county, year of being active, residence status.

C.3 Data Cleaning Process

C.3.1 Create *case-level* court data

Since the main data records are at a different level, an important step in data cleaning is to transform the charge-level offense records to the case level and combine them with their associated cases. Charges in the offense records are the most granular unit of observation, and it is common for a case to contain multiple charges.

Starting with the offense records, where multiple offenses may be linked to the same case, we retain only the most serious offense charged at arrest per case. Court costs and waivers, though reported at the offense-level data, are assessed at the case level After keeping one offense observation per case, we merge the offense records with their corresponding case-level information, resulting in a case-level dataset.

We keep casse were disposed between January 1, 2013, and November 30, 2017. In the final step we drop cases were the defendant was NOT found guilty, the ruling was not by a judge, the final disposition is pending probation cases, offenses that are not being tried due to defendants being tried for other offenses, offenses where there's been a change of venue or a transfer to other district court, as the newly tried offense is in the data in another jurisdiction, cases remanded to district court and where appeals are withdrawn, i.e., that are sent back to lower courts after an appeal.

[37] https://www.nccourts.gov/judicial-directory

[38] https://www.ncsbe.gov/results-data/candidate-lists