Crime and (Monetary) Punishment

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Abstract

This paper examines the effects of monetary sanctions (fines and court fees) on criminal defendants. There is limited causal evidence on the direct effects of monetary sanctions due to them both not being levied randomly, as well as typically being bundled with other penalties. I identify the causal effect of monetary sanctions by leveraging the quasi-random assignment of judges and isolate their effect by studying low level misdemeanors in North Carolina, where penalties are limited to fines and fees only. I find no impact of fines and fees on the likelihood of defendants engaging in subsequent criminal activity (-0.058, SE=0.054). There are strong negative effects (-0.069, SE=0.030) for financially motivated offenses. Defendants living in wealthier areas are the most strongly deterred (-0.087, SE=0.029), I cannot rule out some criminogenic effects for defendants living in poorer areas. Policies that aim to recognize defendants' ability-to-pay are recommended.

Keywords: Monetary sanctions, Legal financial obligations, LFO, Specific deterrence.

JEL Codes: J64, K14, K42.

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1 Introduction

Every year over 16 million people go to court in the United States,[1] and even though relatively few end up doing any prison time, the vast majority of them end up owing money–oftentimes considerable amounts–in criminal debt because of fines and court fees[AVERAGE IN LITERATURE AND IN MY SAMPLE].[2] Total debt owed to the criminal justice system exceeds 50 billion dollars (Beckett and Harris, 2011).

Despite monetary sanctions having always been part of the U.S. criminal justice system (Ruback and Bergstrom, 2006), the system has expanded dramatically[3] these past few decades and rising expenditures[4] have prompted state and local governments, who pay many of the operational costs of the criminal justice system, to turn increasingly towards monetary sanctions–fines and fees–as a source of additional revenue.[5,6]

This revenue-generating motive has prompted increased attention these past few years, especially following the police killing of Michael Brown Jr. in Ferguson, Missouri, as the U.S. Department of Justice's investigation that followed highlighted the focus of Ferguson law enforcement on revenue generation. Attention has been mainly on the extent to which the use of monetary penalties disproportionately impacts the poor, because of their general inability to pay, and, in turn, because of the higher percentage of African Americans, Hispanics and other minorities in this group, on how most of the burden of monetary sanctions fall on these groups.

However, despite this high–and growing–incidence of monetary sanctions, there is little evidence of their consequences for defendants. Claims have been made in recent years of a "path to crime" for poorer defendants as monetary sanctions trap them in poverty (Bannon et al., 2010 and Harris, 2016), but with no causal backing.

What are the effects of monetary sanctions on defendants[BE SPECIFIC–INCLUDE

[1]Between 3 and 4 million felony cases are filed annually in state and federal courts, and over 13 million misdemeanor cases (Natapoff, 2018; Stevenson and Mayson, 2018).

[2]All fifteen states in Bannon et al. (2010) imposed fees upon conviction, for example.

[3]Between 1990 and 2014, incarceration rates increased by 61 percent, and in 2014, over 2.2 million people were incarcerated in local jails or in State and Federal prisons (Cohen, 1991 and Carson and Anderson, 2015)

[4]Between 1993 and 2012, total real annual criminal justice expenditures grew by 74 percent from $157 to $273 billion, with local spending comprising approximately half of total expenditures. State corrections expenditures represent 7 percent of the total State general funds on average, and 11 States spent more on corrections than higher education in 2013 (Council of Economic Advisers, 2015).

[5]Monetary sanctions, usually referred to as legal financial obligations (LFOs) as well, also consider restitution and forfeitures (See Appendix C for a full taxonomy). In my data I only see fines and court fees, so I will refer to monetary sanctions either as such or as fines and fees throughout.

[6]In 1986, 12 percent of those incarcerated were also fined, while in 2004 this number had increased to 37 percent. When including fees as well, the total rises to 66 percent of all prison inmates. In 2014, 44 States charged offenders for probation and parole supervision, up from 26 in 1990 (Council of Economic Advisers, 2015).

OUTCOMES]? In this paper I investigate the effects of monetary sanctions on future reoffending using administrative data from North Carolina, from 2014 until 2021. I also assess the differential effects of monetary sanctions on poorer defendants and evaluate the mechanisms that can explain this heterogeneity.

[THERE ARE 3 MAIN ISSUES:] Teasing out the effects of monetary sanctions is complicated by the fact that in current practice monetary sanctions are usually levied in addition to other common penalties such as community service, probation, parole, or incarceration (Harris et al., 2011)[7]. I address this challenge by focusing on defendants targeted by North Carolina's 2013 Appropriations Act, which limits the scope of sanctions for these defendants, effectively making them susceptible only to monetary sanctions. This subsample is relevant in and of itself, as these are mostly first-time offenders, encountering the criminal justice system for the first time and, studying ways to avoid reentry is of major policy relevance (CITATION).[8] I leverage the fact that in North Carolina defendants are randomly assigned to judges that differ in their propensity to levy monetary sanctions in order to recover a local average treatment effect (LATE) for individuals at the margin of being levied higher monetary sanctions, i.e., what's commonly referred to now as the "judge fixed effects design" (EXPLAIN).[9]

I measure judges' "fining" propensity using a leave-one-out–residualized measure, as in Dahl et al., 2014, Dobbie et al., 2018, Bhuller et al., 2020, Agan et al., 2021– mean of judges' choices regarding fines, fees, and restitution. This measure is highly predictive of the amount of monetary sanctions defendants endure, but uncorrelated with case and defendant characteristics. Going from the most lenient to the least lenient judge increases a defendant's expected monetary sanction by XX percentage points.

I first estimate the effects of monetary sanctions on reoffending. I find that defendants receiving monetary sanctions are XX percentage points less likely to recidivate within two years after their trial, XX percentage points less likely to recidivate committing a misdemeanor, and XX percentage points less likely to commit a felony. I also see reductions in property (XX% pp) and XX crimes (XX% pp). The results are not so clear for violent and drug offenses, where I cannot rule out increases in reoffending rates of XX and XX percentage points, respectively. I do not find criminogenic evidence stemming from monetary sanctions

[7] One approach to address multiple treatments such as these is Mueller-Smith (2015)....

[8] Furthermore, while the use of fines and fees has grown for all sentencing groups, they remain more common in cases of misdemeanors, infractions, and other relatively less serious crimes. Therefore, an individual's first encounter with the criminal justice system will probably involve monetary sanctions.

[9] Examples of papers exploiting this research design include Kling, 2006, Aizer and Doyle Jr, 2015, Mueller-Smith, 2015, and Bhuller et al., 2020, studying the effects of incarceration; Dobbie et al., 2018 assessing the consequences of pretrial detention; Norris et al., 2021 estimating the impact of parental incarceration; and Agan et al., 2021 looking at the effects of misdemeanor prosecution.

though, only deterrence.

When thinking of offenses that would be affected the most following the experience of monetary sanctions, I characterize offenses as either being or not financially motivated (Tuttle, 2019). I find strong negative effects, XX pp, of monetary sanctions on reoffending for these kind of offenses. One would expect that the impact of monetary sanctions on these type of offenses to be a direct function of defendants' wealth. In order to study this possible heterogeneity I split the sample in income quartiles (proxying wealth with the median household income in the census tract where the defendant lives) and estimate the effects of monetary sanctions separately in each subsample. I can see a clear pattern, where financially motivated offenses are deterred only for those wealthier defendants.

Even though it is a widely accepted conclusion of the economic literature on optimal law enforcement that nonmonetary sanctions carry no social costs and, implicitly, that agents do not react to their experience, (Becker, 1968; Polinsky and Shavell, 1984, 2000; Garoupa, 1997), there is considerable evidence that the experience of monetary punishment can have substantial effects on behavior in the space of regulatory violations (Gray and Jones, 1991; Weil, 1996; Ko et al., 2010; Stafford, 2003; Eckert, 2004; Stafford, 2014; Gray and Deily, 1996; Nadeau, 1997; Gray and Shadbegian, 2005; Keohane et al., 2009; Magat and Viscusi, 1990; Laplante and Rilstone, 1996; Earnhart, 2004b; Earnhart, 2004a; Shimshack and Ward, 2005; Glicksman and Earnhart, 2007; Shimshack and Ward, 2008; Earnhart and Segerson, 2012; Makofske, 2020).[10,11,12] Furthermore, in a result similar to what I find in this paper, Earnhart and Segerson, 2012 find the effectiveness of increased enforcement–regarding firms' environmental performance–depends on firms' financial status.

Additionally, the wealth of evidence regarding the disincentives imprisonment has on criminal offending (Helland and Tabarrok, 2007; Drago et al., 2009; Bell et al., 2014; among others), as well as the effects of experiencing prison terms, both on criminals themselves as well as their families (Kling, 2006; Mueller-Smith, 2015; Bhuller et al., 2020; Bayer et al., 2009; Stevenson, 2017; Norris et al., 2021) contrasts with the total lack of any for monetary sanctions, even though they are the most common form of punishment in the US.

This paper contributes broadly to the literature on both criminogenic factors stemming

[10] Gray and Jones, 1991, Weil, 1996, Ko et al., 2010 OSHA–Occupational Safety and Health Administration– inspections on future compliance of inspected facilities

[11] Stafford, 2003; Eckert, 2004 Environmental Protection Agency in toxic, hazardous, and household waste contexts is mixed. Nevertheless, some significant specific deterrence is typically detected in most studies. Gray and Deily, 1996 Nadeau, 1997 Gray and Shadbegian, 2005 Keohane et al., 2009 air pollutants. Magat and Viscusi, 1990 Laplante and Rilstone, 1996 Earnhart, 2004b Earnhart, 2004a Shimshack and Ward, 2005 Glicksman and Earnhart, 2007 Shimshack and Ward, 2008 Earnhart and Segerson, 2012 CWA. See Alm and Shimshack, 2014 for an overview of the literature.

[12] Makofske, 2020 studies how food service establishments respond to one-letter downgrades in health inspections and finds that restaurants are assessed 17%–27% fewer demerits following a downgrade.

from punishment, as well as prisoner reentry, specifically that which explores the effects of financial support for released offenders. This literature has focused mostly on incarceration, finding effects that range from XX to XX (Kling, 2006; Bayer et al., 2009; Mueller-Smith, 2015; Stevenson, 2018) for each additional year in their sentence. There has also been some observational research concerning monetary sanctions but not much regarding their consequences.[13,14] Gordon and Glaser, 1991, in California's lower courts, find that, relative to jail sentences, monetary sanctions were associated with lower incidence of reoffending. However, among those receiving only monetary penalties, the amount had no relationship with reoffending. Financial penalties seemed to neither encourage nor deter future criminality. Piquero and Jennings, 2017 find that assessing monetary sanctions on juvenile offenders and their families increases the likelihood of recidivism. Furthermore, Schneider (1986) and Butts and Snyder (1992) study randomized trials and find that restitution, compared to other non-monetary sanctions, is associated with higher recidivism rates. Finally, Raphael (2011) and Jacob and Ludwig (2012) study how greater financial assistance following release reduces recidivism rates.

Second, I also contribute new evidence highlighting the relationship between financial need and criminal behavior, which links to the the broader literature in specific deterrence, which focuses mainly on business regulation. The paper most closely related to mine in this area is Earnhart and Segerson, 2012's study of how businesses' financial status affects their behavior following punishment for violation of environmental standards.

Finally, by considering recent studies looking at incarceration as well as alternative punishments (declining to prosecute, diversion, dismissal, pretrial probation, and deferred adjudication) for lesser offenses (Mueller-Smith and T. Schnepel, 2020, Agan et al., 2021) this paper speaks to the question of what punishment schemes should be on the table.

[IMPLICATIONS]

The remainder of the paper is structured as follows. Section 2 provides a brief overview of North Carolina and judge assignment in this context, as well as describe my data and provide some summary statistics. Section 3 develops a simple conceptual framework in order to focus the analysis. Section 4 describes my empirical strategy. Section 5 presents the results, and some interpretation, and Section 6 concludes. An Appendix provides additional results and

[13] (Albrecht & Johnson, 1980; Glaser & Gordon, 1988; MacDonald, Greene, & Worzella, 1992). Administrative or process based (cf. Hillsman,1990). Focused on the extent to which the use of monetary penalties disproportionately impacts poor defendants because of their general inability to pay (Beckett et al., 2008; Council of Economic Advisers, 2015).

[14] An exception to the observational literature is Lurigio and Davis, 1990, who randomly assigned adult probationers who were delinquent in paying restitution to receive reminder informing them the amount they owed and threatening with sanctions in the event of noncompliance. Defendants who received this notification were significantly more likely to pay restitution, with stronger effects for those with greater payment ability.

detailed information on administrative information and alternative outcomes used in the analysis.

[MENTION ABILITY TO PAY - Fernandes et al 2019]

[MENTION LOSING DRIVER'S LICENSE – CITE MYSELF? HAHAHA]

2 Conceptual framework

In this section I lay out a framework in order to understand the mechanisms through which monetary sanctions operate. There are three channels through which monetary sanctions may affect reoffending which I dub: deterrence, signaling, and income. I'll go over them in detail now.

2.1 Deterrence

By deterrence I mean the way in which the "experience" of the fine affects reoffending.[15] Defendants may have expected lower fines in the event of apprehension, or not be aware of the extent of court fees, for example. Defendants, upon experiencing fines and court fees, then, would update their information and, if they expected fines and fees to be lower (higher) they would be more (less) deterred from reoffending in the future as expected costs would increase (decrease) in their analysis.

It can also be the case that defendants' preferences change altogether. The payment of fines or fees may be much worse than a simple transfer due to the court system hassle, for example.

Through the deterrence fines can lead to either more or less reoffending, depending on defendants' prior expectations. In regards to their relationship with income, since prior could be a function of income in principle, it's hard to say. One would expect heterogeneity in the types of crimes that experience deterrence though. If defendants are updating their expectations regarding the financial costs of criminal activity one should expect deterrence for those criminal offenses that are motivated by economic gain only.

2.2 Signaling

Fines and fees that are too steep may be interpreted by defendants as a signal regarding the operation of the criminal justice system as a whole (D'Antoni and Galbiati, 2007): "I

[15] In criminology general deterrence is distinguished from specific deterrence (Chalfin and McCrary, 2017). General deterrence corresponds to XX, while specific deterrence speaks to XX. With regards to this nomenclature I am referring to specific deterrence.

understand you have to pay your way, and the court has to pay its way, and they got to collect off somebody. But it seems to me like the way our criminal justice system works, you know, there's too many people making money out of corrections, and the corrections isn't correcting anything" (Harris, 2016).

If criminals have altruistic motives and are uncertain about the harmfulness of their actions, a situation where the harshness of sanctions may convey information about the social costs of offenses, high monetary sanctions can affect the "credibility" of the public enforcer, having criminals question that the enforcement policy is more about revenue maximization for the enforcer than aimed at deterring socially costly violations.

This signaling mechanism then predicts that higher fines would lead to more reoffending, as defendants revise down their expectations of the social costs of their actions. This signaling should affect all types of offenses, as the updating is with regards to the public enforcer, not monetary sanctions specifically.

2.3 Income effects

By income effects[16] I refer to this, as of late, popular story of people needing to supplement their income through illegal means due to the harsh negative income shock these monetary sanctions represent.

The negative shock to a defendant's income that monetary sanctions represent may push them towards–financially-motivated–criminal endeavors, in order to supplement their consumption needs. A more extreme version of this argument argues that "[i]n an attempt to escape sanctions, defendants sever the 'bonds of conformity' (steady employment, stable housing, social relationships) that are associated with criminal desistance. As a result, fines and fees can foster marginalization and recidivism" (Harris, 2016). This need not occur right away; a defendant may initially forgo payment of rent or utilities in order to pay their legal financial obligations: as Natapoff (2018) recounts, upon asking a criminal defendant how he payed off his legal financial obligations, "I rob Peter to pay Paul... [Not paying] rent, and car payments, insurance payments...". Some defendants may thus start on a debt spiral that eventually makes it that much more appealing to resort to crime: "one defendant we interviewed, recalled that when he had to choose, he paid fines and fees over child support because he thought he was less likely to go to jail that way. He also sold narcotics to pay both debts. As he noted, 'why not do more crimes if you're already in trouble?' " (Nichol and Hunt, 2018). Even monetary sanctions of low amounts may impact defendants through this "income effect" channel: unpaid legal financial obligations can trigger additional

[16] What I refer to as income effects are not the usual "parallel expansions" of budget sets; I use loosely this term to refer to agents' responses to income shocks.

sanctions that vary in scope and severity; as unpaid legal financial obligations can grow over time as interest and other payment penalties accrue; they can also have non-justice related consequences including the suspension of, or inability to renew, a driver's license. Finally, because the assessment of fees and fines is not scaled to a defendants' income or employment status and, therefore, monetary sanctions of the same amount are technically harsher for poorer defendants, thus suggesting a relationship between a defendant's income and their response to the experience of monetary sanctions. Summarizing, I would expect that monetary sanctions operating through the "income" channel would affect mostly poorer defendants, probably with a lag of a few months, increasing their reoffending specifically through financially-motivated offenses.

2.4 Predictions

Deterrence in terms of updating should be somewhat invariant to income. This to the extent that priors do not differ within this margin. In terms of the negative signal steep monetary sanctions may convey, one would expect this to be stronger for lower income groups. Income effects, on the other hand, should operate only on poorer defendants. One would also expect this to kick in with a lag, as the mechanisms, missed rent payments, worsened credit score due to legal financial obligations accruement, loss of driver's license, etc. take time to kick in. Additionally, this channel should be accompanied with failure to pay the financial obligations in the first place.

[let's we ignore the signaling story, i can't speak to it (only looking at average fines). results cant speak as to whether different priors or if some monetary channel. suggestive evidence from moving (different addresses–with lower median income– upon recidivating)]

[THEREFORE, ONE PREDICTS THERE'LL BE DETERRENCE ACROSS INCOME LEVELS, AND AN INCREASE IN CRIMINALITY FOR LOWER INCOME LEVELS DUE TO INCOME EFFECTS]

While this coordination effect is likely to apply to both property and violent crime, we do not find evidence of it below, and thus focus our discussion on the incapacitation and concentration effects

Pérez and Kiss (2012)

3 Setting: North Carolina

There are three main challenges when investigating the effects of monetary sanctions. First, high-quality data on total fees and fines assessed are difficult to obtain. Second, the endogeneity of monetary sanctions and subsequent outcomes. And third, the fact that monetary sanctions are typically being bundled with other penalties.

I use data from North Carolina because it allows me to address each of these concerns. The data provided by North Carolina's Administrative Office of the Courts (NCAOC) provides detailed information regarding fines, court costs, and restitution. Furthermore, the quasi-random assignment of district court judges allows me to identify causal effects by using a leniency design. Finally, because of reforms that went into effect in 2014, there is a subset of offenses that are only liable to monetary sanctions, allowing me to study their effect in isolation. In this section I address each of these in detail.

Let me begin with an overview of the North Carolina criminal justice system and its monetary sanctions policies.

3.1 The North Carolina Criminal Justice System

I use data on criminal cases prosecuted in North Carolina's District Courts. The court system in North Carolina consists of two trial court divisions: the Superior Court division and the District Court division.[17] Superior Courts are the highest of the general trial courts and, broadly speaking, have jurisdiction over all felony cases, while District Courts have jurisdiction over misdemeanors and infractions.[18,19]

North Carolina is divided into Superior Court divisions, which are then subdivided into districts (5 divisions and 48 districts as of 2019). In the same way the state is also subdivided into 41–as of 2019– District Court districts. These divisions serve both electoral and administrative purposes.[20] See Figures C1 and C2 in the Appendix.

All Superior Court cases brought to trial are decided by a jury of 12, who determines whether the defendant is guilty. A criminal trial in District Court, on the other hand, is always a "bench trial", a judge decides the verdict instead of a jury. [21]

[17] There is also an appellate division, which comprises the Supreme Court and the Court of Appeals. More details are provided in Appendix D.

[18] Technically, the Superior Courts have exclusive jurisdiction over all felony cases, as well as over civil cases involving large amounts of money and misdemeanor and infraction cases appealed from a decision in District Courts. District Courts, then, have exclusive "original" jurisdiction over all misdemeanors and infractions, as all misdemeanor crimes and infractions are tried initially in District Courts (unless the misdemeanor was committed as part of the same act as a felony, in which case both are tried together in Superior Court).

[19] An infraction is not a criminal offense and may be punished only by a fine.

[20] All judges and district attorneys participate in partisan–as of 2018– elections in even-numbered years. Superior Court judges serve eight-year terms, while District Court judges and district attorneys serve for four years.

[21] because the Sixth Amendment to the United States Constitution guarantees a person charged with a crime the right to be tried by a jury, a defendant convicted of a misdemeanor in district court has the right to appeal his conviction to the superior court for a new trial (also called a trial "de novo"), in which the trial must be before a jury. If a defendant pleads guilty to a low-level felony in district court and appeals

In addition to judges, prosecutors, and defense attorneys, the other District Court official that plays a role in the disposition of criminal cases is the magistrate. [22] Magistrates are generally the first judicial officials involved in criminal cases, because they usually issue the criminal process (e.g., a warrant for arrest) that begins most criminal cases. The magistrate also generally sets the initial conditions for pretrial release (bail) for persons who have been arrested. More importantly, and relevant for the present study, in disposing of criminal cases, magistrates have jurisdiction to accept waivers of trial and guilty pleas to certain minor misdemeanors and pleas of responsibility to infractions. The minor misdemeanors and infractions for which magistrates may accept waivers of trial and pleas of guilt or responsibility, as well as the fines associated with each of them, are listed in uniform statewide schedules (called "waiver lists"), which are developed by the chief district court judges at their annual conference. See Figure XX for an example of one such list.

It is important to note that the North Carolina court system uses a structured sentencing scheme since 1994,[23] that classifies felony charges into ten classes (A, B1, B2, C, D, E, F, G, H, and I, where A is the most severe one and I, the least), misdemeanor charges into three (A1, 1, 2, and 3, where A1 is the most severe and 3, the least), and defendants facing felony (misdemeanor) charges into six (three) different criminal history levels (I-VI or I-III, where higher levels indicate more severity). The law stipulates a sentence range[24] for each combination of offense class and prior record level, and the sentence may be active (i.e. the offender needs to be under custody) or suspended. For certain class-record combinations, the judge has to decide whether the sentence should be active or suspended. The current punishment charts for both misdemeanors and felonies committed are depicted in Figures C3 and C4.

the judgment, there is no new trial in superior court. Because the plea is treated as if it had been done in superior court, any appeal from the judgment goes to the appellate division. A person charged with an infraction initially appears before the district court, but if the person is found responsible for committing the infraction he may appeal to the superior court for a new hearing. Unlike felonies and misdemeanors, a person found responsible for an infraction cannot be sent to jail or prison for the infraction, so the state constitution's requirement that a jury decide criminal cases does not apply. A person who appeals a district court finding of responsibility for an infraction, therefore, can have a bench trial in superior court.

[22] Magistrates are not elected, but are nominated for office by the clerk of superior court, appointed by the senior resident superior court judge, and supervised by the chief district court judge. A magistrate serves an initial term of two years, with subsequent terms of four years.

[23] N.C. GEN. STAT. §15A-81B, added by 1993 N.C. Sess. Laws 538.

[24] If the judge determines the sentence should be active the defendant is required to serve the full minimum of the range, and may serve less than the maximum with good behavior.

3.1.1 Monetary sanctions in North Carolina

Within North Carolina's structured sentencing scheme, both fines and fees are ubiquitous. Any person convicted of a crime may be ordered to pay a fine as part of the sentence.[25] And the same goes for court fees.[26] Restitution, on the other hand, is restricted to offenses that fall under the Crime Victims' Rights Act (CRVA).[27] Judges have complete discretion regarding whether to impose, and the amount of, fines[28,29] and court fees.[30,31], and restitution[32]

The expenditures financed via monetary sanctions vary. In North Carolina, the proceedings of all fines go towards maintaining public schools.[33] Court fees, on the other hand, aim to finance the court system. The most relevant items, common to all dispositions, are the general court fee, which amounts to around $150, facility fees of $12 and $30 for District and Superior Courts, respectively, and phones fees of $4.[34,35,36] Restitution payments always go to the victim.[37,38]

An important consideration for any monetary obligation is the defendant's ability to pay. North Carolina law either requires or encourages the court to consider a defendant's ability to pay before imposing obligations[39,40] Some courts compare the defendant's income to the

[25] N.C. GEN. STAT. §§15A-1361, -1340.17 (felonies), and -1340.23 (misdemeanors).

[26] *Id.* §7A-304

[27] *Id.* Art. 46

[28] *Id.* §§15A-1362 and 15A-1363

[29] Exceptions are Class 2 and 3 misdemeanors, as well as local ordinance violations, whose maximum amount is capped. For Class 2 misdemeanors fines cannot exceed $1,000; for Class 3 misdemeanors the maximum is $200; and for local ordinance violations the maximum fine is $50, unless the ordinance provides for a larger amount, up to $500 (*Id.* §14-4).

[30] Judicial discretion regards court fees waivers, as all court fees are capped at the amounts outlined in *Id.* §7A-304

[31] *Id.* §§7A-304(a) and 15A-1363—see also State v. Patterson, 223 N.C. App. 280, 2012.

[32] *Id.* §§15A-1340.34(a) and 15A-1340.38

[33] N.C. Const. Art. IX, §7

[34] There are also fees intended to fund law enforcement retirement/insurance and training of $4 and $7.50, respectively (common to both cases in District and Superior Courts). Finally, there are service fees of $5 common also to both courts. For criminal cases, there is also a DNA fee of $2, for the support and services of the State DNA Database and DNA Databank. And the conviction of any motor vehicle offense carries with it an additional fee of $10.

[35] Defendants appearing in District Court can expect to pay a minimum fee amount of $178 for an infraction and $180 for a misdemeanor, while in Superior Court defendants face fees starting at $205.

[36] There are also fees for the provision of indigent defense (at least $60), house arrest monitoring (one-time $90 and $4.37 daily), etc. See Figures C5 and C6 for a more comprehensive list of cost items and amounts.

[37] N.C. GEN. STAT. §§15A-1340.34(a) and 15A-1340.37(b)

[38] Although, the court may order the defendant to make restitution to a person other than the victim, or to any organization, corporation, or association, including the Crime Victims Compensation Fund, that provided assistance to the victim. Restitution shall be made to the victim or the victim's estate before it is made to any other recipient (*Id.* §15A-1340.37(b))

[39] N.C. GEN. STAT. §§15A-1340.36(a) and 15A-1362.

[40] make Bearden meaningful, courts should also examine a defendant's ability to pay at sentencing, when contemplating the assessment of fees and fines, rather than waiting until failure to pay the imposed obligation.

Federal Poverty Guidelines (See Table XX) in order to determine a defendant's ability to pay. An inability to pay is presumed if the defendant's annual income is at or below a certain percentage of the guidelines. No threshold percentage is defined by law, but a judicial district may wish to establish one by local rule (Abrams et al., 2019). Many programs view the 100 percent guideline as outdated and use another multiplier though (Markham, 2018).[41]

Monetary obligations from criminal and infraction cases are due at the time of the conviction, but in some cases, payment might be delayed to a later date or paid over time. If the defendant's conviction results in probation, payment usually can be made any time during the period of probation. For persons not placed on probation, the court might allow some additional time to pay. Note that if all monetary obligations are not paid in full at the time of conviction, the courts are required to assess a one-time fee of $20 to cover the State's costs of processing future payments.

If the total amount is not paid within 40 days of the conviction (or within 40 days of the date allowed by the court, if a later date) this triggers what's referred to as a "failure to comply" (FTC). In this event an additional fee of $50[42] will be levied and the court or prosecutor may require the defendant to appear and "show cause", i.e., to explain why they should not be jailed or otherwise penalized for their failure to comply.[43]

However, in order for the court to imprison a defendant, it needs to be established that the nonpayment was willful, as well as consider the defendant's ability to pay.[44] The burden of proof regarding inability to pay lies in the defendant though.[45] If it were shown that the defendant had indeed the ability to pay, the court may order the suspended sentence activated or, if no suspended sentence was imposed, order imprisonment—not exceeding 30 days[46]— and, because the defendant is at risk of being imprisoned as a result of these hearings, he or she must be afforded counsel.[47] If it's the case that nonpayment was not willful, the court may grant additional time for payment, reduce the owed amount, or revoke

Fundamental notions of due process of law, at a minimum, demand notice to the defendant of the centrality of ability to pay to the punishment determination and an opportunity to explain financial exigency and hardship. Many courts in North Carolina fail to meet such a basic standard Nichol and Hunt, 2018.

[41] Additionally, in order to consider a defendant's ability to pay the court may consider his or her eligibility for appointed counsel, their resources, including all real and personal property and the income derived from that property,their ability to earn or work, including any limitations due to disability, health, lack of transportation, or driving privileges, obligations to support dependents (including children, the elderly, and the disabled), the receipt of any public assistance, whether monetary obligations already owed to the court, or to another court, etc.

[42] N.C. GEN. STAT. §7A-304(a)(6)

[43] *Id.* §§15A-1362(c) and 15A-1364.

[44] Bearden v. Georgia, 461 U.S. 660 (1983).

[45] State v. Tate, 187 N.C. App. 593 (2007).

[46] N.C. GEN. STAT. §15A-1364

[47] Hammock v. Bencini, 98 N.C. App. 510 (1990).

the monetary obligation altogether.[48]

Finally, if a defendant has defaulted in payment of fines, fees, or other monetary obligations, the court may order that unpaid fines or costs be docketed as a civil judgment, a lien on the defendant's real estate.[49]

3.2 Identifying the effect of fines alone

In current practice in the United States monetary sanctions are usually levied in addition to other penalties, e.g., community service, probation or parole, incarceration, etc.. This creates an identification challenge, in the sense that agents experience multiple treatments simultaneously. In order to address this I take advantage of North Carolina's particular treatment of its lowest-level misdemeanors following December 2013, when reforms aimed at reducing costs in their provision of defense representation for poor defendants.

Counsel for criminal defendants may be provided either by privately retained attorneys or by what's known as indigent defense representation. In the U.S., indigent people accused of crimes have a constitutional right to legal representation free of charge. In North Carolina, depending on the jurisdiction this can be provided either by public defenders—full-time state employees— or by private attorneys who choose to participate in an assigned counsel system. More specifically, for misdemeanors, a defendant has a Sixth Amendment right to counsel only if an active or suspended sentence of imprisonment is imposed.[50] In contrast, the Sixth Amendment guarantees the right to counsel to any indigent person accused of a felony, regardless of the possible punishment.[51] North Carolina law provides indigent criminal defendants with a slightly broader right to counsel, providing for appointed counsel in "[a]ny case in which imprisonment, or a fine of five hundred dollars . . . or more, is likely to be adjudged."[52]

[48]It's important to note also that for motor vehicle–traffic–offenses in the event of an FTC the court must report the person to the DMV, which will issue an order revoking the person's driver's license, effective on the sixtieth day after the order is mailed or delivered (N.C. GEN. STAT. §§20-24.1(b) and 20-24.2). A license revoked in this way remains revoked until the person settles the financial obligations ordered by the court, demonstrates an inability, and good-faith efforts, to pay, or shows the penalty, fine, or costs should be remitted.

[49]N.C. GEN. STAT. §§15A-1365, 7A-455, 7A-455.1, and 15A-1340.38.

[50]The formulation of this right has developed over a series of U.S. Supreme Court decisions. See Argersinger v. Hamlin, 407 U.S. 25 (1972) (recognizing basic right to counsel in misdemeanor cases); Scott v. Illinois, 440 U.S. 367, 373–74 (1979) (in misdemeanor cases, "the Sixth and Fourteenth Amendments to the United States Constitution require only that no indigent criminal defendant be sentenced to a term of imprisonment unless the State has afforded him the right to assistance of appointed counsel"); Alabama v. Shelton, 535 U.S. 654 (2002) (indigent defendant has right to appointed counsel in misdemeanor case if court imposes suspended sentence of imprisonment).

[51]Gideon v. Wainwright, 372 U.S. 335 (1963).

[52]N.C. GEN. STAT. §7A-451(a)(1)

In 2013, North Carolina made major changes to its criminal justice system as part of the 2013 Appropriations Act. Seemingly attempting to save money on appointed counsel,[53] North Carolina's General Assembly enacted a new punishment scheme for Class 3 misdemeanors, limiting the punishment to a fine for many defendants.[55] The change applies to offenses committed on or after December 1, 2013 and, in addition to changing the punishment for Class 3 misdemeanors, the reform reclassifies some Class 1 and 2 misdemeanors as Class 3 misdemeanors, as well as some Class 3 misdemeanors as infractions.[56] The punishment for offenses reclassified as Class 3 misdemeanors is likewise limited to a fine for many defendants. Furthermore, because due to other structured sentencing rules, the maximum fine is usually limited to $200 for Class 3 misdemeanors–which has always been the case for traffic violations– these defendants would not be entitled to indigent defense as per North Carolina provisions.

4 Data and sample

In this paper, I analyze case-level data provided by the North Carolina Administrative Office of the Courts (NCAOC), which comprise the universe of felony, misdemeanor, and infraction cases filed at District and Superior Courts from 2013 until 2019.

The data include detailed information on sentencing decisions, arrest charges, and characteristics of the defendants. For each case, the data also identify the judge, district attorney, and defense attorney, and whether the latter is privately retained or providing indigent counsel.

I merged these administrative court records with several other datasets. First, I obtained information from the North Carolina State Bar on the characteristics of all attorneys licensed to practice in North Carolina. Specifically, information on when the attorney was licensed in the state, their gender, and the location of their offices. I complement this data with the law school from which attorneys graduated as well as the institution from where they obtained their undergraduate degree, which I obtained from the website Avvo.com.[57]

[53]The report accompanying the bill[54] states that Indigent Defense Services' budget would be reduced by $2,000,000 annually because the budget "[r]eclassifies low-level misdemeanors that rarely result in incarceration as Class 3 misdemeanors or infractions and modifies the sentencing structure for Class 3 misdemeanors so that the first [four] charges are fineable offenses. With no possibility of incarceration, these offenses do not require legal counsel."

[55]Current Operations and Capital Improvements Appropriations Act of 2013, §18B.13, 2013 N.C. Sess. Laws 995, 1303–04.

[56]*Id.* §§18B.14 and §18B.15, 2013 N.C. Sess. Laws 995, 1304–09, amended by 2013 N.C. Sess. Laws 1594, §§4–6.

[57]This is an online marketplace for legal services that provides lawyer referrals and access to a database of legal information consisting primarily of previously answered questions, but that also includes—in addition to the lawyers' offices location and abridged resumes—client reviews, disciplinary actions, and peer endorsements.

The case-level data includes defendants' home addresses, which I use to include census block information from the 2014-2018 American Community Survey.

Finally, in order to study possible mechanisms, I also use case records for all summary ejectment (eviction) and lien cases led in North Carolina from 2013 to 2019, provided by the NCAOC as well.

For the purpose of the analysis, defendants charged with multiple offenses–or recharged for the same crime after a mistrial, in the case of misdemeanors–are collapsed to a single observation. In this scenario, I retain only the earliest filing date, charge characteristics and original sentencing outcomes. When a defendant faces multiple charges, I only consider the most severe one, where the most severe charge is the charge associated with the most severe sentencing class. This is done since court fees are assessed at the case level, and because for many low-level offenses when more than one charge is made, defendants are fined only for the offense carrying the highest fine.[58,59] Additionally, in order to deal with outliers in LFOs, in my analysis I winsorize this variable at the 2.5 percent level.

4.1 Analysis sample

I make three main restrictions to the sample to facilitate my analysis. First, I restrict the sample to defendants charged with Class 3 misdemeanors as their most serious offense. I do this in order to limit what Mueller-Smith (2015) calls "omitted treatment bias" that stems from judges having influence over several different court outcomes (e.g., guilt or innocence, incarceration versus probation, etc.). As mentioned above, following North Carolina's 2013 Appropriations Act, defendants charged with Class 3 misdemeanors can face, in addition to court fees, at most a fine. This greatly limits the scope for omitted treatment bias. I focus, then, on defendants with at most 3 prior convictions that are being charged with at most a Class 3 misdemeanor after December 1, 2013.

Second, I restrict my sample to offenses where defendants cannot waive their right to be present at trial. The right to be present at trial is a personal right, which may be waived in all cases except capital ones.[60] This means that non-capital trials may be held *in absentia*, when the defendant has waived the right to be present (Smith, 2013).[61] These trial *in absentia* present a problem for my identification as they are usually handled by magistrates,

[58] N.C. GEN. STAT. 7A-148

[59] Estimates considering monetary sanctions aggregated to the case level are available upon request.

[60] State v. Braswell, 312 N.C. 553, 558 (1985); State v. Daniels, 337 N.C. 243, 256 (1994); State v. Huff, 325 N.C. 1, 29 (1989), vacated on other grounds sub nom., Huff v. North Carolina, 497 U.S. 1021 (1990); ; State v. Hayes, 291 N.C. 293, 296-97 (1976).

[61] However, there can be no sentencing in absentia when corporal punishment is imposed, i.e., imprisonment. Therefore, appearance in court is mandatory for all felonies.

who are not judges and, thus, are not randomly assigned. As mentioned above, every year the Conference of Chief District Judges puts out a list of offenses for which magistrates and clerks of court may accept written appearances, waivers of trial or hearing and pleas of guilty or admissions of responsibility, as well as a list of "non-waivable" offenses.[62]. I restrict my sample to those cases in the "non-waivable" list.

Finally, I also drop all cases where the defendant is also facing any traffic offense, as non-payment of monetary sanctions in those cases also carries the possibility of driver's license revocation.[63] Additionally, I also drop cases for repeat offenders where the reoffending upgrades the misdemeanor to Class 2, as is the case of shoplifting under N.C. GEN. STAT. §14-72.1.

In combination, these restrictions leave me with XX cases (out of XX total cases filed in North Carolina in the period, and XX Class 3 misdemeanors), overseen by XX judges (out of XX). See Tables A10 and A11 for more details on the sample selection.

Additionally, I further restrict my estimation sample to those Class 3 misdemeanor cases overseen by a district judge who oversees at least 50 other Class 3 misdemeanor cases, and to those cases that are not "singletons" within the set of district-by-time fixed effects.

4.2 Descriptive statistics

Table 1 reports descriptive statistics for my analysis sample. The main data set includes XX cases with final dates of disposition between 2013 and 2019. Details on this population's demographic characteristics are provided in Panel A of Table XX. The sample is predominantly black (XX%) and male (XX%), overrepresented relative to North Carolina's population (XX% and YY%, respectively). The sample is quite young as well, with over xx% of defendants are below the age of 30, and almost XX% below the age of 24.

The study population is middle-class: based on addresses from the court records, the average defendant lives in a neighborhood in which the median income is XX, and where XX% of households earn below the poverty line.

Because of the sample selection mentioned above, cases are all Class 3 misdemeanors. The majority of which are XXXX offenses; the rest being XXX and XXX. Specifically, XX% of cases correspond to XXX offenses. There are no violent, firearms, or XXX charges. XX% of these cases result in a conviction, with XX% of these achieved via pleas.

XX% of defendants face some monetary sanction. These stem either from fines (XX%) or courts fees (XX%), with no restitution being levied on any defendant in the sample.

[62] List that also establishes the schedule of penalties or fines for these offenses (N.C. GEN. STAT. §7A-148)

[63] For this same reason I also drop cases of underage purchase of alcohol, pursuant to N.C. GEN. STAT. §18B-302

Monetary sanctions average \$XX, with the breakdown between fines and fees being XX% and XX%, respectively.

As we can see in Table A8 Class 3 misdemeanor cases where defendants face no monetary sanctions are clearly different from cases where defendants do. Defendants not facing any monetary sanction tend to be minorities more frequently, as well as somewhat younger. They also tend to live in neighborhoods with larger median household incomes. Defendants that end up paying any monetary sanction are charged for more offenses and have more priors. Additionally, they are more likely to be facing a drug charge and less likely to have been charged for a property or XXX offense. Cases also tend to move faster, as it they're more likely to be disposed of via guilty pleads.

Defendants levied monetary sanctions are also more likely to either retain private attorneys, or to represent themselves. Finally, defendants levied monetary sanctions are also more likely to engage in any criminal activity within two years, and more likely to engage in XX and XX.

5 Identification approach

I want to estimate the effect of monetary sanctions on future criminal involvement–proxied by arrests.[64] Unobservables (to us) associated with future criminality that influence judges' decisions regarding monetary sanctions would render OLS regressions biased. I address this endogeneity of monetary sanctions with an IV approach, leveraging the random assignment of cases to district court judges, i.e., using a "judge fixed effects" design.

In judge fixed effects designs it is crucial that the treatment variable of interest be binary (Frandsen et al., 2019, so I consider a dummy variable indicating if the defendant gets levied any LFO, Any LFO $= \mathbb{1}_{LFO>0}$. I consider, then, the following model:

$$Y_{ict} = \beta_1 \text{Any LFO}_{ict} + \beta_2 \mathbf{X}_{ict} + \gamma_{ct} + \varepsilon_{ict} \tag{1}$$

where Y_{ict} is the outcome of interest for individual i in case c and year t, such as future criminality, for example, $\mathbf{X}_{ict}$ is a vector of case- and defendant-level control variables, γ_{ict} are district-by-time fixed effects, and ε_{ict} is an error term.

The key problem for causal inference in this setting is that OLS estimates of equation (1) are likely biased, due to correlation between the having been levied monetary sanctions and unobserved defendant characteristics that are correlated with the outcome. The sign of

[64]Police officers are the charging agency in North Carolina so court records capture close to the universe of arrests (Rose, 2018).

this correlation, and therefore the bias stemming from it, is unclear. For example, judges may be more likely to fine on defendant that display less regret who, in turn, are more likely to reoffend. At the same time, judges could be inclined to fine to defendants they perceive as having a higher ability to pay; defendants with a higher ability to pay probably have a stronger attachment to the legal labor market, and are thus less likely to reoffend.

In order to address this issue I need variation in whether a defendant gets levied fines or fees that is orthogonal to unobserved defendant characteristics. The quasi-random assignment of district judges provides exactly this type of variation. In this way I can use the quasi-randomly-assigned judges as instruments for defendants get monetary sanctions, suggesting the following first stage in a 2SLS setup:

$$\text{Any LFO}_{ict} = \sum_{j} \alpha_{1j} \mathbb{1}_{j(i)=j} + \alpha_2 \mathbf{X}_{ict} + \gamma_{ct} + \eta_{ict} \tag{2}$$

with j indexing judges and $j(i)$ indicating judge assignment for individual i. This design identifies the local average treatment effect (LATE) for each pair of judges and corresponds to the average treatment effect for individuals who would get a fine or fee if assigned to the stricter judge of the two, but would not if assigned to the more lenient judge.

The problem with this approach is that it is well known that when many instruments are used, 2SLS may be severely biased (Bound et al., 1995). The usual recommendation to address this is to use JIVE or LIML. JIVE–jackknife instrumental variable estimator–, which seems to be the solution the literature has settled on, first suggested by Phillips and Hale (1977) and later by Angrist et al. (1999) and Blomquist and Dahlberg (1999), attempts to improve finite-sample properties by replacing the usual fitted values from the reduced form regression(s) by "omit-one" fitted values which omit observation i when estimating the i-th fitted value, thus eliminating the correlation between the fitted values and the structural equation errors.

It has been argued, though, that LIML is a better alternative than JIVE (Davidson and MacKinnon, 2006), as even though the small-sample bias of JIVE does not depend on the degree of overidentification, it does increase in the number of exogenous covariates present in the second-stage equation (Ackerberg and Devereux, 2009). However, LIML is not consistent with heteroskedastic data (Chao and Swanson, 2004 and Hausman et al., 2012) and, additionally, Kolesár (2013) shows that in the presence of treatment effect heterogeneity the estimand of LIML may even lie outside of the convex hull of LATEs. Kolesár (2013) proposes a modification of the JIVE, the unbiased JIVE (UJIVE) estimator, that remains consistent even in the presence of many instruments and covariates.

In my setting, judge assignment is random only when conditioned on district-by-time fixed effects, as-if randomization of cases to judges takes place within judicial districts and within time periods. Therefore, the construction of the leave-out mean of JIVE requires that first I residualize out district-by-time fixed effects, in order to limit the comparison to defendants at risk of being assigned the same set of judges. Because of this large number of fixed effects I present results using the UJIVE estimator in my main tables.[65]

JIVE and UJIVE are equivalent to 2SLS, in that sense that they initially construct a single instrument, a predictor of treatment status based on the first-stage and, on a second step, they use this constructed instrument as a single instrument to estimate the treatment effect. For the case of UJIVE that constructed instrument is algebraically equivalent to

$$Z_{ict} = \left(\frac{1}{n_{tj(i)} - n_{itj(i)}}\right)\left(\sum_{k=0}^{n_{tj(i)}} \text{Any LFO}^*_{ikt} - \sum_{l=0}^{n_{itj(i)}} \text{Any LFO}^*_{ilt}\right) \tag{3}$$

where $n_{tj(i)}$ is the number of cases assigned to judge j and $n_{itj(i)}$ is the number of cases involving defendant i seen by judge j in year t. Any LFO^*_{ict} is the residual likelihood of receiving a monetary sanction after removing the effect of district-by-time fixed effects.

I estimate the causal effect of having to pay a fine or court fees, then, using this measure of the likelihood of being levied a monetary sanction by a quasi-randomly-assigned judge as an instrument for having any legal financial obligation at the conclusion of a defendant's trial. Basically, I compare future criminal involvement for defendants assigned to judges with different propensities to levy financial obligations, and interpret the differences as the causal effect of being levied monetary sanctions associated with the difference in fining propensities of the assigned judges.

Variation in judge leniency

As mentioned above, I restrict the sample to exclude cases overseen by judges assigned to fewer than 50 cases, as well as cases that are "singletons" within the set of district-by-time fixed effects. Over XX percent of judge-by-year cells have more than 50 cases. After dropping these cases my sample includes XX district judges.[66]

Figure 1 reports the distribution of the residualized judge leniency measure for monetary sanctions. My sample comprises XX judges. The median number of cases overseen by a judge is XX cases and the average is XX cases. See Table A7 for more details. After residualizing out the set of district-by-time effects, the judge measure ranges from -XX to XX, with a

[65] I also explore additional estimation strategies, 2SLS using all judge dummies, LIML, JIVE, and Belloni et al. (2014)'s IV Lasso in Appendix B.2.

[66] As mentioned above, in any given year there are around XX district judges in North Carolina (see Table C1), and these are elected through–partisan–elections that take place every 2 years.

standard deviation of XX. That is, moving from the first to the ninety-ninth percentile of judge leniency increases the amount of monetary sanctions by XX, an XX% change from the mean sanction of $XX.

As mentioned above, the variation in the judge leniency measure comes from two sources, as there are no cases warranting restitution in my sample. Judges may choose to levy harsher or more lenient fines, as well as whether to waive–all or part– court fees. Figure A1 shows the distribution of residualized judge leniency for these two margins separately. In my preferred specification I collapse both of these measures into one, as that captures what I consider the relevant margin for defendants.

Finally, as mentioned above, I use this variation in judge leniency to instrument for whether a defendant gets levied a monetary sanction in order to identify the (local) average treatment effect of monetary sanctions for defendants whose likelihood to be levied any monetary obligations vary due to judge assignment. I do this via 2SLS estimation of Equation 1, with the first stage given by Equation 4 below. In order to interpret these two-stage least squares estimates as causal I need the usual LATE assumptions to hold: (i) for judge assignment to be associated with monetary sanctions (relevance), (ii) for judge assignment to impact future criminal involvement only through monetary sanctions (restriction), and (iii) for defendants facing a fine with a lenient judge to be at least as likely to face a fine if facing a stricter judge (monotonicity).

5.1 Instrument validity

5.1.1 First stage

To consider the first-stage relationship between judge assignment and the amount of monetary sanctions, I estimate the following equation for defendant i and case c, assigned to judge $j(i)$ at time t:

$$\text{Any LFO}_{ict} = \alpha_1 Z_{ict} + \alpha_2 \mathbf{X}_{ict} + \gamma_{ct} + \eta_{ict} \tag{4}$$

where the vector $\mathbf{X}_{ict}$ includes case- and defendant-level covariates, Z_{ict} are the leave-out measures of judge leniency described above, and γ_{ct} are district-by-time fixed effects.Robust standard errors are clustered at the individual and judge level.

Figure 1 illustrates graphically the first-stage relationship, described in Equation (4), between the residualized measure of judge leniency and whether a defendant gets levied any monetary sanctions, controlling for district-by-time fixed effects, overlaid over the distribution of judge leniency. It plots a local linear regression of the likelihood of receiving a monetary sanctions against judge leniency, after controlling for district-by-time fixed effects. This likelihood of receiving a monetary sanction is monotonically, and approximately linearly, increasing in the judge leniency measure. A XX percentage point increase in the residualized judge's fining rate in other cases is associated with an approximately XX p.p. increase in the likelihood of being levied a monetary sanction.

Table 2 presents formal first-stage results from Equation (4). Column 2 begins by reporting results only with district-by-time fixed effects. Column 3 adds baseline case and defendant controls: race, gender, age, the number of charged offenses, indicators for crime type and the type of defense representation, as well as the median household income for the census block group where the defendant resides. The results in Table 2 are consistent with Figure 1: the residualized judge instrument is highly predictive of whether a defendant faces any monetary sanctions. Including controls in column 3 changes very little the magnitude of the estimated first-stage effect, consistent with the quasi-randomness of judge assignment. With all controls my results show that a defendant assigned to a district judge that is 10 percentage points more likely to levy a fine or court fees on a defendant is 6.8 percentage points more likely to receive a monetary sanction.

The instrument is strong, with first stage F-statistics greater than 120. These F-statistics are Kleibergen-Paap robust F-statistics, which in the just-identified case are equivalent to the effective F-statistic of Montiel Olea and Pflueger (2013). Both of these F-statistics exceed 12.28, which is the critical value they propose for just-identified models with $\tau = 10\%$ of worst case bias.[67,68]

5.1.2 Conditional independence

In order to be able to interpret my IV estimates as a LATE, it must be the case that judge assignment only impacts defendant outcomes through monetary sanctions, i.e., that judge assignment is orthogonal to unobserved defendant and case characteristics (conditional on court-by-time fixed effects).

I can study this by examining whether observed characteristics of defendants and their cases differ by judge. Table 3 provides strong empirical evidence of the random assignment of cases to district judges within each court in a given time period. The first column of Table 3 tests whether case and defendant characteristics are predictive of whether a defendant receives a monetary sanction. I control for court-by-time fixed effects and cluster the standard errors at the individual and judge level. I find that for each additional concurrent offense defendants are 12 percentage points less likely to be levied any fines or fees, a 26 percent decrease from the from the baseline mean of 46 percent. Defendants with a prior

[67] This cutoff corresponds to a test of IV relative bias of no more than 10 % with a significance level of 5 %, analogous to the Stock and Yogo (2005)'s cutoff of 10.

[68] It is not clear how to evaluate many-weak-instrument bias in leniency/examiner designs though (Hull, 2017; Frandsen et al., 2019; Bhuller et al., 2020).

offense are 12 percentage points more likely to be to be fined, compared to defendants with no prior offense, a 26 percent increase. Additionally, defendants arrested for property offenses are almost 7 percentage points less likely to be fined than those arrested for XX, a 15 percent decrease. Finally, individuals who have private representation or that represent themselves are both close to 14 percentage points more likely to be fined compared to those under public representation, a 30 percent increase. Column 2 assesses whether these same case and defendant characteristics are predictive of the judge leniency measure under the same specification. I cannot reject the null hypothesis of all coefficients being zero (joint p-value = 0.37). I find evidence, then, in support of district judges of differing tendencies being assigned very similar defendants.[69]

5.1.3 Monotonicity

The impact of judge assignment on monetary sanctions needs to be monotonic across defendants in order for me to be able to interpret my estimates as a well-defined LATE. This monotonicity assumption implies that defendants who are spared any fines by stricter judges would also be spared by more lenient judges, and that defendants levied fines by more lenient judges would be levied fines as well by stricter judges.

However, as with any assumption, I cannot test it directly. A testable implication of the monotonicity assumption, though, is that first-stage estimates should be positive for any subsample. Tables A5 and A6 present these first-stage results separately by type of offense, type of representation, whether defendants have a prior record, by defendant race, and by income quintile (using the full sample of cases to calculate judge leniency). I find that the residualized measure of judge leniency is consistently positive and sizable in all subsamples.

Furthermore, Frandsen et al. (2019) provide a test for the joint null hypothesis that the exclusion and monotonicity assumptions hold. Table A4 shows that I fail to reject this null within each district in my data, controlling for all the case and defendant characteristics, as well as time fixed effects.

5.2 Understanding the LATE

The IV estimates represent the LATE for defendants who would have received a different fining decision had their case been assigned to a different judge. To better understand this

[69] In Table A9 I pool judges according to their leniency and test whether the characteristics of defendants differ based on whether they are assigned to a judge with a high, medium, or low fining propensity (defined by bottom, middle, or top tercile of the distribution of fining propensity) relative to other judges in the same district-by-time cell. Results also show that judges with high, medium, and low fining propensities are assigned defendants that are extremely similar in terms of their age, gender, race, and income.

LATE, I characterize the number of compliers and their characteristics following the approach developed by Abadie (2003) and extended by Dahl et al. (2014) and Frandsen et al. (2019).[70] See online Appendix B.1 for a more detailed description of these calculations.

In Table A12 I estimate these shares. I find that the complier share is approximately 48 percent, thus the IV estimates are relevant for a large share of the sampled population. 36 percent of the sample are "never takers," and 15 percent are "always takers."[71]

Individual compliers cannot be identified, but it is possible to describe their observable characteristics following Frandsen et al. (2019). I do this in Table See A13. Compliers in the sample are 6 percentage points less likely to be charged with more than one offense, 13 percentage points less likely to be charged with a property offense, 10 percentage points more likely to be charged with a drug offense, 14 percentage points less likely to be represented by a private attorney, 16 percentage points more likely to represent themselves in court, 8 percentage points less likely to be younger than 25 years old, 7 percentage points more likely to be between 25 and 34 years old, and 6 percent less likely to be in the first quartile of household income and 11 percentage points more likely to be in the fourth, compared to the average defendant.[72] Compliers are not systematically different from the average defendant by race or gender, however.

6 Results

Tables 4 and 5 present OLS and 2SLS estimates of the impacts of higher fines on future criminal involvement. Table 4 looks at aggregate effects and then breaks it down by seriousness of the crime–whether it was a felony or a misdemeanor. In the main specification, with district-by-time fixed effects as well as case and defendant covariates, I can reject positive effects of monetary sanctions larger than XX on average, an XX percent increase over the sample mean–XX percent over the mean for compliers. Unfortunately, I do not have the statistical power to produce a more precise range of possible effect sizes. When I break this down by type of offense in Table 5, the effects are mostly small, negative, and statistically insignificant. The only exception is a marginally statistically significant negative effect for

[70] Frandsen et al. (2019) show that the weighted complier mean for a characteristic can be recovered through a regression of the treatment interacted with that characteristic on the treatment instrumented with the judge IV. This result generalizes the Abadie (2003) approach to estimating complier means, which is formulated in terms of a binary instrument.

[71] Under Frandsen et al. (2019)'s weaker average monotonicity condition $\alpha(Z_{1-\rho} - Z_{\rho})$ is a lower bound on the complier share. This can be seen by noting that under this definition, compliers are all individuals whose treatment status varies across judges. For any two judges $j' > j$, $\alpha(Z_{j'} - Z_j)$ bounds the share of compliers, but by construction this bound is largest for judges $1 - \rho$ and ρ.

[72] Where household income is proxied with ACS' median household income in the census tract where they reside.

property crime.

However, we shouldn't expect any effects on offenses that do not entail economic gain. In Table 6 I look at whether the recidivating offenses had a financial motive. Panel A shows the likelihood of financially motivated criminal involvement within 2 years of the date of disposition of the current offense. I estimate that monetary sanctions decrease financially-motivated recidivism by about XX percentage points on average. The baseline recidivism rate for these types of offenses in this sample is about XX percent (XX percent for compliers). Panel B presents the effects of monetary sanctions on the probability of non-financially-motivated reoffending. The results in Panel B suggest that fines and fees have no effect on non-financially motivated recidivism. Both of these results are consistent with XX. Finally, the increase in recidivism for financially motivated crimes is significantly different from the change in non-financial crimes at the XX percent level (p-value = XX).

6.1 Complier weights

Another possible explanation for the differences between the IV and OLS estimates is effect heterogeneity. To explore this possibility, it is useful to characterize compliers by their observable characteristics. I begin by splitting our sample into 10 mutually exclusive and collectively exhaustive subgroups based on the predicted probability of being levied any monetary sanction. I then estimate the first-stage equation (2) separately for each subsample, calculating the proportion of compliers by subgroup. I then reweight the estimation sample so that the proportion of compliers in a given subgroup matches the share of the estimation sample for that subgroup. The third column of tables 4 and 7 presents OLS estimates based on this reweighted sample. The results suggest that differences between the OLS and IV estimates are not driven by different complier weights.

7 Treatment effect heterogeneity

7.1 Income

It is important to note that the results from Table 6 could be masking important heterogeneity, as we are concerned with monetary sanctions inflcuencing poorer defendants either by the income channel or through the signaling or deterrence channel heterogeneously (poorer defendants may have held different priors to begin with, or be more prone to distrust the public enforcer)

In Table 7, in line with the predictions from XX, I find that deterrence effects seem to depend on income. In Table 8 I also find some weak evidence of monetary sanctions pushing the poorest people into crime. However, I cannot rule out the null of no effect.

7.1.1 Poverty crimes

In North Carolina, as in most of the US (CONFIRM), there are certain behaviors that are criminalized that would not fit the usual standard of crimes. For example, behaviors such as panhandling or sleeping in public places are characterized as crimes.

In the context of the present study it is important to distinguish if these are the types of offenses driving the income heterogeneity we see in Table 7.

Table A16

A17

7.2 Marginal treatment effects

Finally, I also explore heterogeneity by analyzing marginal treatment effects (Heckman and Vytlacil, 2005, Heckman et al., 2006). Thinking in terms of potential outcomes and ignoring subscripts, let the observed outcome Y equal $DY(1) + (1 - D)Y(0)$, where D is an indicator for treatment (having to pay any fine or fee) and $Y(0)$ and $Y(1)$ are the potential outcomes. The decision of whether to levy any fines or fees is made by a district judge taking into account both observable–to the econometrician–, X, and unobservable factors, which can be modeled as being given by $D = \mathbb{1}_{v(X,Z)-U}$, where v is an unknown function, U is an unobserved continuous random variable, and Z is the judge leniency. It is straightforward to show that $v(X, Z)$ is equivalent to the propensity score $\Pr[D = 1 \mid X = x, Z = z]$: the probability of receiving any monetary sanction conditional on observables X and judge leniency Z.[73]

Marginal treatment effects are defined then as $E[y(1) - Y(0) \mid U = u, X = x]$. The dependence of the MTE on U for a fixed X reflects unobserved heterogeneity in treatment effects, as indexed by a judge's latent propensity to choose whether to fine a defendant (where U captures unobserved characteristics of the defendant, which influence the judge's choice). The choice equation implies that, given X, defendants with lower values of U are more likely to take treatment, regardless of their realization of Z.

Identification of the MTEs requires the same assumptions as the LATE framework, including monotonicity, plus the additional assumption that there is additive separability between the observed and unobserved heterogeneity in the treatment effects, needed when the propensity score does not have full support, as in this case (see, e.g., Brinch et al., 2017, Mogstad and Torgovitsky, 2018, Andresen, 2018).

[73] XX

Panel (a) in Figure A6 graphs the propensity score distributions for the treated and untreated subgroups. The dashed lines indicate the upper and lower bounds of the propensity score where there is common support (after trimming 1% from both the treated and untreated samples). Panel (b) of Figure A6 plots MTE estimates by the unobserved "resistance to treatment", the latent variable U, based on a local IV approach using a global cubic polynomial specification. The MTE estimates are least negative for those with a low unobserved resistance to treatment and decrease as unobserved resistance to treatment increases. This implies that receiving monetary sanctions reduces recidivism the most for defendants whose unobservables would make them very unlikely to receive any monetary sanctions, regardless of the stringency of their judge. At the same time, defendants whose unobservables would make them very likely to be fined don't seem to experience increases in recidivism due to treatment, although these estimates are very noisy.

The weighting scheme underlying IV estimators is not always policy relevant. Heckman and Vytlacil, 1999, 2005, 2007 show that all conventional treatment parameters can be expressed as different weighted averages of the MTEs. Recovering these treatment parameters for the entire population, however, requires full support of the propensity score on the unit interval. Since I do not have full support, I rescale the weights on the MTEs for those parameters to integrate over the common support shown, following Carneiro et al., 2011.

Table A3 uses the MTE estimates to construct these rescaled estimates of the ATT, ATE, and ATUT. These weighted averages are obtained by integrating the MTE over the propensity score for the relevant sample. The ATT estimates reveal that the recidivism effects of monetary sanctions are XX for the treated; for example, the linear specification yields an estimate of XX, which is more negative than either the LATE or the ATE. By comparison, the estimated ATE (also plotted as the dashed horizontal line in Figure A6) is XX to the LATE. The ATUT, in contrast, is XX.

8 Mechanisms

As stated above, I consider two possible mechanisms that may be driving these findings. First, there's a deterrence effect: defendants update their prior regarding the costs of going through the criminal justice, for example, be it regarding amounts of monetary sanctions, time losses, or other non-pecuniary costs of going through bureaucratic hassle. Second, monetary sanctions may be relatively high enough that, some defendants may engage in criminal activity to satisfy consumption or because they've simply detached from civil society.

In Table A18 I can see that results are driven by those defendants with no prior criminal record. This is consistent with a deterrence story, where defendants update their cost expectations. The fact that I don't see any effects for defendants that have gone through the system before is consistent with them being aware of the extent of fines and court fees.

We can see from Table A19 that the results are not consistent with an income channel. I cannot reject the null that all coefficients are the same (the joint F-test of the null that all coefficients across samples are the same has an F-value of 0.27 and a p-value of 0.7640)

9 Robustness checks

In this section I explore possible threats to both the causal and conceptual interpretation of my results.

9.1 Idiosyncratic subsets of judges per income quartile

When looking at the heterogeneity by income one wonders if it could be the case that different judges, therefore estimating different LATEs, serve population of different income. From Figures XX and XX one can see that there is considerable heterogeneity in income within judicial districts in order to ignore this concern. Additionally, Figure XX shows the distribution of judge leniency by income quartile.

9.2 Model misspecification

The results in Tables XX and XX suggest the possibility of model misspecification, as predicted values lie outside of an acceptable range. In order to gauge the extent of the problems this poses for my analysis I estimate these same tables again in Tables XX and XX using alternative specifications (logit and probit).

The results are consistent with... I

9.3 External validity

On August 16, 2018 the School of Government of the University of North Carolina, Chapel Hill published a "bench card"[74] written by James Markham with the intent to bring clarity regarding monetary sanctions and ability to pay in North Carolina. There had been instances where judges had pleaded ignorance regarding their discretion in setting monetary sanctions as the reason for nonleniency.

[74] Sort of "cheat sheet" that provides judges with useful questions and guidelines to help make decisions on certain topics.

The main objective of the card was to help bring greater precision to matters related to money in criminal court. First, there is precision as to the type of obligation in question, as there are many different types of monetary obligations–costs, attorney fees, other fees, fines, and restitution–and the statutory rules applicable to them vary. The card groups all of the possible obligations into categories and lists them.

As mentioned above, there is precision as to available relief. There has been a lot of talk about the limitations on judges' authority to waive and remit certain obligations, but waiver and remission are not the only avenues for relief. The card shows five distinct categories of permissible relief (waiver, ordering partial restitution, exemption, remission, and modification upon default), each of which derives from a different statute, and only some of which require findings, notice, or a hearing.

The card includes some suggested guideposts for thinking about a defendant's ability to pay any monetary obligation–both on the front end when imposing it, and on the back end when responding to a failure to pay it. It also includes a collection of additional issues (like installment plans, civil judgments, and driver license revocation) related to monetary obligations.

Though the card catalogues the available options for each type of monetary obligation, it takes no position on what a judge ought to do in any case. A district may wish to consider local policies on issues related to money (for example, a presumption of just cause to waive costs based on pre-defined circumstances, or a limitation on the use of arrest or imprisonment in money-only cases).

Because the Mecklenburg judicial district had already implemented reforms regarding ability-to-pay considerations, I can study the impact of the publishing of this bench card taking Mecklenburg as a control group.

9.4 Exclusion restriction

As mentioned above, in order to be able to interpret my results as causal, the instrument needs to affect defendants' outcomes only through monetary sanctions. In this setting there is one more channel through which defendant outcomes may be affected, as defendants, besides monetary sanctions, face a misdemeanor record, which we know impacts reoffending (Agan et al., 2021, Mueller-Smith and T. Schnepel, 2020).

In order to address this concern, first I test whether the judge leniency measure is predictive of defendants getting a criminal conviction. Second, I test whether a separate leave-out measure based on conviction has any additional predictive value for conviction beyond my preferred leave-out instrument. These results are reported in online Appendix

Table XX. Consistent with the exclusion restriction, I find that my preferred leave-out instrument is not predictive of conviction and that there is no additional explanatory value of the separate conviction leave-out measure.

9.5 Alternative identification approaches

Table A20 in the Appendix explores alternative specifications that account for potential biases from the construction of the leniency measure: using all the judge dummies directly as instruments, using Lasso to pick the most informative dummies (Belloni et al., 2014), and using the unbiased JIVE estimation strategy proposed by Kolesár, 2013. Across all these different estimations strategies I consistently find a negative relationship between monetary sanctions and financial–as well as overall– recidivism.

10 Conclusion

Misdemeanor cases make up over 80 percent of the cases processed by the U.S. criminal justice system. In most of these cases monetary sanctions are levied on defendants. However, we know nothing about the causal effects of these sanctions on their reoffending. I report the first estimates of the causal effects of monetary sanctions on rates of future criminal involvement. To do this, I leverage the as-if random assignment of cases to judges in the state of North Carolina. My findings imply that monetary sanctions don't increase the likelihood of defendants engaging in any criminal activity and, in fact, strongly deter certain type of offenses. Wealthy defendants–as proxied by their address– are the most strongly deterred, while I cannot rule out some criminogenic effects for poorer defendants. These results are consistent with both "deterrence" and "income" effects operating jointly, with the latter being the reason estimates for poorer defendants are closer to zero.

As incarceration rates in the United States continue to increase the upsides to an increased use of monetary sanctions are obvious. The only caveat is the possibility of ending up criminalizing the poor. There is a explicit recognition in statutes and policy of differential ability to pay. Allowances for more judicial discretion, payment plans, or alternative sanctions may help make the most of this type of punishment. However, this may be better achieved through alternative proportional punishment, what are termed "day-fines", that scale monetary sanctions according to defendants' income.

Alternatively, inquiries into defendants' ability to pay should be done before assessing costs. Ability-to-pay inquiries are not constitutionally required at this stage (only before jailing a defendant), but it would make far more sense for that determination to occur at sentencing. In this way it will not be the case that defendants may go out of their way, foregoing rent or utility payments, trying to make payments, while also saving courts having to spend time and money trying to collect money that cannot be collected.

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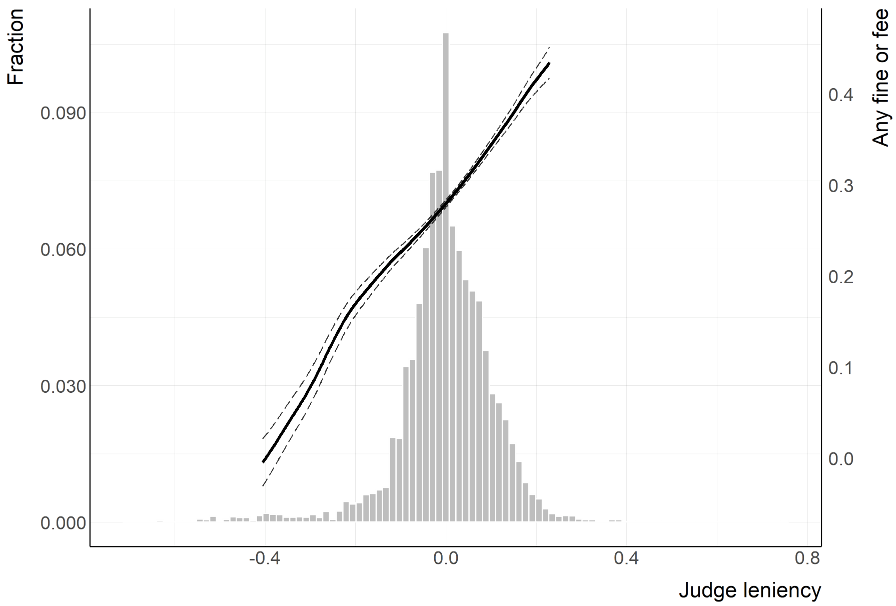
11 Figures and tables

Figure 1: Distribution of judge leniency and first stage



Notes: This figure shows the distribution of my leave-out mean measure of judge leniency, residualized by district-by-time fixed effects. More lenient judges levy higher fines and fees. The solid line is a local linear regression of the amount of fines and fees on judge leniency, along with the 95% confidence interval.

Table 1: Case characteristics and outcomes

	Mean	Std. Dev.	Observations
Panel A: Defendant Characteristics			
Male	0.729		10,373
Non-Hispanic White	0.359		10,373
Black	0.565		10,373
Hispanic	0.049		10,373
Other	0.027		10,373
Age	29.946	12.481	10,373
Income ($1,000s)	51.184	24.100	10,373
Panel B: Charge Characteristics			
Number of offenses	1.243	0.436	10,373
Any prior record	0.232		10,373
Previous criminal charges	1.604	0.738	2,406
Type of offense			
Property	0.247		10,373
Drug	0.517		10,373
Other	0.235		10,373
Panel C: Attorney Characteristics			
Court appointed	0.047		10,373
Public defender	0.094		10,373
Privately retained	0.676		10,373
Self-represented	0.184		10,373

	Mean	Std. Dev.	Observations
Panel D: Case Outcomes			
Monetary bail	0.218		10,373
Bail amount ($1,000s)	1.124	5.103	2,266
Method of disposition			
Dismissed	0.300		10,373
Judge	0.700		10,373
Convicted	0.688		10,373
Guilty plea	0.674		10,373
Any fine	0.267		10,373
Fine ($)	47.836	44.833	2,767
Any court fees	0.448		10,373
Court fees ($)	223.548	74.101	4,646
Unpaid fines or fees	0.383		4,794
Panel E: Recidivism outcomes			
Reoffend within 2 years	0.300		10,373
Type of offense			
Violent	0.118		3,107
Property	0.201		3,107
Drug	0.192		3,107
Other	0.202		3,107

Notes: This table reports descriptive statistics for the analysis sample described in Section 4.1. “Poverty” offenses correspond to Vagrancy offenses, such as panhandling, begging for money, sleeping in a public place, etc., as well as offenses such as driving with a revoked license due to unpaid traffic tickets. “Income” is proxied by the ACS median household income in the defendant’s home address census tract and is in 2019 dollars.

Table 2: First stage: Judge leniency and fines and fees

	(1)	(2)
Judge leniency	0.748***	0.680***
	(0.064)	(0.060)
District × Time FE	Yes	Yes
Case/Def. controls	No	Yes
Mean any fines or fees	0.462	
Kleibergen-Paap rk Wald F-Stat	137.70	127.03
Observations	10,373	10,373

Notes: This table reports first-stage results. Judge leniency is estimated using data from other cases assigned to the same district judge following the procedure described in the text. Column (1) reports results controlling for my full set of district-by-time fixed effects. Column (2) adds defendant and case controls: defendant race, defendant gender, defendant age, number of offenses, indicators for the type of offense the defendant is arrested for, and census block group median income. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in columns (1) and (2).

Table 3: Testing for random assignment of cases to judges

	Any Fines or fees	Judge leniency
Age	-0.00082	-0.00030
	(0.00057)	(0.00021)
Male	-0.00338	-0.00337
	(0.01080)	(0.00285)
Minority	0.00679	-0.00279
	(0.01085)	(0.00365)
Number of offenses	-0.12255$***$	-0.00194
	(0.01430)	(0.00309)
Property offense	-0.06477$***$	-0.01538$*$
	(0.01776)	(0.00620)
Drug offense	0.02585	0.00490
	(0.02177)	(0.00457)
Prior record	0.12113$***$	-0.00642
	(0.01620)	(0.00394)
Private attorney	0.15011$***$	0.00854
	(0.01842)	(0.00599)
Self-represented	0.13828$***$	0.00997
	(0.02651)	(0.01107)
Income below poverty level	-0.03537	0.00454
	(0.02324)	(0.00277)
Joint F-test p-value	0.00000	0.29845
Observations	10,373	10,373

Notes: This table reports regressions testing the random assignment of cases to district judges. Judge leniency is estimated following the procedure described in the text. Column (1) reports estimates from an OLS regression of whether the defendant is levied any monetary sanction on the variables listed and district-by-time fixed effects. Column (2) reports estimates from an OLS regression of judge leniency on the variables listed and district-by-time fixed effects. A defendant is a minority if their reported race/ethnicity is either Black, Hispanic, or Other. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars. Poverty is defined as having an income below the federal poverty income threshold. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses. The p-value reported at the bottom of columns (1) and (2) is for an F-test of the joint significance of the variables listed with standard errors two-way clustered at the individual and judge level. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table 4: Fines and fees and criminal involvement within 2 years

	OLS			UJIVE	
	(1)	(2)	(3)	(4)	(5)
Panel A: Any criminal involvement within 2 years					
Any fine or fee	–0.021	–0.005	0.002	–0.083*	–0.058
	(0.013)	(0.013)	(0.013)	(0.046)	(0.054)
Mean of dep. var.	0.365				
Mean of dep. var. for compliers	0.345				
Panel B: Any misdemeanor criminal involvement within 2 years					
Any fine or fee	–0.014	–0.003	0.003	–0.044	–0.031
	(0.012)	(0.013)	(0.013)	(0.043)	(0.050)
Mean of dep. var.	0.317				
Mean of dep. var. for compliers	0.296				
Panel C: Any felony criminal involvement within 2 years					
Any fine or fee	–0.007	–0.002	–0.001	–0.039	–0.027
	(0.006)	(0.006)	(0.005)	(0.025)	(0.026)
Mean of dep. var.	0.048				
Mean of dep. var. for compliers	0.049				
District × Time FE	Yes	Yes	Yes	Yes	Yes
Case/Def. controls	No	Yes	Yes	No	Yes
Complier weights	No	No	Yes	No	No
Observations	10,373	10,373	10,373	10,373	10,373

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. "Financially motivated" crimes are: property crimes (excluding property damage crimes such as vandalism), selling/manufacturing/distributing drugs, drug trafficking, fraud, forgery, racketeering, prostitution, counterfeiting, crimes containing "sale", or "sell" in the charge description, and begging/panhandling. Crimes with a non-financial motive are defined as all crimes that are not categorized as financially motivated. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$** p < 0.05$,$*p < 0.10$.

Table 5: Fines and fees and criminal involvement within 2 years by offense category

	(1)	(2)	(3)	(4)
	Violent		Property	
	OLS	UJIVE	OLS	UJIVE
Any fine or fee	0.004	0.001	-0.023***	-0.038*
	(0.005)	(0.019)	(0.007)	(0.022)
Mean of dep. var.	0.035		0.060	
Mean of dep. var. for compliers	0.024		0.022	
	Drug		Other	
Any fine or fee	0.002	0.032	-0.009	-0.061
	(0.006)	(0.024)	(0.008)	(0.039)
Mean of dep. var.	0.058		0.147	
Mean of dep. var. for compliers	0.108		0.100	
District × Time FE	Yes	Yes	Yes	Yes
Observations	10,373	10,373	10,373	10,373

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. Types of offenses are compared according to broad UCR classifications, e.g., assault, robbery, larceny, etc. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table 6: Fines and fees and criminal involvement within 2 years

	OLS			UJIVE	
	(1)	(2)	(3)	(4)	(5)
Panel A: Financially motivated criminal involvement within 2 years					
Any fine or fee	–0.043***	–0.033***	–0.025***	–0.118***	–0.069**
	(0.009)	(0.008)	(0.008)	(0.028)	(0.030)
Mean of dep. var.	0.088				
Mean of dep. var. for compliers	0.050				
Panel B: Non-financially motivated criminal involvement within 2 years					
Any fine or fee	0.023**	0.028***	0.027**	0.035	0.010
	(0.010)	(0.010)	(0.011)	(0.041)	(0.044)
Mean of dep. var.	0.276				
Mean of dep. var. for compliers	0.295				
District × Time FE	Yes	Yes	Yes	Yes	Yes
Case/Def. controls	No	Yes	Yes	No	Yes
Complier weights	No	No	Yes	No	No
Observations	10,373	10,373	10,373	10,373	10,373

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. "Financially motivated" crimes are: property crimes (excluding property damage crimes such as vandalism), selling/manufacturing/distributing drugs, drug trafficking, fraud, forgery, racketeering, prostitution, counterfeiting, crimes containing "sale", or "sell" in the charge description, and begging/panhandling. Crimes with a non-financial motive are defined as all crimes that are not categorized as financially motivated. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table 7: Fines and fees and criminal involvement within 2 years by census tract median household income

	HH income quartile			
	< \$33k	\$33–46k	\$46–63k	> \$63k
Panel A: Financially motivated criminal involvement within 2 years				
Any fine or fee	–0.001	–0.019	–0.137**	–0.121*
	(0.094)	(0.074)	(0.061)	(0.067)
Mean of dep. var.	0.119	0.081	0.081	0.076
Mean of dep. var. for compliers	0.090	0.002	0.030	0.080
Panel B: Non-financially motivated criminal involvement within 2 years				
Any fine or fee	–0.187	0.063	0.104	–0.098
	(0.121)	(0.092)	(0.127)	(0.101)
Mean of dep. var.	0.268	0.280	0.271	0.287
Mean of dep. var. for compliers	0.233	0.346	0.363	0.236
District × Time FE	Yes	Yes	Yes	Yes
Case/Def. controls	Yes	Yes	Yes	Yes
Observations	2,089	2,733	2,588	2,144

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table 8: Fines and fees and criminal involvement within 2 years for defendants above and below the federal poverty line

	HH income (above and below poverty line)	
	$<$ \$26k	$\geq$ \$26k
Panel A: Financially motivated criminal involvement within 2 years		
Any fine or fee	0.037	–0.087***
	(0.268)	(0.029)
Mean of dep. var.	0.138	0.083
Mean of dep. var. for compliers	0.087	0.047
Panel B: Non-financially motivated criminal involvement within 2 years		
Any fine or fee	0.083	0.020
	(0.288)	(0.043)
Mean of dep. var.	0.269	0.277
Mean of dep. var. for compliers	0.284	0.296
District $\times$ Time FE	Yes	Yes
Case/Def. controls	Yes	Yes
Observations	869	9,283

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. Types of offenses are compared according to broad UCR classifications, e.g., assault, robbery, larceny, etc. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Appendices

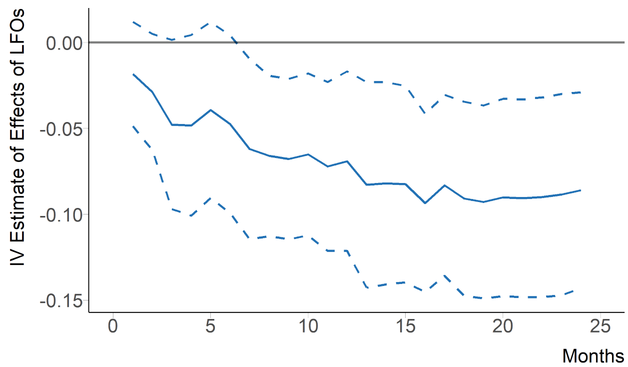
A Additional figures and tables

Figure A1: Distribution of judge leniency for fines and court fees

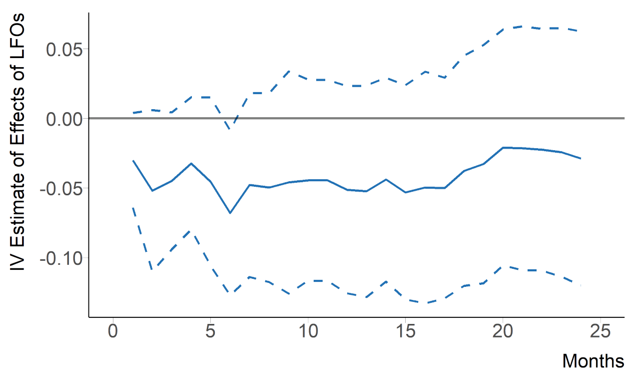
Notes: This figure shows the distribution of my leave-out mean measure of judge leniency, residualized by district-by-time fixed effects. More lenient judges levy higher fines and fees. The solid line is a local linear regression of the amount of fines and fees on judge leniency, along with the 95% confidence interval.

Figure A2: Treatment effects over time by financial incentives

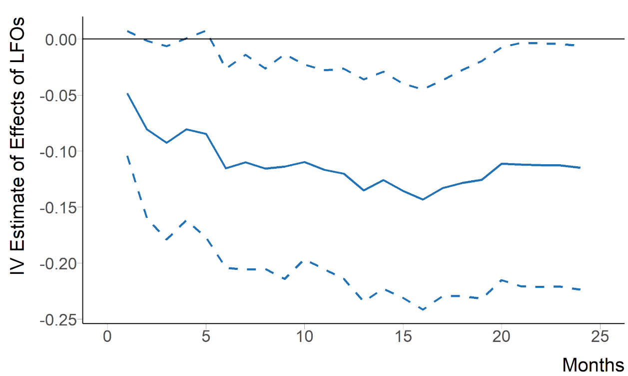
(a) Financially motivated



(b) Non-financially motivated

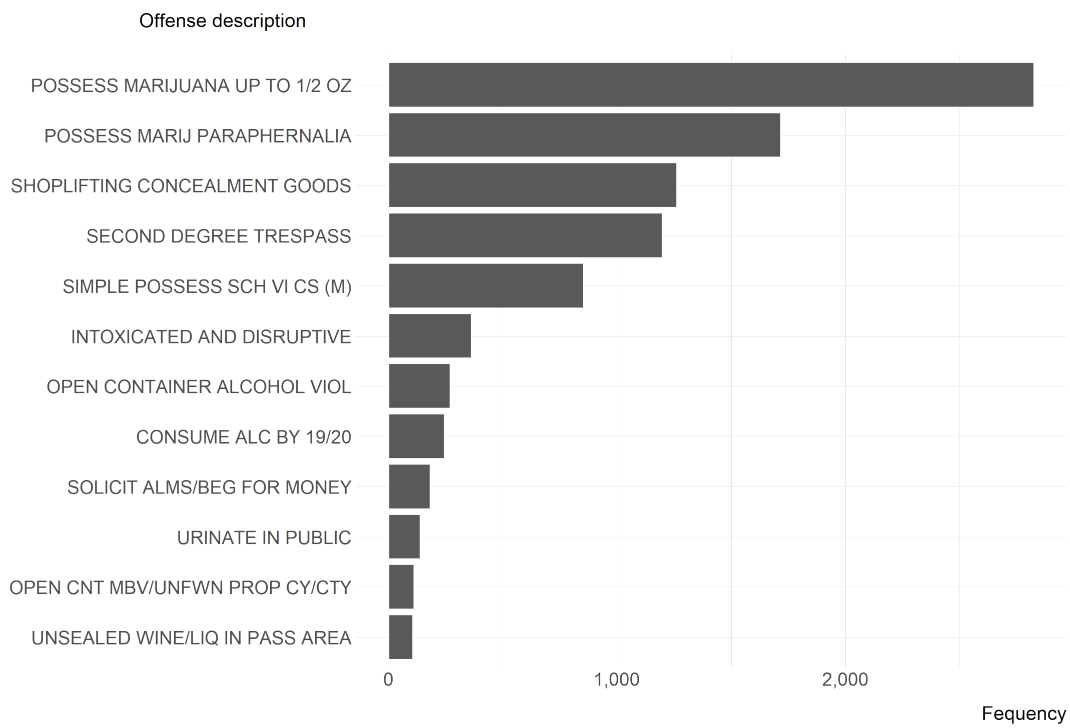


(c) Any offense



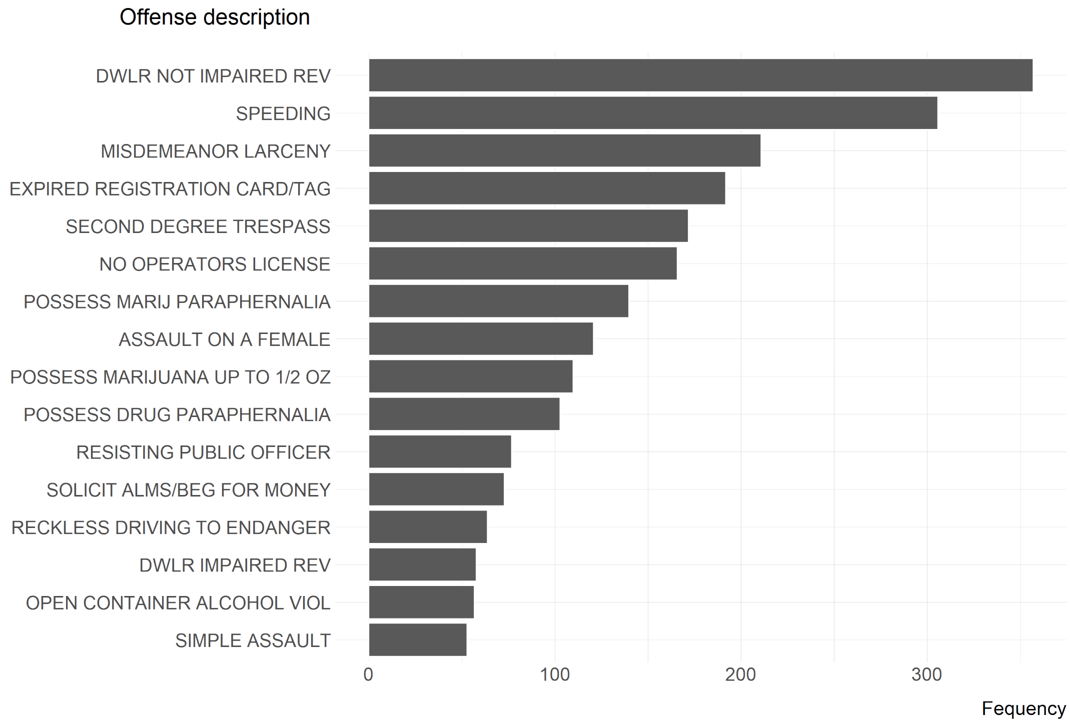
Notes: This figure shows the local average treatment effect of additional \$100 in fines and fees on the likelihood of criminal involvement within a given number of months after disposition. Estimates are based on UJIVE regressions including covariates (the equivalent of Column (4) in Table **??**). Dashed lines represent 95% confidence intervals clustered at the judge and defendant level.

Figure A3: Most common offenses



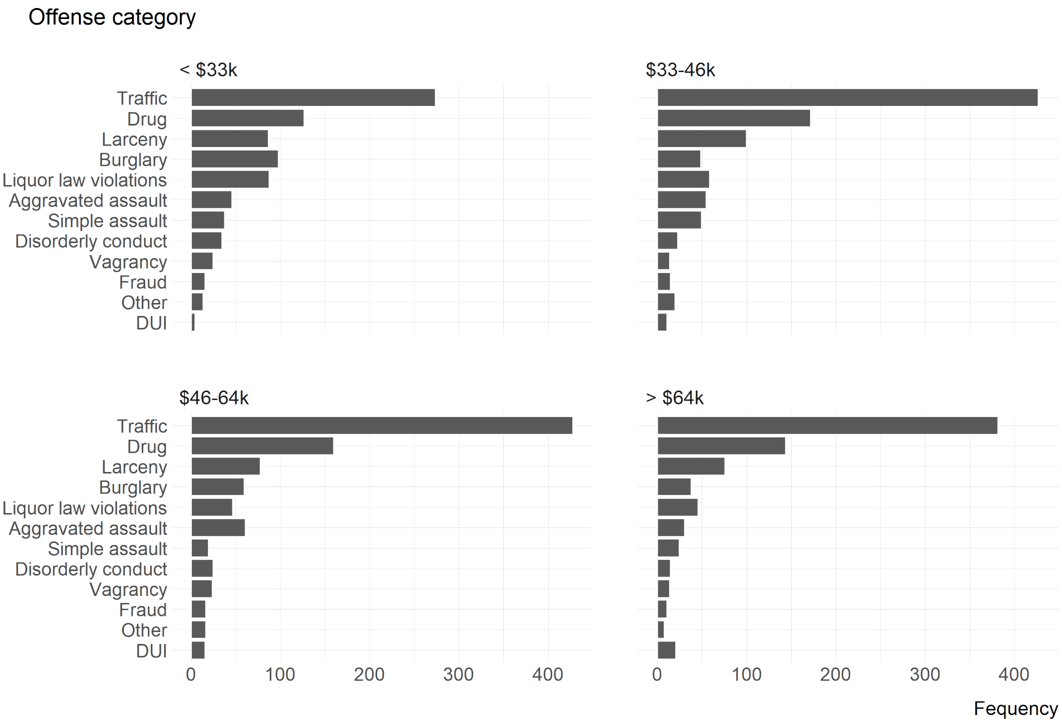
Notes: This figure shows the frequency of the most common charges defendants face in my sample.

Figure A4: Most common reoffending offenses



Notes: This figure shows the frequency of the most common offenses defendants commit when reoffending– within 2 years– in my sample.

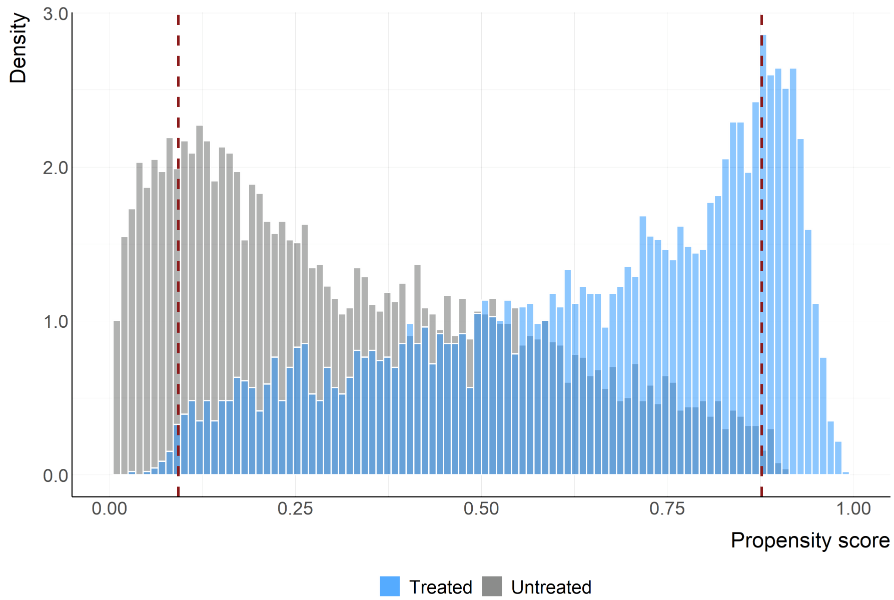
Figure A5: Most common reoffending offenses by income



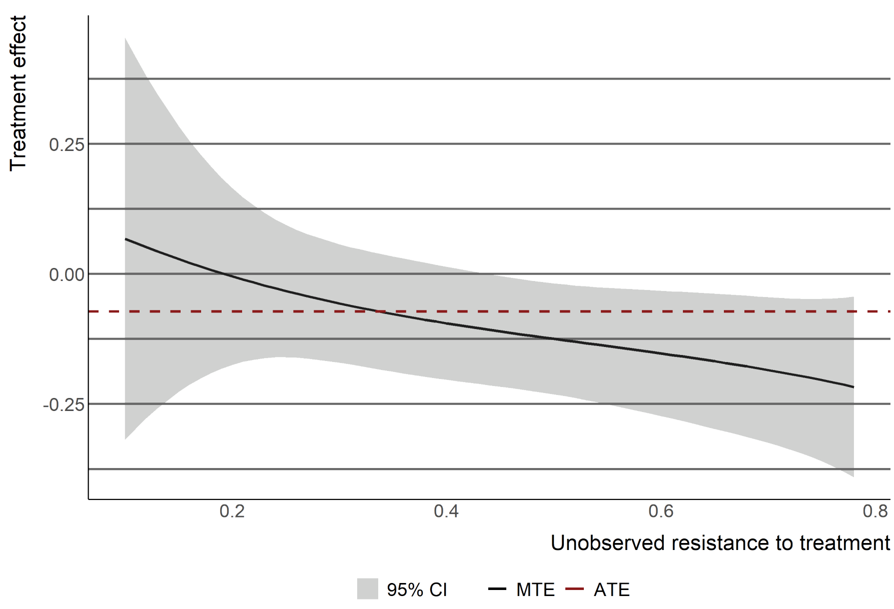
Notes: This figure shows the frequency of the most common offenses defendants commit when reoffending– within 2 years– in my sample.

Figure A6: Marginal treatment effects

(a) Common support



(b) MTE



Notes: Common support and MTEs. In (a) the dashed lines represent the upper and lower bounds on the common support of the propensity score (based on 1% trimming). In (b) the MTE estimation is based on a local IV using a cubic polynomial specification in the sample with common support. Standard errors and resulting 95% confidence intervals are estimated using 100 bootstrap replications. The outcome of interest is the probability of reoffending within two years. All estimations were done via the mtefe package in Stata (Andresen, 2018).

Table A3: Measures of treatment effects based on 2SLS and MTE

Notes: The rescaled treatment parameters are weighted averages (for the treated (ATT), for all (ATE), and for the untreated (ATUT)) over the MTE curves over the area with common support (weights sum to 1). The semiparametric specification is a local linear regression with 100 gridpoints. Standard errors are constructed based on 100 bootstrap replications.

Table A4: Frandsen et al. (2019) Test of Joint Null of Exclusion and Monotonicity by Disctrict Court district

Notes: This table presents results from the test proposed in Frandsen et al. (2019) for the joint null hypothesis that the monotonicity and exclusion restrictions hold. I test this null within each District Court district in the data, controlling by day of week-by-court session as well as year-by-month fixed effects along with case and defendant characteristics. A failure to reject the null implies that I cannot reject the hypothesis that the monotonicity and exclusion restrictions hold jointly. This test was implemented in Stata using the package testjfe (Frandsen, 2020).

Table A5: First stage results by case and attorney characteristics

	Offense type				Attorney type		
	Property	Drug	Other	Financial	Private	Public	Self
Judge leniency	0.951***	0.559***	0.760***	0.905***	0.575***	0.694***	0.945***
	(0.087)	(0.058)	(0.111)	(0.083)	(0.091)	(0.120)	(0.074)
Mean of dep. var.	0.247	0.517	0.235	0.285	0.676	0.141	0.184
Mean of dep. var. for compliers	0.123	0.616	0.262	0.146	0.529	0.125	0.346
District × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case/Def. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,395	5,250	2,272	2,793	6,934	1,265	1,786

Notes: This table reports first stage results for selected case types. The regressions are estimated on the sample as described in the notes to Table XX. Judge leniency is estimated using all cases assigned to a district judge in the same year following the procedure described in Section XX. All specifications control for court-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses and the mean of the dependent variable is reported in brackets in all specifications. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A6: First stage results by defendant characteristics

	Prior record		Defendant race		Defendant HH income quintile				
	Any prior	No prior	White	Minority	$<$ \$30k	\$30–40k	\$40–52k	\$52–67k	$>$ \$67k
Judge leniency	0.861***	0.671***	0.701***	0.813***	0.952***	0.861***	0.794***	0.676***	0.716***
	(0.088)	(0.094)	(0.105)	(0.047)	(0.107)	(0.115)	(0.092)	(0.086)	(0.090)
Mean of dep. var.	0.232	0.768	0.359	0.641	0.195	0.194	0.196	0.195	0.220
Mean of dep. var. for compliers	0.265	0.735	0.295	0.705	0.166	0.161	0.186	0.194	0.293
District $\times$ Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case/Def. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,234	7,904	3,572	6,518	1,843	1,793	1,839	1,810	2,106

Notes: This table reports first stage results for selected case types. The regressions are estimated on the sample as described in the notes to Table XX. Judge leniency is estimated using all cases assigned to a district judge in the same year following the procedure described in Section XX. All specifications control for court-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses and the mean of the dependent variable is reported in brackets in all specifications. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A7: District judges case distribution

Notes: This table presents results from the test proposed in Frandsen et al. (2019) for the joint null hypothesis that the monotonicity and exclusion restrictions hold. We test this null within courts using day-of-week and year-month fixed effects along with our main covariates. A failure to reject the null implies that we cannot reject the hypothesis that the monotonicity and exclusion restrictions jointly hold. This test was implemented in Stata via the package testjfe (Frandsen, 2020).

Table A8: Case characteristics and outcomes

	All	No fines nor fees	Any fines or fees
Defendant Characteristics			
Any fines or fees	0.462	0.000	1.000
Non-Hispanic White	0.359	0.378	0.337
Minority	0.641	0.622	0.663
Male	0.729	0.710	0.752
Age	29.946	30.002	29.880
	(12.481)	(13.042)	(11.795)
Income ($1,000s)	51.165	48.409	54.357
	(26.314)	(25.650)	(26.713)
Charge Characteristics			
Property offense	0.247	0.284	0.204
Drug offense	0.517	0.488	0.551
Other offense	0.235	0.227	0.244
Number of offenses	1.243	1.280	1.200
	(0.436)	(0.459)	(0.403)
Outcomes			
Case dismissed	0.300	0.558	0.000
Case disposed by judge	0.700	0.442	1.000
Convicted	0.688	0.420	1.000
Guilty plea	0.674	0.412	0.978
Case length (days)	218.803	232.847	202.460
	(218.478)	(215.197)	(221.138)
Attorney Characteristics			
Male	0.719	0.701	0.750
Court appointed	0.047	0.048	0.046
Public defender	0.094	0.124	0.058
Privately retained	0.676	0.683	0.667
Observations	10,373	5,579	4,794

Notes: This table reports descriptive statistics for the analysis sample described in Section 4.1. "Poverty" offenses correspond to Vagrancy offenses, such as panhandling, begging for money, sleeping in a public place, etc., as well as offenses such as driving with a revoked license due to unpaid traffic tickets. A defendant is a minority if their reported race/ethnicity is either Black, Hispanic, or Other. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars.

Table A9: Testing for random assignment of cases to judges

	Z distribution				
	Bottom tercile	Middle tercile	Top tercile	Middle vs. bottom p-value	Top vs. bottom p-value
Age	30.143	30.091	29.663	(0.690)	(0.543)
Male	0.722	0.730	0.736	(0.518)	(0.973)
Minority	0.636	0.607	0.676	(0.101)	(0.112)
Number of offenses	1.237	1.245	1.249	(0.038)	(0.226)
Property offense	0.276	0.257	0.207	(0.567)	(0.004)
Drug offense	0.494	0.496	0.558	(0.821)	(0.076)
Prior record	0.429	0.286	0.403	(0.086)	(0.224)
Private attorney	0.668	0.735	0.628	(0.368)	(0.973)
Self-represented	0.175	0.137	0.237	(0.183)	(0.077)
Income below poverty level	0.142	0.143	0.115	(0.142)	(0.194)

Notes: p-values reported in parentheses were calculated from separate regression models of each characteristic on indicators that the judge's incarceration rate (Z) was in the middle or top tercile along with district-by-time fixed effects using standard errors clustered at the judge and defendant level. A defendant is a minority if their reported race/ethnicity is either Black, Hispanic, or Other. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars. Poverty is defined as having an income below the federal poverty income threshold. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A10: Analysis sample description

Sample	Observations
All NC criminal cases	4,435,571
Class 3 misdemeanors	3,395,066
Only fines	2,879,730
Non-waived court appearance	316,045
Non motor vehicle cases	25,242

Notes: This table reports sample sizes and basic desciptive statistics as I restrict the universe of criminal offenses in North Carolina to construct my analysis sample.

Table A11: Analysis sample comparison

Notes: This table reports descriptive statistics for both the full sample (Class 3 misdemeanors that can be subject to a fine at most), as well as the analysis sample described in Section 4.1. "Poverty" offenses correspond to Vagrancy offenses, such as panhandling, begging for money, sleeping in a public place, etc., as well as offenses such as driving with a revoked license due to unpaid traffic tickets. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars.

Table A12: Sample share by compliance type

	Linear model			Local linear model		
	1%	1.5%	2%	1%	1.5%	2%
Compliers	0.48	0.43	0.37	0.49	0.44	0.39
Always takers	0.16	0.19	0.24	0.18	0.20	0.24
Never takers	0.37	0.38	0.39	0.34	0.36	0.37

Notes: This table estimates the shares of the sample that are compliers, always-takers, and never-takers. The fraction of always-takers, π_a, is estimated by the share of the defendants who are fined by the most lenient district judge; the fraction of never-takers, π_n, by the share not fined by the least lenient district judge; and compliers as 1 - π_a - π_n. Most lenient district judges are defined by being at the 1st, 2nd, or 3rd percentile of the residualized district judge leniency distribution, and least lenient are defined as being at the 99, 98, or 97th percentile. The first three columns use a linear specification of the first stage, as in Equation (2); the latter three use a local linear specification.

Table A13: Characteristics of marginal defendants

	$\Pr[X = x]$	$\Pr[X = x \mid D(1) > D(0)]$	Ratio
Offenses = 1	0.76	0.82	1.08
Offenses > 1	0.24	0.18	0.75
Any prior record	0.23	0.27	1.14
Property offense	0.25	0.12	0.50
Drug offense	0.52	0.62	1.19
Other offense	0.24	0.26	1.12
Private attorney	0.68	0.53	0.78
Indigent defense	0.14	0.13	0.89
Self-represented	0.18	0.35	1.88
Age $\leq$ 24	0.42	0.35	0.83
Age 25–34	0.25	0.31	1.23
Age 35–44	0.12	0.13	1.08
Age 45–54	0.10	0.08	0.85
Age $\geq$ 55	0.06	0.07	1.15
< \$33k	0.22	0.17	0.75
\$33–46k	0.28	0.26	0.91
\$46–63k	0.27	0.24	0.90
> \$63k	0.22	0.33	1.49
Male	0.73	0.73	1.00
Minority	0.64	0.70	1.10
White	0.36	0.29	0.82

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. The complier share calculations here rely on a linear first-stage estimation and a 1% cut-off to define district judge leniency.

Table A14: Characteristics of marginal defendants relative to overall sample by household income quartile

	< \$33k		\$33–46k		\$46–63k		> \$63k	
	Subsample	Compliers	Subsample	Compliers	Subsample	Compliers	Subsample	Compliers
Offenses = 1	0.77	0.76	0.75	0.77	0.79	0.76	0.92	0.81
Offenses > 1	0.23	0.25	0.25	0.23	0.21	0.24	0.08	0.19
Any prior record	0.27	0.23	0.22	0.21	0.44	0.34	0.12	0.22
Property offense	0.32	0.25	0.21	0.22	0.16	0.16	0.07	0.11
Drug offense	0.43	0.54	0.55	0.54	0.54	0.59	0.74	0.58
Other offense	0.26	0.22	0.23	0.24	0.30	0.25	0.19	0.30
Private attorney	0.71	0.68	0.66	0.65	0.64	0.55	0.49	0.49
Indigent defense	0.18	0.13	0.14	0.10	0.17	0.12	0.12	0.11
Self-represented	0.11	0.19	0.19	0.25	0.19	0.34	0.39	0.41
Age $\leq$ 24	0.33	0.43	0.42	0.49	0.27	0.24	0.30	0.51
Age 25–34	0.27	0.26	0.25	0.23	0.28	0.33	0.39	0.25
Age 35–44	0.14	0.12	0.13	0.10	0.26	0.22	0.07	0.05
Age 45–54	0.13	0.09	0.09	0.08	0.08	0.09	0.08	0.08
Age $\geq$ 55	0.08	0.05	0.06	0.05	0.09	0.05	0.09	0.06
Male	0.71	0.71	0.74	0.75	0.70	0.68	0.87	0.68
Minority	0.75	0.70	0.62	0.49	0.90	0.68	0.78	0.57
White	0.26	0.30	0.38	0.51	0.10	0.32	0.22	0.43

Notes: This table describes the observable characteristics of the complier sample relative to the full sample for each different quartile of household income, where the latter is proxied by census tract median household income. Each column shows the ratio of the share of compliers, within the subsample defined by the respective covariate, relative to the share for the overall sample. The complier share calculations here rely on a linear first-stage estimation and a 1% cut-off to define district judge leniency. See Section XX for more detail.

Table A15: Fines and fees and criminal involvement within 2 years by defendant age and race

	Male	Female	White	Black	Hispanic
	(1)	(2)	(3)	(4)	(5)
Any fine or fee	–0.084**	–0.047	–0.068	–0.062**	–0.253
	(0.034)	(0.074)	(0.076)	(0.030)	(0.348)
Mean of dep. var.	0.089	0.085	0.093	0.090	0.047
Mean of dep. var. for compliers	0.034	0.092	0.122	0.032	0.014
Observations	7,463	2,610	3,563	5,699	321
	Age < 18	Age $18 - -23$	Age $24 - 30$	Age $31 - 40$	Age > 40
Any fine or fee	–0.014	–0.076	–0.164**	–0.101	0.027
	(0.529)	(0.087)	(0.080)	(0.077)	(0.071)
Mean of dep. var.	0.089	0.071	0.075	0.098	0.126
Mean of dep. var. for compliers	0.089	0.078	–0.012	0.055	0.094
Observations	411	3,561	2,104	1,336	1,901

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. Types of offenses are compared according to broad UCR classifications, e.g., assault, robbery, larceny, etc. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A16: Fines and fees and criminal involvement by census tract median household income

	HH income quintile			
	< \$33k	\$33–46k	\$46–63k	> \$63k
Panel A: Financially motivated criminal involvement within 2 years				
Any fine or fee	–0.041	–0.011	–0.084*	–0.126*
	(0.086)	(0.075)	(0.051)	(0.066)
Mean of dep. var.	0.110	0.076	0.073	0.070
Mean of dep. var. for compliers	0.091	–0.017	0.017	0.076
Panel B: Poverty-associated criminal involvement within 2 years				
Any fine or fee	0.030	–0.023	–0.020	–0.071
	(0.063)	(0.056)	(0.060)	(0.047)
Mean of dep. var.	0.063	0.060	0.073	0.064
Mean of dep. var. for compliers	0.094	0.098	0.167	0.031
Panel C: Non-financially motivated criminal involvement within 2 years				
Any fine or fee	–0.177	0.079	0.072	–0.023
	(0.131)	(0.092)	(0.113)	(0.108)
Mean of dep. var.	0.214	0.224	0.206	0.228
Mean of dep. var. for compliers	0.138	0.268	0.209	0.210
Observations	2,089	2,733	2,588	2,144

Notes: This table reports UJIVE estimates of the impact of fines and fees on the probability of a defendant's subsequent criminal involvement within two years. These UJIVE estimates instrument whether the defendant was levied any fines or fees using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. "Financially motivated" crimes are: property crimes (excluding property damage crimes such as vandalism), selling/manufacturing/distributing drugs, drug trafficking, fraud, forgery, racketeering, prostitution, counterfeiting, crimes containing "sale", or "sell" in the charge description, and begging/panhandling. Crimes with a non-financial motive are defined as all crimes that are not categorized as financially motivated. "Poverty" offenses correspond to Vagrancy offenses, such as panhandling, begging for money, sleeping in a public place, etc., as well as offenses such as driving with a revoked license due to unpaid traffic tickets. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars. These are UJIVE estimates that instrument whether the defendant was levied any fines or fees using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A17: Fines and fees and criminal involvement by census tract median household income

	HH income (above and below poverty line)	
	$< \$26k$	$\geq \$26k$
Panel A: Financially motivated criminal involvement within 2 years		
Any fine or fee	–0.040	–0.071***
	(0.244)	(0.027)
Mean of dep. var.	0.123	0.077
Mean of dep. var. for compliers	0.086	0.037
Panel B: Poverty-associated motivated criminal involvement within 2 years		
Any fine or fee	0.174*	–0.000
	(0.102)	(0.025)
Mean of dep. var.	0.059	0.066
Mean of dep. var. for compliers	0.093	0.092
Panel C: Non-financially motivated criminal involvement within 2 years		
Any fine or fee	–0.013	0.005
	(0.279)	(0.042)
Mean of dep. var.	0.225	0.217
Mean of dep. var. for compliers	0.192	0.214
District $\times$ Time FE	Yes	Yes
Case/Def. controls	Yes	Yes
Observations	869	9,283

Notes: This table reports UJIVE estimates of the impact of fines and fees on the probability of a defendant's subsequent criminal involvement within two years. These UJIVE estimates instrument whether the defendant was levied any fines or fees using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. "Financially motivated" crimes are: property crimes (excluding property damage crimes such as vandalism), selling/manufacturing/distributing drugs, drug trafficking, fraud, forgery, racketeering, prostitution, counterfeiting, crimes containing "sale", or "sell" in the charge description, and begging/panhandling. Crimes with a non-financial motive are defined as all crimes that are not categorized as financially motivated. "Poverty" offenses correspond to Vagrancy offenses, such as panhandling, begging for money, sleeping in a public place, etc., as well as offenses such as driving with a revoked license due to unpaid traffic tickets. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A18: Fines and fees and criminal involvement within 2 years by prior criminal record

	Defendant prior criminal record	
	Any prior record	No prior record
Panel A: Financially motivated criminal involvement within 2 years		
Any fine or fee	–0.086	–0.091**
	(0.080)	(0.039)
Mean of dep. var.	0.108	0.082
Mean of dep. var. for compliers	0.040	0.053
Panel B: Non-financially motivated criminal involvement within 2 years		
Any fine or fee	0.127	–0.004
	(0.135)	(0.066)
Mean of dep. var.	0.290	0.272
Mean of dep. var. for compliers	0.363	0.271
Observations	2,225	7,902

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a subsequent criminal involvement within two years. UJIVE estimates instrument monetary sanctions using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. "Financially motivated" crimes are: property crimes (excluding property damage crimes such as vandalism), selling/manufacturing/distributing drugs, drug trafficking, fraud, forgery, racketeering, prostitution, counterfeiting, crimes containing "sale", or "sell" in the charge description, and begging/panhandling. Crimes with a non-financial motive are defined as all crimes that are not categorized as financially motivated. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01, **p < 0.05, *p < 0.10$.

Table A19: "Failure to comply" by census tract median household income

	HH income quartile			
	< \$33k	\$33–46k	\$46–63k	> \$63k
Any fine or fee	0.576***	0.438***	0.589***	0.477***
	(0.110)	(0.101)	(0.135)	(0.123)
Mean of dep. var.	0.181	0.201	0.219	0.210
Mean of dep. var. for compliers	0.552	0.391	0.545	0.455
District × Time FE	Yes	Yes	Yes	Yes
Case/Def. controls	Yes	Yes	Yes	Yes
Observations	2,089	2,733	2,588	2,144

Notes: This table reports OLS and UJIVE estimates of the impact of fines and fees on the probability of a defendant's "failure to comply", i.e., pay the total amount of fines and fees owed, within 40 days of conviction. These are UJIVE estimates that instrument whether the defendant was levied any fines or fees using a judge leniency measure that is estimated using data from other cases assigned to a judge following the procedure described in the text. All specifications control for district-by-time fixed effects. Robust standard errors two-way clustered at the individual and judge level are reported in parentheses in Columns (1)-(4). $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A20: Alternative IV strategies

	(1)	(2)	(3)	(4)	(5)
	UJIVE	JIVE	2SLS	LIML	IV Lasso
Any fine or fee	-0.066	-0.067	-0.059	-0.065	-0.125***
	(0.050)	(0.049)	(0.036)	(0.043)	(0.016)
District × Time FE	Yes	Yes	Yes	Yes	Yes
Attorney type FE	Yes	Yes	Yes	Yes	Yes
Case/Def. controls	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F-Stat	127.03	183.87	2,420.66	2,420.66	287.10
Any fine or fee	0.462				
Observations	10,373	10,373	10,373	10,373	10,373

Notes: This table reports two-stage least squares estimates using various estimation strategies for the instrument, as indicated in the column headers. All specifications control for court-by-time fixed effects and case/defendant covariates. The OLS estimate for this specification can be found in Table XX Column (2), and is XX (se=XX). Robust standard errors two-way clustered at the individual and judge level are reported in parentheses. Column (1) repeats my main 2SLS estimates using Kolesár (2013)'s UJIVE estimator. In Column (2) I present estimates using the JIVE estimator. In Column (3) I use all XX judge dummy variables directly as instruments in the first stage. Column (3) uses limited information maximum likelihood estimation with all of the dummies as instruments as well. Column (5) uses post-lasso from Belloni et al. (2014) to choose the most informative judge dummy variables; the algorithm chooses XX of the judge dummies as instruments. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

B Technical appendix

B.1 Understanding compliers

This section includes additional details on how I calculate the number and characteristics of defendants categorized as always takers, never takers, and compliers in my sample.

Overview: Following Dahl et al., 2014, I define compliers as defendants whose fining decision would have been different had their case been assigned to the most lenient instead of the most strict judge:

$$\pi_c = \Pr\left[\text{Any LFO}_i = 1 \mid Z_i = \bar{z}\right] - \Pr\left[\text{Any LFO}_i = 1 \mid Z_i = \underline{z}\right] = \Pr\left[\text{Any LFO}_i\left(\bar{z}\right) > \text{Any LFO}_i\left(\underline{z}\right)\right]$$

where $\bar{z}$ represents the maximum value of our judge instrument (the most lenient judge) and $\underline{z}$ represents the minimum value of our instrument (the most strict judge).

Always-takers are defendants who would always be fined, regardless of the judge assigned to their case. Because of the monotonicity and independence assumptions, the fraction of always takers is given by the probability of being fined for the most strict judge:

$$\pi_a = \Pr\left[\text{Any LFO}_i = 1 \mid Z_i = \underline{z}\right] = \Pr\left[\text{Any LFO}_i\left(\bar{z}\right) = \text{Any LFO}_i\left(\underline{z}\right) = 1\right]$$

Finally, never-takers are defendants who would never be fined, with the fraction of never-takers given by the probability of being fined by the most lenient judge:

$$\pi_n = \Pr\left[\text{Any LFO}_i = 0 \mid Z_i = \bar{z}\right] = \Pr\left[\text{Any LFO}_i\left(\bar{z}\right) = \text{Any LFO}_i\left(\underline{z}\right) = 0\right]$$

Number of compliers: I calculate the shares of defendants in each category by looking at the pretrial release rates for defendants assigned to the "most lenient" and "most strict" judges. Following Dahl et al., 2014, we begin by defining the "most strict" judge as the bottom 1 percentile of judge leniency and the "most lenient" judge as the top 1 percentile of judge leniency.

In the first three columns of Table A12, I estimate a local linear regression of receiving any LFO on my residualized measure of judge leniency controlling for court-by-time fixed effects. Under this more flexible analog to my first stage equation, I find that XX percent of my sample are compliers, XX percent are never takers, and XX percent are always takers.

In the last XX columns of Table A12, I estimate the linear specification of the first stage, given by Equation 2. Under this specification, I can recover π_c as $\hat{\alpha}_1(\bar{z} - \underline{z})$, π_a as $\hat{\alpha}_0 + \hat{\alpha}_1\underline{z}$, and π_n as $1 - \hat{\alpha}_0 - \hat{\alpha}_1\bar{z}$ where $\hat{\alpha}_0$ and $\hat{\alpha}_1$ are the estimated first stage coefficients. Under this linear specification, I find that XX percent of my sample are compliers, XX percent are never takers, and XX percent are always takers. I also explore the sensitivity of the estimated share of compliers, always takers, and never takers to the exact choice of cutoff for the most lenient and most strict judge. My results are robust to the particular model specification and cutoff.

B.2 Alternative estimating strategies

My main instrument is a residualized leave-out mean leniency measure that is estimated from the other cases that a judge has decided on. For my main analyses I proceed by implementing this instrument in an 'as-if just-identified' manner: I report robust F-statistics that do not adjust for the fact that the instrument is estimated (although I also do not use these F-statistics directly in a threshold test). Performing the estimation in this way is standard (Dahl et al., 2014; Aizer and Doyle Jr, 2015; Dobbie et al., 2018; Bhuller et al., 2020) and has some attractive properties. I have XX judges in my sample, each of whom could serve as a potential instrument. With this many instruments, estimation using the judge dummies can suffer from bias from many (potentially weak) instruments (Bekker, 1994; Bound et al., 1995; Hausman et al., 2012). I also have many fixed effects in the covariate set, necessary to identify the set of cases for which judges are as-if randomly assigned, which can also cause bias in jackknife instrumental variable estimators (JIVE) (Ackerberg and Devereux, 2009; Kolesár, 2013). It is also clear in the just-identified case how to handle inference in the second stage that is robust to (potential) weak instrument issues (Andrews et al., 2019). The continuous instrument also allows for the estimation of marginal treatment effects (Heckman and Vytlacil, 2005). While this estimation strategy is convenient for the reasons mentioned above, it does not take into account that the instrument itself is constructed. In this subsection we explore the robustness of our main estimates to alternative estimation strategies in this setting. One alternative approach is to estimate the 2SLS model using the full set of XX judge dummy variables as instruments in the first stage. These results are shown in Table B.2, Column (XX) (Column (XX) repeats our main 2SLS results using the residualized leave-out mean leniency as an instrument). The estimated coefficient is XX, smaller in absolute value and closer to OLS than our main leave-out mean 2SLS estimate, which is unsurprising given that the bias from weak instruments moves estimates closer to the OLS estimate. Several strategies are suggested when IV estimates suffer from bias from many (weak) instruments. In Column (XX) I estimate a limited information maximum likelihood (LIML) model with all the dummies as instruments (Bekker, 1994; Chao and Swanson, 2004; Angrist and Frandsen, 2019). The coefficient in this model is XX, closer to our main leave-out mean 2SLS estimate than the estimate in Column (XX) with all the judge dummy variables. LIML however is not consistent with heteroskedastic errors or with heterogeneous treatment effects (Hausman et al., 2012; Kolesár, 2013), which is the motivation for the UJIVE estimator we also use. In Column (XX) I estimate the unbiased JIVE (UJIVE) estimator of Kolesár (2013).48 JIVE estimators are generally suggested when the number of instruments is large Angrist et al. (1999), although they can be biased with many covariates Kolesár (2013). The UJIVE estimator is consistent (for a convex combination of LATE estimates) with a large number of covariates. Here the coefficient is XX, again closer to my main leave-out mean 2SLS estimate than the estimate in Column (XX) with all the judge dummy variables. Another way to handle the potential bias from many (weak) instruments is to reduce the number of instruments by using lasso to pick the most informative judge dummies in a 2SLS regression. We do this in Column (5) using a post-lasso first stage via the procedures of Belloni et al. (2014).[75] In each case the coefficients I estimate with the alternative strategies are XX, XX, and XX, implying that XX decreases XX within two years post-arraignment between XX-X% relative to XX compliers. For the most part, given the estimated standard errors, I cannot reject the null that these coefficients are the same as the UJIVE estimates.[76]

[75]In practice implemented via the user-written package ivlasso in Stata (Ahrens et al., 2019), using the post-lasso results and using the ivlasso defaults with a plug-in penalty. The procedure retains XX out of XX instruments (similarly in the Angrist and Frandsen (2019) implementation of the plug-in penalty, lasso retains two instruments out of 180 in a re-estimation of the Angrist and Krueger (1991) QOB study). We also implemented a version of ivlasso with a cross-validated penalty; see Angrist and Frandsen (2019) for details on implementation. The algorithm with the CV penalty chooses more instruments, namely 173 out of the 315 in our case. The estimated post-lasso coefficient is smaller in absolute value (XX, se=XX). The simulation results of Angrist et al. (1999) and Belloni et al. (2012) imply that the plug-in penalty will have less bias although will also be less precise than the CV penalty estimates.

[76]Standard errors reported here for 2SLS or LIML using all the dummy variables have been adjusted to take into account the potential for weak instruments, following Montiel Olea and Pflueger (2013).

C Taxonomy of monetary sanctions

Fines represent a punishment imposed upon conviction for a criminal offense

Restitution is sentenced to compensate victims for losses or damages as a result of a particular offense. These damages could include damage to property, medical expenses, child support, or other costs recognized by the court caused by the offense.

User fees and costs are charged to people with criminal justice contact to offset the expenses associated with the administration of justice or for services provided by courts or policing or supervisory agencies. These include, but are not limited to, court costs, probation costs, fees for screening and use of public attorneys, costs associated with the prosecution of a case, and costs of incarceration.

Surcharges (sometimes called "assessments") are proportional or flat charges imposed on broad categories of convictions. Like fees and costs, surcharges are often used to fund criminal justice and other government services. Surcharges are generally directed to particular funds for designated purposes such as law enforcement training, indigent defense, or jail and prison construction (Harris et al., 2017).

D North Carolina institutional information

The General Court of Justice consists of three divisions: the appellate division, the superior court division and the district court division. The appellate division comprises the Supreme Court and the Court of Appeals. The Supreme Court is the state's highest court. This court has a Chief Justice and six associate justices, who sit as a body and decide cases appealed from lower courts (including the Court of Appeals). The Court of Appeals is an intermediate appellate court that was created to relieve the Supreme Court of a portion of its heavy caseload. It has fifteen judges, who sit in panels of three to hear cases. One of the judges is the Chief Judge of the Court of Appeals, appointed by the Chief Justice of the Supreme Court. Most of the court's sessions are held in Raleigh, but individual panels sometimes meet in other locations throughout the state. The Supreme Court and the Court of Appeals are located in downtown Raleigh. Each court has a clerk, who is the court's administrative officer. see Figure C1 for a brief overview of the courts' organizational structure.

The Superior and District Court divisions are the trial court divisions. The superior court division consists of the superior court, which is the court with general trial jurisdiction. The superior court "sits" (holds court) at least twice a year in each county of the state. In the busiest counties, several sessions may be held concurrently each week. The district court sits in the county seat of each county as well, although it may sit in certain other cities and towns if authorized by the General Assembly. Most counties have only one seat of court, but a few counties have several.

The State is divided into superior court districts for both electoral and administrative purposes. Where the superior court district is composed of less than a full county for electoral purposes, several electoral districts become one district for administrative purposes. For example, Wake County has four superior court electoral districts–10A, 10B, 10C and 10D–each of which has a separate election for the judge(s) from that district, but all are joined together for administrative purposes as the 10th District.

Each administrative superior court district has a senior resident superior court judge who manages the administrative duties of the court. The superior court sits only in the county seat of each county, except for Guilford County where the court sits in Greensboro (the county seat) and High Point.[77] There are 46 superior court districts, which are further grouped into eight divisions (48 districts and 5 divisions as of 2019–see Figure **??**), and the State's constitution requires superior court judges to rotate, or "ride the circuit," from one

[77]In addition to meeting in the county seat of each county, the superior court must meet regularly in any city in the state that was not a county seat but had a population over 35,000 in the 1960 U.S. census. G.S. 7A-42(a). High Point was the only city in North Carolina that fit that description in 1960.

district to another within their divisions. Judges are assigned to a judicial district for a six-month period and then rotated to another district for the same time period, and so on.

Like the superior court division, the state is divided into district court districts, of which there are 41, for electoral purposes and administrative purposes (see Figure **??**). Unlike the superior court though, the district court districts are not grouped into larger judicial divisions. Each administrative district court district has a chief district court judge who manages the administrative duties of the court.

Finally, Magistrates hold court in both civil and criminal matters as officers of the district court under the supervisory authority of the chief district court judge. Magistrates do not preside over a separate trial division of the General Court of Justice, so technically there is no such court as "magistrate's court." In the civil context, magistrates generally are assigned by the chief district court judge to preside over "small claims" court. For criminal matters, magistrates conduct certain preliminary proceedings and are authorized to dispose of some cases by pleas of guilty or by trial.

The criminal jurisdiction of the trial courts depends on the type of offense charged, but ultimately all crimes are within the jurisdiction of the superior court. With a few exceptions, the superior court has exclusive jurisdiction over all felonies. The district court has jurisdiction over a felony to conduct a preliminary hearing to determine whether or not there is probable cause to believe that the defendant committed the offense. If so, the district court orders that the defendant stand trial in superior court and the case is transferred there. With the consent of the district attorney and the defendant, the district court also may take guilty pleas to certain less serious felonies, but the district court in those cases operates as if the plea was entered in superior court and must follow the superior court's procedures.

For misdemeanor cases, the district court has exclusive "original" jurisdiction, which means that all misdemeanor crimes are tried initially in district court (unless the misdemeanor was committed as part of the same act as a felony, in which case both are tried together in superior court). A criminal trial in district court is always a "bench trial"–in which the judge decides the verdict instead of a jury. However, because the Sixth Amendment to the United States Constitution guarantees a person charged with a crime the right to be tried by a jury, a defendant convicted of a misdemeanor in district court has the right to appeal his conviction to the superior court for a new trial (also called a trial "de novo"), in which the trial must be before a jury. If a defendant pleads guilty to a low-level felony in district court and appeals the judgment, there is no new trial in superior court. Because the plea is treated as if it had been done in superior court, any appeal from the judgment goes to the appellate division.

In addition to misdemeanors, the district court has original jurisdiction over infractions.

An infraction is not a criminal offense and may be punished only by a fine. A person charged with an infraction initially appears before the district court, but if the person is found responsible for committing the infraction he may appeal to the superior court for a new hearing. Unlike felonies and misdemeanors, a person found responsible for an infraction cannot be sent to jail or prison for the infraction, so the state constitution's requirement that a jury decide criminal cases does not apply. A person who appeals a district court finding of responsibility for an infraction, therefore, can have a bench trial in superior court.

As officers of the district court, magistrates generally are the first judicial officials involved in criminal cases, because they usually issue the criminal process (e.g., a warrant for arrest) that begins most criminal cases. The magistrate also generally sets the initial conditions for pretrial release (bail) for persons who have been arrested. In disposing of criminal cases, magistrates have jurisdiction to accept waivers of trial and guilty pleas to certain minor misdemeanors and pleas of responsibility to infractions. If specifically authorized by the chief district court judge, a magistrate also may try cases and enter judgment for defendants who plead not guilty to charges of writing worthless checks.

The minor misdemeanors and infractions for which magistrates may accept waivers of trial and pleas of guilt or responsibility generally are traffic, wildlife, boating, marine fisheries, state park recreation and alcoholic beverage offenses. The fine for each offense for which the magistrate can accept a plea of guilty is set by uniform statewide schedules (called the "waiver lists"), which are developed by the chief district court judges at their annual conference.

D.1 Indigent Defense

Counsel for criminal defendants in North Carolina may be provided either by privately retained attorneys or by what's known as indigent defense representation. In the U.S., indigent people accused of crimes have a constitutional right to legal representation free of charge. Depending on the jurisdiction this can be provided either by public defenders— full-time state employees— or by private attorneys who choose to participate in an assigned counsel system.

More specifically, for misdemeanors, a defendant has a Sixth Amendment right to counsel only if an active or suspended sentence of imprisonment is imposed[78]. In contrast, the Sixth

[78] The formulation of this right has developed over a series of U.S. Supreme Court decisions. See Argersinger v. Hamlin, 407 U.S. 25 (1972) (recognizing basic right to counsel in misdemeanor cases); Scott v. Illinois, 440 U.S. 367, 373–74 (1979) (in misdemeanor cases, "the Sixth and Fourteenth Amendments to the United States Constitution require only that no indigent criminal defendant be sentenced to a term of imprisonment unless the State has afforded him the right to assistance of appointed counsel"); Alabama v. Shelton, 535 U.S. 654 (2002) (indigent defendant has right to appointed counsel in misdemeanor case if court imposes

Amendment guarantees the right to counsel to any indigent person accused of a felony, regardless of the possible punishment.[79]

North Carolina law provides indigent criminal defendants with a slightly broader right to counsel, providing for appointed counsel in "[a]ny case in which imprisonment, or a fine of five hundred dollars . . . or more, is likely to be adjudged."[80] This provision will not come into play for most Class 3 misdemeanors if the defendant has three or fewer prior convictions: following 2013's Appropriations Act, for Class 3 misdemeanors imprisonment is generally impermissible; and under other structured sentencing rules, the maximum fine is usually limited to $200. This has always been the case for traffic violations.

Public defender offices are present in 17 judicial districts in North Carolina (see Figure XXXXX). Additionally, specialty or "statewide" offices provide representation in capital cases (Office of the Capital Defender), appeals (Office of the Appellate Defender), parent representation (Office of Parent Representation), and special proceedings (Office of Special Counsel).

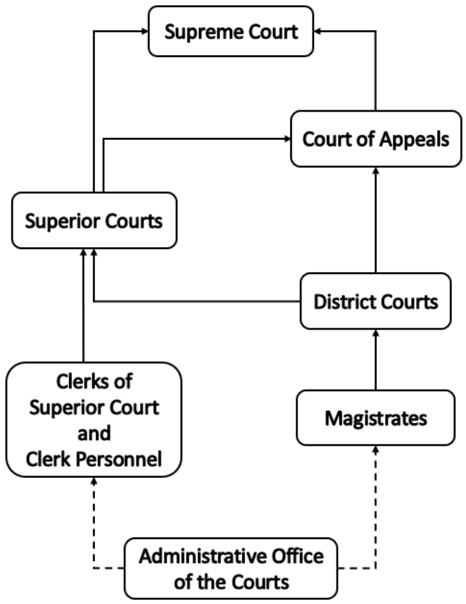
In those judicial districts where there is no public defender's office, as well as cases in which the public defender has a conflict of interest or is overloaded, indigent defendants are entitled to representation by court-appointed private attorneys. It bears noticing that these counsel services are not actually free or charge. They are provided at a subsidized rate and, in the event of a conviction, the defendant has to reimburse the state.

suspended sentence of imprisonment).

[79] Gideon v. Wainwright, 372 U.S. 335 (1963).

[80] N.C. GEN. STAT. §7A-451(a)(1)

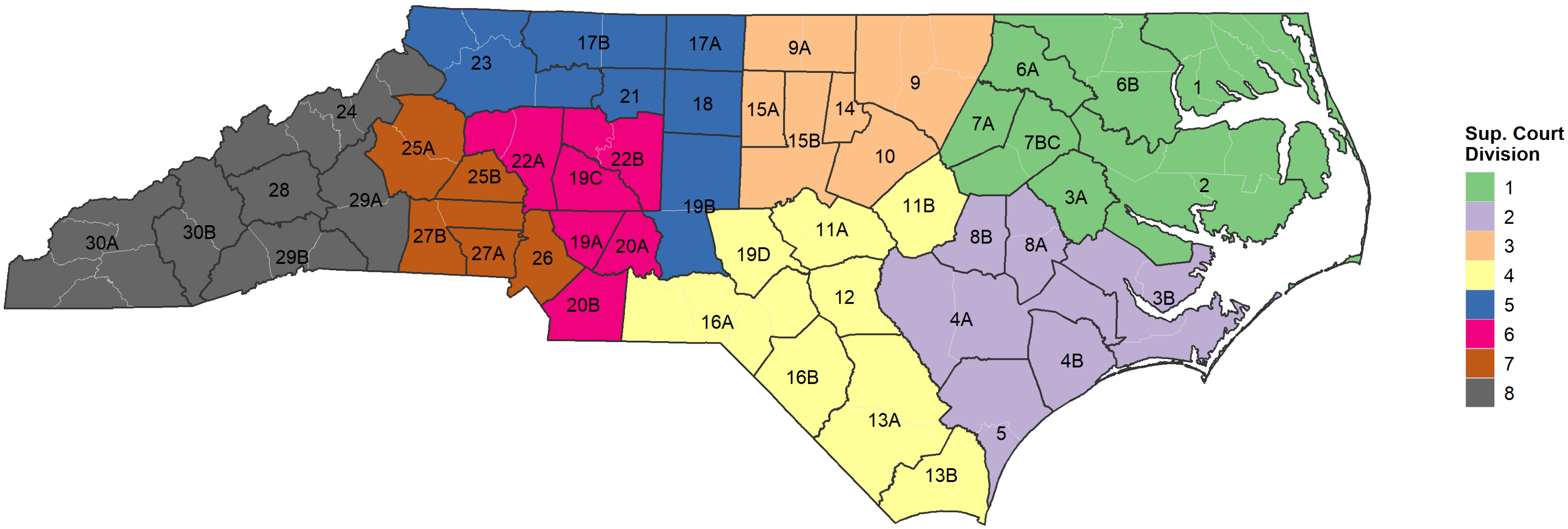
Table C1: North Carolina Judicial System



Judicial Branch Personnel	
Supreme Court justices	7
Court of appeal judges	15
Superior Court judges	107
District Court judges	273
Clerks of superior court	100
District attorneys	43
Public defenders	287

Sources: North Carolina Judicial Branch Statistics–Fiscal Year 2019-20– and North Carolina Office of Indigent Defense Services Workload Assessment, February 2019.

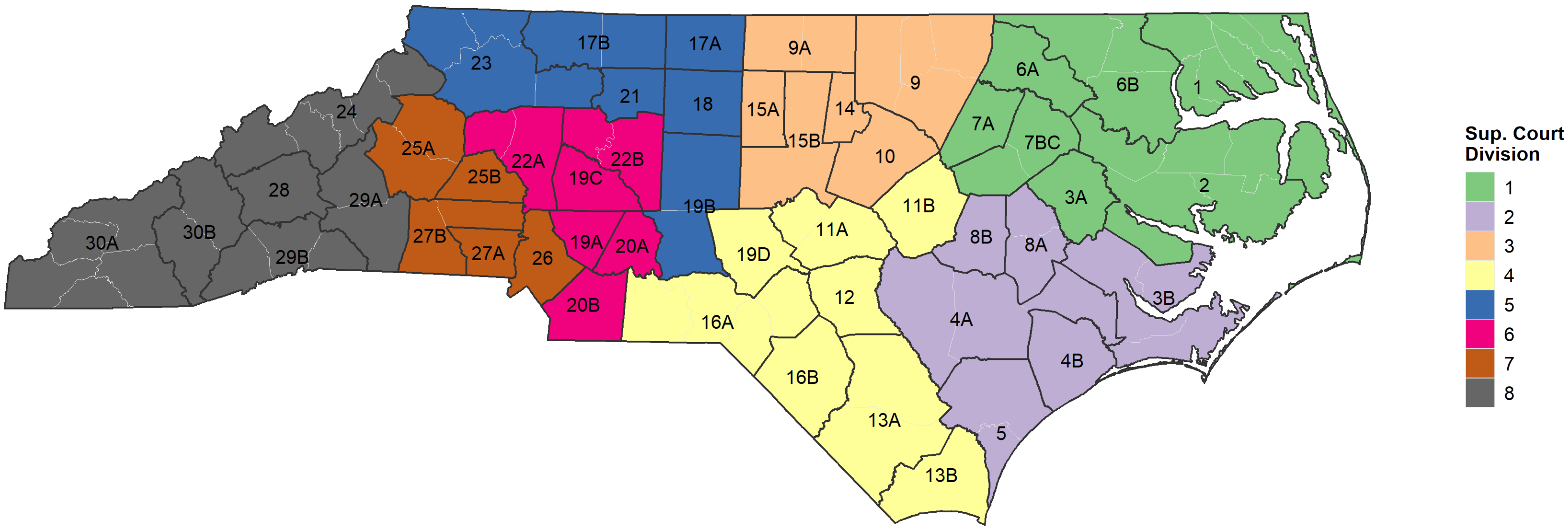
Figure C1: North Carolina Superior Court districts and divisions



Notes: Effective January 1, 2015–January 1, 2019.

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

Figure C2: North Carolina District Court districts



Notes: Effective January 1, 2015–January 1, 2019.

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

Figure C3: Sentencing guidelines for felonies

PRIOR RECORD LEVEL

OFFENSE CLASS	I 0-1 Pt	II 2-5 Pts	III 6-9 Pts	IV 10-13 Pts	V 14-17 Pts	VI 18+ Pts	
A	**Death or Life Without Parole** **Defendant Under 18 at Time of Offense: Life With or Without Parole**						
B1	**A**	**A**	**A**	**A**	**A**	**A**	**DISPOSITION**
	240 - 300	*276 - 345*	*317 -397*	*365 - 456*	*Life Without Parole*	*Life Without Parole*	*Aggravated Range*
	192 - 240	**221 - 276**	**254 - 317**	**292 - 365**	**336 - 420**	**386 - 483**	**PRESUMPTIVE RANGE**
	144 - 192	*166 - 221*	*190 - 254*	*219 - 292*	*252 - 336*	*290 - 386*	*Mitigated Range*
B2	**A**	**A**	**A**	**A**	**A**	**A**	
	157 - 196	*180 - 225*	*207 - 258*	*238 - 297*	*273 - 342*	*314 - 393*	
	125 - 157	**144 - 180**	**165 - 207**	**190 - 238**	**219 - 273**	**251 - 314**	
	94 - 125	*108 - 144*	*124 - 165*	*143 - 190*	*164 - 219*	*189 - 251*	
C	**A**	**A**	**A**	**A**	**A**	**A**	
	73 – 92	*83 - 104*	*96 - 120*	*110 - 138*	*127 - 159*	*146 - 182*	
	58 - 73	**67 - 83**	**77 - 96**	**88 - 110**	**101 - 127**	**117 - 146**	
	44 - 58	*50 - 67*	*58 - 77*	*66 - 88*	*76 - 101*	*87 - 117*	
D	**A**	**A**	**A**	**A**	**A**	**A**	
	64 - 80	*73 - 92*	*84 - 105*	*97 - 121*	*111 - 139*	*128 - 160*	
	51 - 64	**59 - 73**	**67 - 84**	**78 - 97**	**89 - 111**	**103 - 128**	
	38 - 51	*44 - 59*	*51 - 67*	*58 - 78*	*67 - 89*	*77 - 103*	
E	**I/A**	**I/A**	**A**	**A**	**A**	**A**	
	25 - 31	*29 - 36*	*33 - 41*	*38 - 48*	*44 - 55*	*50 - 63*	
	20 - 25	**23 - 29**	**26 - 33**	**30 - 38**	**35 - 44**	**40 - 50**	
	15 - 20	*17 - 23*	*20 - 26*	*23 - 30*	*26 - 35*	*30 - 40*	
F	**I/A**	**I/A**	**I/A**	**A**	**A**	**A**	
	16 - 20	*19 - 23*	*21 - 27*	*25 - 31*	*28 - 36*	*33 - 41*	
	13 - 16	**15 - 19**	**17 - 21**	**20 - 25**	**23 - 28**	**26 - 33**	
	10 - 13	*11 - 15*	*13 - 17*	*15 - 20*	*17 - 23*	*20 - 26*	
G	**I/A**	**I/A**	**I/A**	**I/A**	**A**	**A**	
	13 - 16	*14 - 18*	*17 - 21*	*19 - 24*	*22 - 27*	*25 - 31*	
	10 - 13	**12 - 14**	**13 - 17**	**15 - 19**	**17 - 22**	**20 - 25**	
	8 - 10	*9 - 12*	*10 - 13*	*11 - 15*	*13 - 17*	*15 - 20*	
H	**C/I/A**	**I/A**	**I/A**	**I/A**	**I/A**	**A**	
	6 - 8	*8 - 10*	*10 - 12*	*11 - 14*	*15 - 19*	*20 - 25*	
	5 - 6	**6 - 8**	**8 - 10**	**9 - 11**	**12 - 15**	**16 - 20**	
	4 - 5	*4 - 6*	*6 - 8*	*7 - 9*	*9 - 12*	*12 - 16*	
I	**C**	**C/I**	**I**	**I/A**	**I/A**	**I/A**	
	6 - 8	*6 - 8*	*6 - 8*	*8 - 10*	*9 - 11*	*10 - 12*	
	4 - 6	**4 - 6**	**5 - 6**	**6 - 8**	**7 - 9**	**8 - 10**	
	3 - 4	*3 - 4*	*4 - 5*	*4 - 6*	*5 - 7*	*6 - 8*	

A – Active Punishment **I – Intermediate Punishment** **C – Community Punishment**
Numbers shown are in months and represent the range of <u>minimum</u> sentences

Revised: 09-09-13

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

Figure C4: 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><td>One to Three Prior Convictions</td><td>Four Prior Convictions</td><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

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

Figure C5: Court fees schedule

COURT COSTS AND FEES CHART

The chart below shows court costs in effect as of **December 1, 2019**[1] and applies to all costs assessed or collected on or after that date, except where otherwise noted, and unless subject to the "waiver exception" of G.S. 7A-304(g).

<table>
<tr><th colspan="3">CRIMINAL COURT COSTS
G.S. 7A-304, unless otherwise specified</th><th>AMOUNT</th></tr>
<tr><td colspan="4">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.</td></tr>
<tr><td colspan="4">DISTRICT COURT (including criminal cases before magistrates)</td></tr>
<tr><td rowspan="2">General Court of Justice Fee.
G.S. 7A-304(a)(4).</td><td>General Fund</td><td>146.55</td><td rowspan="2">147.50</td></tr>
<tr><td>State Bar Legal Aid Account (LAA)</td><td>.95[2]</td></tr>
<tr><td colspan="3">Facilities Fee. G.S. 7A-304(a)(2).</td><td>12.00</td></tr>
<tr><td colspan="3">Telecommunications and Data Connectivity Fee. G.S. 7A-304(a)(2a).[3]</td><td>4.00</td></tr>
<tr><td colspan="3">LEO Retirement/Insurance. G.S. 7A-304(a)(3) & (3a).</td><td>7.50</td></tr>
<tr><td colspan="3">LEO Training and Certification Fee. G.S. 7A-304(a)(3b).</td><td>2.00</td></tr>
<tr><td colspan="3">TOTAL</td><td>173.00</td></tr>
<tr><td colspan="3">Chapter 20 Fee. G.S. 7A-304(a)(4a) (for conviction of any Chapter 20 offense).</td><td>+10.00[4]</td></tr>
<tr><td colspan="3">DNA Fee. G.S. 7A-304(a)(9) (criminal offenses, only; does not apply to infractions).</td><td>+2.00</td></tr>
<tr><td colspan="3">Plus $5.00 service fee for each arrest or service of criminal process, including citations and subpoenas. G.S. 7A-304(a)(1).</td><td>+5.00</td></tr>
<tr><td colspan="4">SUPERIOR COURT</td></tr>
<tr><td rowspan="2">General Court of Justice Fee.
G.S. 7A-304(a)(4).</td><td>General Fund</td><td>153.55</td><td rowspan="2">154.50</td></tr>
<tr><td>State Bar Legal Aid Account (LAA)</td><td>.95[5]</td></tr>
<tr><td colspan="3">Facilities Fee. G.S. 7A-304(a)(2).</td><td>30.00</td></tr>
<tr><td colspan="3">Telecommunications and Data Connectivity Fee. G.S. 7A-304(a)(2a).</td><td>4.00</td></tr>
<tr><td colspan="3">LEO Retirement/Insurance. G.S. 7A-304(a)(3) & (3a).</td><td>7.50</td></tr>
<tr><td colspan="3">LEO Training and Certification Fee. G.S. 7A-304(a)(3b).</td><td>2.00</td></tr>
<tr><td colspan="3">TOTAL</td><td>198.00[6]</td></tr>
<tr><td colspan="3">Chapter 20 Fee. G.S. 7A-304(a)(4a) (for conviction of any Chapter 20 offense).</td><td>+10.00</td></tr>
<tr><td colspan="3">DNA Fee. G.S. 7A-304(a)(9) (criminal offenses, only; does not apply to infractions).</td><td>+2.00</td></tr>
<tr><td colspan="3">Plus $5.00 service fee for each arrest or service of criminal process, including citations and subpoenas.</td><td>+5.00</td></tr>
</table>

Figure C6: Court fees schedule (continued)

OTHER CRIMINAL FEES	AMOUNT
Appointment of Counsel Fee for Indigent Defendants. G.S. 7A-455.1.	60.00
Certificate of Relief Fee. G.S. 15A-173.2(h).[7]	50.00
Civil Revocation Fee (impaired driving CVRs, only). G.S. 20-16.5(j).	100.00
Community Service Fee. G.S. 143B-708.	250.00
Continuous Alcohol Monitoring (CAM) Fee (offenses prior to Dec. 1, 2012). G.S. 20-179.[8]	Varies[9]
Continuous Alcohol Monitoring (CAM) Fee (parolees, only). G.S. 15A-1374.[10]	Varies
Criminal Record Check Fee. G.S. 7A-308(a)(17).	25.00
Dispute Resolution Fee. G.S. 7A-38.3D and G.S. 7A-38.7.	60.00 per mediation
Expunction Fee, petitions under G.S. 15A-145, 15A-145.1, 15A-145.2, 15A-145.3, 15A-145.4, and 15A-145.7.	175.00
Expunction Fee, petitions under G.S. 15A-145.5.	175.00
Expunction Fee, petitions under G.S. 15A-146.[11]	175.00
Failure to Appear Fee. G.S. 7A-304(a)(6).	200.00
Failure to Comply Fee. G.S. 7A-304(a)(6).	50.00
House Arrest with Electronic Monitoring (EHA) One-Time Fee. G.S. 15A-1343(c2).	90.00
House Arrest with Electronic Monitoring (EHA) Daily Fee. G.S. 15A-1343(c2).	4.48/day
Impaired Driving Fee. G.S. 7A-304(a)(10). **Note:** Applies only to offenses committed on or after December 1, 2011.	100.00
Improper Equipment Fee. G.S. 7A-304(a)(4b).[12]	50.00
Installment Payments Fee. G.S. 7A-304(f).	20.00
Jail Fees (pre-conviction). G.S. 7A-313.	10.00 per 24 hours or fraction thereof
Jail Fees (split sentence served in local facility). G.S. 7A-313 and G.S. 148-29.	40.00 per day
Limited Driving Privilege Fee – Petitions under G.S. 20-20.1. At petition/Application: If Issued: (G.S. 20-20.2).	CVD Costs +100.00
Limited Driving Privilege Fee – Other than under G.S. 20-20.1. If Issued: (G.S. 20-20.2) Note: If there is no underlying conviction in the county, Charge civil filing fees as explained on form AOC-CV-350.	+100.00
Pretrial Release Service Fee (county). G.S. 7A-304(a)(5).[13]	15.00
Satellite-Based Monitoring Fee for Sex Offenders. G.S. 14-208.45.	90.00
State Crime Lab Fee. G.S. 7A-304(a)(7).	600.00
Local Government Lab Fee. G.S. 7A-304(a)(8).	600.00
Private Hospital Lab Fee. G.S. 7A-304(a)(8a).[14]	600.00
State Lab Analyst Expert Witness Fee. G.S. 7A-304(a)(11).[15]	600.00
Local Lab Analyst Expert Witness Fee. G.S. 7A-304(a)(12).[16]	600.00
Private Hospital Analyst Expert Witness Fee. G.S. 7A-304(a)(13).[17]	600.00
State Crime Lab Digital Forensics Fee. G.S. 7A-304(a)(9a).[18]	600.00
Local Lab Digital Forensics Fee. G.S. 7A-304(a)(9b).[19]	600.00
Seat Belt Violations (adult, front seat) and Motorcycle/Moped Helmet Violations. G.S. 20-135.2A and G.S. 20-140.4. General Court of Justice Fee, G.S. 7A-304(a)(4). Telecommunications and Data Connectivity Fee. G.S. 7A-304(a)(2a). LEO Training and Certification Fee, G.S. 7A-304(a)(3b).	25.50 fine +costs below: 147.50 (Dist.) 154.50 (Sup.) 4.00 2.00
TOTAL	179.00 (Dist.) 186.00 (Sup.)
Seat Belt Violations (adult, rear seat). G.S. 20-135.2A(e).	No Costs 10.00 fine only
Supervision Fee. G.S. 15A-1343, G.S. 15A-1368.4, and G.S. 15A-1374.	40.00 per month
Worthless Check Program Fee. G.S. 7A-308(c).[20]	60.00

Figure C7: Judicial Discretion

Criminal Monetary Obligations 2018

		AMOUNT	PERMISSIBLE RELIEF: Waive	Order Partial	Exempt	Remit	Modify upon Default	CIVIL JUDGMENT: Permissibility	Interest
Basic Costs *(applicable by default)*									
General Court of Justice Fee (District)	*G.S. 7A-304(a)(4)*	$147.50	■			▲	●	● [1]	
General Court of Justice Fee (Superior)	*G.S. 7A-304(a)(4)*	154.50	■			▲	●	●	
Facilities Fee (District)	*G.S. 7A-304(a)(2)*	12	■			▲	●	●	
Facilities Fee (Superior)	*G.S. 7A-304(a)(2)*	30	■			▲	●	●	
Telecom/Data Fee	*G.S. 7A-304(a)(2a)*	4	■			▲	●	●	
LEO Retirement Fee	*G.S. 7A-304(a)(3)–(3a)*	7.50	■			▲	●	●	
LEO Training Fee	*G.S. 7A-304(a)(3b)*	2	■			▲	●	●	
DNA Fee[2]	*G.S. 7A-304(a)(9)*	2	■			▲	●	●	
Contingent Costs *(applicable in certain circumstances)*									
Arrest/Process Fee	*G.S. 7A-304(a)(1)*	5/service	■			▲	●	●	
Chapter 20 Fee	*G.S. 7A-304(a)(4a)*	10	■			▲	●	●	
Improper Equipment Fee	*G.S. 7A-304(a)(4b)*	50	■			▲	●	●	
Impaired Driving Fee[3]	*G.S. 7A-304(a)(10)*	100	■			▲	●	●	
Pretrial Jail Fee[4]	*G.S. 7A-313*	10/day	■			▲	●	●	
Pretrial Release Services Fee[5]	*G.S. 7A-304(a)(5)*	15	■			▲	●	●	
State/Local/Hospital Lab Fee[6]	*G.S. 7A-304(a)(7)–(8a)*	600	R			▲	●	●	
Digital Forensics Lab Fee[7]	*G.S. 7A-304(a)(9a)–(9b)*	600	■			▲	●	●	
Testifying Lab Expert Fee[8]	*G.S. 7A-304(a)(11)–(13)*	600	R			▲	●	●	
Witness Fee	*G.S. 7A-314*	Varies[9]	■			▲	●	●	
Blood Test (Parentage) Fee	*G.S. 8-50.1*	Varies	■			▲	●	●	
Installment Plan Setup Fee[10]	*G.S. 7A-304(f)*	20	■			▲	●	●	
Failure to Appear Fee[11]	*G.S. 7A-304(a)(6)*	200	■			▲	●	●	
Failure to Comply Fee[12]	*G.S. 7A-304(a)(6)*	50	■			▲	●	●	
Discretionary Costs									
Probationary Jail Fee[13]	*G.S. 7A-313*	40/day				▲	●	●	
Non-Cost Fees									
Probation Supervision Fee	*G.S. 15A-1343(c1)*	40/month			●				
EHA Fee	*G.S. 15A-1343(c2)*	90+4.48/day			●				
Community Service Fee[14]	*G.S. 143B-708(c)*	250							
Satellite-Based Monitoring (SBM) Fee	*G.S. 14-208.45*	90			●				
Attorney Fees									
Attorney Fees	*G.S. 7A-455*	IDS Rules						● [15]	●
Attorney Appointment Fee[16]	*G.S. 7A-455.1*	60	Mandatory; shall not be remitted or revoked[17]					● [18]	
Fines									
Fines	*G.S. 15A-1361*	Varies				▲	●	● [19]	●
Restitution									
Crime Victims' Rights Act (CVRA) Restitution[20]		Varies		▲		▲		● [21]	● [22]
Non-CVRA Restitution		Varies		▲		▲			
Non-Victim Restitution		Varies		▲		▲			

Note: Blank areas on the table indicate that no law expressly allows or prohibits the indicated action.

● The court has clear statutory authority to take the indicated action, with no requirement for findings or notice to affected parties.

▲ The court may take the indicated action after satisfying the following requirement:

Order partial restitution. The court must state on the record the reasons for ordering partial restitution. G.S. 15A-1340.36(a).

Remit costs or fines. The court must give 15-day written notice and an opportunity to be heard for directly affected government entities. G.S. 7A-304(a). The AOC's statewide monthly notice might satisfy this requirement.

Remit restitution. The court must give 15-day written notice and an opportunity to be heard for the district attorney, the victim, the victim's estate, or any other recipient of restitution. G.S. 15A-1340.39.

■ The court may take the indicated action after satisfying the following two requirements:
1. The court must enter a written order, supported by findings of fact and conclusions of law, determining that there is just cause for the waiver; and
2. The court must give 15-day written notice and an opportunity to be heard for directly affected government entities. G.S. 7A-304(a). The AOC's statewide monthly notice might satisfy this requirement.

R Indicates that the authority to waive the cost includes the authority to reduce it at the point of imposition.

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