Crime and (Monetary) Punishment*

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Abstract

This paper examines the effects of fines and court fees on re-offense among criminal defendants. There is limited causal evidence on the direct effects of monetary sanctions on crime, due to the fact that fines and fees are typically not levied randomly and are usually bundled with other penalties. I identify the causal effect of monetary sanctions by leveraging the quasi-random assignment of judges and isolate the effects of these fines and fees by studying low-level misdemeanors in North Carolina, where penalties are limited to fines and fees only. I find strong negative (deterrent) effects of fines and fees on recidivism, reducing the likelihood of a financially motivated offense within two years of the crime by 78 percent; effects are driven by defendants living in wealthier neighborhoods (105 percent decrease with respect to the sample mean). Fines and fees do not increase crime, even among the most poor. However, I cannot reject large criminogenic effects for this group and I do find evidence of increased financial distress for them.

Keywords: Monetary sanctions, Legal financial obligations, LFO, Specific deterrence, Recidivism, Judge leniency, Inequality.

JEL Codes: H72, H76, J64, K14, K42.

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1 Introduction

Every year, over 16 million people go to court in the United States.[1] Although relatively few defendants end up doing prison time, the vast majority end up owing money in criminal debt due to fines and court fees.[2] Further, the growth of the criminal justice system in the past few decades and the accompanying rising expenditures have prompted state and local governments–who pay many of the operational costs of the criminal justice system–to turn increasingly towards monetary sanctions as a source of additional revenue.[3] The increased reliance on fines and fees came under scrutiny following the police killing of Michael Brown Jr. in Ferguson, Missouri, as the investigation that followed brought attention to the extent to which the use of monetary penalties disproportionately impacts the poor (United States Department of Justice, 2015). Particularly concerning are claims that fines and fees actually incentivize individuals to commit crime.[4] As the system continues to expand and become more dependent on fines and court fees for financing, it is important to understand what consequences, if any, levying monetary sanctions has on defendants, especially for the most vulnerable, and whether fines and fees may be driving people further into crime. To date, the empirical evidence of the impact of fines and fees is limited.

This paper presents the first evidence of the causal effect of fines and fees on reoffending, and separately isolates the direct effect of fines and fees from other types of penalties.

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

[2] Monetary sanctions or legal financial obligations, comprise fines, court fees, restitution and forfeitures. In my data, only fines and court fees are present, so I refer to monetary sanctions either as such or as fines and fees throughout. According to data from the Survey of Inmates in State and Federal Correctional Facilities, 66% of prison inmates in the United States had court-imposed fines, fees, or restitution (Bureau of Justice Statistics, 2004; Liu et al., 2019). Alabama, Arizona, California, Florida, Georgia, Illinois, Louisiana, Michigan, Missouri, New York, North Carolina, Ohio, Pennsylvania, Texas, and Virginia all impose fees upon conviction (Bannon et al., 2010).

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

[4] This is a possibility long recognized, even by the Supreme Court: "[T]he perverse effect of inducing the [debtor] to use illegal means to acquire funds...." (Bearden v. Georgia, 461 U.S. 660, 1983). Cook (2014) reports that 17% of participants admitted to criminal activity for the purpose of paying economic sanctions. "[F]rankly, I mean, I'm not trying or wanting to do any crime, and I still can't quite commit myself to do prostitution, but I think about it sometimes.., at least that way I could pay some of these damn fines" (Harris et al., 2010). "I know people selling drugs and paying [criminal debt] every month. They like, 'Hey, I'm doing what they told me, 'aint I?" (Human Rights Watch, 2014)

Why would fines and fees (or leniency absolving a defendant of the obligation to pay), affect reoffending of future crimes? First, much of the literature in criminology suggests that fines and fees (and punishment more generally), serve as a deterrent to committing future offenses (Chalfin and McCrary, 2017). Conditional on already committing an offense, levying a fine or fee (as opposed to granting leniency), may deter a person from a future crime, if for instance he/she learns new information about the probability of punishment, responds to the salience of the punishment being imposed, or reciprocates in favor of or opposition to the justice system with the decision to–or not to-reoffend.[5]

Another channel through which fines and fees can affect future crimes is through an income channel. This would be particularly binding for poorer defendants who may resort to robbery, theft, or other financially motivated crimes to generate income to pay off court fees (Harris, 2016; Natapoff, 2018).[6] It is important to note that even fines and fees of low amounts may impact individuals through this income channel.[7] Additionally, unpaid legal financial obligations can trigger additional sanctions; if unpaid these obligations also grow over time as interest and other payment penalties accrue, and they can also have non-justice-related consequences, including the suspension of individuals' driver's licenses.

To tease out the different channels affecting reoffending, I perform a variety of heterogeneity analyses. Both the deterrence and income channels should affect exclusively financially motivated reoffending.[8] Deterrence may occur for any income level, but the income channel may cause low-income defendants to commit more, rather than fewer, financially motivated offenses. I estimate effects for different types of offenses, distinguishing if defendants had previous interactions with the criminal justice system, and studying reoffending behavior over time. I also distinguish the impact of fines and fees across defendants' neighborhood income.

Identifying the causal effects of monetary sanctions alone is difficult for three main

[5]They may also respond to levied (or forgone) fines and fees via the gift-exchange channel, for example, if they recidivate out of spite ("Someone who is subject to punishment he sees as unjust, may be so embittered that he is more likely to offend than if punishment had been lower. Thus, offenses may increase with punishment over a certain range." (Carr-Hill and Stern, 1979))

[6]"[O]ne defendant...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).

[7]Individuals sometimes forego payment of rent or utilities in order to pay their legal financial obligations which may start individuals down a debt spiral eventually making it more appealing to resort to crime. "[To pay off my legal financial obligations] I rob Peter to pay Paul... [Not paying] rent, and car payments, insurance payments..." (Natapoff, 2018).

[8]I follow Tuttle (2019) and consider crimes to be financially motivated if they are property crimes (excluding those that do not entail economic gains, such as arson), drug offenses that involve their sale, manufacture, or distribution, 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.

reasons: first, high-quality data on total fees and fines assessed to defendants is difficult to obtain; second, in current practice, monetary sanctions are usually bundled with other common penalties such as community service, probation, parole, or incarceration (Harris et al., 2011); and third, the levying of fines and fees is correlated with unobservable criminality.

To address the data limitations and to isolate the effects of fines and fees, I use administrative data from North Carolina between 2014 and 2019, including detailed information regarding the universe of misdemeanors and felonies, fines, and court fees. To avoid confounding multiple treatments (e.g., fines and fees vs. other penalties), I focus my analysis on defendants who are (and can only be) levied fines and fees. In North Carolina, a reform passed in 2014 that effectively limited criminal sanctions for lower-level defendants without much prior involvement with the criminal justice system to fines and fees (Current Operations and Capital Improvements Appropriations Act of 2013, §18B.13, 2013 N.C. Sess. Laws 995, 1303–04).

To recover causal effects and avoid selection bias I need exogenous variation in the probability to receive a monetary sanction. I exploit the fact that in North Carolina's lower courts defendants are randomly assigned to judges that differ in their propensity to levy fines and fees. Following a growing literature (Kling, 2006; Aizer and Doyle Jr, 2015; Dobbie et al., 2018), I use a "judge fixed effects design" to recover a local average treatment effect (LATE) for individuals at the margin of being levied a fine or court fee.[9]

I first measure judges' propensity for levying fines or fees using a leave-out, residualized measure, based on all other cases that a judge has ruled on that do not involve a given defendant. This residualized measure considers leave-out measures of all covariates' estimates, thus correcting for the bias of propensity measure when the number of covariates is large.[10] This measure is highly predictive of judge decisions regarding fines or fees, but uncorrelated with case and defendant characteristics. Going from the most lenient to the least lenient judge increases a defendant's likelihood of being levied a fine or a fee by 15 percentage points.

I find that defendants receiving a fine or a fee are 6.9 percentage points less likely to commit a subsequent financially motivated crime, within two years, than defendants shown leniency. This is a 78 percent change with respect to the sample mean of 8.8 percent ($p < 0.05$). I find no effects for non-financially motivated offenses; the point estimate is small and statistically insignificant (0.010, SE=0.044). I also find evidence of a deterrence channel. Fines and fees reduce financially motivated reoffending by 9.1 percentage points

[9]Other examples of papers exploiting this research design include Mueller-Smith, 2015 and Bhuller et al., 2020, studying the effects of incarceration; Norris et al., 2021 estimating the impact of parental incarceration; and Agan et al., 2021 looking at the effects of misdemeanor prosecution.

[10]This is the UJIVE estimator of (Kolesár, 2013). I also explore additional estimation strategies, 2SLS using all judge dummies, LIML, JIVE, and Belloni et al. (2014)'s IV Lasso in Appendix B.

for individuals with no prior involvement with the criminal justice system (111%; $p < 0.05$), while I see no effects for defendants with a prior record.

The effect of fines and fees is driven by defendants living in wealthier neighborhoods. Defendants living in census tracts in the third and fourth quartiles of median household income are 13.7 and 12.1 percentage points less likely to engage in financially motivated crime 2 years following their disposition. This corresponds to 169 ($p < 0.05$) and 161 ($p < 0.1$) percent decreases with respect to their respective sample means. I find no effects for defendants living in the first and second quartiles.

To study the effects for poorer defendants income quartiles are too coarse (the first quartile is $33,000). For this reason I also split the sample according to the federal poverty line in North Carolina for each year, which in 2018 was $25,465 for a family of four with two children, for example. Fines and fees reduce the likelihood of reoffending by 8.7 percentage points for defendants living in census tracts with median household incomes above the federal poverty line. This is a 105 percent decrease with respect to the sample mean ($p < 0.01$). I cannot reject a null effect of fines and fees for defendants living in census tracts with median household incomes below the poverty line. However, this estimate is noisy and the confidence interval is large.[11]

Even though I find no evidence of fines and fees driving financially motivated recidivism, they do seem to be causing financial distress. I find that monetary sanctions increase reoffending in crimes associated with poverty, such as panhandling or sleeping in public places, by 17.4 percentage points (295%; $p < 0.1$).

My 2SLS estimates are larger in absolute value than my OLS estimates. This difference could be due to selection bias in the OLS estimates and/or the composition of the complier population. To explore this possibility, it is useful to characterize compliers by their observable characteristics. I follow a procedure similar to that developed by Bhuller et al. (2020). Reweighted OLS estimates suggest that the differences between the UJIVE and OLS estimates cannot be accounted for by heterogeneity in effects, at least due to observables.

I also run a number of additional checks to support the validity of my instrumental variable design and my heterogeneity analyses. I demonstrate that the first stage is positive and significant at conventional thresholds across all covariate subgroups, in line with the assumption of average monotonicity required to interpret the estimates as LATEs (Frandsen et al., 2019).

This paper contributes to several areas of research. First, it contributes to the literature

[11]The 90 percent confidence interval goes from -40.4 percentage points to 47.8 percentage points, which implies that fines and fees may have decreased recidivism by as much as -293 percent, or increased it by up to 346 percent. Unfortunately, I do not have the statistical power to produce more precise estimates.

on specific deterrence, i.e., on how the experience of punishment affects reoffending. This literature has focused mostly on incarceration, finding conflicting results: some find reductions in future criminality (Kuziemko, 2013; Bhuller et al., 2020; Rose and Shem-Tov, 2021), while others find increases (Bayer et al., 2009; Stevenson, 2017; Mueller-Smith, 2015). Observational studies focusing on the experience of monetary sanctions offer mixed evidence as well, finding that higher fines are associated with both reductions (Yu, 1994) and increases (Mann et al., 1991) of recidivism for drunk drivers in New York and Ontario. Moffatt and Poynton (2007) reports finding no relationship between fine amount and the likelihood of a defendant reoffending, for a sample of driving offenders in New South Wales. Studies focusing not just on driving-related offenses find either a positive (Piquero and Jennings, 2017) or no association between monetary sanctions on reoffending (Gordon and Glaser, 1991).[12]

I provide the first evidence of the causal effect of monetary sanctions on reoffending–a topic of major policy interest and severely understudied.[13]

There is an older literature in Criminology that emerged during the penal expansion of the 1980s and 1990s assessing the appropriateness of fines as alternatives to incarceration. Observational studies at the time showed that fines performed at least as good as incarceration at preventing reoffending, and considerably better for certain types of offenses Albrecht and Johnson, 1980; Gordon and Glaser, 1991.[14] There were two main arguments against fines. First, there was a general concern that fines were not punitive enough to be deterrent, and that they may be seen more as a "price" of conduct (Gneezy and Rustichini, 2000). By identifying the presence of a specific deterrence channel driven by information updating, I provide evidence of actual deterrent effects of fines. Furthermore, I identify specifically which types of offenses are susceptible of being deterred by monetary sanctions: financially-motivated ones.

Second, besides the worry of fines not being punitive enough, there was a concern that they may be disparately punitive towards poorer individuals. This motivated a series of papers studying "day-fines"–fines linked to the offender's ability to pay–, which were already at the time widely used in countries in Western Europe (Hillsman et al., 1984; Hillsman, 1988, 1990; Hillsman and Greene, 1988; Turner and Petersilia, 1996). There was also a worry for

[12]It is important to note that, besides suffering from selection bias, these studies estimate effects of monetary sanctions for samples of probationers, where nonpayment may trigger a probation revocation.

[13]There is sizable literature on the effects of monetary punishment–from regulatory violations– on firms' behavior (see Alm and Shimshack, 2014 for an overview of the literature). In a similar spirit as this paper, Earnhart and Segerson, 2012 find that the effectiveness of increased enforcement–regarding firms' environmental performance–depends on firms' financial status. Increased enforcement can actually lead to worse environmental performance if firms are financially constrained. Also, in a video rental establishment, Haselhuhn et al. (2012) finds that individuals are less likely to return rentals late after paying a fine.

[14]It was recognized, though, that this could have been more a function of the detrimental effects of incarceration than of the deterrent effects of fines.

fines driving people to commit more crimes in order to pay them Nagin (2008). This mirrors more current Law research arguing for graduated sanctions (Colgan, 2014, 2017, 2018), as well as concerns in the Sociology literature of the ways in which monetary sanctions impact disproportionately the poor and how they may drive them to engage in crime (Beckett et al., 2008; Harris et al., 2010; Harris, 2016). To the extent that defendants' neighborhood income is a good proxy for their personal income, I provide evidence of the differential impacts of monetary sanctions across income levels.

Finally, I also contribute new evidence highlighting the relationship between financial need and criminal behavior. There is a long literature in economics and criminology that argues the role of financial motivations behind criminal behavior. Becker (1968) already points out the trade-off between participation in the legal and the illegal labor markets. Gould et al. (2002) find that unemployment and wages for low-skilled men are significantly related to crime within a county. Raphael (2011) studies how greater financial assistance following release reduces recidivism rates. Carr and Packham (2019) find that theft in grocery stores in Chicago fell dramatically after Illinois implemented a staggered disbursement schedule for the Supplemental Nutrition Assistance Program (SNAP, formerly named food stamps). Tuttle (2019) finds that the ban for many offenders from receiving SNAP that took place in 1996 increases recidivism among drug traffickers. This increase is driven by financially motivated crimes, suggesting that ex-convicts return to crime to make up for the lost transfer income.

The remainder of the paper is structured as follows. Section 2 provides a brief overview of North Carolina and how monetary sanctions and judge assignment operate in this context. Section 3 describes my data and provides some summary statistics. Section 4 describes my identification approach. Section 5 presents the results and studies heterogeneity and mechanisms. Section 6 presents some robustness checks and Section 7 concludes. An Appendix provides additional results and detailed information on administrative information and alternative outcomes used in the analysis.

2 Identifying Effects of Fines and Fees in North Carolina

There are three main challenges to investigating the causal effects of monetary sanctions. First, high-quality data on total fees and fines assessed are difficult to obtain. Second, monetary sanctions are typically correlated to unobservables related to criminality. And third, monetary sanctions are typically bundled with other penalties.

In this section, I outline how the setting and data from North Carolina allow me to address each of these concerns. The administrative data from North Carolina provides detailed information regarding fines, fees, and re-offending. Quasi-random assignment of district court judges allows me to identify causal effects by leveraging a judge leniency design. Finally, reforms enacted 2014 create a subset of offenses that are liable only to monetary sanctions, allowing me to study their effect in isolation.

I first discuss the North Carolina criminal justice system and particular context important for my study, I then discuss how fines and fees are levied in the state. Lastly, I discuss the 2014 reform that limited penalties of low-level misdemeanors to fines and fees alone. I describe the Data and Sample in Section 3, below.

2.1 The North Carolina Criminal Justice System

District Courts and Judges

I use data on criminal cases prosecuted in North Carolina's District Courts.[15] District Courts 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).[16] In 2014, there were 41 District Court divisions for administrative purposes.[17] See Figures C1 and C2 in the Appendix.

Criminal trials in District Courts are "bench trials" in which a judge decides the verdict, rather than relying on the decision of a jury.[18] The North Carolina court system has used a structured sentencing scheme since 1994 that classifies felony charges into ten classes (from most to least severe: A, B1, B2, C, D, E, F, G, H, and I), misdemeanor charges into three classes (from most to least severe: A1, 1, 2, and 3), and defendants facing

[15]The court system in North Carolina consists of two trial court divisions: the Superior Court division and the District Court division. There is also an appellate division, which comprises the Supreme Court and the Court of Appeals. See Appendix C. Superior Courts are the highest of the general trial courts and, broadly speaking, have 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. Superior Court divisions are subdivided into districts (5 divisions and 48 districts in of 2019).

[16]An infraction is not a criminal offense and may be punished only by a fine. I study both in this paper.

[17]Divisions serve both electoral and administrative purposes. 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.

[18]Because the Sixth Amendment to the United States Constitution guarantees a person charged with a crime the right to be tried by 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 by jury (trial "de novo"). 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. The plea is treated as if it had been tried in superior court and any appeal goes to the appellate division. Any defendant found guilty of an infraction in district court 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 of trial by jury does not apply. These type of appeals are not included in my analyses. All Superior Court cases are decided by a jury of 12.

felony/misdemeanor) charges into six/three different criminal history levels I-VI/I-III, where higher levels indicate more severity).[19] The law stipulates a sentence range 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 must decide whether the sentence should be active or suspended.[20] The current punishment charts for both misdemeanors and felonies committed are depicted in Figures C3 and C4. In District court, judges are responsible for sentencing.[21] In each District Court district the chief district court judge creates the schedule of court sessions and assigns judges to preside over those sessions. Defendants calendared for a given session are then randomly assigned to one of the judges scheduled for that day (Abrams and Fackler, 2018).

Monetary Sanctions

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 or court fees as part of the sentence.[22] In North Carolina, the proceedings of all fines go towards maintaining public schools while court fees finance the court system.[23] Common to all dispositions, are general court fees, which amount to around \$150, facility fees of \$12 and \$30 for District and Superior Courts, respectively, and phones fees of \$4. 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.[24] See Figures C5 and C6 for a more comprehensive list of cost items and amounts.

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

[20] If a 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.

[21] Magistrates also play role in the disposition of criminal cases. Magistrates 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. Magistrates are generally the first judicial officials involved in criminal cases, usually issuing the criminal process (e.g., a warrant for arrest) that begins most criminal cases and also generally sets the initial conditions for pretrial release (bail). 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.

[22] N.C. GEN. STAT. §§15A-1361, 15A-1340.17 (felonies), 15A-1340.23 (misdemeanors), and 7A-304

[23] N.C. Const. Art. IX, §7

[24] There are also fees for the provision of indigent defense (at least \$60), house arrest monitoring (one-time \$90 and \$4.37 daily), and 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. The conviction of any motor vehicle offense carries an additional fee of \$10.

Judges have complete discretion regarding the sentencing, whether to impose, and the amount of, fines, court fees, and restitution.[25]

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.[26] Some courts compare the defendant's income to the Federal Poverty Guidelines 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 (Markham, 2018).[27]

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 is referred to as a "failure to comply" (FTC). In this event an additional fee of $50[28] 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.[29]

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.[30] The burden

[25] N.C. GEN. STAT. §§15A-1362 and 15A-1363 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). Judicial discretion regards court fees waivers, as all court fees are capped at the amounts outlined in *Id.* §7A-304 *Id.* §§7A-304(a) and 15A-1363—see also State v. Patterson, 223 N.C. App. 280, 2012. *Id.* §§15A-1340.34(a) and 15A-1340.38

[26] *Id.* §§15A-1340.36(a) and 15A-1362.

[27] 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.

[28] N.C. GEN. STAT. §7A-304(a)(6)

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

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

of proof regarding inability to pay lies in the defendant though.[31] 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[32]— and, because the defendant is at risk of being imprisoned as a result of these hearings, he or she must be afforded counsel.[33] If it is the case that nonpayment was not willful, the court may grant additional time for payment, reduce the owed amount, or revoke the monetary obligation altogether.[34]

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.[35]

2.2 2013 North Carolina Appropriations Act

Throughout most of the United States, monetary sanctions are usually levied in addition to other penalties such as community service, probation, parole, or incarceration. This creates an identification challenge, in the sense that agents experience both fines and fees, and other punishments simultaneously. To isolate the effects of fines and fees, I take advantage of the 2013 Appropriations Act, a reform in North Carolina that in December 2013 removed further punishments–other than fines and fees–for the lowest-level misdemeanors.

In the United States, counsel for criminal defendants may be provided either by a privately retained attorney or by what is known as indigent defense representation, consisting of legal representation free of charge. In North Carolina, depending on the jurisdiction, indigent defense is provided either by public defenders—full-time state employees— or by private attorneys who choose to participate in an assigned counsel system.[36])

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

[32]N.C. GEN. STAT. §15A-1364

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

[34]It is important to note 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.

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

[36]More specifically, for misdemeanors, a defendant has a Sixth Amendment right to counsel only if an active or suspended sentence of imprisonment is imposed. 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). North

To save money on indigent defense expenses, North Carolina made major changes to its criminal justice system as part of the 2013 Appropriations Act.[37]

Under this Act, North Carolina's General Assembly enacted a new punishment scheme for the least serious class of misdemeanors (Class 3), limiting the punishment to a fine for most defendants. The change applied to offenses committed on or after December 1, 2013. In addition to changing the punishment for Class 3 misdemeanors, the reform reclassified some higher-level misdemeanors (Class 1 and 2) as Class 3 misdemeanors, as well as some Class 3 misdemeanors as infractions.[38]

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.

3 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.

3.1 Data

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

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" (N.C. GEN. STAT. §7A-451(a)(1)

[37] Current Operations and Capital Improvements Appropriations Act of 2013, §18B.13, 2013 N.C. Sess. Laws 995, 1303–04. The Joint Conference Committee Report on the Continuation, Expansion, and Capital Budgets, (2013), states that Indigent Defense Services' budget would be reduced by $2,000,000 annually.

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

their undergraduate degree, which I obtained from the website Avvo.com.[39]

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

Finally, 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.[40]

3.2 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.[41] This means that non-capital trials may be held *in absentia*, when the defendant has waived the right to be present (Smith, 2013).[42] These trials *in*

[39] This is an online marketplace for legal services that provides lawyer referrals and access to a database of legal information consisting of previously answered questions, lawyers' offices location, abridged resumes, client reviews, disciplinary actions, and peer endorsements.

[40] Estimates considering monetary sanctions aggregated to the case level are available upon request. N.C. GEN. STAT. §7A-148

[41] 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).

[42] However, there can be no sentencing in absentia when corporal punishment is imposed, i.e.,

absentia present a problem for my identification as they are usually handled by magistrates, 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.[43]. I restrict my sample to those cases in the "non-waivable" list.

I 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.[44] Finally, I 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 25,242 cases (out of 4,435,571 total cases filed in North Carolina during the time period, and 3,395,066 Class 3 misdemeanors), overseen by 104 judges (out of ~ 270). See Tables A1 and **??** 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.

3.3 Descriptive statistics

Table 1 reports descriptive statistics for my analysis sample. The main data set includes 10,373 cases with final dates of disposition between 2013 and 2019. Details on this population's demographic characteristics are provided in Panel A. The sample is predominantly black (57%) and male (73%), overrepresented relative to North Carolina's population (22% and 37%, respectively). The sample is quite young as well, with 67% of defendants below the age of 35, and 42% 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 $51,000, and where 20% of households earn below the poverty line.

Cases are all Class 3 misdemeanors. The majority of which are drug possession offenses; the rest being property and other, such as liquor laws violations (open container violations, being intoxicated and disruptive in public, etc.). There are no violent charges. 70% of these cases result in a conviction, with almost all of these achieved via pleas.

imprisonment. Therefore, appearance in court is mandatory for all felonies.

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

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

46% of defendants face some monetary sanction. These stem either from fines (27%) or courts fees (45%), with no restitution being levied on any defendant in the sample.

Monetary sanctions average \$243 for those that receive any, with the breakdown between fines and fees being \$48 and \$224, respectively.

As we can see in Table A2, 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 fewer 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 offense. Cases also tend to move faster; they are more likely to be disposed of via guilty pleas as well. Defendants who are levied monetary sanctions are also less likely to have public representation and more likely to represent themselves. Finally, defendants levied monetary sanctions are also slightly less likely to engage in any criminal activity within two years.

4 Identification Approach

Overall Approach

I want to estimate the effect of monetary sanctions on future criminal involvement–proxied by arrests.[45] 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)

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

are likely biased, due to correlation between them having been levied monetary sanctions and unobserved defendant characteristics that are correlated with the outcome. The sign of this correlation, and therefore the bias stemming from it, is unclear. For example, judges may be more likely to fine defendants that display less regret who, in turn, may be more likely to reoffend. At the same time, judges could be inclined to fine 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 whether 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.

However, it has been argued 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.[46]

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. Essentially, 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. 30% percent of judge-by-year cells have more than 50 cases. After dropping these cases my sample includes 104 district judges.[47]

Figure 1 reports the distribution of the residualized judge leniency measure for monetary sanctions. My sample comprises 104 judges. The median number of cases overseen by a

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

[47] As mentioned above, in any given year there are around 270 district judges in North Carolina (see Table C1), and these are elected through–partisan–elections that take place every 2 years.

judge is 79 cases and the average is 100 cases. After residualizing out the set of district-by-time effects, the judge measure ranges from -0.708 to 0.749, with a standard deviation of 0.108. Moving from the first to the ninety-ninth percentile of judge leniency increases the likelihood of receiving a fine or a fee by 64 percentage points, a 139% change from the mean likelihood of 46%.

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 of the– court fees. Figure **??** 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 I use this variation in judge leniency to instrument for whether a defendant gets levied a monetary sanction. This allows me 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. 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).

4.1 Instrument Validity

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 sanction 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 10 percentage point increase in the residualized judge's fining rate in other cases is associated with an approximately 6.8 percentage points 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 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 to test an IV relative bias of no more than 10% with a significance level of 5.[48]

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 baseline mean of 46 percent. Defendants with a prior offense are

[48]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).

12 percentage points more likely 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 other types of offenses, 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.

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, I cannot test this directly. A testable implication of the monotonicity assumption, though, is that first-stage estimates should be positive for any subsample. Tables A3 and A4 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 A5 shows that I fail to reject this null for various numbers of knots in the spline function. I implement this test choosing various weights, but the focus should be on larger weights since with a large number of judges, the slope component of the test has little power.[49]

[49] Frandsen et al. (2019)'s test hinges on two observations: first, average outcomes conditional on judge assignment should fit a continuous function of judge propensities; second, the slope of that continuous function should be bounded in magnitude by the width of the outcome variable's support. Frandsen et al. (2019) combine the fit and slope components via a weighted Bonferroni procedure to produce a single joint test.

4.2 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 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).[50] See online Appendix B for a more detailed description of these calculations.

In Table A6 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."

Individual compliers cannot be identified, but it is possible to describe their observable characteristics following Frandsen et al. (2019). I do this in Table A7. 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.[51] Compliers are not systematically different from the average defendant by race or gender, however.

5 Results

In this section, I present my main results on the effects of fines and fees on the likelihood of defendants reoffending on financially and non-financially motivated offenses. I then report the heterogeneity of these results with respect to income, as all the channels through which fines and fees operate may interact with income. Finally, I distinguish different types of financially motivated crimes in order to provide some clarity in regard to which channels dominate.

[50] Frandsen et al. (2019) generalize Abadie (2003) and show that the 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.

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

5.1 Main Effects

Table 4 presents OLS and UJIVE estimates of the impacts of fines and fees on future criminal involvement that is financially (Panel A) and non-financially (Panel B) motivated. Columns (1)–(3) report OLS estimates. Column (1) begins by reporting results only with district-by-time fixed effects. Column (2) adds baseline case and defendant controls. Column (3) reports OLS estimates under the same specification as Column (2), but reweighted so that the proportion of compliers matches the share of the estimation sample. Finally, Columns (4) and (5) report UJIVE estimates where I instrument for whether the defendant was levied any fines or fees using the leave-out measure of judge leniency described in Section 4, with (Column 4) and without (Column 5) baseline controls. All standard errors are clustered at the individual- and judge-level.

Panel A results show that for all specifications, fines and fees are negatively associated with financially motivated reoffending. The magnitudes of the OLS estimates are moderately sensitive to the addition of baseline case and defendant controls: in OLS results with only district-by-time fixed effects I find that a defendant who is levied a fine or fee is 4.3 percentage points less likely to reoffend, a 48.9 percent decrease from the sample mean (Column 1). When I add case and defendant controls, the estimate drops to 3.3 percentage points (Column 2).

Estimates in Column (2) could still be biased if judges are choosing on average to levy fines or fees on defendants who have lower risks of reoffending, despite controlling for a rich set of district-by-time fixed effects and case and defendant controls as well. It is for this reason that my identification strategy involves using the quasi-randomly assigned judges as instruments for whether defendants get levied any fines or fees. Recall from Section 4, however, that in overidentified models such as that of Equation (2) where you instrument one endogenous variable with many instruments (hundreds of judge dummies in this case), first-stage overfitting will generate small-sample bias. Arguably the best way to address this bias, the JIVE estimator, is biased as well if there are many covariates in the second stage, as is my case with the large number of district-by-time fixed effects. It is for this reason that my preferred specification in Column (5) uses the UJIVE estimator proposed by Kolesár (2013). Results using this specification show that marginal defendants experiencing fines or fees are 6.9 percentage points less likely to engage in any criminal activity within two years, a 78.4 percent decrease from the sample mean (138 percent decrease relative to the mean for compliers). The direction of the selection bias then was positive, judges on average levy fines and fees on defendants more likely to recidivate.

Panel B reports estimates for the effects of monetary sanctions on non-financially motivated reoffending. OLS results in Panel B paint the opposite picture as Panel A: fines and fees seem to drive non-financially motivated reoffending. Estimates from Column (1) indicate that defendants are 2.3 percentage points more likely to reoffend when levied fines or fees. OLS estimates are again somewhat sensitive to the addition of baseline case and defendant controls, their magnitude is increased 0.5 percentage points when moving from Column (1) to Column (2). Taking UJIVE estimates from Column (5) as my preferred specification suggests that after controlling for selection bias there is no relationship between fines and fees and non-financially motivated recidivism.

It is important to remember that IV estimates an average treatment effect for the complier population and that therefore, besides selection bias, another possible explanation for differences between IV and OLS estimates is effect heterogeneity, in that the average causal effect for compliers may differ to the mean impact for the whole sample. In order to explore this possibility, it is useful to characterize compliers by their observable characteristics. I follow a procedure similar to that developed by Bhuller et al. (2020). Specifically, I begin by splitting the sample into 10 mutually exclusive and collectively exhaustive subgroups based on the predicted probability of being levied any fines or fees. This predicted probability is a composite index of all the observable characteristic. I then estimate the first-stage equation (2) separately for each subgroup, calculating the proportion of compliers in each. 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. Reweighted OLS estimates are presented in Column (3) of Table 4. Results suggest that the differences between the UJIVE and OLS estimates cannot be accounted for by heterogeneity in effects, at least due to observables.

5.2 Heterogeneity and Mechanisms

The results of the previous section point to individuals that, upon receiving a fine and/or having to pay for court fees, revise upwards their expectations of either the likelihood or the amount of future monetary punishment. Higher expected costs then deter them from reoffending in financially motivated crimes. It is also possible that defendants' priors regarding monetary sanctions are accurate, but that their experience makes them more salient. It is possible as well that a "spite" channel is also in effect, but that gets overshadowed by these previous two. Finally, these are average effects and could be masking important heterogeneity across income, as the income channel is associated with reoffending only for those poorest defendants.

Types of Offenses and Timing

Results in Table 4 are consistent with a deterrence story, where defendants have inaccurate information regarding monetary sanctions–either about their likelihood or their amounts. Deterrence stems from this information being revised upwards. And this deterrence is only for financially motivated offenses, as that is the relevant margin of offenses.

Through the gift-exchange channel I would expect increased recidivism due to fines or fees for all types of offenses. In Table 4 the estimate for financially motivated offenses is significantly negative ($p < 0.05$), while the estimate for non-financially motivated offenses is small and nonsignificant (0.010, SE = 0.044). Additionally, in Figure 2 I see no effects of fines and fees for any of the broad crime categories, except for property offenses where they have a negative effect (-0.038; $p < 0.1$). This is still consistent with the deterrence channel, as most property offenses are for economic gain.

Finally, my main results use a two-year follow-up period for all defendants when considering the effects of fines and fees on reoffending. Figure 3 shows the evolution over time of these effects. The figure presents UJIVE estimates of Equation 1 similar to Column (5) of Table 4 but for one-month increments in the follow-up period. These results are inconsistent with a salience argument. There is a steady drop in the likelihood of a new financially motivated criminal involvement within the first year which then remains steady throughout. If salience were the driving mechanism we would see, if anything, the opposite temporal pattern.

Prior Involvement with the Criminal Justice System

One way to investigate if it is a deterrence channel–inaccurate information regarding monetary sanctions–what is driving the negative effects I report in Table 4 is to study the effects of monetary sanctions separately for defendants with and without experience in the criminal justice system, as individuals with experience probably have better information regarding monetary sanctions, having experienced them before, and should not respond to monetary sanctions due to a deterrence channel.

In Table A12 I report estimates of the effects of monetary sanctions separately for samples of individuals with and without prior experience in the criminal justice system. Defendants with no prior knowledge of the criminal justice system are the ones that are driving the results. Upon experiencing a fine or having to pay court fees these defendants are 9.1 percentage points less likely to engage in financially motivated reoffending, a 111 percent decrease from the mean ($p < 0.05$). For defendants without any prior experience with the criminal justice system the effects are not significant (-0.086, SE = 0.080).

Income

Results so far present evidence for the effects of monetary sanctions on reoffending working through defendants' ignorance of the likelihood and/or amounts of monetary sanctions. The fact that those effects are negative is, a priori, particular to this sample, as defendants may underestimate, overestimate, or estimate just right elsewhere. In a sense, this is to say that the presence of this negative effects is more a statement of the degree with which information regarding criminal penalties is publicly known than on the effects of the penalties themselves.

To assess whether an income channel is driving poorer defendants toward crime I estimate Equation 1 separately within subsamples defined by quartiles of defendants' proxied income.[52] I find strong negative effects for defendants living in wealthier neighborhoods (see Figure 4).[53] Defendants living in census tracts in the third and fourth quartiles of median household income are 13.7 and 12.1 percentage points less likely to engage in financially motivated crime 2 years following their disposition. This corresponds to 169 ($p < 0.05$) and 161 ($p < 0.1$) percent decreases with respect to their respective sample means. I find no effects for defendants living in the first and second quartiles (-0.001, SE=0.94; -0.019, SE=0.074).

Because the first quartile is relatively high, \$33,000, in Table A9 I also split the sample by whether defendants' census tract median household income lies above or below the federal poverty line for North Carolina.[54] I find that fines and fees reduce the likelihood of reoffending by 8.7 percentage points for defendants living in census tracts with median household incomes above the federal poverty line. This is a 105 percent decrease with respect to the sample mean ($p < 0.01$). I cannot reject a null effect of fines and fees for defendants living in census tracts with median household incomes below the poverty line. However, this estimate is noisy and the confidence interval is large. The 90 percent confidence interval goes from -40.4 percentage points to 47.8 percentage points, compared to a sample mean of 0.138.

It is important to note that this heterogeneity across income is consistent with either a deterrence or an income story, as it would be possible for prior beliefs to depend on income, and for poorer defendants to have higher expectations of monetary sanctions.

Poverty crimes

So far, since I cannot rule out differential deterrence across income, I cannot dismiss an income channel criminalizing poorer defendants. One way to gain some insight into this

[52] One limitation of the data is that it does not include any information regarding defendants' income. I deal with this by matching defendants' addresses to census tracts and then proxying their income with American Community Survey estimates of the median household income within the census tract where they reside.

[53] Table A8 reports these results as well.

[54] This was \$25,465 for a family of four with two children in 2018, for example.

channel is to study heterogeneity in regard to different types of financially motivated offenses.

In the US there are certain behaviors that are criminalized that would not fit the usual standard of crimes. For example, what are dubbed "Vagrancy" crimes according to the FBI Uniform Crime Reports, such as panhandling or sleeping in public places, or as driving with a license revoked due to the nonpayment of fines or court fees, specifically for North Carolina.[55] It is important to distinguish if these are the types of offenses driving the income heterogeneity we see in Figure 4, as this type of offenses, if positively encouraged due to fines or court fees, most likely signal financial distress. For this reason I will refer to this type of offenses as "poverty" offenses.

Results from Figure 5 show that fines and fees do indeed drive up these poverty offenses among poorer defendants.[56] For defendants living in census tracts with median household incomes below the poverty line I find that fines and fees increase the likelihood of reoffending in these "poverty" offenses by 17.4 percentage points. This is a 295 percent increase with respect to the sample mean ($p < 0.1$). For wealthier defendants the effect is small and nonsignificant (-0.000, SE=0.025).

6 Robustness Checks

In this section I explore possible threats to both the causal and conceptual interpretations of my results. First, I check whether the heterogeneity by income described before is driven by treatment effect heterogeneity along margins other than income, but that covary with it. This could happen, for instance, if it is private representation what is driving the effects, and more defendants are privately represented at higher income quartiles. Second, I check if it is treatment "intensity" what varies with income, in the sense that judges levy higher fees and court fees in districts that comprise census tracts with higher median incomes. Third, I also check the robustness of my results to alternative model specifications, since the baseline outcome means are very low and a linear probability model may be misspecified in such situations. Fourth, I check for violations to the exclusion restriction, specifically if I am confounding fines and fees with convictions, and study also alternatives to the UJIVE to identify the effects of fees and fines. Finally, I assess the external validity of these results using a natural experiment that took place in mid 2018.

[55] This is the most common type of reoffending in my sample. See Figure A2.

[56] These results are also reported in Tables A9 and A11.

6.1 Complier Population Heterogeneity

An alternative explanation for the results in Figure 5 is treatment effect heterogeneity. After all, instrumental variables estimations recover "local" average treatment effects, as in for the complier population. When analyzing heterogeneity by income quartiles I am effectively looking at different populations and, therefore, possibly different complier populations as well. If treatment effects vary across these different population, it could be the case that this is what is driving the heterogeneity.

Individual compliers cannot identified, but it is possible to describe their observable characteristics (Frandsen et al., 2019). Columns (2)-(3) of Table A7 and Columns (2)-(6) of Table A10 show the shares of defendants satisfying each characteristic for both the whole sample and within the complier population. Stronger effects for defendants in higher income quartiles could be due to a higher concentration of compliers in those subsamples. In Table A7 we can see that is not the case. However, both drug offenses and self-representation seem to be overrepresented in the complier population and, if those are differentially distributed across the income distribution that could be driving the heterogeneity. In Table A10 I can see that even though the shares of defendants charged with property and drug offenses, as well as those that self-represented defendants is very different across subsamples (35% and 15%, 35% and 55%, and 8% compared to 22%), the complier samplings relative to each subsample are quite similar.

6.2 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 besides through monetary sanctions. Sanctioned defendants also get a misdemeanor record, which may impact defendants by increasing their expected future punishments were they to reoffend, a "general" deterrence channel.

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 Table **??**. 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.

6.3 Alternative Identification Approaches

Table A13 in the Appendix explores alternative specifications that account for potential biases from the construction of the leniency measure. I report results using all the judge dummies directly as instruments, using Lasso to pick the most informative dummies (Belloni et al., 2014), as well as the more traditional JIVE measure of Dahl et al., 2014; Dobbie et al., 2018. Across all these different estimations strategies I consistently find a negative relationship between monetary sanctions and financially motivated recidivism.

7 Conclusion

Over 16 million people go through the criminal justice system every year. Most do not suffer any consequences beyond having to pay a fine or the court-associated fees. However, there is limited evidence regarding the effects these sanctions have on reoffending. As the system continues to expand and become more dependent on monetary sanctions for financing, it is of great relevance to understand what consequences, if any, these have on recidivism, especially if they may be incentivizing the poorest individuals to commit crimes to pay for them.

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 district judges in the state of North Carolina. My findings imply that monetary sanctions, on average, do not increase the likelihood of defendants engaging in any future criminal activity and, in fact, strongly deter offenses that entail economic gains. These effects are driven by defendants living in wealthier neighborhoods but there do not seem to be any criminogenic effects for defendants living in poorer areas.

It is important to note that I do not see evidence of reoffending for these defendants, in the sense of them resorting to financially motivated crime in order to supplement their income. However, I do find evidence of monetary sanctions putting them in severe financial distress. For defendants living in poorer neighborhoods I see a higher likelihood of them being involved in crimes associated with poverty, such as panhandling, sleeping in public spaces, or driving with a revoked license due to unpaid fines or court fees.

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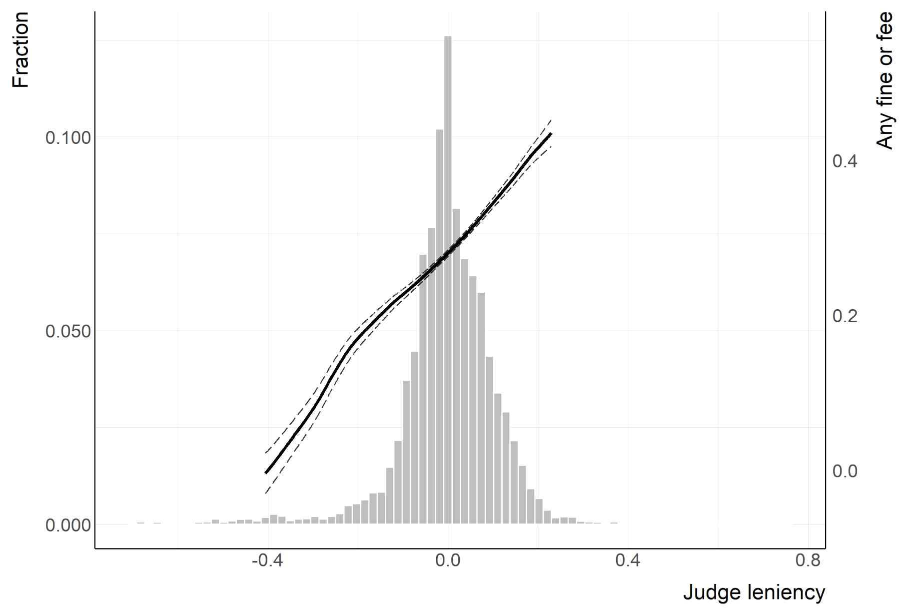
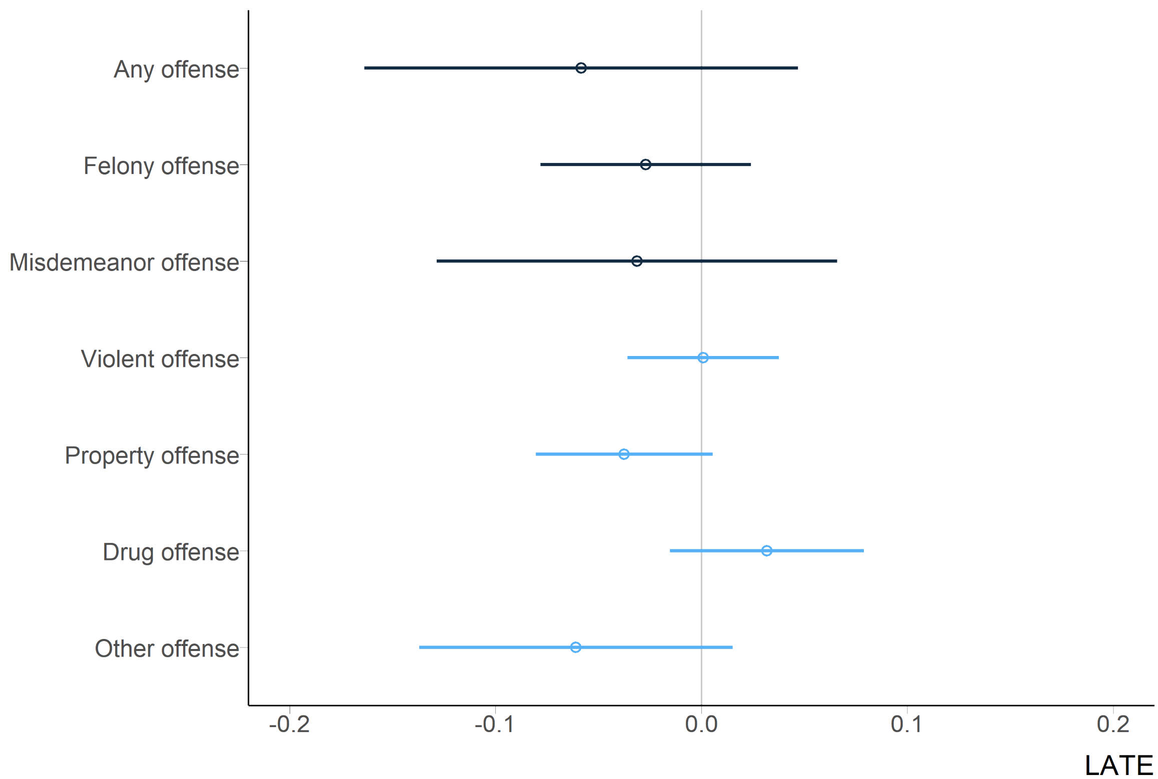
8 Figures and tables

Figure 1: Distribution of judge leniency and first stage



Notes: This figure shows the distribution of my leave-out mean measure of judge leniency, residualizing out district-by-time fixed effects as described in Section 4. The solid line shows a local linear regression of a dummy for whether a defendant has to pay a fine or court fees on judge leniency, estimated from the 1st to the 99th percentile of judge leniency. Dashed lines show 95% confidence intervals.

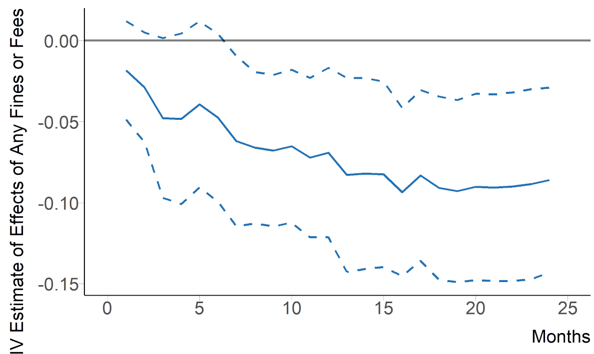
Figure 2: Treatment effects over by seriousness and type of recidivating offense



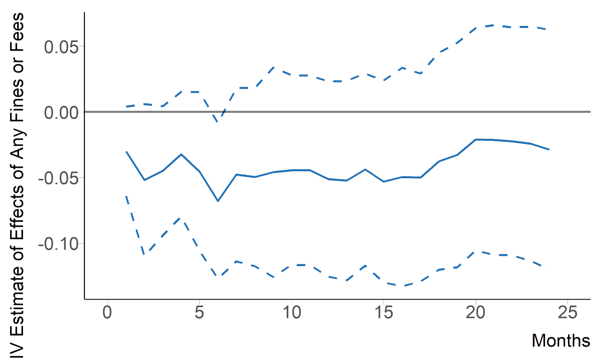
Notes: This figure reports local average treatment effects of being levied any fines or fees on the likelihood of criminal involvement within two years of disposition for the type of offenses indicated on the y-axis. Estimates are based on the UJIVE approach, equivalent to Column (5) of Table 4. Dashed lines represent 95% confidence intervals clustered at the judge and defendant level.

Figure 3: Treatment effects over time by financial incentives

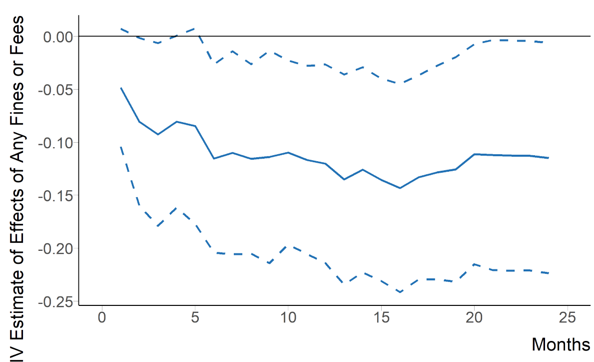
(a) Financially motivated



(b) Non-financially motivated

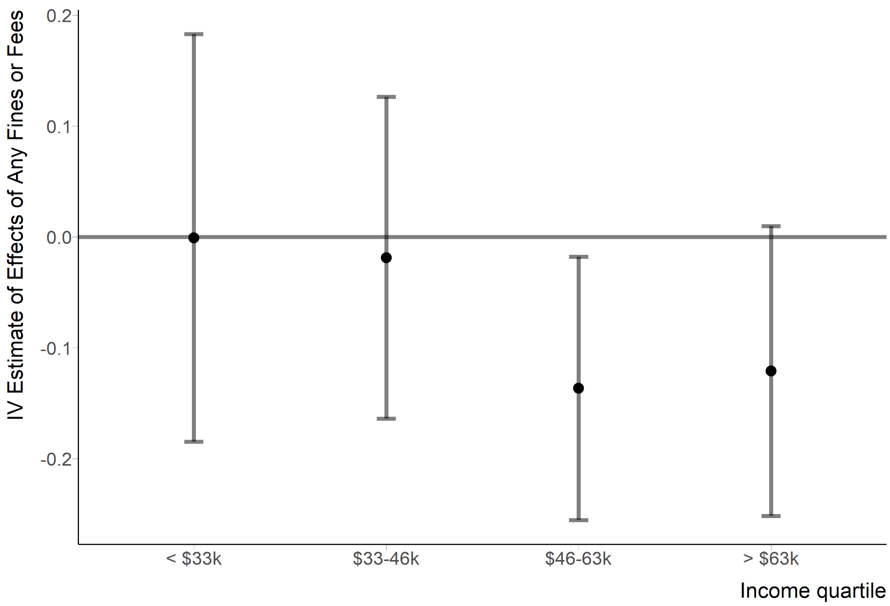


(c) Any offense



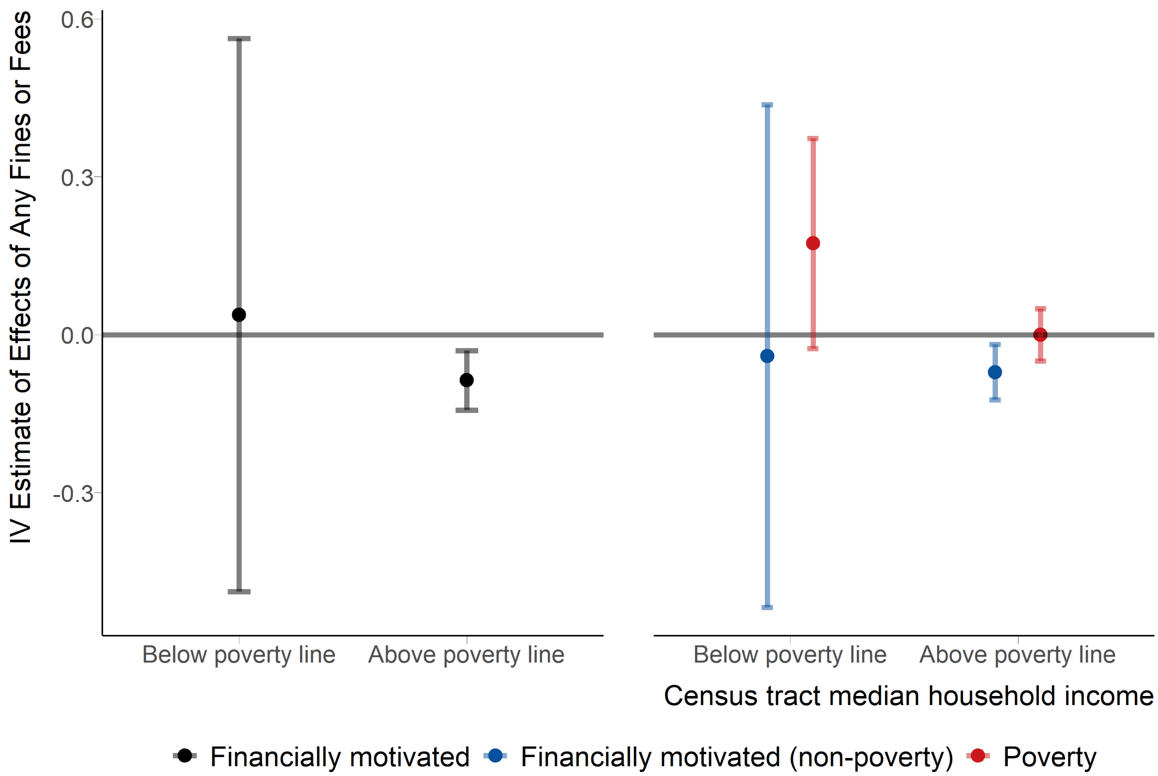
Notes: This figure shows the local average treatment effect of being levied any fines or fees on the likelihood of criminal involvement within a given number of months after disposition. Estimates are based on the UJIVE estimator of Kolesár (2013), equivalent to Column (5) in Table 4. Dashed lines represent 95% confidence intervals clustered at the judge and defendant level.

Figure 4: Fines and fees and financially motivated criminal involvement within 2 years by census tract median household income



Notes: This figure reports two-stage least squares estimates of being levied any fines or fees on the likelihood of financially motivated criminal involvement within two years after disposition by defendants' income level. Estimates are based on the UJIVE estimator, equivalent of Column (5) in Table 4. "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. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars. Dashed lines represent 95% confidence intervals clustered at the judge and defendant level.

Figure 5: Treatment effects by seriousness and type of recidivating offense



Notes: This figure reports the local average treatment effect of being levied any fines or fees on the likelihood of different types of criminal involvement within two years after disposition. These are UJIVE estimates, equivalent to those of Column (5) in Table 4. "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. "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. Dashed lines represent 95% confidence intervals clustered at the judge and defendant level.

Table 1: Case characteristics and outcomes

	Mean	Std. Dev.	Observations
Panel A: Defendant Characteristics			
Male	0.73		10,373
Non-Hispanic White	0.36		10,373
Black	0.56		10,373
Hispanic	0.05		10,373
Other	0.03		10,373
Age	29.95	12.48	10,373
Income ($1,000s)	51.18	24.10	10,373
Panel B: Charge Characteristics			
Number of offenses	1.24	0.44	10,373
Any prior record	0.23		10,373
Previous criminal charges	1.60	0.74	2,406
Type of offense			
Property	0.25		10,373
Drug	0.52		10,373
Other	0.24		10,373
Panel C: Attorney Characteristics			
Court appointed	0.05		10,373
Public defender	0.09		10,373
Privately retained	0.68		10,373
Self-represented	0.18		10,373

	Mean	Std. Dev.	Observations
Panel D: Case Outcomes			
Monetary bail	0.22		10,373
Bail amount ($1,000s)	1.12	5.10	2,266
Method of disposition			
Dismissed	0.30		10,373
Judge	0.70		10,373
Convicted	0.69		10,373
Guilty plea	0.67		10,373
Any fine	0.27		10,373
Fine ($)	47.84	44.83	2,767
Any court fees	0.45		10,373
Court fees ($)	223.55	74.10	4,646
Unpaid fines or fees	0.38		4,794
Panel E: Recidivism outcomes			
Reoffend within 2 years	0.36		10,373
Type of offense			
Violent	0.10		3,783
Property	0.16		3,783
Drug	0.16		3,783
Other	0.17		3,783

Notes: This table reports descriptive statistics for the analysis sample described in Section 3.2. “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 $\times$ 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 Section 4. 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 fines or fees 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

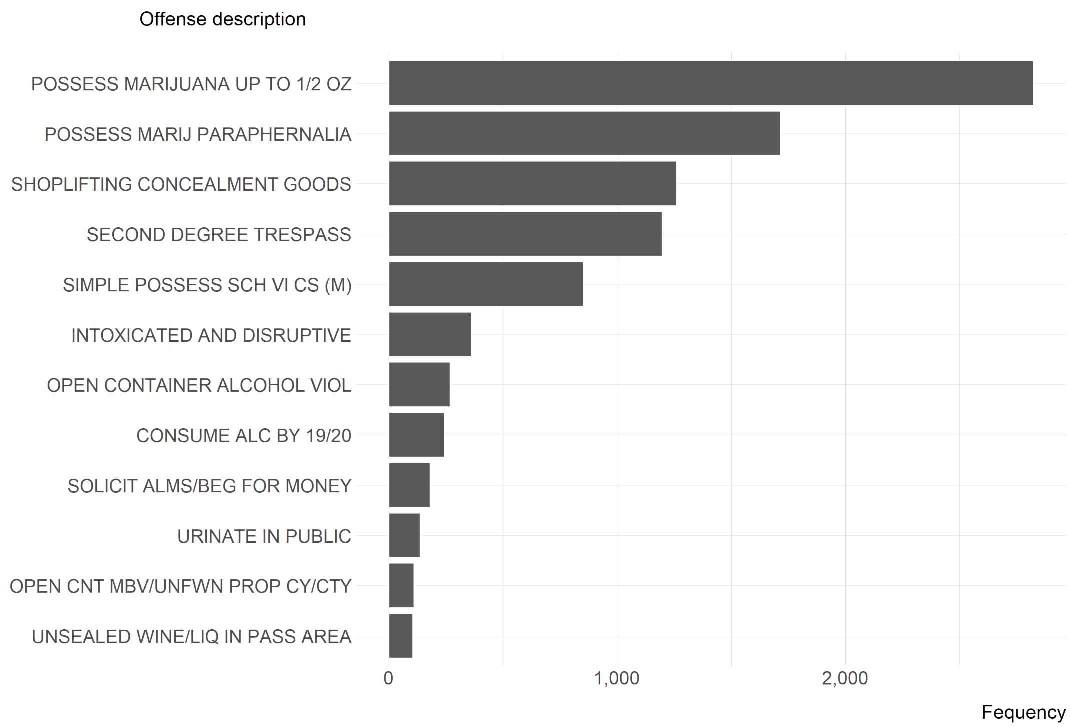
	OLS			UJIVE	
	(1)	(2)	(3)	(4)	(5)
Panel A: Financially motivated criminal involvement within 2 years					
Any fines or fees	–0.043***	–0.033***	–0.025***	–0.118***	–0.069**
	(0.009)	(0.008)	(0.008)	(0.028)	(0.030)
Mean of dep. var.	0.088				
Mean of dep. var. for compliers	0.050				
Panel B: Non-financially motivated criminal involvement within 2 years					
Any fines or fees	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. Columns (1) and (4) report results controlling for my full set of district-by-time fixed effects. Columns (2) and (5) add defendant and case controls: defendant race, defendant gender, defendant age, number of offenses, prior criminal involvement, indicators for the type of offense the defendant is arrested for, indicators for the type of defense representation, and census block group median income. Column (3) reweights Column (2) estimates to match the sample of compliers, as described in Section 5.1. UJIVE estimates instrument whether a 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 Section 4. "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. "Income" is proxied by the ACS median household income in the defendant's home address census tract and is in 2019 dollars. 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

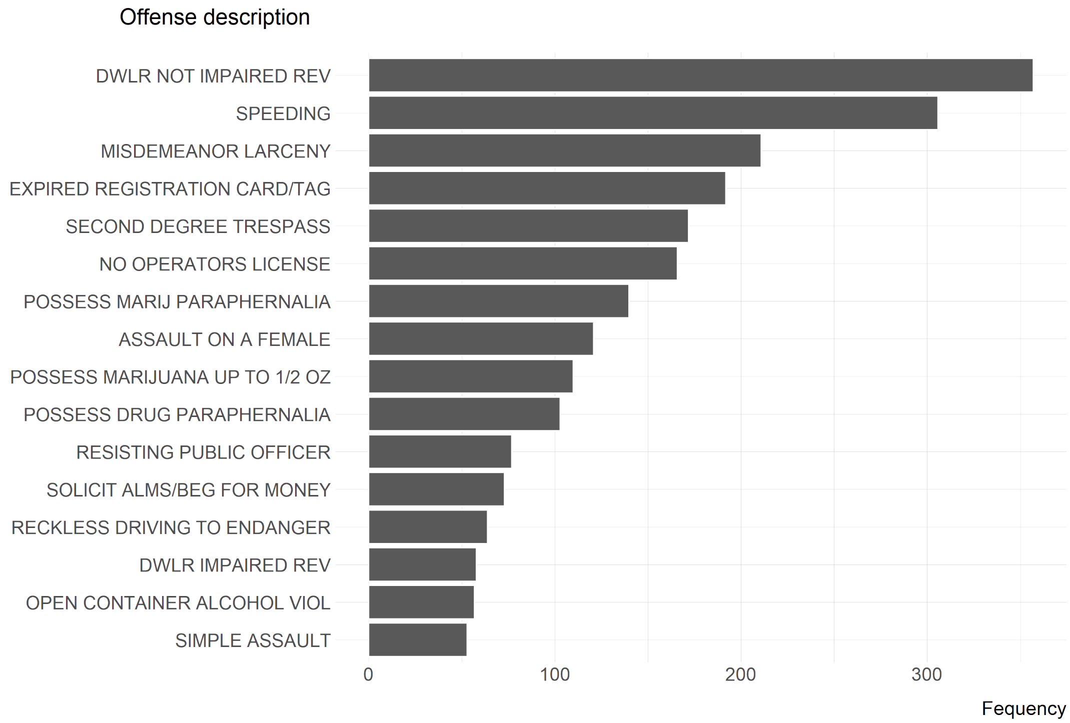
A Additional figures and tables

Figure A1: Most common offenses



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

Figure A2: 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.

Table A1: 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 descriptive statistics as I restrict the universe of criminal offenses in North Carolina to construct my analysis sample.

Table A2: 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 3.2. 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 A3: 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 $\times$ 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 by offense and attorney type. Judge leniency is estimated using all cases assigned to a district judge in the same year following the procedure described in Section 4. 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. $***p < 0.01$, $**p < 0.05$, $*p < 0.10$.

Table A4: 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 × 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 by demographic group and prior criminal involvement. Judge leniency is estimated using all cases assigned to a district judge in the same year following the procedure described in Section 4. 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. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

Table A5: Frandsen et al. (2019) test of joint null of exclusion and monotonicity

	5 knots	10 knots	15 knots	20 knots
	96.12	95.64	96.59	93.86
	(94)	(89)	(84)	(79)
$\omega = 1.0$	[0.42]	[0.30]	[0.16]	[0.12]
$\omega = 0.8$	[0.52]	[0.37]	[0.21]	[0.15]
$\omega = 0.5$	[0.84]	[0.59]	[0.33]	[0.24]
$\omega = 0.3$	[1.00]	[0.99]	[0.55]	[0.41]

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. The rows in the first panel report test statistics and degrees of freedom from the fit component of the test. The rows in the second panel report p-values associated with different weighting schemes between the fit and slope components of the test. Each column displays results using a different number of knots in the spline function. A failure to reject the null implies that I 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 A6: 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 A7: 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 A8: Fines and fees and criminal involvement within 2 years by census tract median household income

	Household income quartile			
	< $33k	$33–46k	$46–63k	> $63k
Panel A: Financially motivated criminal involvement within 2 years				
Any fines or fees	–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 fines or fees	–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 local average treatment effects of the impact of fines and fees on the probability of a subsequent criminal involvement within two years by census tract median household income. These are UJIVE estimates that instrument whether a 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 Section 4. All specifications control for case and defendant controls, as well as district-by-time fixed effects. Case and defendant controls are: defendant race, defendant gender, defendant age, number of offenses, prior criminal involvement, indicators for the type of offense the defendant is arrested for, indicators for the type of defense representation, and census tract median household income. "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. 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 A9: Fines and fees and criminal involvement within 2 years for defendants above and below the federal poverty line

	Household income	
	< \$26k	≥ \$26k
Panel A: Financially motivated criminal involvement within 2 years		
Any fines or fees	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 fines or fees	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 × Time FE	Yes	Yes
Case/Def. controls	Yes	Yes
Observations	869	9,283

Notes: This table reports local average treatment effects of the impact of fines and fees on the probability of a subsequent criminal involvement within two years, by whether defendant's census tract median household income lies above or below the federal poverty line in North Carolina. These are UJIVE estimates that instrument whether a 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 Section 4. All specifications control for case and defendant controls, as well as district-by-time fixed effects. Case and defendant controls are: defendant race, defendant gender, defendant age, number of offenses, prior criminal involvement, indicators for the type of offense the defendant is arrested for, indicators for the type of defense representation, and census tract median household income. "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. 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 A10: Characteristics of marginal defendants relative to overall sample by whether household income is below or above poverty line

	$<$ \$26k		$\geq$ \$26k	
	Subsample	Compliers	Subsample	Compliers
Offenses = 1	0.77	0.76	0.73	0.83
Offenses > 1	0.23	0.24	0.27	0.17
Any prior record	0.30	0.22	0.44	0.25
Property offense	0.35	0.24	0.15	0.12
Drug offense	0.35	0.54	0.55	0.62
Other offense	0.30	0.23	0.30	0.26
Private attorney	0.73	0.67	0.60	0.52
Indigent defense	0.19	0.14	0.19	0.12
Self-represented	0.08	0.20	0.22	0.36
Age $\leq$ 24	0.27	0.44	0.28	0.35
Age 25–34	0.26	0.25	0.23	0.32
Age 35–44	0.16	0.12	0.36	0.12
Age 45–54	0.17	0.09	0.06	0.08
Age $\geq$ 55	0.11	0.06	0.08	0.07
Male	0.74	0.73	0.72	0.73
Minority	0.68	0.64	0.88	0.69
White	0.32	0.36	0.12	0.31

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.

Table A11: Fines and fees and criminal involvement by census tract median household income

	Household income	
	< \$26k	≥ \$26k
Panel A: Financially motivated criminal involvement within 2 years		
Any fines or fees	–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 fines or fees	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 fines or fees	–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 × Time FE	Yes	Yes
Case/Def. controls	Yes	Yes
Observations	869	9,283

Notes: This table reports local average treatment effects estimates of the impact of fines and fees on the probability of a defendant's subsequent criminal involvement within two years, by whether defendant's census tract median household income lies above or below the federal poverty line in North Carolina. These are UJIVE estimates that instrument whether a 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 Section 4. All specifications control for case and defendant controls, as well as district-by-time fixed effects. Case and defendant controls are: defendant race, defendant gender, defendant age, number of offenses, prior criminal involvement, indicators for the type of offense the defendant is arrested for, indicators for the type of defense representation, and census tract median household income. "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. 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 A12: 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 fines or fees	–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 fines or fees	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 local average treatment effects of the impact of fines and fees on the probability of a subsequent criminal involvement within two years, by whether defendants had any prior involvement with the criminal justice system. These are UJIVE estimates that instrument whether a 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 Section 4. All specifications control for case and defendant controls, as well as district-by-time fixed effects. Case and defendant controls are: defendant race, defendant gender, defendant age, number of offenses, prior criminal involvement, indicators for the type of offense the defendant is arrested for, indicators for the type of defense representation, and census tract median household income. "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. 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 A13: Alternative IV strategies

	(1)	(2)	(3)	(4)	(5)
	UJIVE	JIVE	2SLS	LIML	IV Lasso
Any fines or fees	-0.069**	-0.084***	-0.062***	-0.070**	-0.051***
	(0.030)	(0.030)	(0.023)	(0.028)	(0.009)
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	296.72
Any fines or fees	0.462				
Observations	10,373	10,373	10,373	10,373	10,373

Notes: This table reports two-stage least squares estimates of the effects of monetary sanctions on financially motivated recidivism using various estimation strategies for the instrument, as indicated in the column headers. All specifications control for case and defendant controls, as well as district-by-time fixed effects. Case and defendant controls are: defendant race, defendant gender, defendant age, number of offenses, prior criminal involvement, indicators for the type of offense the defendant is arrested for, indicators for the type of defense representation, and census tract median household income. The OLS estimate for this specification can be found in Table 4 Column (2), and is -0.033 (SE=0.008). 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 104 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 22 of the 104 judge dummies as instruments. $***p < 0.01$,$**p < 0.05$,$*p < 0.10$.

B Technical Appendix

Understanding Compliers

In this section I describe the details on how I calculate the shares and characteristics of compliers, always-takers, and never-takers.

I follow Dahl et al. (2014), same as Dobbie et al. (2018), Bhuller et al. (2020), and Agan et al. (2021), and first define compliers as defendants for whom the decision of whether to charge them fines or court fees would have been different had their case been assigned to the most lenient instead of the most strict judge. Thus, their share is given by

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

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

Always-takers, then, are those defendants who would always be levied fines or fees, regardless of the judge they are assigned to. Now, because of the monotonicity and independence assumptions, the share of always takers is given by the probability of having to pay fines or fees when assigned to the most lenient 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 levied fines or fees. The fraction of never-takers is given by the probability of being levied no fines or fees by the most strict judge:

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

Now, to calculate these shares I begin by defining the "most lenient" judge as the bottom 1 percentile of judge leniency and the "most strict" judge as the top 1 percentile, and using a linear regression specification of the first stage Equation 4. Column (1) of Table A6 reports estimates of this specification, controlling for court-by-time fixed effects. 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. I find that 48 percent of my sample are compliers, 37 percent are never takers, and 16 percent are always takers. Columns (2) and (3) of Table A6 report estimates using alternative cutoffs to define the most lenient and most strict judges. Additionally, to explore the sensitivity of these shares to the model specification, in Columns (4)–(6) of Table A6 I also report estimates from a local linear specification of Equation 4. My results are robust to both the particular model specification and the cutoff choice.

Alternative Estimating Strategies

The main analyses in this paper are done using as an instrument a residualized leave-out mean leniency measure that is estimated from the other cases that a judge has decided on. One could use the full set of judge dummies as instruments, but then estimates may be severely biased (Bekker, 1994; Bound et al., 1995; Hausman et al., 2012). Popular solutions to this problem, JIVE and LIML, are biased as well when the number of covariates is large and with heterogenous treatment effects, respectively (Ackerberg and Devereux, 2009; Kolesár, 2013). And even though UJIVE addresses both of these issues it is still not clear how to assess many-weak-instrument bias with constructed instruments such as JIVE or UJIVE (Hull, 2017; Frandsen et al., 2019; Bhuller et al., 2020).

In this subsection I explore the robustness of my main estimates to alternative estimation strategies. These results are shown in Table A13. Column (1) repeats my main UJIVE results and Columns (2)–(4) report estimates using JIVE and 2SLS and LIML using the full set of judge dummies. Column (5) reports estimates using Belloni et al. (2014)'s post-lasso to reduce the number of overidentifying restrictions as an alternative to handle the potential bias from many (weak) instruments.[57]

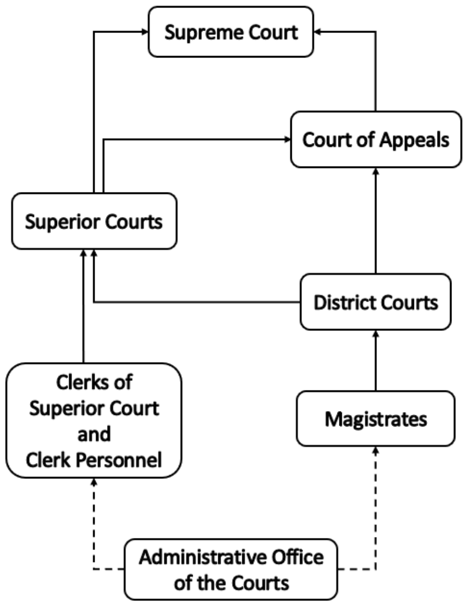
All coefficients are very similar and statistically significant. These estimates imply that within two years following their trial, defendants are between 58% and 95% less likely to reoffend, compared to the sample mean, I cannot reject the null that these coefficients are the same as the UJIVE estimates.[58]

[57] 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 (as recommended by Angrist and Frandsen (2019)). The procedure retains 22 out of 104 instruments.

[58] Standard errors reported here for 2SLS or LIML are Montiel Olea and Pflueger (2013)'s robust first-stage F-statistics.

C North Carolina institutional information

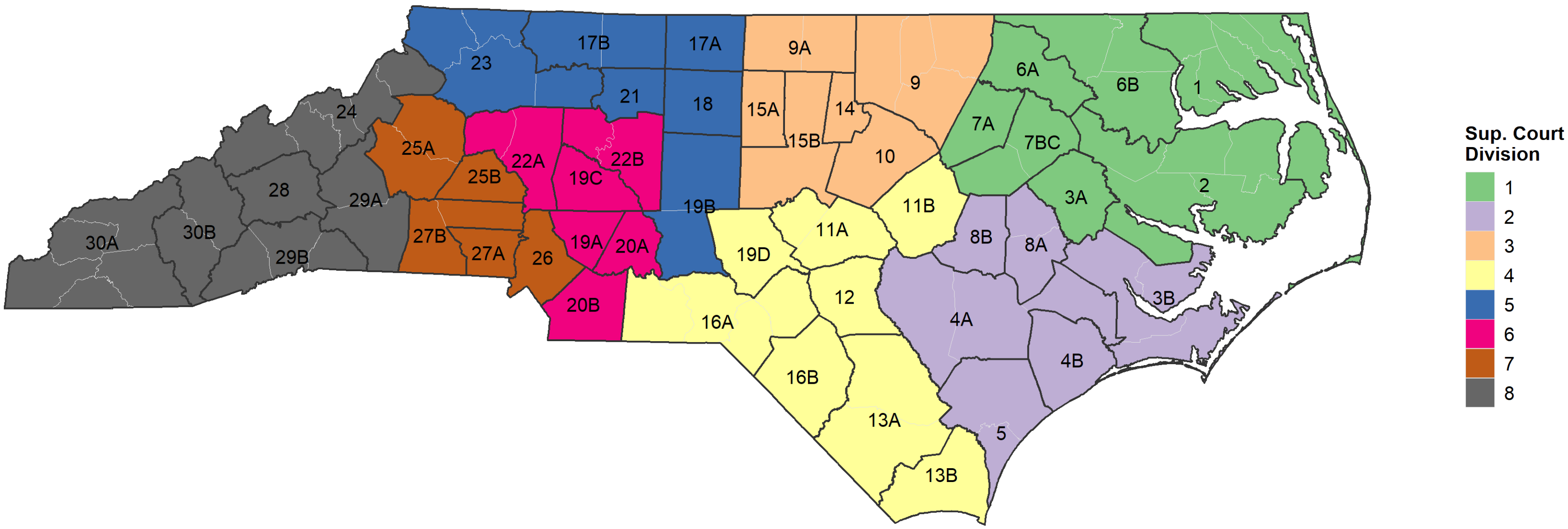
Table C1: North Carolina Judicial System



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.

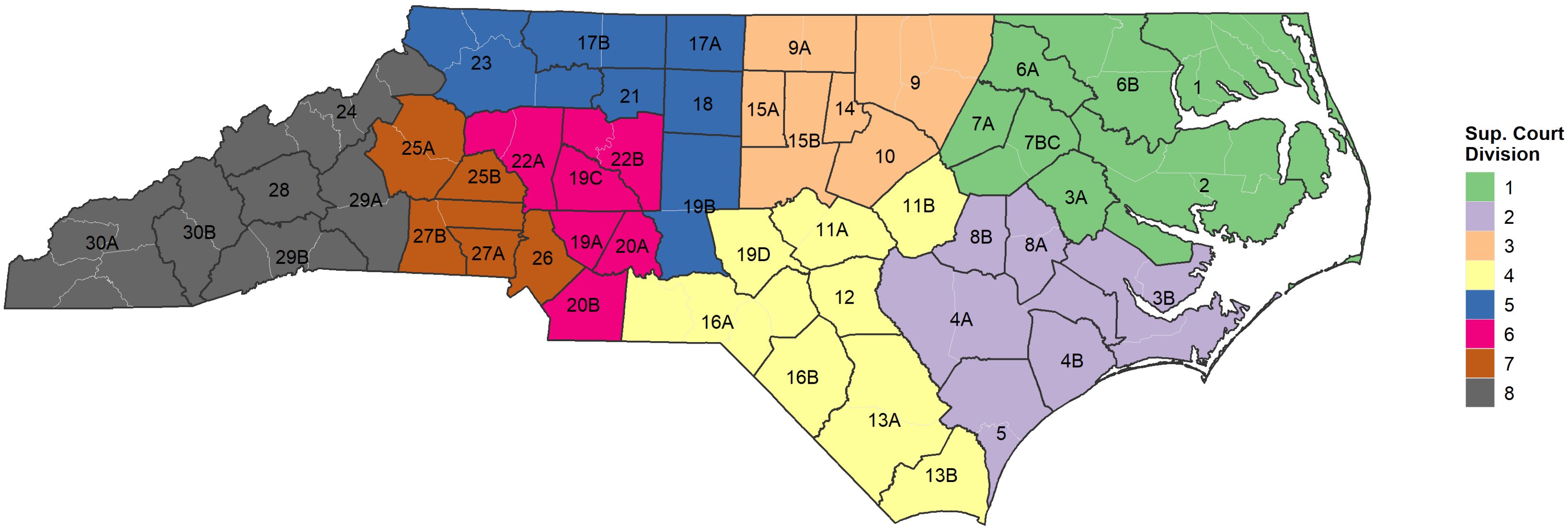
Figure C1: North Carolina Superior Court districts and divisions



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 minimum 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).

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

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					CIVIL JUDGMENT	
			Waive	Order Partial	Exempt	Remit	Modify upon Default	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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