Laffer's Day in Court: The Revenue Effects of Criminal Justice Fees and Fines

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Abstract

Many jurisdictions levy sizable fines and fees (legal financial obligations, or LFOs) on criminal defendants. Proponents argue LFOs are a "tax on crime" that funds courts and provides deterrence; opponents argue they do neither. We examine the fiscal implications of lowering LFOs. Incentives to default generate a "Laffer" curve with revenue eventually decreasing in LFOs. Using detailed administrative data, however, we find few defendants demonstrably on the right-hand side of the curve. Those who are tend to be poor, Black, and charged with felonies. As a result, decreasing LFOs for the average defendant would come at substantial cost to governments.

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In many jurisdictions in the United States, convicted criminal defendants are assessed fees and fines that must be paid in addition to any other punishment. These legal financial obligations (LFOs) serve two main purposes: to raise money to fund court operations, and to deter potential criminals by increasing the cost of crime (Becker, 1968). LFOs mostly take the form of lump sum "user fees" covering the costs of investigation, prosecution, and legal defense, rather than crime-specific fines or restitution paid to victims (Harris et al., 2010, 2022). The number and prevalence of these fees has risen dramatically in recent decades. The share of state and federal prisoners with some outstanding LFOs rose from 25% in 1991 to more than 60% in 2016 (Department of Justice, 1993a,b, 2021). The typical LFO amounts to hundreds of dollars; for some defendants it can surpass $1,000 (Diller et al., 2010).

As LFOs have become more pervasive, so have concerns about whether they fulfill their twin purposes. First, recent research finds LFOs have limited deterrence effects on top of conviction and other non-financial punishments (Finlay et al., 2021; Giles, 2023; Pager et al., 2022). One reason why may be that potential offenders appear to have little understanding of how fees and fines are determined or what they can expect to pay for new crimes (Ruback et al., 2006). Another explanation may be that LFOs are simply not a substantial burden on top of other challenges defendants face already, such as a criminal record and a probation or incarceration sentence. Consistent with this idea, recent research has found no evidence that LFOs affect defendants' labor market activity, household expenditures, or other measures of well-being (Lieberman et al., 2023).

Second, LFOs may not raise much revenue for local governments. Criminal defendants are typically very poor; Garin et al. (2023) finds that felony defendants in Ohio and North Carolina earn approximately $5,000 per year prior to their court date. In Florida, where this study's data come from, less than 40% of LFOs assessed in fiscal year 2019 were collected (FCCC, 2019). If the costs of LFO defaults—which include both time spent by court administrators and the impacts of punishments for nonpayment, such as driver's license suspensions—outweigh the revenue raised, increasing LFOs may actually cost governments money on net (Diller et al., 2010; Gentzler, 2017).

If LFOs have no deterrence benefits and raise little revenue, it may be better to decrease them. This paper studies when doing so would be beneficial for both local governments and defendants simultaneously. The analysis is motivated by a simple model of a local government tasked with deterring crime and raising revenue. Residents decide whether to commit crimes based on the expected costs and benefits, and, if they are convicted, choose whether to pay any LFOs or default and face a punishment. The government's net revenue is the sum of payments minus the costs of defaults. Because there is no benefit to partial payment, defendants choose to pay the entire amount when LFOs are low, but eventually switch to nonpayment for higher amounts, a pattern clearly evident in our data. Thus, although higher LFOs deter crime and increase revenue per payer, as LFOs rise so do defaults. This combination leads to a familiar hump-shaped Laffer curve where increasing LFOs enough may eventually decrease both gross and net revenue.

From the perspective of the model, to be beneficial LFO decreases must at a minimum target defendants on the revenue-decreasing side of the Laffer curve. We show that identifying these defendants requires finding groups whose expected payment rate is below their semi-elasticity of payment with respect to LFOs charged, adjusted for default costs. A special case occurs when the expected payment rate approaches zero, where LFO decreases can only weakly increase revenue. In the absence of deterrence effects, which the best available evidence suggests are negligible in criminal cases, the government should always reduce LFOs for these groups. Otherwise, it should do so if the increased revenue is valued more than the reduction in deterrence.

We then attempt to measure the size of the population on the revenue-decreasing side of the Laffer curve using data from three Florida counties. In each jurisdiction, we obtained administrative data on criminal charges, LFOs levied and—more unusually—payments made. We merge these records to detailed credit report data. Since we also observe defendants' attestations about their own financial situation (those without the resources to hire their own lawyer are *indigent*), the combined data closely approximate the information the court might use when setting LFOs. We use these data to train machine learning models that estimate first-time defendant's payment propensities as a smooth function of assigned LFOs. We then use the model to both predict payment rates under status quo LFO assignments and responses to small LFO changes. While some recent work has focused on payment responses to traffic fines (Gonçalves and Mello, 2023; Traxler and Dusek, 2022), we focus on criminal cases, where payment rates are lower and have more scope to increase.

We begin by assessing the distribution of expected payment rates across defendants, which our model shows partly determines whether any are on the revenue-decreasing side of the Laffer curve. This requires only estimates of conditional payment rates—a task at which machine learning excels. Indeed, our model explains over 70% of the variation out of sample. We find substantial heterogeneity in payment rates across crime types: among felony cases, 39% of defendants have predicted payment rates below 20%. At this level, to increase gross revenue a 10% decrease in LFOs needs to increase payment rates by 2 p.p., which is roughly the semi-elasticity implied by the cross-sectional relationship between LFOs and payment at the median LFO amount and twice as large as the semi-elasticity we estimate using year-to-year variation in LFOs within granular groups defined by crime type and demographics.[1] In contrast, only 3.1% of misdemeanor and criminal traffic defendants have payment rates below 20%. Surprisingly, the credit report data has little impact on these estimates, increasing the share of predicted payment rates below 20% by less than 2 p.p. for each case type. These findings suggest that even with sophisticated methods and data, courts are unlikely to be able to identify non-payers ex-ante except among the relatively small share of the overall caseload charged with the most serious crimes.

We next incorporate the payment responses to LFO reductions by using the machine learning model to predict the change in revenue from a small reduction in LFOs. This exercise requires the model to accurately predict how much defendant's payment rates would increase if they were assigned a lower LFO amount. Estimating these responses from our data requires observed LFO assignments to be uncorrelated with other determinants of payment conditional on our rich set of controls, an assumption that could be violated and is difficult to test. We find, however, that the model can accurately forecast payment responses to shifts in LFOs over time due to policy and other changes, suggesting that our estimates may provide an accurate guide to responses to LFO reductions.

The results show that most criminal traffic and misdemeanor defendants have small behavioral responses relative to their predicted payment rates, which means that marginal reductions in LFOs decrease revenue substantially. A $1 decrease in LFOs for all defendants would reduce revenue by 62 cents, on average. In contrast, however, a $1 decrease for felony defendants would decrease revenue by only 13 cents on average. Most strikingly, decreasing LFOs would *increase* revenue for an identifiable 31% of felony defendants, suggesting substantial scope for targeted decreases. These benchmark estimates assume default costs are negligible because we find limited evidence that courts engage in costly enforcement activity.[2] Nevertheless, our core conclusions change little when considering a range of default costs.

To better characterize which defendants are the most obvious candidates for LFO reductions, we compute summary statistics for samples split by the predicted revenue impacts of a $1 decrease in LFOs. Defendants on the right-hand side of the Laffer curve are disproportionately Black and poor, are much more likely to have been charged with a felony, and have higher LFOs and substantially lower payment rates than other defendants. Despite these

[1]This semi-elasticity is also approximately the behavioral payment response estimated in other recent work studying LFOs (Giles, 2023).

[2]Despite having the authority, the counties in our study do not seize property or compel court appearances. While driver's license suspensions are a common punishment, as noted above recent research has found little evidence of social spillovers from LFOs and the punishments for defaulting (Lieberman et al., 2023).

observable differences, broad-based LFO reductions targeting these groups, such as eliminating the $50 charge felony defendants pay to apply for a public defender, would still reduce revenue. Instead, profitably decreasing LFOs requires more detailed tailoring of LFOs to individual defendants' ability to pay.

We conclude that reducing LFOs for certain defendants may increase government revenues. However, these opportunities are concentrated among highly disadvantaged defendants charged with serious crimes, and who account for only 7% of defendants overall. Most policies that would reduce LFOs—particularly those for non-felony defendants—would likely come at substantial revenue costs to local governments, as in Emanuel and Ho (2023). In this sense, our results may rationalize the dramatic increase in LFOs over the last 25 years in Florida. They are also consistent with a view of LFOs as a regressive tax that transfers resources from disproportionately poor defendants to the broader taxpayer population. Indeed, the bottom half of the population ranked by zipcode income accounts for 63% of LFOs assigned and 58% of payments, but only 28% of income and 17% of federal income taxes.

2 Economic model

This section describes a simple model of individuals' decisions to commit crimes and whether to default on LFOs assessed as part of a conviction. It then considers the problem faced by a government tasked with minimizing crime and maximizing revenue net of the costs of enforcing LFO payment. The key message is that LFO revenues may follow a Laffer curve, where both gross and net revenues are decreasing in LFOs at sufficiently high levels. We derive a simple expression for the overall effects of marginal LFO policy changes on the government's objective which we later use to determine whether any identifiable groups are on the "wrong" side of the Laffer curve.

2.1 Defendant's problem and aggregates

Consider an individual's decision to commit a specific type of crime. We assume this decision depends on the expected benefits of the activity, B, and the costs of punishment.[3] Punishment involves the utility costs of consumption foregone to pay LFOs, denoted $U(D)$, or the utility costs of the consequences of nonpayment, P. We assume that $U(D)$ satisfies the

[3] For simplicity, we abstract from the probability of apprehension. Costs of crime can simply be viewed as expected utility costs accounting for uncertainty. We also abstract from other punishments, such as incarceration. B can be viewed as the benefits of crime net of any non-LFO punishments.

standard properties that $U(0) = 0$ and $U'(D) > 0$. There is no benefit to partial payment, so the defendant will default if nonpayment is less costly than payment. Total punishment is thus $F(D) \equiv min\{U(D), P\}$.[4]

The crime rate, denoted $C(D)$, is the share of the population that finds it optimal to commit a crime either because the sanction for nonpayment of LFOs or the costs of LFO payment itself is sufficiently low.

$$C(D) = Pr(F(D) < B) = \underbrace{Pr(P < B)}_{\textit{Not deterrable}} + \underbrace{Pr(U(D) < B < P)}_{\textit{Deterrable}}$$

For some portion of the population, the level of LFOs is irrelevant to their decision to commit crime because they already prefer to default. Any deterrence responses must therefore be driven by offenders who find the costs of LFOs, but not the costs of any nonpayment sanctions, to be lower than the benefits of crime.

Revenue per capita, denoted $R(D)$, depends on the size of the population that finds it optimal to both commit crime and pay the resulting LFOs. Like crime, revenue can also be attributed to payments from deterrable and non-deterrable populations:

$$\begin{aligned} R(D) &= D \cdot Pr\big(\underbrace{F(D) < B}_{\textit{commits crime}}, \underbrace{U(D) < P}_{\textit{pays LFO}}\big) \\ &= D\left(\underbrace{Pr(U(D) < P < B)}_{\textit{Not deterrable payers}} + \underbrace{Pr(U(D) < B < P)}_{\textit{Deterrable payers}}\right) \end{aligned}$$

Combining these expressions allows us to derive a simple formula for the marginal revenue effects of increasing LFOs:

$$\frac{\partial R(D)}{\partial D} = \underbrace{\frac{R(D)}{D}}_{\textit{Mechanical effect}} + \underbrace{\frac{\partial Pr(U(D) < P, P < B)}{\partial log(D)}}_{\textit{Default effect}} + \underbrace{\frac{\partial C(D)}{\partial log(D)}}_{\textit{Deterrent effect}}$$

The first term, which equals the share of the population that commits a crime and pays the LFO, simply reflects the mechanical increase in revenue from charging offenders slightly higher LFOs. The second two terms capture behavioral responses to the change. The *default* effect is the decrease in revenues due to offenders who continue to find it optimal to commit

[4] B and P are random variables and U is a random function that could be indexed with i subscripts, which we omit for simplicity.

crime but no longer prefer payment to the consequences of nonpayment. The *deterrent* effect captures the decrease in revenue from offenders who no longer find it worthwhile to commit a crime at all.

Since $R(D) \geq 0$, the mechanical effect is always weakly positive. Since we assume that $U'(D) > 0$, the default and deterrent effects are always negative. These two facts combined imply that there may exist a "Laffer curve" for LFO revenues, which are initially increasing in D, reach a peak, and then decrease. As $D \to \infty$ and the default effect dominates, decreasing LFOs becomes more likely to increase revenue.

2.2 Government's problem

The government seeks to balance the social costs of crime against the revenues and costs from collecting LFOs. Everyone who does not pay their LFOs must suffer the consequences of nonpayment. We use H to denote the dollar-denominated cost of these defaults, which can include both costly enforcement (e.g., administrative hearings) as well as any other social costs. Because all nonpayers incur these costs, total costs of defaults are simply given by H times the share of nonpayers, $E(D) = H(C(D) - R(D)/D)$.[5] Likewise, we use S to denote the dollar-denominated costs of each crime, so that total crime costs are $SC(D)$.

The government's problem is thus:

$$\max_{D} \; W(D) = R(D) - E(D) - SC(D) \tag{1}$$

$$= R(D)\left(1 + \frac{H}{D}\right) - (H+S)C(D) \tag{2}$$

To understand the tradeoffs in this problem, consider the derivative of the government's objective with respect to D.

$$W'(D) = \underbrace{R'(D)}_{\text{marg. revenue}} \underbrace{- H\left(\frac{R(D)/D - R'(D)}{D} + C'(D)\right)}_{\text{default costs}} - \underbrace{SC'(D)}_{\text{costs of crime}} \tag{3}$$

This expression consists of the marginal revenue effect studied above, a potential increase in default costs, and a reduction in crime (recall that $C'(D) \leq 0$). The revenue effect depends on the balance of the mechanical, default, and deterrent effects. Even if revenue increases, however, these increases may be offset by increases in default costs if increasing

[5] Because we focus on marginal LFO changes, we abstract from fixed costs of enforcement.

D also leads to more nonpayment. These costs are equal to H times the gap between the mechanical and marginal revenue effects, with an adjustment for any decreases in revenue due to additional deterrence. That is, additional enforcement costs are incurred whenever increasing fees reduces crime by less than it reduces payment.

Figure 1 illustrates the government's problem. Increasing fees has a direct effect on revenue $R(D)$, which can be positive or negative depending on the magnitudes of the mechanical and behavioral responses. It also has an effect on the social costs of crime through deterrence effects. As D increases and nonpayment increases, revenue may begin to decline, enforcement costs increase, and deterrence benefits subside. Because $C(D)$ is monotonically decreasing, in general optimal LFOs are set at or beyond the net-revenue maximizing level. However, if the government faced a choice between multiple tax instruments, distributional concerns might motivate setting lower LFOs and raising revenue through other, progressive sources instead. We abstract from these considerations here.

In the presence of deterrence effects, a necessary condition for LFOs to be too high overall is that they are too high in a revenue-maximizing sense. The following theorem establishes this condition under an intuitive assumption about the costs of crime:

Theorem 1 (Revenue elasticity)**.** *Suppose that $S \geq D$, so that crime is more costly than the LFO amount D.*[6] *Then, a necessary condition for marginal decreases in LFOs to increase the government's objective is that the average payment rate is smaller than the default semi-elasticity among offenders, adjusted for default costs:*

$$\underbrace{\frac{R(D)/D}{C(D)}}_{\textit{Avg. payment rate}} \leq \left(1+\frac{H}{D}\right)\underbrace{-\frac{\partial Pr[U(D)<P|F(D)<B]}{\partial log(D)}}_{\textit{Default semi-elasticity: }\eta(D)} \tag{4}$$

Proof: See Section A.1.

Theorem 1 provides a simple way to assess the potential benefits of adjusting LFOs while looking at existing offenders only. LFO decreases are more likely to increase the government's objective when payment rates are low. They are also more attractive when offenders' default response $\eta(D)$ is larger or default costs H are larger.[7]

Assessing the revenue effects of changes to LFOs becomes simpler if potential offenders do not know or react to LFO levels when deciding whether to commit crimes, so that deterrence

[6] This assumption can be viewed as requiring that the government be unwilling to allow citizens to pay to commit crime at price D.

[7] However, default costs become less important as D increases because as D rises, the revenue costs of defaults increase while default costs themselves do not.

effects are zero and changes in the government's objective are fully captured by changes in revenues. As suggested by a series of recent studies, this special case might best capture the impacts of marginal changes in LFOs in practice. The following corollary establishes that the condition in (4) is necessary and sufficient regardless of the size of S relative to D in this case:

Corollary 1.1. *Suppose $C(D) = C$. Then the condition in (4) is necessary and sufficient for marginal decreases in LFOs to increase the government's objective.*

Proof: See Section A.1.

Finally, one important case of Theorem 1 occurs when payment rates are zero, as we formalize in the next corollary:

Corollary 1.2. *If $\frac{R(D)/D}{C(D)} = 0$, then the condition in (4) is met.*

Proof: See Section A.1.

This corollary says that defendants with payment rates approaching zero are exactly those for whom the government should consider lowering LFOs. We apply this insight in Section 5.2, where we predict defendants' payment rates using machine learning methods.

2.3 Incorporating observables

This simple problem considers setting a single fee for all defendants. In reality, governments have more flexibility to adjust LFOs by crime types and for certain defendant characteristics. If the government had full information and could personalize D for each defendant, it would never be optimal to set $U(D) > P$, since doing so entails loss of revenue, extra default costs, and no additional deterrence benefits (Becker, 1968).

Even without full information, however, the government can do weakly better by customizing LFOs based on defendants' observables. Suppose, for example, that the government can pick a policy $D(X):\ R^K \to R$ that maps case characteristics X into assigned fees D. Case features include information about the defendant's potential ability to pay, such as their indigency status and offenses committed. The government's problem is then:

$$\max_{D(X)\in\tilde{F}} E_X\left[R\big(D(X)\big)-E\big(D(X)\big)-SC\big(D(X)\big)\right]$$

where expectations are taken over the population distribution of X and $\tilde{F}$ is the set of allowable policies. Since this problem nests the previous one when $D(X) = D$, incorporating this additional information can only weakly improve the government's objective.

Our empirical application uses machine learning to identify observable groups where the condition in Theorem 1 is met. As Corollary 1.1 makes clear, this condition is sufficient for decreases in LFOs to increase the government's objective only if deterrent effects are zero. In the presence of deterrence, however, the bar for LFO cuts to increase the objective is more stringent: increases in revenue must offset the social costs of increased crime.

3 Setting and data

3.1 LFOs in Florida

Legal financial obligations consist of dozens of fines and fees that are assessed at disposition and cover different aspects of the criminal and legal process (Diller, 2010). All convicted defendants are assessed at least some LFOs. Fines are typically applied to particular crime types as part of a sanction. Some fees, such as the $225 assessed to defendants convicted of a felony, are mandatory. Others—such as costs of investigation—are more discretionary, while a final category of LFOs are assessed in particular circumstances, such as the $50 fee defendants pay to apply for a public defender.[8] Relatively little attention is paid to ability to pay, and for certain categories of LFOs judges are statutorily required to ignore defendants' financial means. Payment plans are permitted but rarely pursued in our data; in practice LFOs are due within either 90 or 180 days.

In principle, the repercussions for nonpayment can be severe. In each of the courts in our sample, the defendant can be called back to court to answer for nonpayment; failure to appear can result in an arrest warrant being issued. Nonpayment is also grounds for a drivers license suspension. Since driving on a suspended license is a criminal offense, nonpayment creates a risk of a rapidly escalating series of arrests, convictions and LFOs stemming from the initial offense. Finally, payment can be made a condition of probation, and so nonpayment could result in a worsening of the terms of probation or even incarceration.

In practice, however, the costs of nonpayment are relatively mild. None of the courts in our data make payment a condition of probation, or regularly require defendants to appear to answer for nonpayment. Many courts suspend licenses for nonpayment only in criminal traffic cases, which tend to have the wealthiest defendants. The most consistent repercussion of nonpayment is referral of the debt to a collection agency, an action that has been mandatory since 2009. However, collection agencies cannot seize assets or garnish wages. Instead, their

[8] Figure A1 shows an example anonymized payment order.

main tools to compel payment are repeated calls to defendants and reporting nonpayment to credit agencies. We see very few payments made through collection agencies.

3.2 Data

Court data: We collected detailed court records from three Florida counties: Brevard, Broward, and Hillsborough, which encompass the Space Coast and the cities and surrounding suburbs of Fort Lauderdale and Tampa, respectively. The data contain most of the information that would be available when determining LFOs, such as criminal history, prior LFO charges and payments, offense, age, race, sex, indigency status, and date of disposition. They also contain detailed information on the outcome of the case, including whether the defendant was convicted as well as the incarceration and probation sentence and LFOs charged. We only consider LFOs charged as of the initial case disposition to avoid LFOs accumulated as a result of nonpayment (e.g., late fees). We use payment histories to measure the share of these LFOs paid within three years.

We restrict our attention to individuals who were convicted, had LFO assessments larger than \$100 and smaller than the court-specific 95$^{\text{th}}$ percentile, and whose case was filed from 2005 through 2018.[9,10] Table 1 reports descriptive statistics for this sample of cases as well as the subsample of first-time defendants. Our analysis uses only these first-time defendants because prior payment history is a very strong predictor of future payment history.[11] A defendant who has already failed to pay LFOs on their prior case, for example, faces little incentives to pay on any subsequent ones, so marginal adjustments to LFOs for defendants with large outstanding debts are unlikely to induce any behavioral response.

Defendants in the analysis sample are disproportionately male and Black relative to the state averages. About 63% of defendants are accused of a criminal traffic offense (primarily operating a vehicle without a valid license), 23% of a misdemeanor, and 13% of a felony. The average LFO is \$483, and the average payment rate is about 63%. Felony defendants are the poorest and face the largest LFOs; they are twice as likely as misdemeanor defendants and four times as likely as criminal traffic defendants to be indigent, or poor enough to qualify for a public defender.

[9] We exclude data before 2008 in Broward due to high rates of missing variables. See Table A1 for summary statistics by county.

[10] We exclude acquitted defendants since they are not liable for any LFOs. Extremely low LFO amounts may reflect data errors, since all convictions entailed a minimum LFO of at least \$100 for the bulk of our sample period. These cases account for less than 0.2% of the analysis sample. Extremely high LFO amounts occur in exceptional cases with unusual features. The 95$^{\text{th}}$ percentile is \$1858, \$1378, and \$1643 in Brevard, Broward, and Hillsborough, respectively.

[11] Figure A3 shows the distribution of payment rates for second cases conditional on prior payment history.

Panel (a) of Figure 2 shows a histogram of payment rates for the analysis sample. Consistent with the theory in Section 2, payment shares are nearly bimodal with most defendants either paying in full or not at all. Panel (b) shows payment rates as a function of assigned LFOs. Payment likelihood is decreasing in LFOs, but—taking the estimates at face value—not by nearly enough to suggest that on average defendants are on the right-hand side of the LFO Laffer curve. If these estimates could be interpreted causally, reducing LFOs from \$400 to \$200 would reduce revenue from \$234 to \$148. The cross-sectional relationship also suggests that at the median LFO amount (\$345), a 10% reduction in LFOs would increase payment rates by 2.3 p.p., implying a semi-elasticity of 0.23.[12] Interestingly, this figure is comparable to the quasi-experimental estimate in Giles (2023), where a \$279 increase in LFOs over a base of \$594 increased non-payment by 9.3 p.p., implying a semi-elasticity of $0.093/(279/594) = 0.198$.

Finally, Panel (c) of Figure 2 shows that LFO assignments and payments are highly regressive relative to federal income taxes. This figure plots the share of total LFOs assigned and paid ranking the population in the zipcodes of the analysis sample by their zipcode's average 2020 taxable income. For comparison, the figure repeats the exercise for 2020 taxable income and income taxes. While residents of the poorest zipcodes account for small shares of both income and taxes, LFOs are far more regressively distributed. The bottom half of the population ranked by zipcode income accounts for 63% of LFOs assigned and 58% of payments, but only 28% of income and 17% of federal income taxes.

Credit reports: We additionally obtained TransUnion credit reports for the defendants in our sample. These data help approximate other signals of ability to pay that are potentially observed by the court. TransUnion matched credit archives from 2005, 2008, 2011, and 2014 to our sample based on names, dates of birth, and addresses. To assess the potential for false positives, we also sent TransUnion a batch of cases with randomly permuted name, date of birth, and address. Reassuringly, TransUnion matched only 0.6% of these synthetic cases to their records, despite being unaware that these individuals do not exist.

Among real defendants in our sample, Table 1 shows that only 37% match to a recent credit report. While this low match rate may be partially accounted for by data errors, defendants are also often too disconnected from the formal economy to even have a credit report. Conditional on matching, the average credit score is only 536.[13] Figure A2 shows the match rates for cases filed in each calendar year to each year of TU data. Match rates decline

[12] This figure is calculated by regressing payment indicators onto a fifth order polynomial in assessed LFOs.

[13] We use the VantageScore 3.0, which ranges from 300 to 850. Scores below 600 are considered "poor" (TransUnion, 2023).

rapidly as the time between case filing and the date of the credit archive grows. For example, the match rate to the 2011 archive declines from nearly 70% to less than 40% for 2009 versus 2016 cases, consistent with the high residential instability of this population.[14]

4 Methods

We study the effect of LFOs on payments using two approaches. First, we predict which defendants have a low ex-ante probability of payment, which according to Corollary 1.2 are precisely those for whom the court could profitably reduce LFOs. Second, we predict conditional default semi-elasticities and directly apply Theorem 1 to estimate the revenue effects of targeted LFO changes.

A necessary ingredient for both approaches is the conditional payment rate. To estimate this object, we model the likelihood an offender with observables X pays d LFOs as:

$$Pr(U(d) < P | D = d, X, F(D) < B) = f_0(\theta(X), d)$$

Payment rates depend on $\theta(x)$, a finite-dimensional parameter for individuals with characteristics $x \in \mathcal{X}$. We model f_0 as a 2^{nd}-degree polynomial in d with x-specific coefficients. Doing so allows for smooth payment rates as a function of d conditional on observables.

With a small number of covariates, it would be straightforward to estimate $\theta(x)$ by regressing a payment indicator on a polynomial in D using observations with $X = x$ only. Payment responses to assigned LFOs would then be identified by variation in D among defendants with the same characteristics. Semi-elasticites could be computed using the derivative of the polynomial. The data, however, include a very large set of defendant observables. There is limited guidance from either theory or practice about which characteristics should be conditioned on, especially when taking into account their many potential interactions. Rather than taking a specific stand on the appropriate model, we take a more agnostic approach and estimate θ using nonparametric, data-driven procedures.

Specifically, our baseline model uses generalized random forests (Athey et al., 2019) to estimate $\theta(x)$. This method can be thought of as a type of locally weighted estimator that pools observations with "similar" covariates when fitting θ at each test point x in a way that maximizes the heterogeneity in θ, much as traditional regression forests are trained to maximize differences in conditional means (Breiman, 2001). If two covariates groups have

[14] Indeed, other research that has used higher-frequency credit reports has typically achieved match rates close to 70% (Emanuel and Ho, 2023; Giles, 2023).

very different payment rates as a function of D, the model will tend to estimate different θ for each group. Groups with similar payment response will be pooled to estimate a shared θ. In this sense, the model can be viewed as picking which covariates to interact with the polynomial that describes how payment responds to assigned LFOs and which covariates it is safe to ignore.

The models use all available information as features, including case characteristics such as offense type and the specific charges; defendant characteristics such as sex, race, and indigency status; and features of the defendants' zipcodes such as average household income and demographics. We also train models that add information from TransUnion such as credit score and total outstanding credit balances, along with indicators for observations missing these features. We train the models on the early years of our data (through 2013), and test it on the remainder (2014-2018).[15]

Our two different approaches rely on different assumptions. The first exercise, which attempts to identify defendants with a low ex-ante payment probability, requires only that the causal forests approximate the conditional payment likelihood well. Performance on this task is easy to check by examining out-of-sample fit. The second approach, which uses the model-implied conditional payment semi-elasticities $\eta(D, X) = \frac{-\partial f_0(\theta(X), D)}{\partial \log(D)}$, implicity predicts payment behavior under counterfactual LFO assignments. Inferring these responses from observed LFO assignments and payment behavior requires that D is uncorrelated with other, unobserved determinants of payment conditional on our rich set of controls. We discuss tests of this important assumption below.

5 Results

5.1 Validation model predictions

We begin by validating our model for payment behavior. Figure 3 Panel (a) shows that the model is a very strong predictor of LFO payments out of sample. The figure plots average observed payment rates in twenty equally-sized bins of predicted payment rates, along with the slope and R^2 of a least-squares fit. The blue crosses reflect predictions from a model which is trained only on the information available in the court data; the orange circles represent our baseline model, which adds information from credit reports.[16] Both models

[15] An alternative would be to split the train/test sample within each year. We view our approach as approximating what is feasible for existing court systems, which might train on historical data and form predictions for current cases.

[16] In Table A3 we report summary statistics for the model without credit report data, and find that the predictions are remarkably similar. This suggests that information on additional observable characteristics

feature slopes of roughly 1 and explain a large share of the variation in actual payment rates. The R^2 from both models' predictions is roughly 74%.[17] Treating both observed and predicted payment rates as binary by converting them to indicators for being above 50%, both models are also very strong classifiers. The area under the curve (AUC) of both models is above 0.8. A final fit check for our model comes in Panel (c), where we estimate the effect of a $1 decrease in LFOs on court revenue. While we discuss this panel in more detail below, we note here that the predicted revenue effects are above -$1 for nearly all individuals, as is logically required.

5.2 Identifying non-payers ex-ante

As highlighted in Theorem 1, reducing LFOs is more likely to be beneficial for defendants with a low probability of payment, all else equal. Figure 3 Panel (b) assesses how many defendants can be identified ex-ante as likely non-payers by plotting the cumulative distributions of predicted payment rates from the baseline model. The dotted lines capture the share of defendants with predicted payment rates below 20%, for whom as discussed in Section 2.2 relatively small behavioral responses may justify LFO decreases. To capture important differences across case categories, the figure plots distributions for criminal traffic, misdemeanor and felony cases separately.

The results show that identifying likely non-payers ex-ante is relatively easy for felony defendants, of whom 39% have a predicted payment rate lower than 20% and 83.6% have a less than even chance of paying. These defendants are often charged very large LFOs; 44% of total LFO dollars assigned to felony defendants go to those with a less than 20% chance of paying.

The story is quite different among misdemeanor and criminal traffic defendants, who tend to be wealthier, whiter, and have better credit records. Only 7% of the former have payment rates below 20%; virtually none of the latter group do. This suggests that if there are defendants demonstrably on the revenue-decreasing side of the Laffer curve, they are likely disproportionately disadvantaged and charged with the most serious crimes. However, whether decreasing LFOs increases the government's objective depends both on payment rates and behavioral responses, which we turn to next.

of the defendants is unlikely to substantially improve model fit.

[17] Table A2 reports feature importance for the full model, revealing that the case type and indigency status are the most important predictors of payment behavior in each court.

5.3 Assessing the effects of LFO decreases

We next use the model to measure the size of the population for whom the condition in Theorem 1 is satisfied. We do so by assessing the gross revenue impacts of a \$1 decrease in LFOs, $(D-1) \times f_0(\hat{\theta}(X), D-1) - D \times f_0(\hat{\theta}(X), D)$, for each defendant. If this impact is positive, then (4) is satisfied under $H=0$. We explore sensitivity to $H>0$ below.

Panel (c) of Figure 3 shows the results, broken out again by case category. For criminal traffic and misdemeanor offenses, marginally decreasing LFOs would be revenue-decreasing for the vast majority of defendants. The first-order revenue effect dominates the relatively muted behavioral response; on average this policy change would reduce revenue per defendant by \$0.53. Among felony cases, however, there are many more opportunities for courts to increase revenue by decreasing LFOs. On average, decreasing LFOs by \$1 would decrease revenue by 13 cents. However, this masks substantial heterogeneity—revenue would increase for 31% of defendants.[18,19]

To directly characterize defendants on the right-hand side of the Laffer curve, Table 2 reports descriptive statistics for defendants for whom a \$1 decrease in LFOs would result in a revenue loss of more than \$0.50, a loss of no more than \$0.50, and an increase. Reflecting the more severe charges faced by the latter group, these defendants owe an average of \$785, versus only \$459 for the group with the largest revenue decrease. They are also disproportionately black (49.2 versus 20.8%) and indigent (87.4 versus 17.9%), and are less likely to ever appear in the credit files (16.9 versus 43%). Reducing LFOs for this population would therefore slightly increase court revenue while improving equity in the allocation of LFOs and payment outcomes.

We view the small default costs case as the most appropriate benchmark because, as noted in Section 3.1, courts rarely engage in highly costly enforcement activity. Consistent with this fact, recent work also finds that the consequences of nonpayment itself also appear limited in a wide range of settings (Lieberman et al., 2023). Nevertheless, Figure A5 shows that the share of defendants for whom a \$1 LFO decrease would increase net revenue changes little over plausible values of H. If total costs were \$50 per default, for example, 2%, 7%, and 34% of criminal traffic, misdemeanor, and felony defendants would be on the revenue-decreasing side of the Laffer curve.

Finally, we note that although the defendants are disproportionately disadvantaged, LFO

[18] Figure A4 plots the joint distribution of estimated semi-elasticities and payment rates separately. The condition in Theorem 1 is satisfied for individuals above the 45° line when $H = 0$.

[19] In Figure A7 we estimate the effect of larger, non-marginal changes in fines and fees and find that there are fewer defendants with positive revenue effects.

decreases that broadly target marginalized groups typically would not increase revenue. For example, a $1 decrease in LFOs for indigent felony defendants—who are targeted by specific additional fees for accessing a public defender—would decrease revenue by $0.13, compared to $0.125 for all felony defendants.[20] Thus, while Pareto-improving reductions are possible, the most fruitful avenue towards them appears to be expanding courts' consideration of ability to pay rather than broad-based reductions, although this must be balanced against any administrative and hassle costs.

5.4 Additional validation and robustness

While it is straightforward to validate our model's ability to predict status-quo payment rates, the exercises in the previous subsection require the model to accurately forecast the responses to *changes* in LFO assignments. Since our estimates of these responses rely on non-experimental variation in LFOs, they may be biased by unobserved confounders.[21] To validate the model, one would ideally randomly assign LFOs to defendants and compare their payment rates to the model's predictions. We lack such an experiment, but have attempted to approximate it in Table A4. This table splits our data into increasingly narrow groups defined by their covariates and examines how year-to-year variation in LFO assignments affects both payment rates (panel (a)) and forecasted payment in the model (panel (b)).

By holding the covariates fixed, this exercise isolates variation in LFOs among observably identical defendants driven by policy changes, judge behavior, and other factors. The results show strong evidence in support of the model's predictions. The finest covariate grouping, which splits the sample by county, offense statutes, demographics, and case outcomes, and credit data, generates substantial variation in changes in LFOs. We find that a 10% increase in LFOs year-to-year is associated with a 0.01 p.p. decline in payment rates, for a semi elasticity of 0.1. We also find that the model-predicted changes in payment rates caused by year-to-year variation in LFOs are unbiased predictors actual changes—the estimated coefficient is 0.97. While imperfect, this exercise lends some credence to our estimated payment semi-elasticities.

Our baseline model also assumes that individual-specific LFO payment response functions can be characterized by a second-degree polynomial in LFO amounts. Table A3 assesses the

[20] We only observe indigent status in Brevard and Hillsborough; for this analysis we restrict both calculations to this sample.

[21] If, conditional on our rich set of observable defendant and case characteristics, the court assigns higher LFOs to defendants who are unobservably more likely to pay, the causal forest will underestimate elasticity of payment with respect to LFOs. In this case, which we view as the most likely, we would underestimate the share of defendants on the revenue-decreasing side of the Laffer curve.

sensitivity of our main findings to alternative functional forms, such as log-linear models and higher-degree polynomials, as well as to controlling for other possible treatments. The core conclusions change little across models, although log-linear models, which impose a constant semi-elasticity of payment with respect to D, detect smaller behavioral responses. However, our ability to find defendants on the right-hand side of the Laffer curve depends crucially on the forests' use of covariates. In Figure A6 we replicate our main analysis using a simple OLS model that models payment as function of the same covariates and a second-degree polynomial in LFOs, but does not allow for LFO-covariate interactions. While predictive accuracy remains high (Panel (a)), we can find far fewer defendants for whom the government could reduce fees for while increasing revenue (Panels (b) and (c)).

As we highlight in Corollary 1.1, the welfare implications of LFO-induced changes in revenue are clearer when there are no effects on recidivism. In Section A.2 we estimate a version of our causal forest focused on this outcome and find scant evidence for any effect of LFOs on recidivism, consistent with recent quasi-experimental work (Finlay et al., 2021).

6 Conclusion

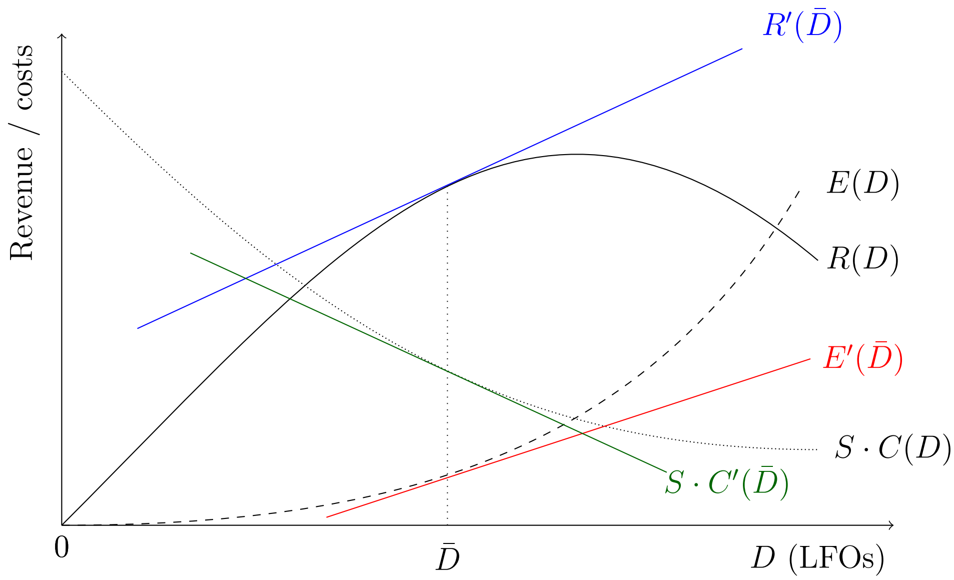
Are the fees, fines, and other legal financial obligations (LFOs) faced by a typical criminal defendant so high that courts would be better off lowering them? Our analysis suggests the answer to this question is generally no. Many defendants, particularly those charged with traffic or misdemeanor offenses, are more likely to pay their LFOs than not. As a result, LFOs raise substantial revenues for local governments and decreasing them across the board would come at a steep cost. This result helps rationalize courts' increasing reliance on LFOs over the past few decades, particularly in Florida, the jurisdiction we study.

Nevertheless, our results also demonstrate that a non-trivial fraction of defendants who are unlikely to pay their LFOs can be identified ex-ante based on their observable characteristics. For some of the most disadvantaged defendants assessed the highest quantities of LFOs, marginal decreases in LFOs may actually *increase* revenue by inducing a small fraction of defendants to begin paying. Doing so would both increase revenue for the courts and improve equity in outcomes. Targeting these defendants requires relatively sophisticated methods, however, since simple tags (e.g., all indigent felony defendants) are insufficiently narrow to isolate groups on the revenue-decreasing side of the Laffer curve.

Despite the revenue costs of decreasing LFOs, local governments may still wish to do so for other reasons not considered in our analysis. LFOs may be inferior to and significantly more regressive than available alternatives, such as sales and property taxes. Concerns about discrimination in earlier parts of the criminal justice pipeline, such as at arrest, may also motivate placing less overall burden on criminal defendants, including through the imposition of hefty LFOs. Alternative schemes not considered here, such as scaling LFOs to defendant's daily income (McDonald et al., 1992), may also be preferable. Our results suggest these arguments may be more compelling motivations for reform than the basic failure of LFOs to deliver revenues to the institutions that impose them.

7 Exhibits

Figure 1: The LFO Laffer Curve



Notes: This figure illustrates the government's problem when setting LFOs to maximize net revenue and minimize the social costs of crime. We model this cost as

$$\underbrace{R(D)}_{\text{Revenue}} - \underbrace{E(D)}_{\text{Default costs}} - \underbrace{SC(D)}_{\text{Social cost of crime}}$$

The solid black curve $R(D)$ traces out revenue per capita as a function of LFOs, the dashed black curve $E(D)$ represents default costs, and the dotted black curve $S \cdot C(D)$ traces out social costs of crime. Due to deterrence and default effects, revenue can be non-increasing in D. The blue line tangent to the revenue curve at $\bar{D}$ describes marginal revenue. The red line tangent to the default costs curve at $\bar{D}$ describes marginal default costs, which are proportional to the gap between average and marginal payment rates net of crime changes. The green line tangent to the crime curve describes marginal crime decreases. At point $\bar{D}$, marginal increases in LFOs increase welfare because $R'(\bar{D}) - E'(\bar{D}) - SC'(\bar{D}) > 0$.

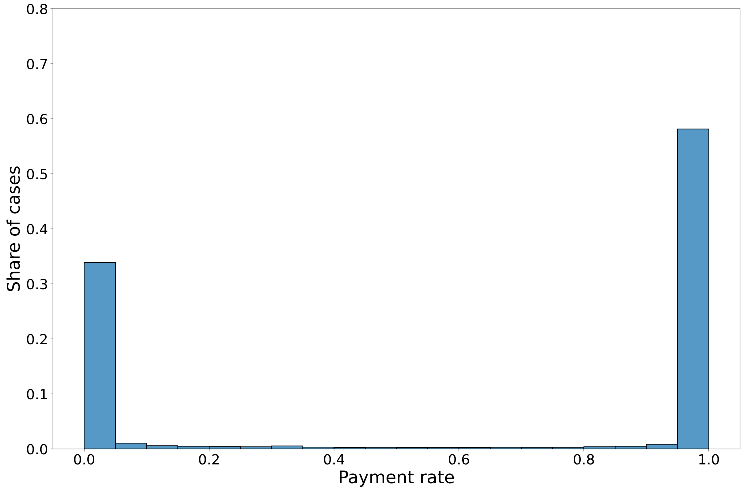
Table 1: Descriptive statistics

	Full sample	First case only			
	All	All	Criminal traffic	Misdemeanor	Felony
Offender characteristics					
Age	33.254	32.872	32.914	32.950	32.156
Male	0.759	0.728	0.727	0.702	0.776
Black	0.382	0.295	0.286	0.282	0.365
White	0.546	0.591	0.555	0.674	0.609
Indigent (qualifies for public def.)	0.338	0.247	0.152	0.309	0.623
Criminal History					
Past criminal traffic	0.524	-	-	-	-
Past felonies	0.811	-	-	-	-
Past misdemeanors	1.050	-	-	-	-
Prior nonpayment	1.408	-	-	-	-
Reoffenses					
Future criminal traffic (3 years)	0.171	0.111	0.129	0.092	0.060
Future felonies (3 years)	0.611	0.172	0.041	0.273	0.638
Future misdemeanors (3 years)	0.799	0.234	0.078	0.472	0.581
LFOs					
Repayment rate	0.471	0.634	0.726	0.582	0.289
Total LFOs assessed	501.072	483.432	408.728	523.048	780.287
Credit score characteristics					
Has a TU match	0.342	0.372	0.398	0.357	0.269
Credit score	519.829	536.281	531.453	554.904	522.017
Number of cases	1,050,336	512,556	322,553	119,312	65,278
Number of defendants	650,313	512,556	322,553	119,312	65,278

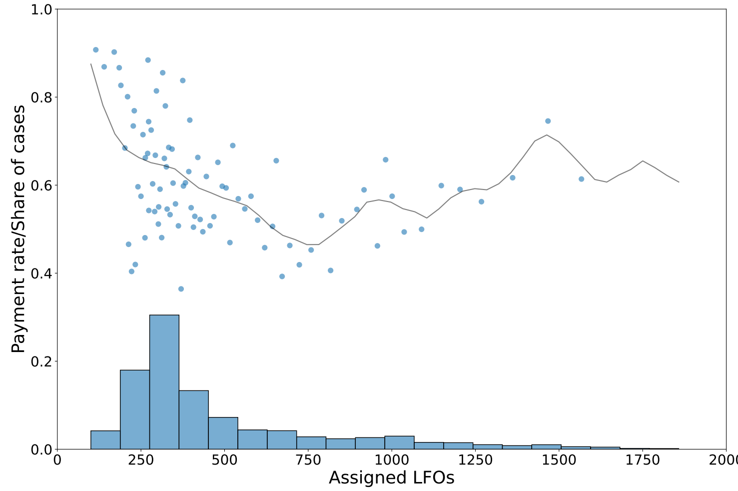
Notes: This table presents descriptive statistics for the full dataset of convicted offenders (Column 1) and the analysis sample of first-time offenders (Column 2). Not all offenders in the full sample appear in the first-time offender subsample because their first offense may have taken place outside of the period we analyze. Columns 3-5 report statistics for first-time offenders convicted of criminal traffic, misdemeanor, and felony offenses, respectively. Information on indigent status is missing in Broward. Criminal histories restrict to the prior three years. Credit scores are conditional on matching to credit report data.

Figure 2: LFO assignments and payment rates

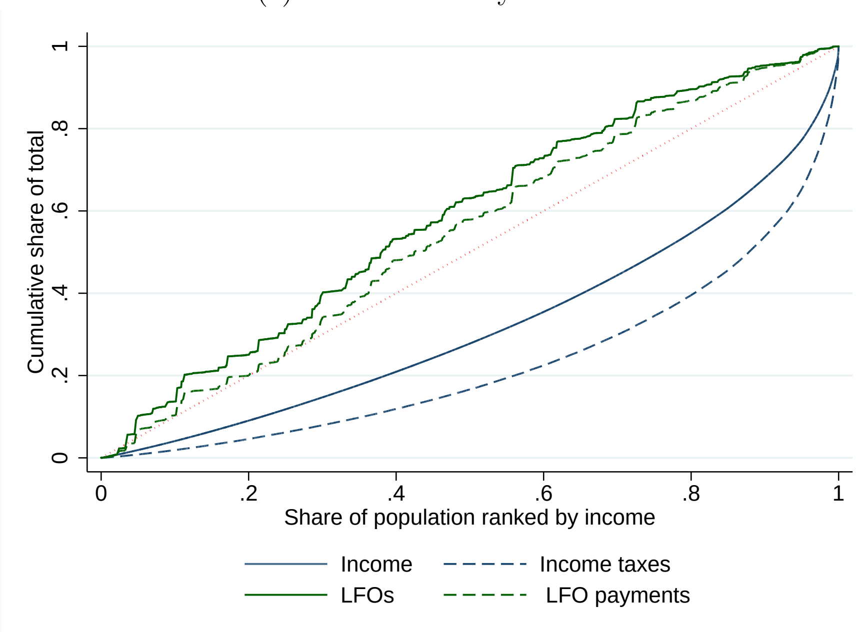
(a) Distribution of payment rates



(b) Payment rates vs. assigned LFOs



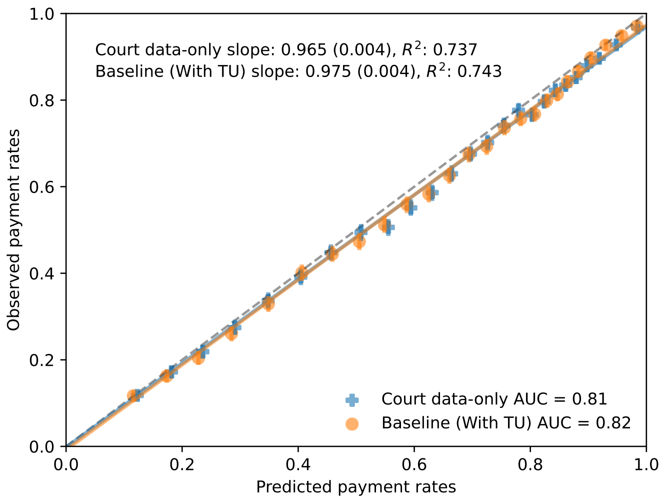
(c) Distribution by income



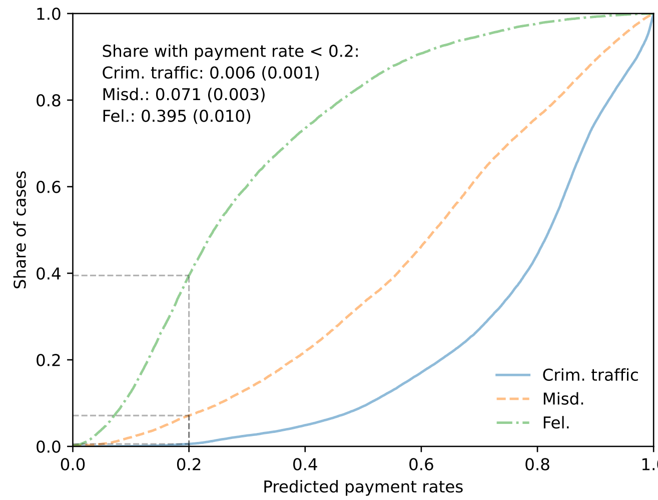
Notes: This figure reports the distribution of assigned LFOs and payment rates for the analysis sample of first-time cases. Panel (a) shows the distribution of payment rates, computed as total payments divided by total LFOs assigned. Panel (b) shows a scatterplot and local linear regression of average payment rates against assigned LFOs. The dots reflect average payment rates in equally sized bins of LFOs. The black line is a local linear fit. The histogram shows the distribution of assigned LFOs. Panel (c) reports the cumulative share of total LFOs assigned and paid by population ranked increasingly by zipcode income. For comparison, the figure reports the same statistics for 2020 taxable income and federal income taxes for the zipcodes in our sample using data from the SOI Tax Stats website: `https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi`.

Figure 3: Identifying populations on the wrong side of the Laffer curve

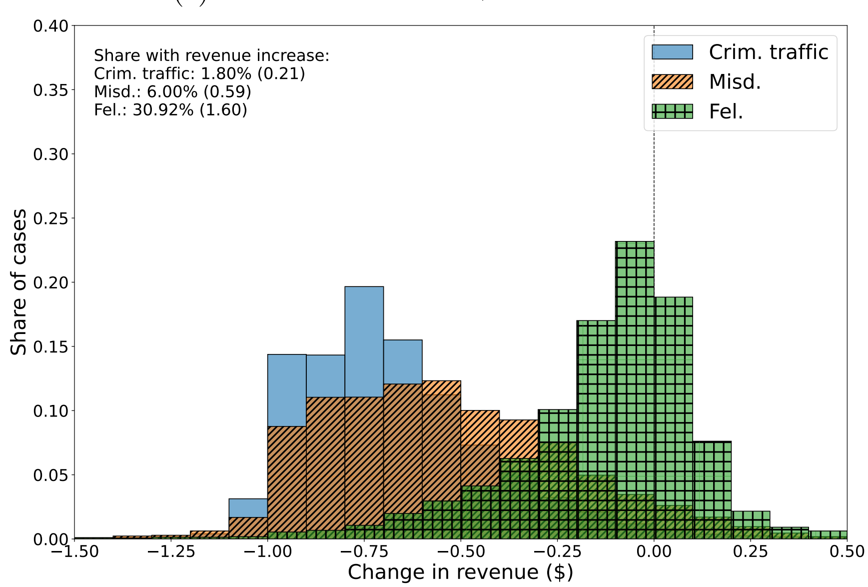
(a) Out-of-sample model fit



(b) Predicted payment rates



(c) Revenue effects of $1 LFO decrease



Notes: This figure reports model fits and CDFs of predicted outcomes for the causal forest model of payment behavior. We report results for the model using only case and defendant characteristics (*court data only*) and the model with credit report variables (*with TU*). All results are computed on the test sample not used to fit the models. Panel (a) reports the within-court linear fit between predicted and actual values and the Area Under the Curve (AUC), a measure of predictive accuracy, when binarizing predictions and payments at 50%. Panel (b) displays the CDF of predicted payment rates by type of case for the model with credit creport variables. Panel (c) plots histograms of the revenue effects of a $1 decrease in LFOs, again estimated using the model with credit report variables. Standard errors in parentheses come from 500 bootstrap repetitions of the estimation procedure.

Table 2: Case characteristics across the Laffer curve

	Full sample	Δ Revenues for 1$ LFO reduction		
	All	< -0.5	$\in [-0.5, 0]$	> 0
Offender Characteristics				
Age	33.839	34.967	32.464	31.030
		(0.086)	(0.149)	(0.300)
Male	0.710	0.696	0.718	0.783
		(0.002)	(0.004)	(0.007)
Black	0.303	0.208	0.432	0.492
		(0.004)	(0.007)	(0.013)
White	0.586	0.644	0.508	0.473
		(0.004)	(0.006)	(0.012)
Indigent (qualifies for public def.)	0.453	0.179	0.701	0.874
		(0.007)	(0.010)	(0.015)
Case characteristics				
Criminal Traffic	0.500	0.663	0.298	0.109
		(0.005)	(0.007)	(0.011)
Misdemeanor	0.312	0.307	0.345	0.226
		(0.005)	(0.008)	(0.015)
Felony	0.175	0.024	0.332	0.653
		(0.002)	(0.007)	(0.018)
Reoffenses				
Future criminal traffic (3 years)	0.082	0.086	0.084	0.050
		(0.001)	(0.002)	(0.003)
Future misdemeanors (3 years)	0.265	0.151	0.400	0.558
		(0.002)	(0.007)	(0.017)
Future felonies (3 years)	0.171	0.070	0.280	0.479
		(0.002)	(0.007)	(0.018)
LFOs				
Total LFOs assessed	526.370	458.897	585.323	785.009
		(3.226)	(5.375)	(12.446)
Repayment rate	0.612	0.775	0.413	0.204
		(0.002)	(0.004)	(0.006)
Change in revenues	-0.533	-0.771	-0.265	0.145
		(0.002)	(0.005)	(0.006)
Credit score characteristics				
Has a TU match	0.357	0.430	0.271	0.169
		(0.003)	(0.005)	(0.007)
Credit score	532.168	553.504	482.078	451.957
		(0.809)	(2.286)	(5.350)
Number of defendants	108,706	64,896	34,816	8,994

Notes: This table reports descriptive statistics for the test sample split by the predicted change in revenue for a $1 reduction in LFOs. For credit report-related variables, we report the share of successful matches, then report the credit score conditional on a successful match. Standard errors in parentheses come from 500 bootstrap repetitions of the entire estimation procedure.

References

Athey, Susan, Julie Tibshirani, and Stefan Wager, "Generalized random forests," *The Annals of Statistics*, 2019, *47* (2), 1148–1178.

Becker, Gary S, "Crime and punishment: An economic approach," *Journal of political economy*, 1968, *76* (2), 169–217.

Breiman, Leo, "Random forests," *Machine learning*, 2001, *45* (1), 5–32.

Department of Justice, "Survey of Inmates of Federal Correctional Facilities, 1991," 1993.

_ , "Survey of Inmates of State Correctional Facilities, 1991: [United States]," 1993.

_ , "Survey of Prison Inmates, United States, 2016," 2021.

Diller, Rebekah, *The hidden costs of Florida's criminal justice fees*, New York: Brennan Center for Justice, 2010.

_ , Alicia Bannon, and Mitali Nagrecha, "Criminal justice debt: A barrier to reentry," 2010.

Emanuel, Natalia and Helen Ho, "Tripping through hoops: The effect of violating compulsory government procedures," *American Economic Journal: Economic Policy*, 2023.

FCCC, "2019 Annual Assessments and Collections Report," Annual Report, The Florida Court Clerks & Comptrollers 2019.

Finlay, Keith, Matthew Gross, , Carl Liebman, Elizabeth Luh, and Michael Mueller-Smith, "The Impact of Criminal Financial Sanctions: A Multi-State Analysis of Survey and Administrative Data," Working Paper 2023.

_ , _ , Elizabeth Luh, and Michael Mueller-Smith, "The Impact of Financial Sanctions in the U.S. Justice System: Regression Discontinuity Evidence from Michigan's Driver Responsibility Program," Working Paper 2021.

Garin, Andrew, Dmitri Koustas, Carl McPherson, Samuel Norris, Matthew Pecenco, Evan K. Rose, Yotam Shem-Tov, and Jeffrey Weaver, "The Impact of Incarceration on Employment and Earnings," 2023.

Gentzler, Ryan, "The Cost Trap: How Excessive Fees Lock Oklahomans Into the Criminal Justice System without Boosting State Revenue: Executive Summary," 2017.

Giles, Tyler, "The Government Revenue, Recidivism, and Financial Health Effects of Criminal Fines and Fees," Working Paper 2023.

Gonçalves, Felipe M and Steven Mello, "Police discretion and public safety," Technical Report, National Bureau of Economic Research 2023.

Harris, Alexes, Heather Evans, and Katherine Beckett, "Drawing Blood from Stones: Legal Debt and Social Inequality in the Contemporary United States," *American Journal of Sociology*, 2010, *115* (6), 1753–1799.

_ , Mary Pattillo, and Bryan L Sykes, "Studying the System of Monetary Sanctions," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2022, *8* (1), 1–33.

Lieberman, Carl, Elizabeth Luh, and Michael Mueller-Smith, "Criminal court fees, earnings, and expenditures: A multi-state RD analysis of survey and administrative data," Technical Report 2023.

McDonald, Douglas, Judith Greene, and Charles Worzella, *Day fines in American courts: the Staten Island and Milwaukee experiments*, Vol. 100, US Department of Justice, Office of Justice Programs, National Institute of Justice, 1992.

Pager, Devah, Rebecca Goldstein, Helen Ho, and Bruce Western, "Criminalizing Poverty: The Consequences of Court Fees in a Randomized Experiment," *American Sociological Review*, 2022.

Ruback, R Barry, Stacy N Hoskins, Alison C Cares, and Ben Feldmeyer, "Perception and payment of economic sanctions: A survey of offenders," *Fed. Probation*, 2006, *70*, 26.

TransUnion, "What Is a Good Credit Score?," `https://www.transunion.com/blog/credit-advice/whats-considered-a-good-credit-score` 2023. Accessed: 2023-04-04.

Traxler, Christian and Libor Dusek, "Fines, Non-Payment, and Revenues: Evidence from Speeding Tickets," *Available at SSRN 4281384*, 2022.

A Appendix

A.1 Proofs

Proof of Theorem 1

The marginal change in the government's objective associated with an increase in D is given by:

$$\begin{aligned} W'(D) &= R'(D) - H\left(\frac{R(D)/D - R'(D)}{D} + C'(D)\right) - SC'(D) \\ &= R'(D)\left(1 + \frac{H}{D}\right) - \frac{H}{D}\frac{R(D)}{D} - (H+S)C'(D) \end{aligned}$$

Marginal revenue can be written as:

$$R'(D) = \frac{R(D)}{D} + \frac{\partial Pr(U(D) < P, P < B)}{\partial log(D)} + DC'(D)$$

This implies:

$$W'(D) = \frac{R(D)}{D} + \left(1 + \frac{H}{D}\right)\frac{\partial Pr(U(D) < P, P < B)}{\partial log(D)} + (D-S)C'(D)$$

Thus if $S \geq D$ and $C'(D) \leq 0$, $W'(D) \leq 0$ implies that:

$$\frac{R(D)}{D} \leq \left(1 + \frac{H}{D}\right)\frac{-\partial Pr(U(D) < P, P < B)}{\partial log(D)} \tag{A1}$$

The semi-elasticity on the right-hand side of this expression represents the change in payment rates among offenders who would commit crimes regardless of the level of D. To rewrite the expression in terms of the semi-elasticity among offenders, note that

$$\begin{aligned}
\frac{\partial Pr[U(D) < P|F(D) < B]}{\partial log(D)} &= \frac{\partial}{\partial log(D)} \frac{Pr[U(D) < P, F(D) < B]}{Pr(F(D) < B)} \\
&= \frac{\partial}{\partial log(D)} \frac{Pr[U(D) < P, P < B] + Pr[U(D) < B < P]}{C(D)} \\
&= \frac{\partial Pr[U(D) < P, P < B]}{\partial log(D)} \frac{1}{C(D)} + \frac{\partial Pr[U(D) < B < P]}{\partial log(D)} \frac{1}{C(D)} \\
&\qquad - \frac{\Pr[U(D) < P, C(D){=}1]}{C(D)^2} \frac{\partial C(D)}{\partial log(D)} \\
&= \frac{\partial Pr[U(D) < P, P < B]}{\partial log(D)} \frac{1}{C(D)} \\
&\qquad + \frac{\partial C(D)}{\partial log(D)} \frac{1}{C(D)} \Big(1 - Pr[U(D) < P|C(D){=}1]\Big) \\
&\leq \frac{\partial Pr[U(D) < P, P < B]}{\partial log(D)} \frac{1}{C(D)}
\end{aligned}$$

where the fourth lines follows because $\frac{\partial C(D)}{\partial log(D)} = \frac{\partial Pr[U(D) < B < P]}{\partial log(D)}$ and the fifth line follows because $\partial C(D)/\partial log(D) \leq 0$. Plugging into (A1) and rearranging gives the expression in Theorem 1.

Proof of Corollary 1.1

First, note that when $C(D) = C$, the expression for the marginal change in the government's objective simplifies to

$$W'(D) = \frac{R(D)}{D} + \left(1 + \frac{H}{D}\right) \frac{\partial Pr(U(D) < P, P < B)}{\partial log(D)}$$

Similarly, we have that

$$\frac{\partial Pr[U(D) < P|C(D){=}1]}{\partial log(D)} = \frac{\partial Pr[U(D) < P, P < B]}{\partial log(D)} \frac{1}{C(D)}$$

and so (A1) can be written with an equality. Combining gives the expression in Corollary 1.1.

Proof of Corollary 1.2

Note that $U'(D) \geq 0$ implies that $\eta(D) \geq 0$, and so (4) is satisfied when $\frac{R(D)D}{C(D)} = 0$.

Appendix Figures

Figure A1: Example LFO worksheet

1/1

Reserved for Recording

IN THE COUNTY COURT, IN AND FOR BREVARD COUNTY, FLORIDA

STATE OF FLORIDA

Case Number: 05-2009-CT-[redacted]-AXXX-XX

vs.

[redacted], DOB:

[redacted]

MELBOURNE, FL 329361874

Filed in Open Court on September 23, 2009 10:22 am.

C. Swift, Deputy Clerk

ORDER FOR FINE / COSTS / FEES

The Defendant is hereby ordered to pay the following sums by March 23, 2010 :

FLORIDA STATUTE		AMOUNT	FUND
	$	50.00	CRIM TRAF FINE WAG
	$	104.00	NONMOVING VIOL 322 & 320
938.04	$	2.50	5% Additional Costs
775.083(2)	$	20.00	Crime Prevention Fund Traffic
938.06	$	20.00	Crime Stopper Trust Fund
939.185	$	65.00	Additional Court Cost Co. Ord. 07-37
318.18(11)(b)	$	3.00	Brevard Police Testing and Certification Account
938.05(1)(b)	$	10.00	Clerk of Court Trust Fund/DOR/General Revenue
938.03	$	50.00	Crimes Compensation Trust Fund
938.05	$	50.00	Local Government Criminal Justice Trust Fund
938.19	$	3.00	Teen Court Co. Ord. 07-37
938.27(8)	$	50.00	Costs of Prosecution

DONE AND ORDERED at Brevard County, Florida, on September 23, 2009.

CATHLEEN B. CLARKE (DIV. 8), County Judge

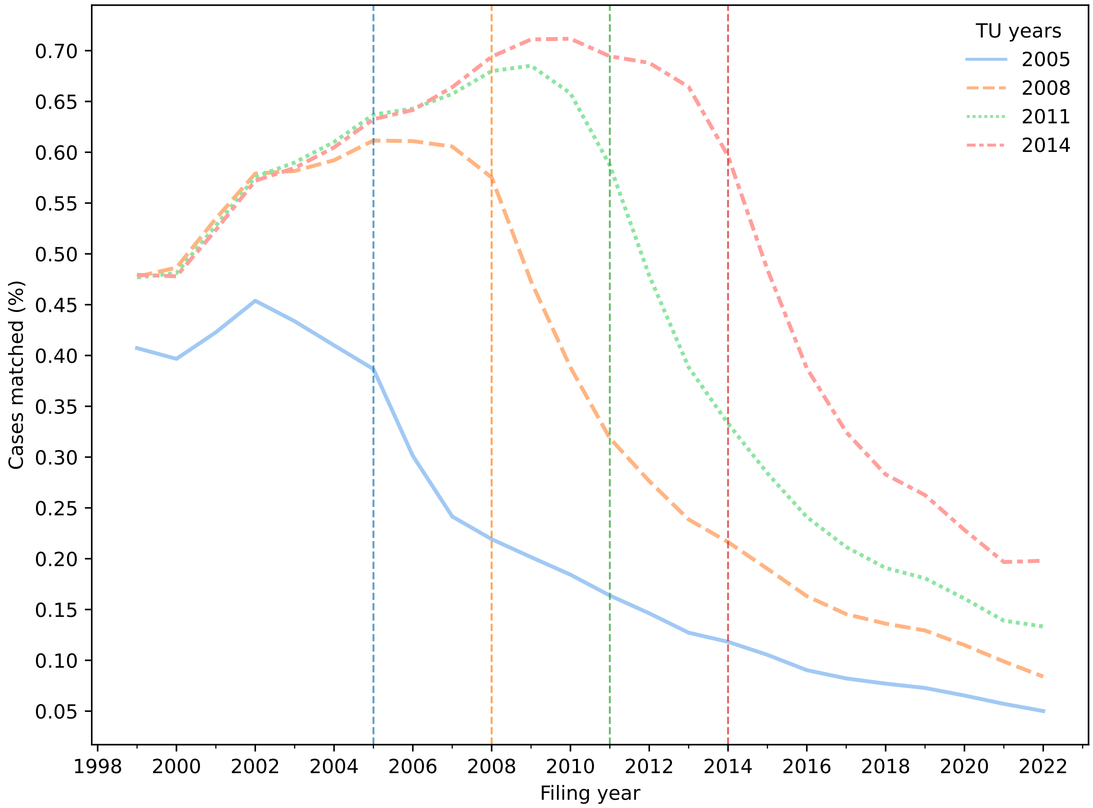
Case # 05-2009-CT-[redacted]-AXXX-XX
Document Page # 6
[redacted]

* *Items marked with *COP, *COCC, and *COS are Conditions of Probation, Community Control, and Suspension*

le JME

Notes: This figure shows an example court order for LFOs for a criminal traffic case disposed in 2009. The defendant's name, date of birth, and address have been redacted, along with the case number. In this case that defendant was given six months to pay the total amount.

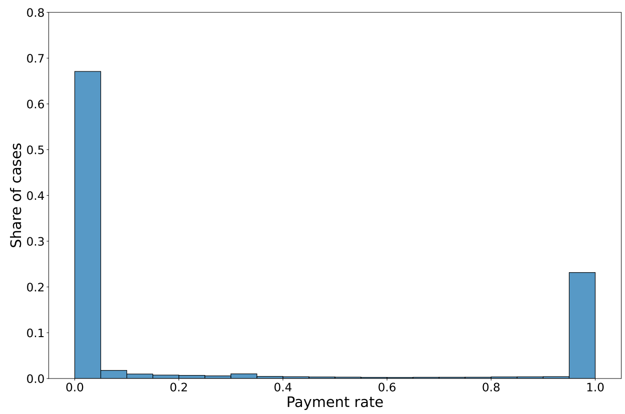
Figure A2: TransUnion match rates over time



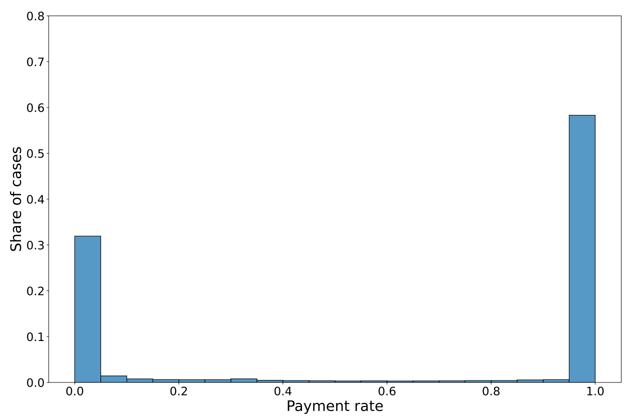
Notes: This figure reports the match rates for cases to each of the 2005, 2008, 2011, and 2014 TransUnion credit archives separately by year of filing.

Figure A3: Payment rates for repeat offenders by prior payment history

(a) 2nd case, prior nonpayer



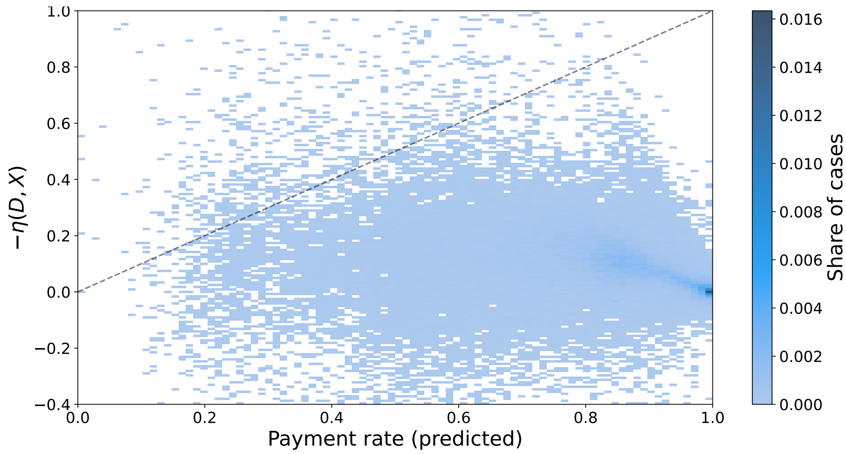
(b) 2nd case, prior payer



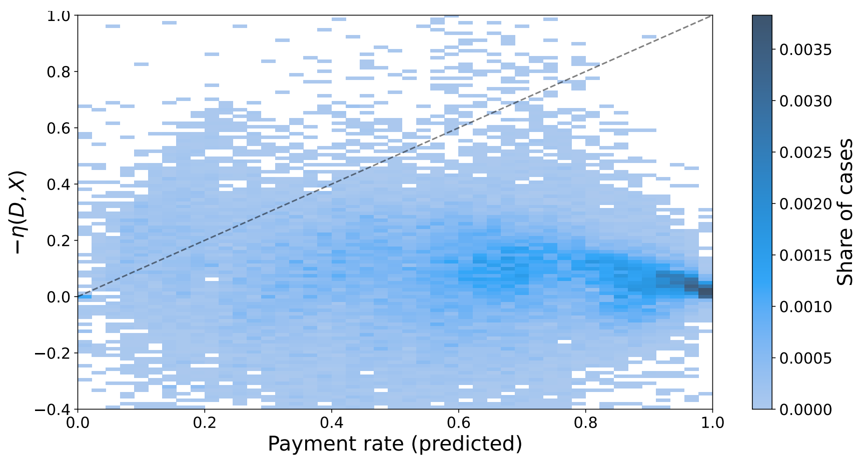
Notes: This figure plots the distribution of payment rates for second-time offenders who did not pay their prior LFOs (Panel A) and did pay them (Panel B).

Figure A4: Predicted semi-elasticities vs. payment levels

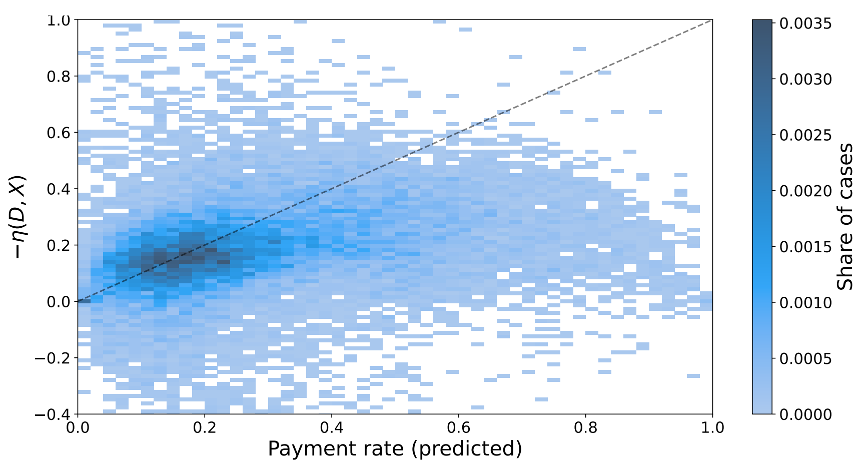
(a) Criminal traffic cases



(b) Misdemeanor cases

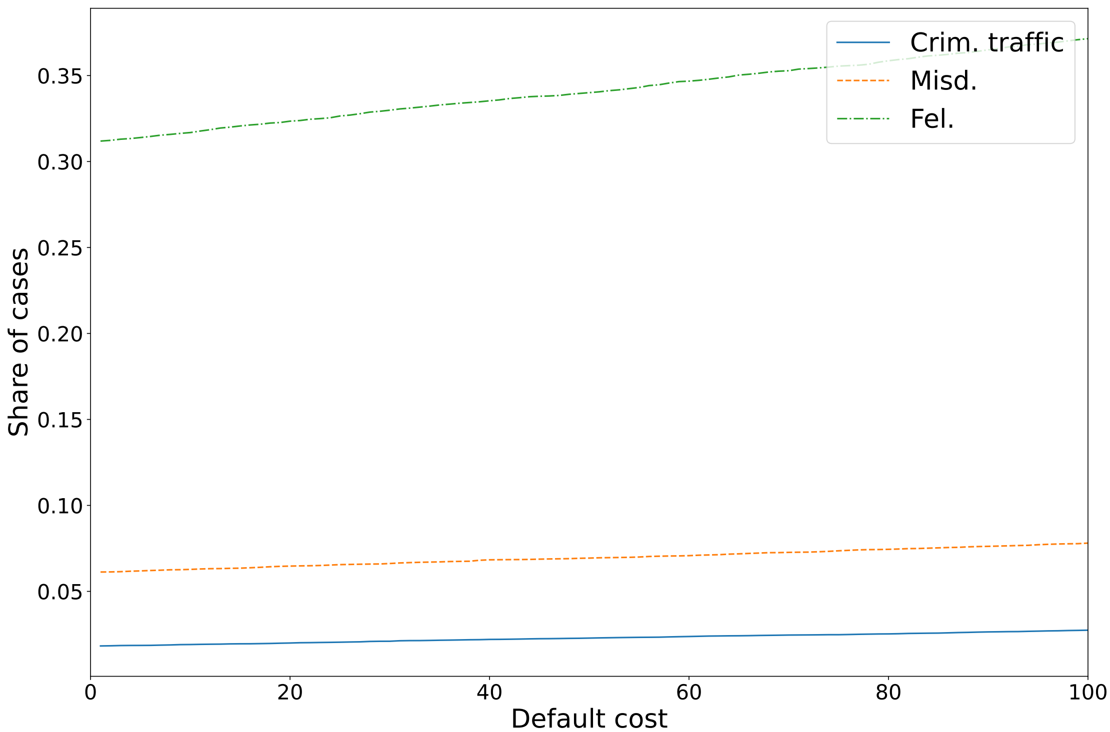


(c) Felony cases



Notes: This figure plots the joint distribution of predicted payment semi-elasiticities and payment rates by case type. All cases above the dotted black lines have positive predicted revenue impacts of a marginal decrease in LFOs. This implies the condition in Theorem 1 is satisfied under $H = 0$.

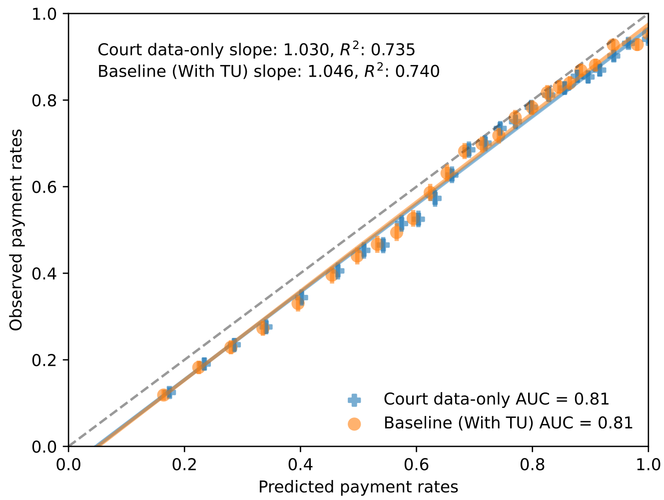
Figure A5: Share of positive net revenue effects of $1 LFO decrease as a function of default costs



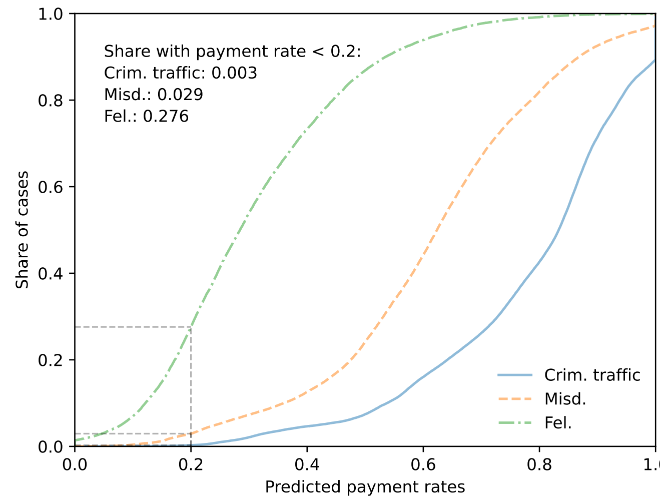
Notes: This figure shows the share of defendants by case type with a positive net revenue effect when reducing LFOs by $1 as a function of default costs, H. The share of defendants with positive net revenues is the share of defendants for whom the condition in 1 is satisfied.

Figure A6: Identifying populations on the revenue-decreasing side of the Laffer curve - OLS

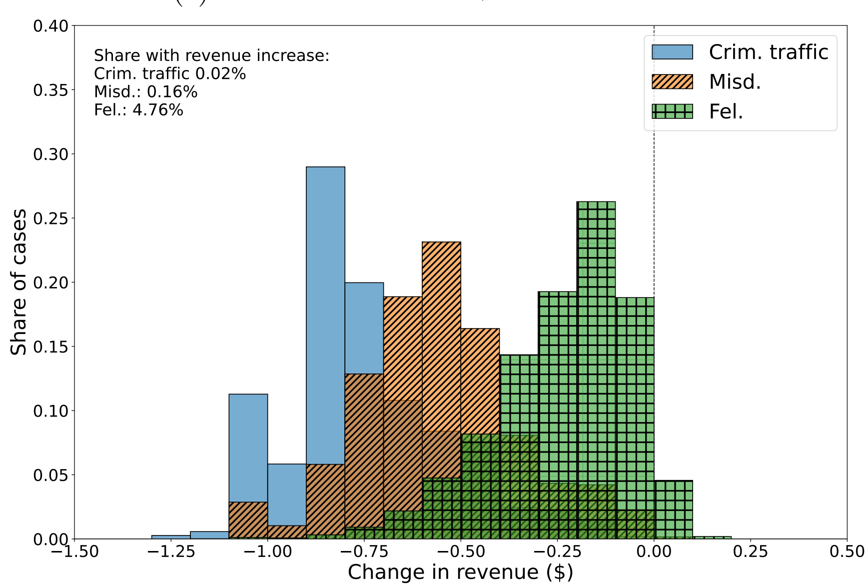
(a) Out-of-sample model fit



(b) Predicted payment rates



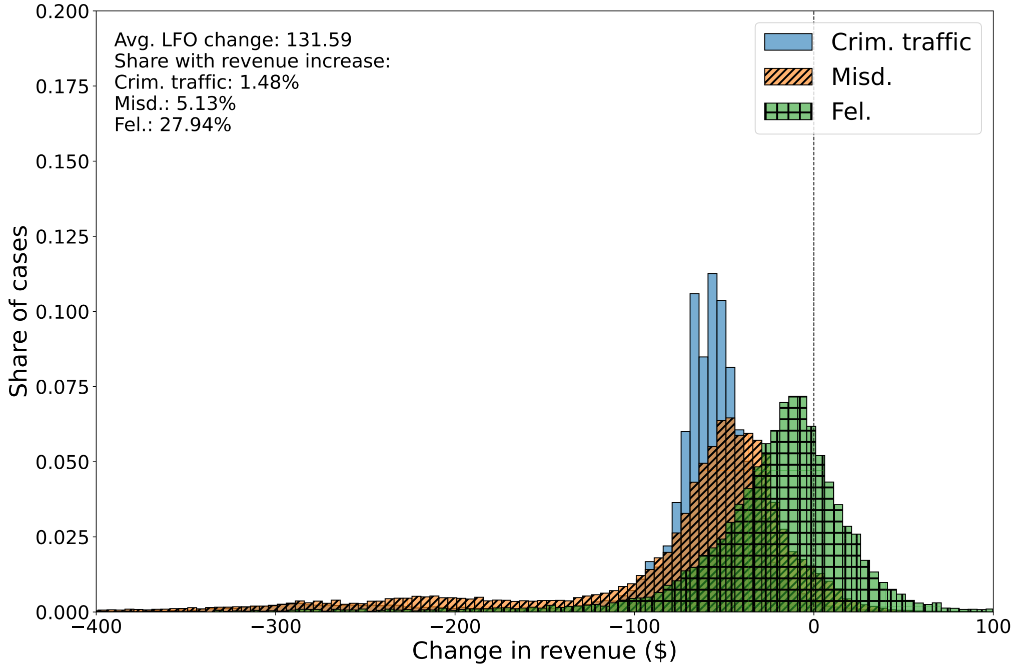
(c) Revenue effects of $1 LFO decrease



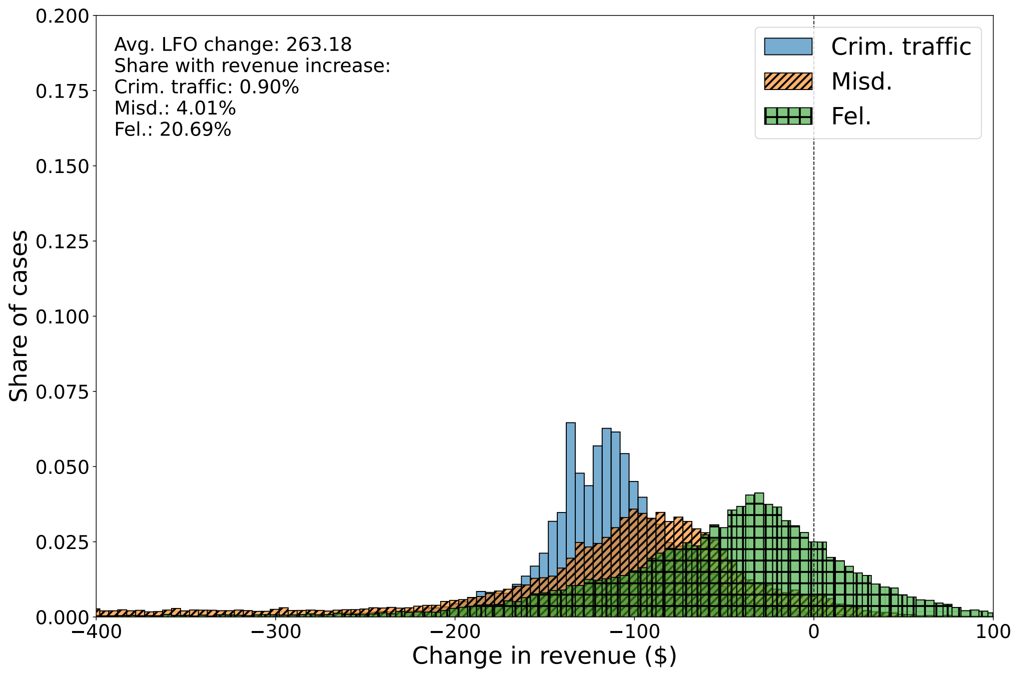
Notes: This figure reports model fits and CDFs of predicted outcomes for the OLS model of payment behavior. We report results for the model using only case and defendant characteristics (*court data only*) and the model with credit report variables (*with TU*). All results are computed on the test sample not used to fit the models. Panel (a) reports the within-court linear fit between predicted and actual values and the Area Under the Curve (AUC), a measure of predictive accuracy, when binarizing predictions and payments at 50%. Panel (b) displays the CDF of predicted payment rates by type of case for the model with credit creport variables. Panel (c) plots histograms of the revenue effects of a $1 decrease in LFOs, again estimated using the model with credit report variables. Standard errors in parentheses come from 500 bootstrap repetitions of the estimation procedure.

Figure A7: Impacts of larger reductions in LFOS

(a) Revenue effects of 25% LFO decrease



(b) Revenue effects of 50% LFO decrease



Notes: This figure plots histograms of the revenue effects of a 25% (panel (a)) and 50% (panel (b)) decrease in LFOs estimated using the model with credit report variables. The methodology is the same as in Figure 3.

Appendix Tables

Table A1: Descriptive statistics by county

	Full sample	First case only			
	All	All	Brevard	Broward	Hillsborough
Offender characteristics					
Age	33.254	32.872	33.410	33.298	32.247
Male	0.759	0.728	0.703	0.702	0.762
Black	0.382	0.295	0.200	0.354	0.289
White	0.546	0.591	0.755	0.578	0.524
Indigent (qualifies for public def.)	0.338	0.247	0.368	-	0.404
Criminal History					
Past criminal traffic	0.524	-	-	-	-
Past misdemeanors	1.050	-	-	-	-
Past felonies	0.811	-	-	-	-
Prior nonpayment	1.408	-	-	-	-
Reoffenses					
Future criminal traffic (3 years)	0.171	0.111	0.130	0.169	0.052
Future misdemeanors (3 years)	0.799	0.234	0.331	0.112	0.296
Future felonies (3 years)	0.611	0.172	0.223	0.062	0.243
Case characteristics					
Criminal Traffic	0.466	0.629	0.365	0.610	0.771
Misdemeanor	0.293	0.233	0.456	0.274	0.092
Felony	0.228	0.127	0.179	0.097	0.130
LFOs					
Repayment rate	0.471	0.634	0.671	0.674	0.582
Total LFOs assessed	501.072	483.432	602.061	404.500	495.967
Credit score characteristics					
Has a TU match	0.342	0.372	0.297	0.414	0.372
Credit score	519.829	536.281	559.151	533.156	530.647
Number of cases	1,050,336	512,556	103,534	190,332	218,690
Number of defendants	650,313	512,556	103,534	190,332	218,690

Notes: This table presents descriptive statistics for the full dataset of convicted offenders (Column 1) and the analysis sample of first-time offenders (Column 2). Not all offenders in the full sample appear in the first-time offender subsample because their first offense may have taken place outside of the period we analyze. Columns 3-5 report statistics for first-time offenders in each county. Information on indigent status is missing in Broward. Criminal histories restrict to the prior three years. Credit scores are conditional on matching to credit report data.

Table A2: Causal forest feature importance

	All	Brevard	Broward	Hillsborough
DUI (CJARS)	0.491	0.789	0.001	0.683
Felony (case type)	0.227	0.040	0.616	0.025
Indigent	0.102	0.014	-	0.191
Criminal Traffic (CJARS)	0.057	0.007	0.163	0.000
Adjudication Withheld	0.023	0.047	0.022	0.000
DL Suspended	0.021	0.001	0.000	0.062
Filing year	0.018	0.008	0.043	0.004
Share of trades never delinquent (TU)	0.015	0.020	0.017	0.007
Credit Score (TU)	0.011	0.008	0.022	0.002
Misdemeanor (case type)	0.007	0.001	0.018	0.002
Age	0.007	0.010	0.009	0.001
Population (zipcode)	0.006	0.008	0.008	0.003
Criminal Traffic (case type)	0.005	0.000	0.011	0.004
Total balance of all trades (TU)	0.005	0.004	0.010	0.002
Median income (zipcode)	0.005	0.006	0.007	0.001
Average household income (zipcode)	0.005	0.005	0.007	0.001
Black pop. share (zipcode)	0.004	0.005	0.006	0.003
Months on file (TU)	0.004	0.003	0.009	0.000
Months since most recent inquiry (TU)	0.004	0.003	0.008	0.001
White pop. share (zipcode)	0.004	0.005	0.006	0.000
Race - Black	0.003	0.003	0.006	0.000
Median home value (zipcode)	0.003	0.004	-	0.002
Number of inquiries (TU)	0.002	0.001	0.003	0.001
Public order (CJARS)	0.002	0.001	0.002	0.002
Flag for multiple first cases	0.001	0.001	0.001	0.000
Drugs (CJARS)	0.001	0.001	0.001	0.000
Gender - Male	0.001	0.000	0.001	0.001
Violent (CJARS)	0.001	0.001	0.001	0.001
Highest delinquency ever on a trade (TU)	0.001	0.001	0.001	0.000
Property (CJARS)	0.000	0.001	0.001	0.000
Gender - Female	0.000	0.000	0.000	0.001
Inquiries flag (TU)	0.000	0.000	0.001	0.000
Race - White	0.000	0.001	0.000	0.000
Race - Unknown	0.000	0.000	0.000	0.000
Home equity flag (TU)	0.000	0.000	0.000	0.000
Other (case type)	0.000	0.000	-	0.000
Has a TU match (TU)	0.000	0.000	0.000	0.000
Race - Hispanic	0.000	0.000	0.000	0.000
Race - Pacific Islander	0.000	-	0.000	0.000
Race - Native	0.000	0.000	-	-
Race - Indian	0.000	-	0.000	0.000
High risk of fraud flag (TU)	0.000	0.000	0.000	0.000
Race - Asian	0.000	0.000	0.000	0.000
Gender - Unknown	0.000	0.000	-	0.000

Notes: This table reports feature importance for the causal forest model in each court and on average. The "-" symbol represents that the covariate is missing in that county. Variables with the (CJARS) tag are classifications of the case description using the CJARS algorithm available here. Variables with the (zipcode) tag are at the zipcode level. Flag for multiple cases is a dummy equal to 1 when an offender had multiple co-occurring first cases; in such situation we kept the one with the biggest LFO. Credit date variables are flagged with (TU). A trade is a debt product such as a credit card or car loan; see here for examples.

Table A3: Specification comparison for causal forests

	(1)	(2)	(3)	(4)	(5)
	d = 2	d = 1, log	d = 3	d = 2, no TU	d = 2, incar/prob
Model fit, R^2	0.743	0.744	0.743	0.737	0.753
Model fit, Slope	0.975	0.984	0.968	0.965	0.981
Below 20%, Criminal Traffic	0.006	0.005	0.006	0.006	0.010
Below 20%, Misdemeanors	0.071	0.070	0.075	0.063	0.083
Below 20%, Felonies	0.395	0.385	0.398	0.374	0.491
Positive revenues, Criminal Traffic	0.018	0.006	0.048	0.026	0.032
Positive revenues, Misdemeanors	0.060	0.020	0.087	0.064	0.034
Positive revenues, Felonies	0.309	0.265	0.330	0.324	0.272
With TU variables	Yes	Yes	Yes	No	Yes
Incarceration/Probation dummies	No	No	No	No	Yes

Notes: This table reports the sensitivity of the main results to different causal forest specifications. Each column represents a different specification of our causal forest estimator: (1) is our baseline specification with a second-degree polynomial in LFOs; (2) uses a log-linear specification; (3) uses a third-degree polynomial in LFOs; (4) uses our baseline specification without TU variables; (5) uses our baseline specification including incarceration and probation dummies. Reported model fits are out of sample. Below 20% refers to the share of offenders by case type with less than 20% predicted payment rates. Positive revenues refers to the share of offenders by case type with positive revenue effects of a 1$ LFO reduction.

Table A4: First-differences regressions within covariate groups as validation exercise

	County	+ off. type	+ statute	+ demos	+ case outcome	+ has cred. score
	(1)	(2)	(3)	(4)	(5)	(6)
	(a) Semi-elasticity estimates					
Change in log(LFOs)	-0.360	-0.138**	-0.139***	-0.119***	-0.103***	-0.104***
	(0.156)	(0.0369)	(0.0322)	(0.0136)	(0.0110)	(0.00924)
	(b) Payment model validation					
Change in predicted payment	2.649	2.074	1.226**	1.135***	1.163***	0.974***
	(5.068)	(5.873)	(0.385)	(0.151)	(0.138)	(0.0871)
N	33	207	1242	8084	12678	18905
First-stage F	0.135	0.0679	4.708	80.55	137.1	449.8
P-value for test = 1	0.745	0.855	0.558	0.373	0.238	0.770

Notes: This table uses changes in LFOs over time among defendants with the same observable characteristics to estimate average payment semi-elasticities (panel a) and validate the causal forest payment model's predictions of counterfactual payment rates (panel b). Each column collapses the data by covariate group and year. Panel a regresses the first-difference in mean payment rates on the first-difference in mean log LFOs, isolating variation in LFO assignments among defendants in each covariate group due to policy changes and other factors. Panel b instruments for the change in predicted payments from the causal forest model with the change in LFOs. If the model correctly predicts payment rates for these defendants under alternative LFOs, the coefficient should be one. The final rows of the table show first-stage F-statistics and p-values for tests that the estimate in panel b equals 1. Column 1 forms covariate groups using county. Column 2 adds coarse offense type (e.g., drug, DUI, property, etc.). Column 3 adds the specific statute of the most serious offense charged. Column 4 adds indigent status, race, and gender. Column 5 adds case outcomes such as whether the defendant was incarcerated. Column 6 adds an indicator for having a credit score. Standard errors clustered by covariate group are shown in parentheses. Predicted payments for each year t are formed from models fit on data from year $t-1$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Recidivism

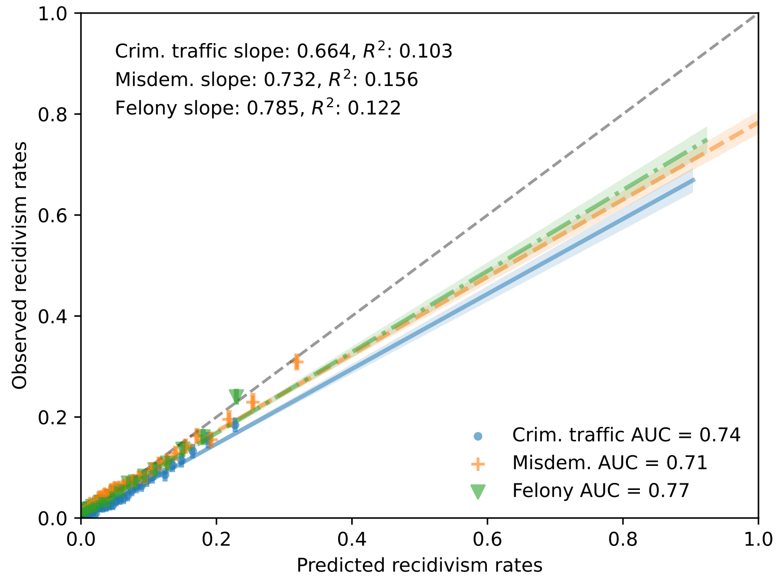
Our analysis assumes that there is no effect of LFOs on recidivism, in line with recent quasi-experimental work (Finlay et al., 2023). In this section we use a causal forest to directly estimate this effect in our setting, and similarly find little evidence that LFOs affect recidivism.

The recidivism models hew as closely as possible to the baseline models; we simply replace the payment rate with a binary indicator for recidivating (measured as any new charges in our data) within three years. Figure A8 displays the results. Panel (a) displays charge type-specific regressions of recidivism on model-predicted recidivism estimated in the hold-out test sample. LFOs and other characteristics have relatively scant predictive power on recidivism; across court cases the R^2 ranges from 0.103 to 0.156. In contrast, the causal forest had good predictive power over payment, with an out-of-sample regression of payment on predicted payment resulting in an R^2 of 0.743 (Figure 3).

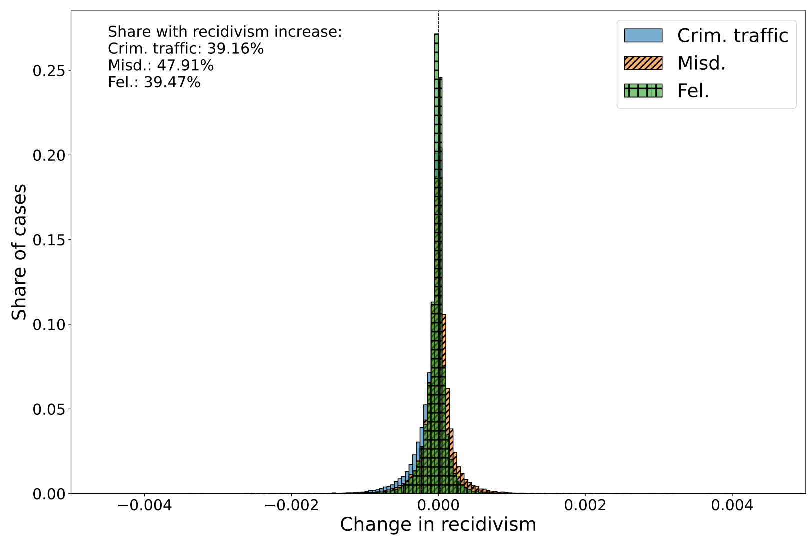
Consistent with this, Panel (b) plots the estimated recidivism effects of a \$1 decrease in LFOs. The analysis reveals that there are no substantive effects of LFOs on recidivism for any identifiable groups; for each type of offense the effects are squarely centered on zero and are nearly never larger than 0.001 in absolutely value. Table A5 shows the estimated effects of an increase in LFOs. For readability we report it as the effect of a \$100 increase, but we estimate it by scaling the \$1 effect by 100 to maximize comparability with the rest of our analysis. We find that decreasing LFOs would slightly *decrease* recidivism, both overall and among the groups we predict would have a positive revenue response. We conclude that consistent with the quasi-experimental evidence, LFOs do not appear to substantively affect recidivism, and if anything accounting for recidivism would slightly increase the set of defendants for whom governments could lower fees on while increasing welfare.

Figure A8: Causal forest estimates of effect of LFOs on recidivism

(a) Out-of-sample model fit



(b) Recidivism effects of $100 LFO decrease



Notes: This figure reports model fits and CDFs of predicted outcomes for the causal forest model of recidivism behavior. We report three models, one for each crime type prediction. All results are computed on the test sample not used to fit the models. Panel (a) reports the within-court linear fit between predicted and actual values and the Area Under the Curve (AUC), a measure of predictive accuracy, when binarizing predictions at 50%. Panel (b) plots histograms of the revenue effects of a $1 decrease in LFOs, again estimated using the model with credit report variables. Standard errors in parenthesis come from 500 bootstrap repetitions of the estimation procedure.

Table A5: Effect of LFO decreases on recidivism by revenue impacts

	Full sample				Δ Revenues for 1$ LFO reduction											
					< 0.5				$\in [-0.5, 0]$				> 0			
	Average	p10	p50	p90	Average	p10	p50	p90	Average	p10	p50	p90	Average	p10	p50	p90
Criminal Traffic (3 year)	-0.006	-0.032	-0.002	0.012	-0.009	-0.036	-0.004	0.012	-0.004	-0.025	-0.000	0.012	-0.001	-0.010	0.000	0.009
Misdemeanor (3 year)	-0.001	-0.021	-0.000	0.019	-0.001	-0.020	-0.000	0.017	-0.001	-0.024	0.000	0.021	-0.002	-0.025	-0.001	0.019
Felony (3 year)	-0.003	-0.019	-0.001	0.009	-0.002	-0.013	-0.000	0.008	-0.005	-0.024	-0.003	0.011	-0.010	-0.032	-0.007	0.009

Notes: This table reports predicted impacts on recidivism of a \$1 decrease in LFOs split by the predicted change in revenue, as in Table 2. Estimates are scaled by 100 for readability. Recidivism is defined as any new criminal charge recorded in the data within three years.