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, LFO decreases must at a minimum target defendants on the wrong side of the Laffer curve to be beneficial. 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, which implies that LFO decreases can only weakly increase revenue. In the absence of deterrence effects, which the best available evidence suggests are negligible, 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 wrong 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 LFO changes. The model performs well out of sample, explaining over 70% of overall variation and forecasting the impacts of large policy changes.

We begin by assessing whether any groups have expected payment rates low enough that they are highly likely to be on the wrong side of the Laffer curve. 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.[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.

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

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 net revenue from a small reduction in LFOs for each defendant. Our benchmark case assumes defaults costs are negligible because we find limited evidence that courts engage in costly enforcement activity. Despite having the authority, the counties in our setting 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). Nevertheless, our core conclusions change little when considering a range of default costs.

The results show that most criminal traffic and misdemeanor defendants have small behavioral responses relative to their high predicted payment rates, which means that marginal reductions in LFOs decrease revenue substantially. A $1 decrease in LFOs for all such 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.

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 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. 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. These transfers are rationalizable under very low welfare weights for criminal defendants.

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 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.[2] 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 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 $F(D) \equiv min\{U(D), P\}$.[3]

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 com-

[2]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.

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

mit 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 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, $E(D) = H(C(D) - R(D)/D)$.[4] 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 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.

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

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.*[5] *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:*

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

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.[6]

Testing whether any defendants are on the wrong side of the Laffer curve becomes simpler if potential offenders do not know or react to LFO levels when deciding whether to commit crimes, so that deterrence 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.

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

[6] 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.

This corollary suggests that defendants with payment rates approaching zero are exactly those for whom the government should consider lowering LFOs. We directly 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 $D(X): R^K \rightarrow R$ 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 methods to identify observable groups where the condition in Theorem 1 is met. As Corollary 1.1 makes clear, this condition is only sufficient for decreases in LFOs to increase the government's objective if deterrent effects are zero. In the presence of deterrence effects, however, the bar for LFO cuts to improve the government's objective only becomes more stringent: increases in net revenue have to offset the social costs of increased crime.

3 Setting and data

3.1 LFOs in Florida

Fees, fines, and other legal financial obligations consist of dozens of "user fees" that are assessed at disposition and cover different aspects of the criminal and legal process (Diller, 2010). Some fees, such as the $225 assessed to all 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.[7] 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 implications of nonpayment are relatively mild. None of the courts in our data regularly require defendants to appear to answer for nonpayment or make payment a condition of probation. Many courts only suspend licenses for nonpayment of LFOs in criminal traffic cases, which tend to have the wealthiest defendants. The most consistent repercussion of nonpayment is that outstanding debt is sent to a collection agency, an action that has been mandatory in Florida since 2009. However, collection agencies cannot seize assets or garnish wages. Instead, their main tools to compel payment are reporting nonpayment to credit agencies and making repeated calls to defendants. 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

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

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 less than the court-specific 95$^{\text{th}}$ percentile, and whose case was filed from 2005 through 2018.[8,9] 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.[10] 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 of first cases are disproportionately male and Black relative to the state averages. About 60% of defendants are accused of a criminal traffic offense, 20% of a misdemeanor, and 10% 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 (see Table A5 for descriptive statistics by case type).

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 not by nearly enough to suggest that on average defendants are on the right-hand-side of the LFO Laffer curve. Taking the estimates at face value, 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

[8]In Broward, the sample begins in 2008 due to data quality issues.

[9]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.

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

0.23.[11] 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 $0.093/(279/594) = 0.198$.

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 but not in our data. TransUnion matched credit archives from 2005, 2008, 2011, and 2014 to our sample based on all available defendant information, including 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.[12] Figure A2 shows the match rates for cases filed in each calendar year to each year of TU data. Match rates decline rapidly as the time between the date of the credit archive and the year of case filing 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.

4 Methods

We model the likelihood an offender with observable characteristics 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$^{\text{nd}}$-degree polynomial in d with x-specific coefficients. Doing so allows for smooth payment rates as a function of d conditional on observables.

It is not obvious, however, which characteristics may affect assignment of LFOs and payment behavior. The data include information on a very large set of defendant observables and there

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

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

is limited guidance from either theory or practice on how to parameterize heterogeneity, especially when taking into account the many potential interactions between covariates. Rather than taking a specific stand on the appropriate model, we take a more agnostic approach and estimate θ using nonparametric, data-driven procedures.

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 of the polynomial coefficients, much as traditional regression forests are trained to maximize differences in conditional means (Breiman, 2001). This method is therefore well-suited to uncovering groups with disparate payment responses.

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. We train the models on the early years of our data (through 2013), and test it on the remainder (2014-2018).

We then use this model to study the predictable variation in payment rates. We also use the model to assess potential behavioral responses by measuring the implied conditional payment semi-elasticity $\eta(D, X) = \frac{\partial f_0(\theta(X), D)}{\partial \log(D)}$ at each value of the observables, allowing us to study the revenue effects of targeted changes to LFOs.

5 Results

5.1 Model validation

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.[13] Both models feature slopes of roughly 1 and explain a large share of the variation in actual payment

[13]In Table A2 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 of the defendants is unlikely to substantially improve model fit.

rates. The R^2 from both models' predictions is roughly 74%.[14] 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 wrong 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.

[14] Table A1 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, or $(D-1) \times f_0(\hat{\theta}(X), D-1) - D \times f_0(\hat{\theta}(X), D)$, for each defendant in the data. 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, 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.[15]

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 \$788, versus only \$459 for the group with the largest revenue decrease. They are also disproportionately black (49 versus 20.8%), indigent (87.3 versus 17.9%), and are much less likely to ever appear in the credit files (17 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 wrong side of the Laffer curve.

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

[15] 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 $H = 0$.

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.[16] 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.

5.4 Additional validation and robustness

Our empirical approach uses machine learning models to estimate the effect of LFO amounts on the probability of payment. Causal forests provide a principled way of using covariates to estimate individual-specific LFO payment response functions, which allow us to estimate the share of defendants for whom the court could profitably decrease LFOs. The cost of this approach is that the estimates fundamentally rely on non-experimental variation in LFOs.[17] In Section A.2, we assess the model's ability to predict the effects of changes in LFOs using an abrupt increase in LFOs that occurred due to a policy change in 2008. We cannot reject that the observed change in payment rates matches the model-predicted change.

Our baseline model also assumes that individual-specific LFO payment response functions can be characterized by a second-degree polynomial in LFO amounts. Table A2 assesses the sensitivity of our main findings to alternative functional form assumptions, 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.

6 Conclusion

Are the fees, fines, and other legal financial obligations (LFOs) faced by a typical criminal defendant so large 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,

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

[17] 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 wrong side of the Laffer curve.

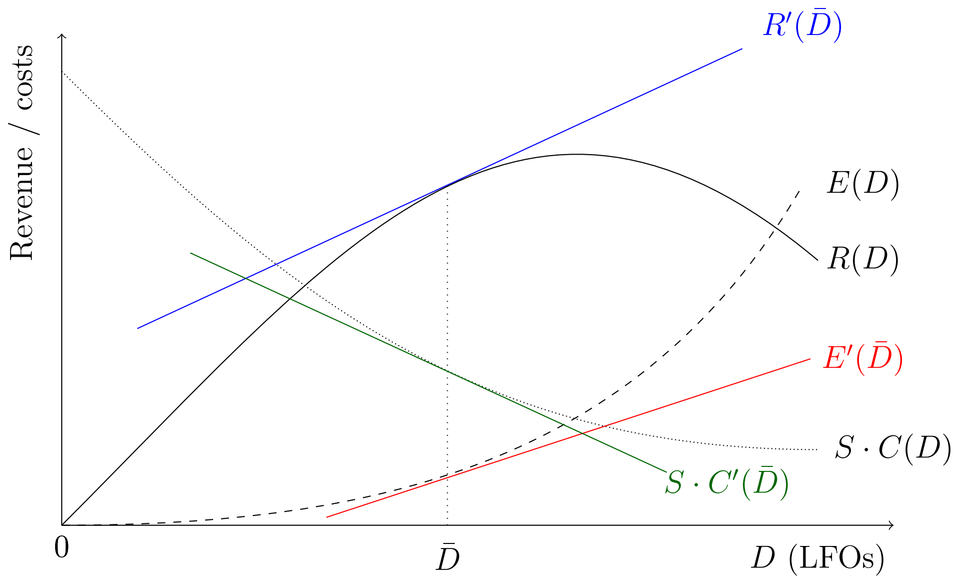
LFOs raise substantial revenues for local governments and decreasing them across the board would come at a steep cost. This result helps rationalize courts' increasing reliance on LFOs to fund their operations over the past few decades, particularly in Florida, the jurisdiction we study.

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 wrong 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 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 $R'(\bar{D}) - E'(\bar{D}) - SC'(\bar{D}) > 0$.

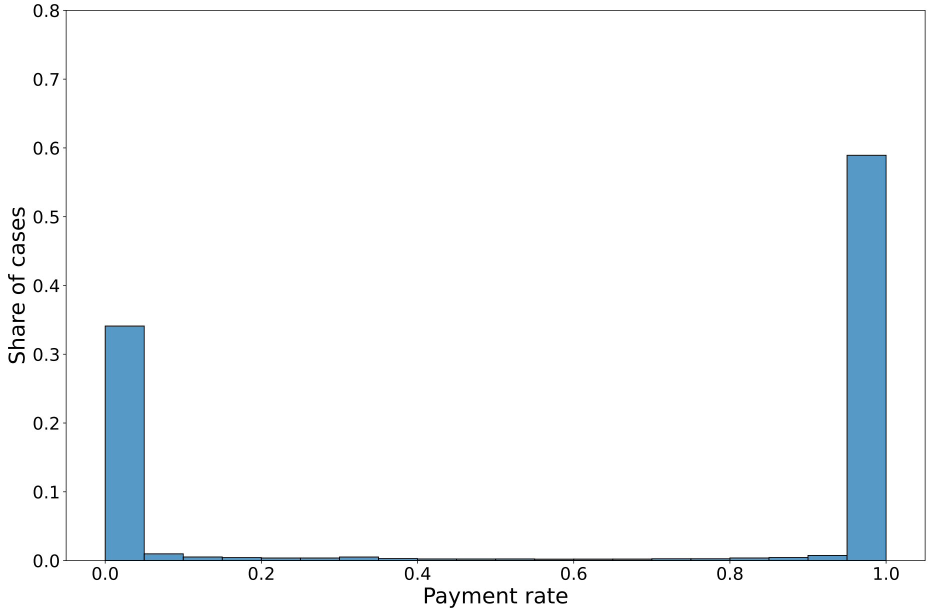
Table 1: Descriptive statistics

	Full sample	First case only			
	All	All	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					
Payment 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 credit report 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

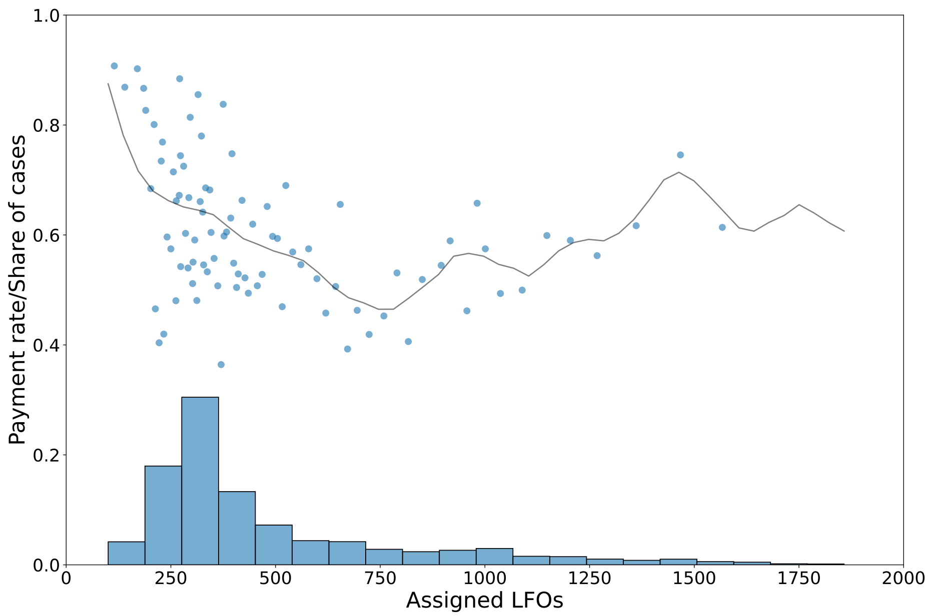
Notes: This table presents descriptive statistics for the full dataset of convicted offenders (Column 1) and the analysis sample of first-time offenders (Column 2). Not all offenders in the full sample appear in the first-time offender subsample because their first offense may have taken place outside 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.

Figure 2: LFO assignments and payment rates

(a) Distribution of payment rates



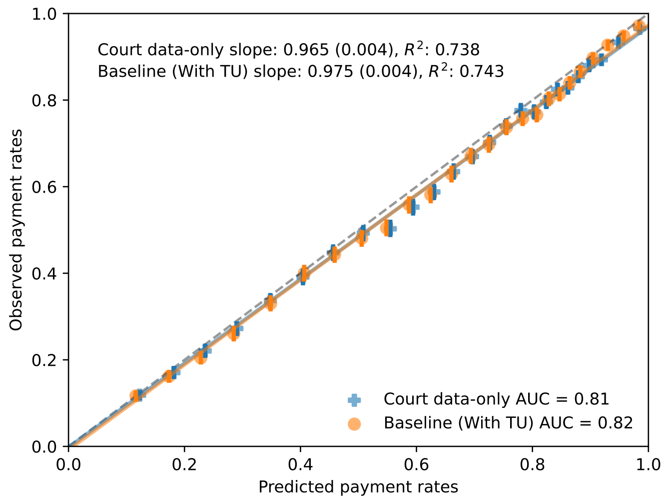
(b) Payment rates vs. assigned LFOs



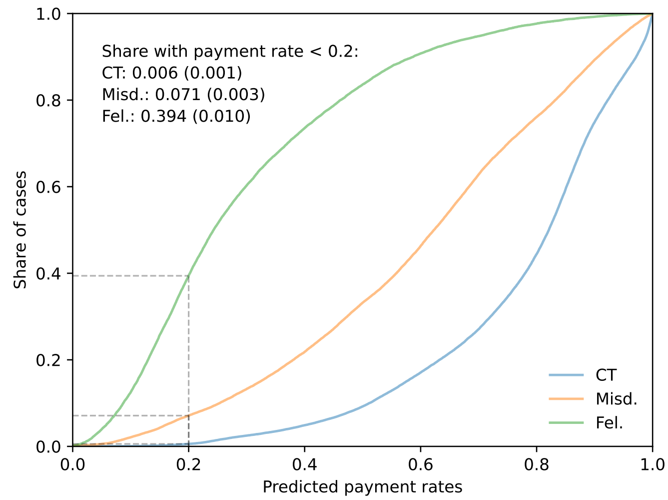
Notes: This figure reports the distribution of assigned LFOs and payment rates for the analysis sample of first-time cases. Panel (a) shows the distribution of payment rates, computed as total payments divided by total LFOs assigned. Panel (b) shows a scatterplot and local linear regression of average 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.

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

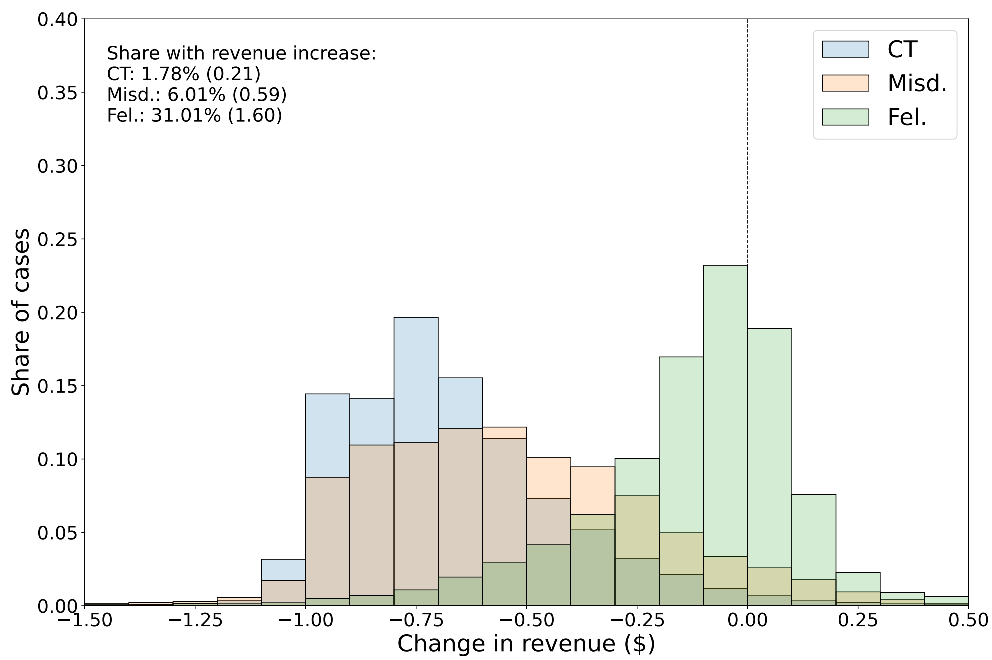
(a) Out-of-sample model fit



(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 parenthesis 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	34.964	32.451	31.108
		(0.085)	(0.149)	(0.299)
Male	0.710	0.696	0.719	0.781
		(0.002)	(0.004)	(0.007)
Black	0.303	0.208	0.433	0.490
		(0.004)	(0.007)	(0.013)
White	0.586	0.643	0.508	0.474
		(0.004)	(0.006)	(0.012)
Indigent (qualifies for public def.)	0.453	0.179	0.702	0.873
		(0.007)	(0.010)	(0.015)
Case characteristics				
Criminal Traffic	0.500	0.664	0.297	0.108
		(0.005)	(0.008)	(0.011)
Misdemeanor	0.312	0.306	0.346	0.227
		(0.005)	(0.008)	(0.015)
Felony	0.175	0.024	0.332	0.654
		(0.002)	(0.007)	(0.018)
Reoffenses				
Future criminal traffic (3 years)	0.082	0.086	0.083	0.052
		(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	459.272	583.788	787.681
		(3.230)	(5.402)	(12.508)
Repayment rate	0.612	0.776	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 credit report match	0.357	0.430	0.271	0.170
		(0.003)	(0.005)	(0.007)
Credit score	532.168	553.507	481.922	453.500
		(0.814)	(2.320)	(5.304)
Number of defendants	108,706	64,873	34,828	9,005

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.

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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

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

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 $\frac{R(D)D}{C(D)} = 0$.

A.2 Policy reform validation of the causal forest models

LFOs have been steadily increasing in Florida for at least the last twenty years. A particularly large increase occurred for cases disposed on or after July 1, 2008. A number of recent papers have used similar policy changes in LFO policy to estimate the effect of LFOs on defendant outcomes in a regression discontinuity framework, and generally found modest or null effects on subsequent behavior (Giles, 2023; Finlay et al., 2021, 2023).

There are two issues with pursuing a similar approach in our setting. First, our focus in this paper is on payment behavior rather than other defendant outcomes. Instrumenting for LFOs with the policy change would recover a mix of average causal responses (Angrist and Imbens, 1995). Since these estimands average the effect of a number of different changes in LFO amounts for potentially different complier groups, they are not directly relevant to our main goal of uncovering the share of defendants for whom the court might profitably decrease LFOs.

Second, as we discuss in the following section, there are small imbalances in defendant characteristics over the policy change that threaten a causal interpretation of such 2SLS estimates.

However, the policy change still provides a useful test of the validity of the causal forest predictions. We implement the test in this section.

A.2.1 Policy reform

Lawmakers in Florida regularly update the LFO schedule. However, the changes in 2008 were particularly broad, and dramatically increased LFOs for certain crimes and types of defendants. In particular, the base fees charged to defendants convicted of a felony case increased from \$200 to \$225, and from \$50 to \$60 for misdemeanor and criminal traffic defendants. For indigent defendants—those who are poor enough to quality for a public defender—the application fee for a public defender increased from \$40 to \$50, and minimum public defender fees were set at \$100 for felonies and \$50 for misdemeanors and criminal traffic cases. The law also set new minimums for fees meant to recover the costs of prosecution, and required these costs to be imposed "notwithstanding defendants' present ability to pay." These policy changes were applied to all cases that were disposed on or after July 1, 2008, when the law took effect.

A.2.2 Placebo tests of the policy reform

We begin by estimating a number of tests of the validity of the policy reform for use in a regression discontinuity in time analysis. Our main concern is exogeneity, since changes in the type and composition of cases in each court may have occurred at the same time as the policy change. To study whether defendant characteristics changed at the same time as the policy, we run regressions of the following form:

$$X_i = \beta_0 + \beta_1 T_i + \beta_2 T_i \times \mathbb{1}[T_i \geq 0] + \beta_3 \mathbb{1}[T_i \geq 0] + \varepsilon_i \tag{A2}$$

where X_i is the defendant characteristic and T_i is the number of days relative to July 1, 2008. We use a triangular weight with a bandwidth of 1 year. As discussed in Section 3.2, the data for Broward is available only after 2008; we focus on Brevard and Hillsborough in this analysis.

Table A3 shows the coefficients of these regressions for a number of defendant characteristics. To serve as an omnibus measure of placebo validity, we predict payment using the full set of pre-case defendant characteristics. The last row uses this predicted payment measure as the relevant characteristic.

The table shows that there are slight but statistically significant changes in defendant characteristics over the time of the policy change. Predicted payment rates are 1.6 and 3.2 percentage points lower in Brevard and Hillsborough respectively after the policy changes. There are also small changes in case composition; in Brevard, for example, the share of cases that are criminal traffic increases by 4 percentage points. This may be due to changes in other policies at the same time as the reform that affected the composition of cases; Florida tends to change a number of policies on July 1 in each year.

A.2.3 Model validation

As discussed in the previous section, there are some slight imbalances in defendant characteristics across the discontinuity. While this suggests that the timing of the policy might not be exogenous with respect to defendant characteristics, we can still use the policy change to evaluate our machine learning models. Specifically, we ask whether the change in the observed payment rates—which reflect both higher LFOs after the reform, as well as compositional changes in defendants—matches the change in the payment rates predicted by the causal forest model, which reflect the same two factors.

Our main causal forest estimates are trained on the years before and including 2013, and then tested on subsequent years. To avoid overfitting for this exercise, however, we retrain the model on cases filed before they would contribute to the RD estimate, e.g. before July 2007. We then use the causal forest to predict payment rates for each individual, and use (A2) to estimate the effect of the reform on predicted payment. The baseline estimates include no additional controls, while an additional specification adds in controls for defendant and case characteristics.

Table A4 presents the results. We begin by estimating the effect of the reform on LFOs charged. Consistent with the broad increases in LFO levels discussed in Section A.2.1, column (2) reveals that the policy increased average LFO amounts by \$70. This slightly decreased payments; the second row indicates that defendants were 0.4 percentage points less likely to pay after the reform. The third row shows the effect of the reform on model-estimated payment; at 2.6 percentage points we cannot reject that the coefficients are the same. In column (3) we add defendant controls; while these slightly change the point estimates we continue to conclude that the model closely approximates the change in payment rates induced by the reform.

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

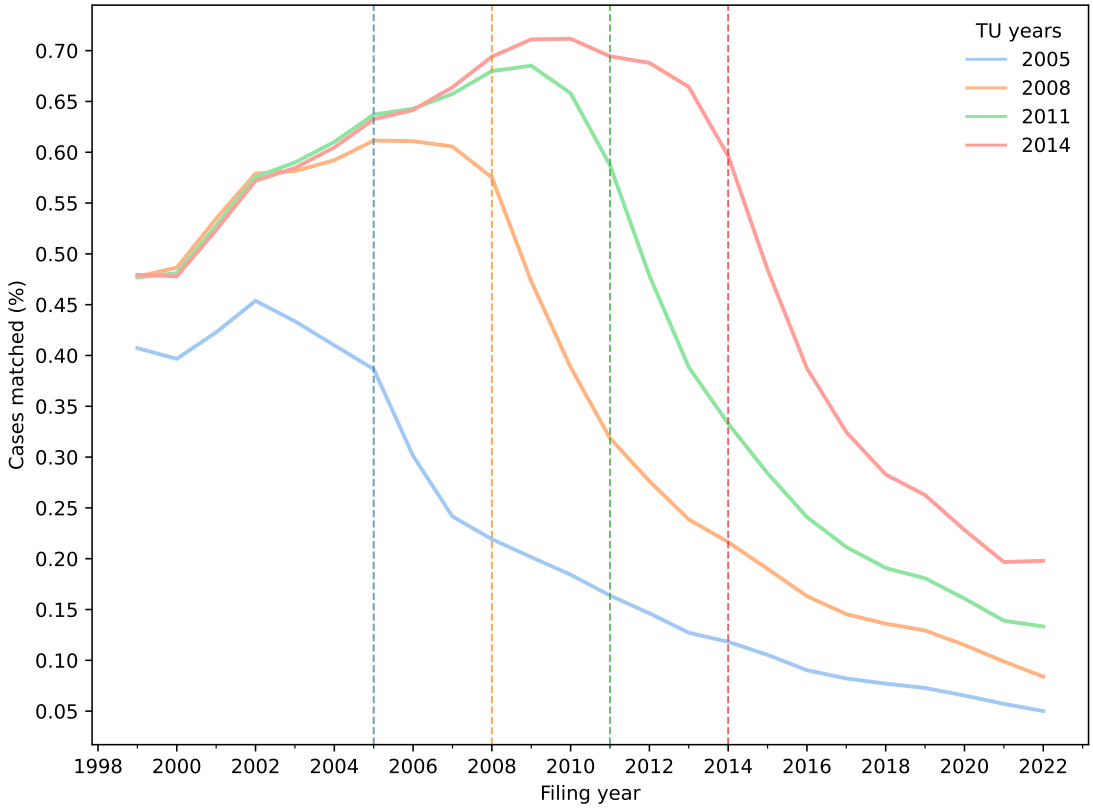
Case # 05-2009-CT-[redacted]-AXXX-XX
Document Page # 6
[redacted]

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

6 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.

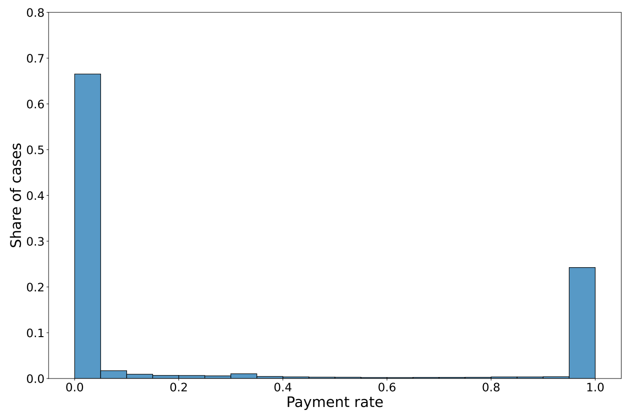
Figure A2: TU: Matches over time



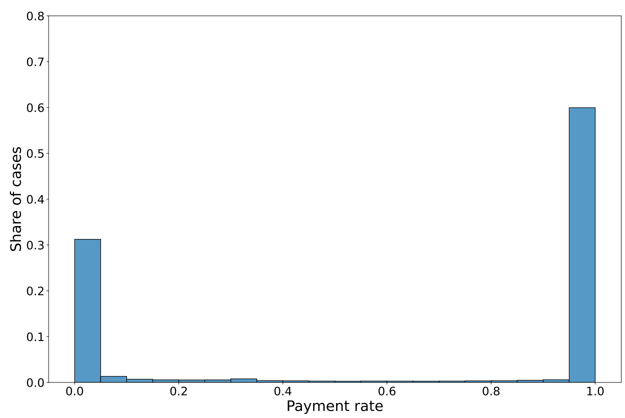
Notes: This figure reports the match rates for cases to each of the 2005, 2008, 2011, and 2014 TransUnion credit archives separately by year of filing.

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

(a) 2nd case, prior nonpayer



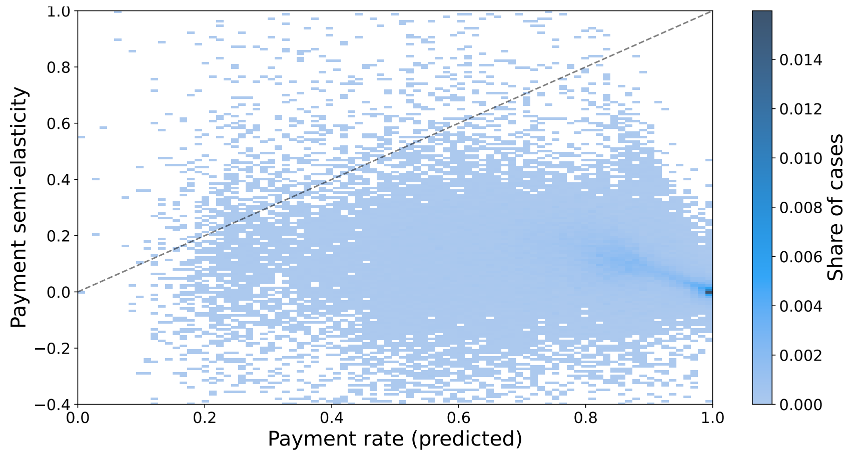
(b) 2nd case, prior payer



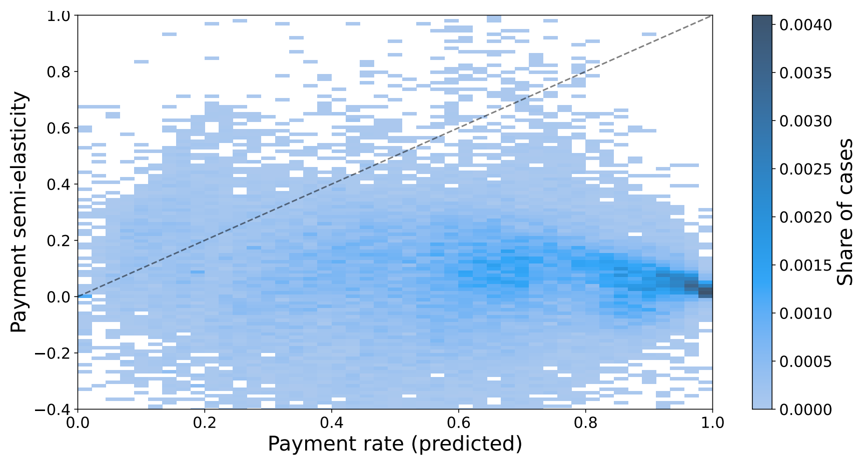
Notes: This figure plots the distribution of payment rates for second-time offenders who did not prior their prior LFOs (Panel a) and did pay them (Panel b).

Figure A4: Predicted semi-elasticities vs. payment levels

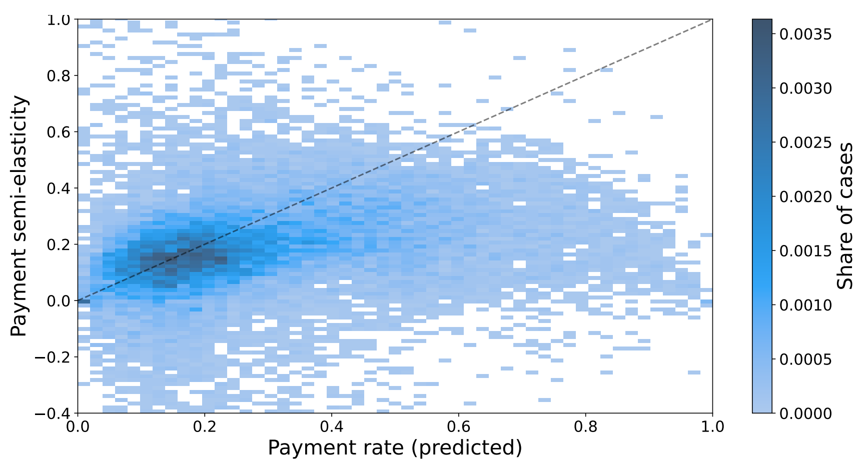
(a) Criminal traffic cases



(b) Misdemeanor cases

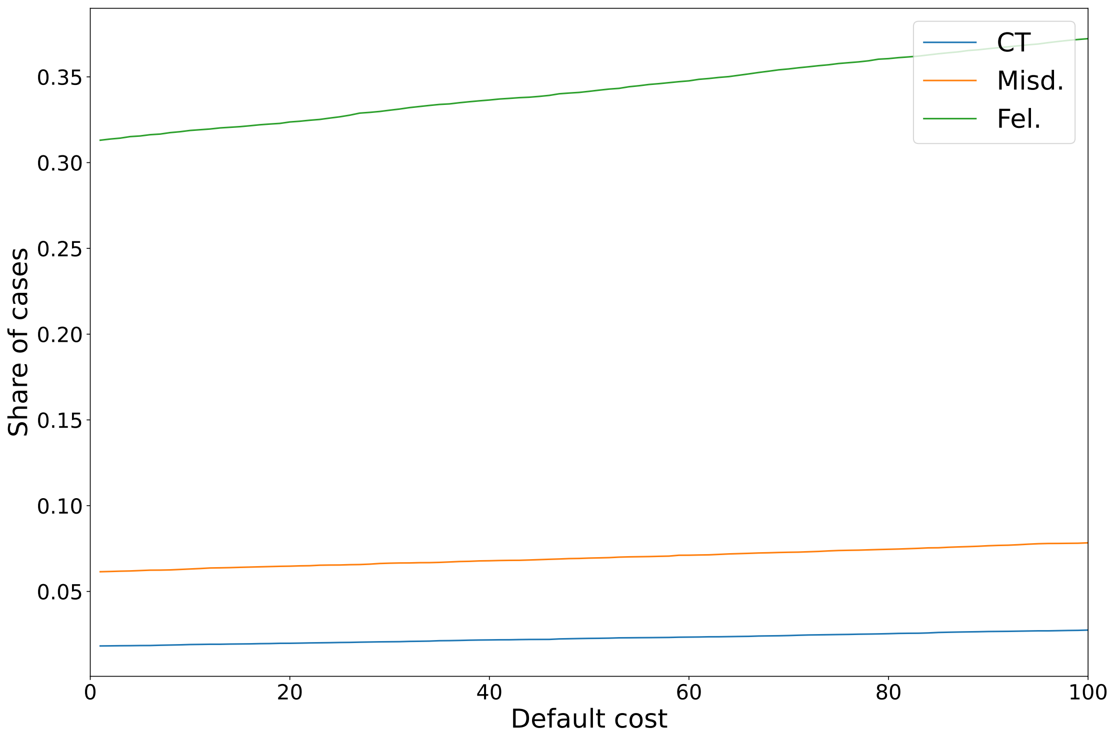


(c) Felony cases



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 defaults 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.

Appendix Tables

Table A1: Causal forest feature importance

	All	Brevard	Broward	Hillsborough
DUI (CJARS)	0.490	0.787	0.001	0.683
Felony (case type)	0.227	0.040	0.615	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	0.007	0.044	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
Population (zipcode)	0.007	0.009	0.009	0.003
Misdemeanor (case type)	0.007	0.001	0.018	0.002
Age	0.007	0.010	0.009	0.001
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
Average household income (zipcode)	0.004	0.004	0.008	0.001
Median income (zipcode)	0.004	0.006	0.006	0.001
Months on file (TU)	0.004	0.003	0.009	0.001
Black pop. share (zipcode)	0.004	0.005	0.005	0.002
Months since most recent inquiry (TU)	0.004	0.003	0.008	0.001
White pop. share (zipcode)	0.004	0.006	0.006	0.000
Median home value (zipcode)	0.003	0.005	-	0.002
Race - Black	0.003	0.003	0.006	0.000
Number of inquiries (TU)	0.002	0.002	0.004	0.001
Public order (CJARS)	0.002	0.001	0.002	0.002
Flag for multiple first cases	0.001	0.002	0.001	0.000
Drugs (CJARS)	0.001	0.001	0.001	0.000
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
Gender - Male	0.001	0.000	0.000	0.001
Inquiries flag (TU)	0.001	0.000	0.001	0.000
Property (CJARS)	0.000	0.001	0.001	0.000
Gender - Female	0.000	0.000	0.001	0.001
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 - Asian	0.000	0.000	0.000	0.000
Race - Pacific Islander	0.000	-	0.000	0.000
Gender - Unknown	0.000	0.000	-	0.000
High risk of fraud flag (TU)	0.000	0.000	0.000	0.000
Race - Indian	0.000	-	0.000	0.000
Race - Native	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 A2: 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	0.738	0.753
Model fit, Slope	0.975	0.984	0.968	0.965	0.980
Below 20%, Criminal Traffic	0.006	0.005	0.006	0.006	0.010
Below 20%, Misdemeanors	0.071	0.071	0.075	0.062	0.082
Below 20%, Felonies	0.394	0.385	0.397	0.373	0.491
Positive revenues, Criminal Traffic	0.018	0.006	0.049	0.026	0.032
Positive revenues, Misdemeanors	0.060	0.020	0.088	0.065	0.034
Positive revenues, Felonies	0.310	0.266	0.328	0.324	0.273
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 A3: Regression discontinuity placebo regressions of case characteristics on the policy change

	Brevard	Hillsborough
Age	-0.0544	-0.0097
	(0.385)	(0.210)
Black	-0.0142	0.0013
	(0.012)	(0.008)
Male	0.0056	0.0049
	(0.014)	(0.008)
Felony	-0.0131	0.01*
	(0.012)	(0.006)
Criminal Traffic	0.041***	-0.0023
	(0.015)	(0.007)
Misdemeanor	-0.028*	-0.0104**
	(0.015)	(0.005)
% with TU match	-0.0122	0.0012
	(0.015)	(0.009)
Predicted payment rate	-0.0158***	-0.0321***
	(0.005)	(0.005)
Avg. payment rate	0.694	0.603
Avg. predicted payment rate	0.708	0.567
Number of cases	37,550	104,507

Notes: This table reports regression discontinuity estimates examining the effect of the July 1, 2008 policy change on defendant characteristics. Models include a post-policy dummy, the time relative to the policy, and their interaction. Each row is a separate regression. We predict payment rates using fixed defendant characteristics. Contrary to the other rows, the predicted payment row includes the other variables in the table as covariates. Standard errors are clustered at the offender level.

Table A4: RD estimates of effect of policy change

	All		
	(1)	(2)	(3)
LFO charged	452.58	70.54***	80.59***
		(5.24)	(3.83)
Payment rate	0.626	-0.004	-0.005
		(0.008)	(0.007)
Predicted payment	0.628	-0.026***	-0.026***
		(0.005)	(0.004)
Actual = predicted (p)	-	0.600	0.473
Number of observations	-	74,322	74,322
Covariates	-	No	Yes

Notes: In this table, we fit a regression discontinuity model of the effect of the policy change on the LFO charged, actual payment rate, and the predicted payment from our tuned causal forest model. Column (1) contains the pre-policy means, and columns (2) and (3) the RD results with and without additional covariates (race, case type, offense type). We report the p-value of a test for the equality of the coefficients for actual and predicted payment rate. The sample for this table includes only Brevard and Hillsborough; data for Broward are available only after the policy change.

Table A5: Descriptive statistics by type of case

	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: Descriptive statistics for guilty offenders - including both first and second offenders. For TU-related variables, we report the % of successful matches, then report all the over variables conditional on a successful match. Trades are everything debt/credit related (*e.g. loan for buying a car; credit cards, etc.*) see link for examples.