# Does Punishment Compel Payment?

## Driver's License Suspensions and Fine Delinquency

Ryan Kessler*

*Brown University*

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**Abstract**

Many state and local governments use the threat of driver's license suspension (DLS) to compel the payment of fines and fees. In this paper, I provide the first quasi-experimental evidence on the efficacy of such threats. Using administrative records from the City of Chicago, I estimate the effect of receiving a threat of DLS on the payment of traffic fines. To isolate the causal effect of receiving a threat, I exploit cross-sectional variation in exposure to a change in the enforcement of DLS policy in a fuzzy difference-in-differences research design. Receiving a threat of DLS increases traffic fine payment by $658 on average over the four years following receipt, representing 40 percent of the average traffic fine debt among drivers in my sample. The effect is significantly smaller among drivers with vehicles registered in higher-poverty ZIP Codes. My estimates suggest that eliminating DLS for the non-payment of traffic fines would reduce annual traffic fine revenue in the city by 4.5 percent.

Keywords: Fines, driver's license suspension, deterrence
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# 1 Introduction

Since the 1990s, many state and local governments in the US have increased the fines and fees associated with civil and criminal offenses — collectively referred to as *legal financial obligations* (LFOs) — in attempt to fill budget shortfalls without raising taxes (Council of Economic Advisors 2015; Menendez et al. 2019). In practice, however, LFOs often go unpaid, with many jurisdictions collecting around \$0.64 on the dollar (Menendez et al. 2019). To help compel payment of LFOs, 41 state governments (as of 2018) and many local governments threaten to suspend the driver's licenses of those who do not pay (Free to Drive 2019). At least seven million drivers had their driver's license suspended for the failure to pay LFOs in 2018, representing more than nine percent of adult drivers in six states (Moyer 2018).

The efficacy of threats of driver's license suspension (DLS) to compel payment of LFOs is subject to debate. Proponents of the policy argue that the threat of DLS is a powerful tool to compel payment among those who are able to pay, consistent with standard models of the economics of crime (Becker 1968). Opponents of the policy argue that DLS increases obstacles to paying off debt and may therefore be counterproductive, consistent with evidence that DLS causes financial distress among drivers (Mello 2018).[1] This debate has seen increased attention among policy makers since the release of a 2015 Department of Justice report highlighting "substantial hardship" imposed by DLS in the revenue-driven police and court practices of the City of Ferguson, Missouri (Department of Justice 2015, p. 50). Several states have since banned the use of DLS to compel payment of LFOs, and others are considering following suit.[2]

The challenge in assessing these arguments is that there is virtually no evidence on the causal effect of threats of DLS on the payment of LFOs (AAMVA 2013; Schwier and James 2016; Crozier and Garrett 2019). It is difficult to isolate the causal effect of the threats of DLS on payment because such threats are often statutorily linked to the non-payment of a certain amount of LFOs. The receipt of a threat of DLS may therefore be associated with adverse life events such as job loss or negative financial shocks that directly reduce ability to pay (Atkinson 2016).

In this paper, I compile administrative records on fines issued by the City of Chicago for violations of the city traffic code and exploit a change in DLS policy enforcement to provide the first quasi-experimental

[1] For example, in the context of California, local governments argued that eliminating DLS would "eliminate any incentive for individuals to pay outstanding debt for traffic violations they received and failed to pay" (CSAC 2016, p.15), while policy advocates argued that DLS policies "make it harder for people to get and keep jobs, further impeding their ability to pay their debt" and that eliminating DLS would "likely increase the amount of money collected" (LCCR 2015, pp. 6-14). California Governor Jerry Brown called for ending the practice in the 2017-2018 budget, saying that "there does not appear to be a strong connection between suspending someone's drivers license and collecting their fine or penalty" (Brown 2017, p. 84).

[2] California ended the practice in 2017 (California Assembly Bill No. 103). Idaho and Washington, DC ended the practice in 2018 (Idaho House Bill No. 599; DC Act No. 22-449). Montana and Mississippi both ended the practice in 2019 (Montana House Bill No. 217; Mississippi House Bill No. 1352). Legislation to restrict the use of DLS is pending in Illinois and Oregon (Illinois House Bill No. 5340; Oregon House Bill No. 2614).

estimates of the effect of receiving a threat of DLS on the payment of LFOs. The City of Chicago issues hundreds of millions of dollars of traffic fines each year, with violations ranging from compliance violations such as not having a city vehicle sticker to automated camera violations such as driving through a red light. To help compel payment of these traffic fines, the city threatens to suspend the driver's license of drivers who accrue unpaid traffic fines for certain numbers and types of traffic code violations. Upon receipt of a threat of DLS, drivers have 45 days to settle their debts with the city before the city suspends their driver's license indefinitely. The administrative records contain detailed information on traffic fine receipt and payment and city threats of DLS for hundreds of thousands of drivers over a period of several years, allowing me to study the evolution of traffic fine payment behavior surrounding many thousands of threats of DLS.

To isolate the causal effect of receiving a threat of DLS, I leverage a recent reform to the city's debt collection policy. In 2011, the city adopted a more aggressive approach to the collection of city debt, including unpaid traffic fines. Recent work studies the reduced-form effects of this reform on racial disparities in bankruptcy chapter choice (Morrison et al. 2019) and household financial well-being (Kessler 2020).

As part of the reform, the city conducted a review of existing debt collection practices and discovered a hole in the enforcement of city DLS policy. The city realized that it was omitting unpaid fines for compliance violations from the balance of unpaid fines that drivers must accrue before becoming eligible for DLS. The city corrected the omission between December 2012 and April 2013 but decided to retroactively count only unpaid fines issued for compliance violations on or after January 1, 2008.

I exploit cross-sectional variation in exposure to the change in DLS policy enforcement in a fuzzy difference-in-differences (FDID) research design (de Chaisemartin and D'Haultfoeuille 2018). I restrict attention to drivers who, as of December 1, 2012, had at least one unpaid fine issued for a compliance violation over the course of 2007 and 2008. I use the share of such fines issued during 2008 as my measure of each driver's exposure to the change in DLS policy enforcement. I show that drivers more exposed to the change in DLS policy enforcement are significantly more likely to receive a threat of DLS between Q4 2012 and Q1 2013. The logic of the FDID research design is to use the magnitude of this relative increase in the likelihood of receiving a threat of DLS, along with any corresponding changes in traffic fine payment, to infer the causal effect of receiving a threat. The identifying assumption is that the traffic fine payment behavior of those more or less exposed to the change in DLS policy enforcement would have evolved similarly in the absence of the change.

Using the FDID research design, I estimate that receiving a threat of DLS increases traffic fine payment by $658.1 on average over the four years following receipt, with a standard error of $84.1. This estimate represents 40 percent of the average traffic fine debt among drivers in my primary analysis sample. The payment response decreases monotonically across years since receipt of the threat of DLS, from \$282.3 in the year of receipt (with a standard error of \$38.1) to \$74.8 in the third year following receipt (with a standard error of \$27.3).

I assess the plausibility of the identifying assumption underlying the FDID research design three ways. First, I compare the dynamics of traffic fine payment among drivers more or less exposed to the change in DLS policy enforcement prior to its enactment. I find little evidence of differential pre-trends. Second, I re-estimate the effect of receiving a threat of DLS on traffic fine payment separately by mode of payment. Upon receipt of a threat of DLS, the city requires drivers to submit all traffic fine payments in person at a city payment center. Consistent with this requirement, I show that my estimate of the effect of receiving a threat of DLS on traffic fine payment is driven almost entirely by an increase in in-person payments at city payment centers. Third, I re-estimate my baseline model restricting attention to drivers who, even after the change in the enforcement of DLS policy, do not meet the statutory thresholds of unpaid traffic fines for DLS eligibility. I show that, among this subset of drivers, those who are more or less exposed to the change in DLS policy enforcement are not differentially likely to receive a threat of DLS or make traffic fine payments to the city.

I extend my analysis by exploring heterogeneity in the estimated effect of receiving a threat of DLS on traffic fine payment by select driver ZIP Code characteristics. Traffic fines have been shown to have outsized impacts on the financial well-being of low-income drivers (Mello 2018). Consistent with this evidence, I find that the effect of receiving a threat of DLS on traffic fine payment is significantly smaller among drivers with vehicles registered in ZIP Codes with higher poverty rates.

I stress two important limitations of my analysis. First, because my analysis focuses on drivers with unpaid traffic fines in Chicago, I cannot (without additional assumptions) generalize my findings to the broader population of individuals with unpaid LFOs. Second, my analysis likely does not capture the full effect of threats of DLS on the payment of traffic fines. This paper estimates the effect of receiving a threat of DLS on subsequent traffic fine payment (the *ex post effect*). The ex post effect has been the focus of many policy discussions (see, for example, LCCR 2015 and Brown 2017). But threats of DLS may also cause would-be non-payers to pay their traffic fines because they expect to receive a threat of DLS if they do not (the *ex ante effect*). If the ex ante effect is large relative to the ex post effect, the results in this paper will not be informative about the overall revenue effects of DLS policy.

With this latter limitation in mind, I conclude by using my estimates of the effect of receiving a threat of DLS on traffic fine payment to estimate the overall revenue costs of policy proposals to restrict the use of DLS threats in the city. I consider two counterfactual DLS policies motivated by recent legislation. The first counterfactual policy restricts the use of threats of DLS to compel payment of fines for automated camera violations, as proposed in the Illinois (IL) License to Work Act (Illinois House Bill No. 5340). The second counterfactual policy completely eliminates the use of threats of DLS, as recently proposed in many other state and local governments (see, for example, Oregon House Bill No. 2614). Under the assumption of no ex ante effect, I find that these counterfactual policies would reduce annual traffic fine revenue by 2.3 percent (with a standard error of 0.3 percent) and 4.5 percent (with a standard error of 0.6 percent), respectively. The former estimate is larger than the city's estimate of the revenue cost of 1.5 percent (Spielman 2019).[3]

The primary contribution of this paper is to provide the first quasi-experimental estimates of the effect of receiving a threat of DLS on the payment of LFOs. This estimate of the revenue benefits of DLS policy can be weighed against estimates of administrative and other costs when contemplating changes to DLS policy.

Despite the fact that within many jurisdictions failure to pay is the most common trigger of DLS (Waller et al. 2005), the existing literature on the effects of DLS policy has focused on non-payment outcomes such as driving behavior (Gehrsitz 2017), financial well-being (Mello 2018), and school enrollment (Kennedy 2020). Two exceptions study effects on payment in the context of a child support enforcement experiment conducted in the 1990s. Pearson et al. (1998) conduct an experiment in which 566 of 2,704 delinquent child support obligors in Colorado in 1995 are randomly assigned to receive a threat of DLS. Pearson et al. (1998) find that the threat of DLS increases child support payments by $73 on average in the eight months following receipt of the threat (p. 12). In a follow-up analysis of the same experiment, Thoennes and Pearson (2000) find that the threat of DLS increases child support payments by $410 on average in the year following receipt of the threat (pp. 4-5).[4] While informative the findings of such studies may fail to generalize to LFOs for many reasons. For example, child support obligations in the US, unlike LFOs, tend to be income-based, suggesting that threats of DLS may be less effective in compelling payment of LFOs (Marsh 2017).

More generally, this paper contributes to the literature on the effect of punishment on crime, recently reviewed in Chalfin and McCrary (2017). Several studies find evidence that punishment deters civil and criminal offenses such as traffic violations both ex ante (see, for example, Ashenfelter and Greenstone 2004, DeAngelo and Hansen 2014, and Traxler et al. 2018) and ex post (see, for example, Hansen 2015, Gehrsitz 2017, and Goncalves and Mello 2017). This paper contributes to this literature by studying whether punishment deters the non-payment of LFOs. Punishment may be less effective in this context given that (i) LFOs tend to be highly concentrated in low-income neighborhoods (Mello 2018) and (ii) low-income

[3] The city estimates that restricting the use of threats of DLS to compel payment of fines for automated camera violations would reduce annual traffic fine revenue by $4.2 million (Spielman 2019). Expressed as a fraction of baseline traffic fine revenue of $288.2 million this estimate implies a reduction of 1.5 percent.

[4] The US Department of Health and Human Services credits the threat of DLS with generating nearly $35 million in child support payments in nine states through March 1995 (Brown 1997, p. 5). Closer to this paper, Carnegie (2007) argues that the threat of DLS was "very effective" in reducing the number of unpaid traffic fines in New Jersey between 1990 and 2004 (p. 44).

households tend to have little to no financial slack (Barr 2012). Indeed, some have argued that the use of punishment to deter the non-payment of LFOs effectively "criminalizes poverty" (Atkinson 2016).[5]

The rest of this paper proceeds as follows. Section 2 provides details regarding the policy context in Chicago. Section 3 describes the data and introduces important definitions. Section 4 describes the research design. Sections 5 and 6 present the results. Section 7 concludes.

# 2 Policy Context in the City of Chicago

## 2.1 Traffic Fine and Driver's License Suspension Policy

The City of Chicago issues fines for violations of the city traffic code.[6] I refer to these fines as *traffic fines*. Traffic fines in the city range from $25 to $500, depending on the violation. Traffic code violations in the city are grouped into three categories: *parking violations* (for example, having an expired parking meter), *compliance violations* (for example, not having a city vehicle sticker), and *automated camera violations* (for example, running a red light).

Traffic fines generate significant revenue for the city, despite many going unpaid and resulting in considerable debt among drivers. If a traffic fine is not paid or contested within approximately three months of issuance, the city assesses a surcharge equal to the amount of the traffic fine. If a traffic fine is not paid or contested within approximately six months of issuance, the city assesses an additional collection fee equal to 22 percent of the traffic fine plus the surcharge. So, for example, if not paid or contested within approximately six months, a traffic fine of $100 can result in $244 in traffic fine debt. In 2018, traffic fines generated $272 million in revenue, representing 7 percent of the city's $3.8 billion operating budget (Ramos and Sanchez 2019). Over the same period, traffic fine debt, dating back to September 1990, reached $1.5 billion (Sanchez and Kambhampati 2018).

To help compel payment of traffic fine debt, the city uses threats of driver's license suspension (DLS). When a driver accumulates 10 unpaid parking or compliance fines or five unpaid automated camera fines the city sends the driver a notice of DLS. Appendix figure A1 presents a template notice of DLS. Upon receipt of a notice of DLS, the driver has 45 days to stop DLS proceedings by paying her traffic fine debt in full or enrolling in a city payment plan. Upon receipt of a notice of DLS, the driver must submit all traffic fine payments in person at a city payment center.

The city offers two payment plans to drivers facing the threat of DLS. The *standard payment plan* allows

[5] Atkinson (2016) argues that "the indigent cannot be deterred from 'crimes' that they must commit because of their poverty, particularly the crime of not paying a fine or fee" (p. 237).

[6] Under city law, traffic code violations are civil offenses punishable by fine and no criminal penalty (Chicago Code of Ordinances § 9-100-020).

drivers to pay their traffic fine debt in equal installments over a period of up to 12 months, following an initial down payment of 50 percent of total debt. The *hardship payment plan* allows drivers to pay their traffic fine debt in equal installments over a period of up to 36 months, following an initial down payment of the minimum of $1,000 or 25 percent of total debt. To be eligible for the hardship payment plan, a driver must be of a member of a particular demographic group (for example, student or senior citizen), be experiencing financial distress (for example, home foreclosure), or be participating in a safety net program (for example, Medicaid). Further details regarding both payment plans and eligibility for the hardship payment plan are presented in appendix figure A2.

If the driver does not stop DLS proceedings, the city certifies the DLS with the IL Secretary of State and the IL Secretary of State suspends the driver's license indefinitely.

## 2.2 Reform to City Debt Collection Policy

The City of Chicago began reforming its debt collection policy in 2011. At the time, the city faced a budget deficit of $636 million (Emanuel 2011a). To help fill this gap without raising taxes, newly-installed Mayor Rahm Emanuel announced that his administration would implement a "smarter more aggressive approach" to the collection of city debt, including unpaid traffic fines (Emanuel 2011b).[7]

### 2.2.1 Change in Enforcement of DLS Policy

As part of the debt collection reform, the city conducted a review of existing debt collection practices and discovered a hole in the enforcement of city DLS policy. The city realized that it was omitting compliance fines from the counts of unpaid fines drivers must accrue before becoming eligible for DLS. So, for example, a driver with five unpaid parking fines and five unpaid compliance fines was deemed ineligible for DLS despite meeting the statutory threshold of having 10 unpaid parking or compliance fines. The city corrected the omission between December 2012 and April 2013 but decided to retroactively count only unpaid compliance fines issued on or after January 1, 2008.

### 2.2.2 Debt Collection via State Payment Garnishment

The city also began collecting on city debt by garnishing payments made to drivers by the State of IL. To help local governments collect on unpaid debt, the State of IL established the Local Debt Recovery Program (LDRP) in January 2012 (Illinois Public Act 097-0632). Under the LDRP, local governments can submit

[7] In a city press release, Emanuel said that "moving forward there will be no more free rides, debt scofflaws will be found and they will pay what they owe the City. That means we will take a smarter more aggressive approach to recover this debt, not only to collect what we are owed but to ensure that it never reaches this level again" (Emanuel 2011b).

eligible debts to the state for payment via the garnishment of state payouts such as state-paid wages and state tax refunds. Eligible debts include fines, fees, and taxes incurred within the last seven years. The city began submitting all eligible traffic fines (i.e., unpaid traffic fines issued after February 2005) to the state for garnishment in February 2012.

# 3 Data and Definitions

## 3.1 Administrative Records from the City of Chicago

I obtained administrative records on several aspects of traffic fine policy in the City of Chicago via Freedom of Information Act (FOIA) requests submitted to the city's Department of Finance between March 2018 and January 2020. I supplement the administrative records with ZIP Code population and demographic information from the 2007-2011 American Community Survey (ACS) (US Census Bureau 2018).[8]

The administrative records include detailed information on traffic fines, traffic fine payment, and notices of DLS. I discuss each of these components in turn.

### 3.1.1 Traffic Fines

The traffic fine records cover the universe of fines issued for violations of the city traffic code between 1996 and 2017. The records include 46.9 million traffic fines worth $3.2 billion.

For each traffic fine, I observe detailed fine characteristics including the date of issuance, fine amount, violation code, violation description, and if/when the fine is paid. I classify each violation as a parking, compliance, or automated camera violation according to the Chicago Code of Ordinances (Chicago Code of Ordinances § 9-100-020). I define a *focal traffic fine* to be a traffic fine issued for a compliance violation over the course of 2007 and 2008 that was left unpaid as of December 1, 2012.

The traffic fine records also include detailed characteristics of the driver and vehicle associated with each fine including a driver account number, license plate type (e.g., passenger, temporary, commercial truck, taxi), license plate state, and the ZIP Code to which the vehicle was registered as of the date the fine was issued. I refer to driver account numbers as *drivers*. I restrict attention to the 39.1 million traffic fines issued to drivers associated only with IL passenger or temporary license plates.

For each driver, I compute traffic fine debt as of December 1, 2012 (both overall and by violation type), the number of focal traffic fines, and the share of focal traffic fines issued in 2008. I use the share of focal traffic fines issued in 2008 as my measure of each driver's exposure to the change in DLS policy enforcement

[8]The ACS data are available for ZIP Code Tabulation Areas (ZCTAs), not ZIP Codes. ZCTAs are generalized areal representations of ZIP Codes. In the analysis that follows, I assign to each ZIP Code the ACS data of its corresponding ZCTA.

outlined in section 2.2.1. I associate with each driver the ZIP Code to which the driver's vehicle is registered, according to the traffic fine received closest to December 1, 2012.

Using the traffic fine records, I estimate that the change in DLS policy enforcement added 1.1 million unpaid compliance fines to the counts of unpaid fines drivers must accrue before becoming eligible for DLS. Among the newly-counted compliance fines, having an expired license plate or temporary registration ("expired plates or temporary registration") and not having a city vehicle sticker ("no city sticker or improper display") were the most common violations. Appendix table A1 shows the number of focal traffic fines and the number of compliance fines added to DLS tallies by violation code.

### 3.1.2 Traffic Fine Payment

The traffic fine payment records cover the universe of traffic fine payments made by drivers to the city between 2010 and 2017. The records include 24.1 million payments totaling $2.1 billion.

For each traffic fine payment, I observe the driver associated with the payment as well as the date, amount, and mode of the payment. Modes of payment include online credit card, check (submitted online or by mail), in-person payment, and state payment garnishment. Across all traffic fine payments, online credit card and in-person payments are the most common, accounting for 42 percent and 40 percent of traffic fine revenue, respectively. State payment garnishments account for 4 percent of traffic fine revenue.

For each driver, I compute the sum of traffic fine payments in each calendar quarter, separately by mode of payment. I define *total traffic fine payment* to be the sum of traffic fine payments across modes of payment, excluding any payments obtained via state payment garnishment. I use total traffic fine payment as my primary measure of driver traffic fine payments to the city. Appendix figure A4 and appendix table A2 present estimates excluding drivers who are ever subject to state payment garnishment.

### 3.1.3 Notices of Driver's License Suspension

The notice of DLS records include the driver and date associated with each of the 177,182 notices of DLS sent by the city between 2007 and 2017.

For each notice of DLS, I compute traffic fine debt as of the notice date, both overall and by violation type. I define a *DLS notice quarter* to be a calendar quarter in which a driver receives a notice of DLS. For each driver, I construct an indicator equal to one in any DLS notice quarter and zero otherwise. I use this indicator as my primary measure of DLS notice receipt.

To help motivate my analysis, I use the notice of DLS records to document trends in and ZIP Code level correlates of DLS notice receipt rates among ZIP Codes in Cook County, IL. I associate with each notice of

DLS the ZIP Code to which the driver's vehicle is registered, according to the traffic fine received closest to the receipt of the notice of DLS. For each ZIP Code and calendar quarter, I compute the total number of notices of DLS sent by the city. I supplement the resulting panel with the number of DLS enacted for the failure to pay traffic fines in each ZIP Code and calendar quarter, according to the IL Secretary of State.[9] I restrict attention to calendar quarters between Q1 2010 and Q4 2017 and ZIP Codes with a plurality of their population in Cook County, IL as of the 2010 Census.

Figure 1 shows the evolution of the total number of notices of DLS and traffic-fine-related DLS enactments per 1000 residents across these ZIP Codes. Consistent with the timing of the change in DLS policy enforcement, the rate of DLS notice receipt exhibits a sharp increase between Q3 2012 and Q1 2013, from 0.6 to 3.4 per calendar quarter per 1000 residents. This increase is mirrored in the rate of traffic-fine-related DLS enactment, with a one-quarter lag, perhaps reflecting the 45 day period required by the city between DLS notice and DLS enactment. Taking the ratio of traffic-fine-related DLS enactments to the one-quarter lag of DLS notices suggests that approximately 46 percent of notices of DLS result in DLS.

Panel A of figure 2 shows the distribution of the average number of notices of DLS per calendar quarter per 1000 residents across these ZIP Codes. Average quarterly DLS notice receipt rates vary widely across ZIP Codes, from less than 0.4 per calendar quarter per 1000 residents on the north side of Chicago to more than 3.0 per calendar quarter per 1000 residents on the west and south sides of Chicago.

Panel B of figure 2 shows ZIP Code level correlates of average quarterly DLS notice receipt rates. The figure presents estimates of an ordinary least squares (OLS) regression of the log of the average number of notices of DLS received per calendar quarter per 1000 residents on ZIP Code level demographics. To facilitate interpretation, I standardize the ZIP Code level demographics to have a mean of zero and standard deviation of one. The figure shows that the share of residents who are black or hispanic, the share of residents who are employed, the share of residents with income below the federal poverty line, and a longer average commute to work are all positively associated with average quarterly DLS notice receipt rates. The share of residents who are black and the share of residents with income below the federal poverty line are the strongest predictors, with a one standard deviation increase in the measures associated with increases in the average quarterly DLS notice receipt rate of 69 and 38 percent, respectively.

[9]In data obtained via a FOIA request to the IL Secretary of State, I observe the number of DLS enactments in each ZIP Code and calendar quarter by DLS type. There are three DLS types tied to the failure to pay traffic fines: "failure to pay fines or penalties for 10 or more parking violations", "outstanding warrant for 10 or more parking violations" , and "failure to pay fines/penalties for 5 automated traffic violations". For each ZIP Code and calendar quarter, I compute the total number of DLS enacted for the failure to pay traffic fines as the sum of DLS enactments across these three suspension types.

### 3.2 Sample Selection

For my primary analysis, I identify 133,107 drivers with at least one focal traffic fine. I exclude from this sample 124 drivers with more than $25,000 in traffic fine debt as of December 1, 2012, leaving me with a final sample of 132,983 drivers. I refer to this sample of drivers as the *primary sample*. Appendix table A2 presents estimates among the subset of drivers in the primary sample with more than one focal traffic fine.

For each driver in the primary sample, I construct a balanced quarterly panel covering measures of traffic fine payment and DLS notice receipt between Q4 2010 and Q4 2017. I exclude from my analysis driver-quarters with values of total traffic fine payment above the 99.99th percentile. Appendix table A2 presents estimates including these driver-quarters.

Table 1 presents summary statistics of select variables among drivers in the primary sample, both overall and separately by whether the driver's share of focal traffic fines is above the median value of 0.5. Column (1) shows that the average driver has 2.8 focal traffic fines, half of which were issued in 2008, and a total of $1,659 in traffic fine debt as of December 1, 2012. Column (1) also shows that the average driver makes $8.2 of traffic fine payments in the average quarter between Q4 2010 and Q3 2012, with the majority of payments made in person at city payment centers. Columns (2) and (3) restrict attention to drivers in the primary sample with below- and above-median shares of focal traffic fines issued in 2008, respectively. Column (4) shows that the differences in means across these subsets of drivers, while in many cases statistically significant, are small relative to cross-sectional variation in the outcomes, representing less than 6 percent of the corresponding overall standard deviation.

## 4 Model and Assumptions

### 4.1 Setup

Let $i \in \{1, \ldots, N\}$ index drivers and $t \in \{1, \ldots, T\}$ index calendar quarters. Define $t^*$ to be the calendar quarter $t$ corresponding to Q4 2012. I model the effect of receiving a notice of DLS on a measure of traffic fine payment $p_{it}$ as

$$p_{it} = \sum_{k=0}^{L} \beta^k n_{i(t-k)} + x_{it}' \kappa + \alpha_i + \delta_t + \varepsilon_{it} \tag{1}$$

where $L$ is a number of lags, $n_{it}$ is an indicator for receipt of a notice of DLS, $x_{it}$ is a vector of time-varying controls, $\kappa$ is a vector of parameters, $\alpha_i$ is a driver fixed effect, $\delta_t$ is a calendar quarter fixed effect, and $\varepsilon_{it}$ is a driver-quarter shock satisfying $E\left(\varepsilon_{it} \middle| \{x_{it}\}_{t=1}^{t=T}, \alpha_i, \delta_t\right) = 0$.

The goal is to estimate the parameters $\beta^k$ encoding the dynamic effects of receiving a notice of DLS on traffic fine payment and the cumulative effect $\beta = \sum_{k=0}^{L} \beta^k$. The primary challenge is that DLS notice receipt is statutorily linked to the receipt and non-payment of certain numbers and types of traffic fines. DLS notice receipt may therefore be associated with adverse life events such as job loss or negative financial shocks that directly reduce ability to pay (Atkinson 2016), suggesting that $\text{Cov}(n_{it}, \varepsilon_{it} | x_{it}, \alpha_i, \delta_t) \neq 0$. A naive estimate of equation (1) that treats DLS notice receipt $n_{it}$ as strictly exogenous with respect to the driver-quarter shock $\varepsilon_{it}$ is therefore likely to provide biased estimates of the effects $\beta^k$ of receiving a notice of DLS on traffic fine payment.

## 4.2 Identification

To overcome this potential endogeneity and estimate the parameters of interest $\beta^k$, I exploit cross-sectional variation in exposure to the change in DLS policy enforcement outlined in section 2.2.1 in a fuzzy difference-in-differences research design (de Chaisemartin and D'Haultfoeuille 2018).

For each driver, define $c_i$ to be the share of focal traffic fines issued on or after January 1, 2008. Appendix figure A3 shows the distribution of $c_i$ across drivers in the primary sample. For each driver-quarter, define $z_{it} = c_i \times \mathbb{1}(t = t^* + 1)$, where $\mathbb{1}(\cdot)$ is the indicator function. I assume the exclusion restriction

$$E\left(\varepsilon_{it} \middle| \{z_{it}\}_{t=1}^{t=T}, \alpha_i, \delta_t\right) = 0, \tag{2}$$

i.e., that $z_{it}$ is strictly exogenous with respect to the driver-quarter shock $\varepsilon_{it}$.

Intuitively, the exclusion restriction in equation (2) implies that the traffic fine payment behavior of drivers more or less exposed to the change in DLS policy enforcement, as measured by $c_i$, would have evolved similarly in the absence of the change in enforcement. The exclusion restriction would be violated if, for example, there is a non-DLS determinant of traffic fine payment that evolves differentially among those with low and high $c_i$ surrounding the change in DLS policy enforcement. I assess the plausibility of the exclusion restriction in section 5. Appendix table A2 presents estimates from an alternative specification in which $z_{it} = \mathbb{1}(c_i \geq 0.5) \times \mathbb{1}(t = t^* + 1)$.

## 4.3 Estimation and Inference

Under the appropriate relevance condition, the exclusion restriction in equation (2) justifies estimating equation (1) via a two-stage least squares (2SLS) regression of $p_{it}$ on $n_{it}, n_{i(t-1)}, \ldots, n_{i(t-L)}$ and driver and calendar quarter fixed effects, with $z_{it}, z_{i(t-1)}, \ldots, z_{i(t-L)}$ as excluded instruments and $x_{it}$ as exogenous controls.

Unless otherwise noted, I consider four-year effects ($L = 15$) and take the vector of time-varying controls $x_{it}$ to be the full set of interactions between the number of focal traffic fines and calendar quarter indicators. I conduct inference using asymptotic standard errors clustered by driver. Appendix table A2 presents estimates under alternative specifications of $L$ and $x_{it}$.

To assess the strength of the first stage relationship and the plausibility of the exclusion restriction in equation (2), I present OLS estimates of dynamic first-stage and reduced-form models of the form

$$y_{it} = \sum_{k=1}^{T} \gamma^{k-t^*} z_{ik} + x_{it}' \tilde{\kappa} + \tilde{\alpha}_i + \tilde{\delta}_t + \tilde{\varepsilon}_{it} \tag{3}$$

where $\gamma^k$ are parameters encoding the dynamic relationship between the outcome $y_{it}$ (namely, $n_{it}$ or $p_{it}$) and the instrument $z_{it}$, and $\tilde{\alpha}_i$, $\tilde{\delta}_t$, and $\tilde{\varepsilon}_{it}$ are defined by analogy with equation (1). I also present estimates of the cumulative effect $\gamma = \sum_{k=0}^{L} \gamma^k$.

When presenting the resulting estimates of $\gamma^k$ I present both pointwise 95 percent confidence bands and uniform 95 percent sup-$t$ confidence bands (Montiel Olea and Plagborg-Møller 2019), with both based on an asymptotic variance-covariance estimator clustered by driver. The pointwise confidence bands are designed for pointwise hypothesis testing. The uniform sup-$t$ confidence bands are designed to contain the true path of the coefficients 95 percent of the time and are therefore arguably more useful for visualizing the range of dynamics that are consistent with the data.

# 5 Results

## 5.1 Effect of DLS Notice Receipt on Traffic Fine Payment

Figure 3 illustrates the dynamic first-stage and reduced-form relationships underlying my primary estimates of the effect of DLS notice receipt on total traffic fine payment. Each plot presents estimates of the parameters $\gamma^k$ from equation (3) along with 95 percent pointwise and sup-$t$ confidence intervals. In panel A, the outcome is an indicator for DLS notice receipt. In panel B, the outcome is total traffic fine payment.

Panels A and B show that, in the two years prior to the change in DLS policy enforcement, the probability of receiving a notice of DLS and total traffic fine payment evolve similarly among drivers more or less exposed to the change. Panel A shows that, between Q3 2012 and Q1 2013, drivers more exposed to the change experience a sharp increase in the probability of receiving a notice of DLS relative to drivers who were less exposed to the change. Panel B shows that, over the same period, drivers more exposed to the change begin making significantly more traffic fine payments to the city than drivers who were less exposed to the change. The estimated relative increase in total traffic fine payments peaks in Q2 2013 and declines gradually thereafter, reaching zero in the fourth year following the change in DLS policy enforcement.

These dynamics seem difficult to reconcile with the hypothesis that the relative increase in total traffic fine payment is driven by differential changes in confounds that are likely to evolve smoothly over time (e.g., driver income). They instead seem consistent with the hypothesis that the relative increase in total traffic fine payment is driven by differential exposure to the sharp change in enforcement of DLS policy.

Columns (1) and (2) of table 2 translate the variation depicted in figure 3 into estimates of cumulative four-year effects. The first row presents estimates of cumulative first-stage and reduced-form effects $\gamma$ based on equation (3). The second row presents estimates of the cumulative effect of DLS notice receipt $\beta$ based on equation (1).

The first row of column (1) shows that, over the four-year period between Q4 2012 and Q3 2016, drivers with a share of focal traffic fines issued in 2008 of one experience 0.049 additional DLS notice quarters (with a standard error of 0.006) than drivers with a share of focal traffic fines issued in 2008 of zero. The first row of column (2) shows that, over the same period, drivers with a share of focal traffic fines issued in 2008 of one make \$35.6 of additional traffic fine payments (with a standard error of \$7.9) than drivers with a share of focal traffic fines issued in 2008 of zero. Imposing the exclusion restriction in equation (2), the second row of column (2) shows that receiving a notice of DLS increases total traffic fine payment by \$658.1 over the four years following receipt, with a standard error of \$84.1. This estimate represents 40 percent of the average traffic fine debt among drivers in the sample.

Figure 4 decomposes the estimate of the cumulative four-year effect of receiving a notice of DLS on total traffic fine payment $\beta$ by years since receipt of the notice. Consistent with the reduced-form dynamics depicted in panel B of figure 3, the effect of receiving a notice of DLS decreases monotonically across years since receipt of the threat, from \$282.3 in the year of receipt (with a standard error of \$38.1) to \$74.8 in the third year following receipt (with a standard error of \$27.3).

## 5.2 Evidence on Plausibility of Identifying Assumption

The validity of the fuzzy difference-in-differences research design hinges on the exclusion restriction in equation (2). In this section, I further assess the plausibility of this assumption via two robustness exercises.

### 5.2.1 Estimates by Mode of Payment

I re-estimate the effect of DLS notice receipt on traffic fine payment, separately by mode of payment. I focus on the two most common modes of payment: in-person payment and online credit card payment. Recall that, upon receipt of a notice of DLS, the city requires drivers to submit all traffic fine payments in person at a city payment center. Under the exclusion restriction in equation (2), the effect of DLS notice receipt on total traffic fine payment should therefore be driven by changes in in-person payment, with online credit card payment going unchanged.

Figure 5 presents the reduced-form dynamics of traffic fine payment depicted in panel B of figure 3, separately by mode of payment. In panel A, the outcome is in-person payment. In panel B, the outcome is online credit card payment. Columns (3) and (4) of table 2 present the corresponding estimates of the cumulative effects $\gamma$ and $\beta$.

Figure 5 shows that, consistent with the city's in-person payment requirement, the relative increase in total traffic fine payments depicted in panel B of figure 3 is driven almost entirely by a relative increase in in-person payment at city payment centers, with online credit card payment going largely unchanged. Columns (3) and (4) of table 2 show that DLS notice receipt increases in-person payment and online credit card payment by \$603.6 (with a standard error of \$81.9) and \$25.3 (with a standard error of \$12.5), respectively.

#### 5.2.2 Estimates Among Drivers Ineligible for DLS

I re-estimate the effect of DLS notice receipt on traffic fine payment restricting attention to drivers in the primary sample who, even after the change in the enforcement of DLS policy, do not meet the statutory thresholds of unpaid traffic fines for DLS eligibility. Among this subset of drivers, those who are more or less exposed to the change in DLS policy enforcement should not be differentially likely to receive a notice of DLS and therefore, under the exclusion restriction in equation (2), should not be differentially likely to make traffic fine payments to the city.

Figure 6 presents the first-stage and reduced-form dynamics among this subset of drivers, paralleling figure 3. In panel A, the outcome is an indicator for DLS notice receipt. In panel B, the outcome is total traffic fine payment. Table 3 presents the corresponding estimates of the cumulative first-stage and reduced-form effects $\gamma$ and compares them to their counterparts based on the full primary sample.

Figure 6 shows that, among this subset of drivers, drivers more or less exposed to the change in DLS policy enforcement are not differentially likely to receive of notice of DLS or make traffic fine payments to the city. Columns (1)-(2) and (4)-(5) of table 3 show that, among this subset of drivers, estimates of the cumulative first-stage and reduced-form effects are nearly an order of magnitude smaller than their counterparts estimated on the full primary sample. Columns (3) and (6) show that I can reject the hypothesis that the first-stage and reduced-form effects are the same across the two samples of drivers.

### 5.3 Heterogeneity in Effect of DLS Notice Receipt

Table 4 explores heterogeneity in the cumulative effect of DLS notice receipt $\beta$ by select driver ZIP Code characteristics. For each ZIP Code characteristic, columns (1) and (2) report estimates of $\beta$ among drivers in the primary sample with below- and above-median values of the characteristic, respectively. Columns (3) reports estimates of the difference between the estimates in columns (2) and (1). Column (4) reports estimates of the same difference, where the estimates in columns (2) and (1) are expressed relative to the average traffic fine debt in their respective samples.

Row (1) shows estimates of heterogeneity by ZIP Code poverty rates. Among drivers associated with ZIP Codes with below-median poverty rates, the estimated cumulative effect of DLS notice receipt is $878.3 (with a standard error of $130.3), representing 67 percent of the average traffic fine debt. Among drivers associated with ZIP Codes with above-median poverty rates, the estimated cumulative effects of DLS notice receipt is $507.2 (with a standard error of $110.8), representing 25 percent of the average traffic fine debt. The difference between these estimates is economically large and statistically significant, both when the estimates are considered in levels and when the estimates are considered relative to the average traffic fine debt in their respective samples.

Rows (2) and (3) show estimates of heterogeneity by ZIP Code racial and ethnic composition. Row (2) shows that, when expressed relative to the average traffic fine debt, the cumulative effect of DLS notice receipt is smaller among drivers associated with ZIP Codes with higher shares of residents who are black. Row (3) shows that there is no such heterogeneity across drivers associated with ZIP Codes with different shares of residents who are hispanic.

## 6 Implications for Traffic Fine Revenue

In this section, I use my estimates of the effect of DLS notice receipt on total traffic fine payment to estimate the overall revenue costs of policy proposals to restrict the use of threats of DLS in the city.

A challenge in this analysis is that threats of DLS may affect traffic fine payment through two primary channels. They may compel drivers to pay upon receipt of the threat, as demonstrated in section 5 (the *ex post effect*). They may also cause would-be non-payers to pay their traffic fines because they expect to receive a threat of DLS if they do not (the *ex ante effect*).

While the results in section 5 provide the first estimates of the ex post effect, there remains no evidence on the ex ante effect. In theory, the ex ante effect could be positive or negative. On the one hand, the threat of DLS could make drivers more likely to pay conditional on receiving a traffic fine. On the other hand, the threat of DLS could result in fewer traffic code violations and therefore fewer traffic fines.

I follow the existing literature and estimate traffic fine revenue in the city under counterfactual DLS policies ignoring any potential ex ante effect (Pearson et al. 1998; Thoennes and Pearson 2000). Under the assumption that the ex ante effect is positive, my estimates provide a lower bound on the change in traffic fine revenue that would result from each counterfactual DLS policy.

I consider two counterfactual DLS policies motivated by recent legislation. For each counterfactual DLS policy, I compute counterfactual annual traffic fine revenue $R^c$ as

$$R^c(\beta, N^c) = R^b + \beta \times (N^c - N^b) \tag{4}$$

where $R^b$ is baseline annual traffic fine revenue, $\beta$ is the cumulative effect of DLS notice receipt on total traffic fine payment, and $N^b$ and $N^c$ are the baseline and counterfactual numbers of notices of DLS sent per year, respectively. I set $R^b$ and $N^b$ equal to their respective averages across years 2013 to 2017 and set $\beta$ equal to my estimate of the cumulative effect of DLS notice receipt on total traffic fine payment reported in the second row and second column of table 2.

The first counterfactual DLS policy restricts the use of threats of DLS to compel payment of fines for automated camera violations, as proposed in the IL License to Work Act (Illinois House Bill No. 5340). I estimate that 50 percent of notices of DLS sent between 2013 and 2017 were associated with drivers with at least 5 unpaid automated camera fines as of the notice date. For this counterfactual policy, I therefore set $N^c = 0.50 \times N^b$.

The second counterfactual DLS policy completely eliminates the use of threats of DLS to compel payment of traffic fines, as recently proposed in many state and local governments (see, for example, Oregon House Bill No. 2614). For this counterfactual policy, I set $N^c = 0$.

Figure 7 presents results from the two counterfactual exercises. Panel A presents estimates of the number of notices of DLS sent at baseline and under each counterfactual DLS policy. Panel B presents analogous estimates for annual traffic fine revenue, along with pointwise 95 percent confidence intervals. Panel B shows that the counterfactual policies of restricting the use of DLS to compel payment of fines for automated camera violations and eliminating the use of DLS entirely would reduce annual traffic fine revenue by \$6.5 million (with a standard error of \$0.8 million) and \$13.1 million (with a standard error of \$1.7 million), respectively. The former estimate is significantly larger than the city's estimate of the revenue cost of \$4.2 million (Spielman 2019). Expressed relative to baseline annual traffic fine revenue these estimates represent decreases in annual traffic fine revenue of 2.3 percent (with a standard error of 0.3 percent) and 4.5 percent (with a standard error of 0.6 percent), respectively.

## 7 Conclusion

In this paper, I compile administrative records on fines issued by the City of Chicago for violations of the city traffic code and exploit a change in DLS policy enforcement to provide the first quasi-experimental estimates of the effect of receiving a threat of DLS on the payment of LFOs. I find that receiving a threat of DLS increases traffic fine payment by $658.1 on average over the four years following receipt, representing 40 percent of the average traffic fine debt among drivers in my sample. The effect is significantly smaller among drivers with vehicles registered in higher-poverty ZIP Codes. My estimates suggest that eliminating DLS for the non-payment of traffic fines would reduce annual traffic fine revenue in the city by 4.5 percent.

An important limitation of my analysis is that it likely does not capture the full effect of threats of DLS on traffic fine payment. In addition to affecting the traffic fine payment behavior of those who receive a threat of DLS, DLS policy may also cause would-be non-payers to pay their traffic fines because they expect to receive a threat of DLS if they do not. Evidence on the sign and magnitude of such ex ante effects would be useful in evaluating the overall effects of DLS policy on LFO revenue.

Ultimately, the efficacy of DLS policy will depend not only its effects on LFO revenue but also on its costs. DLS policy is costly to administer and could lead to increased spending on other government services such as law enforcement and safety net programs (AAMVA 2013; LCCR 2015). Evidence on such administrative and spillover costs would be useful in evaluating the overall efficacy of DLS policy.

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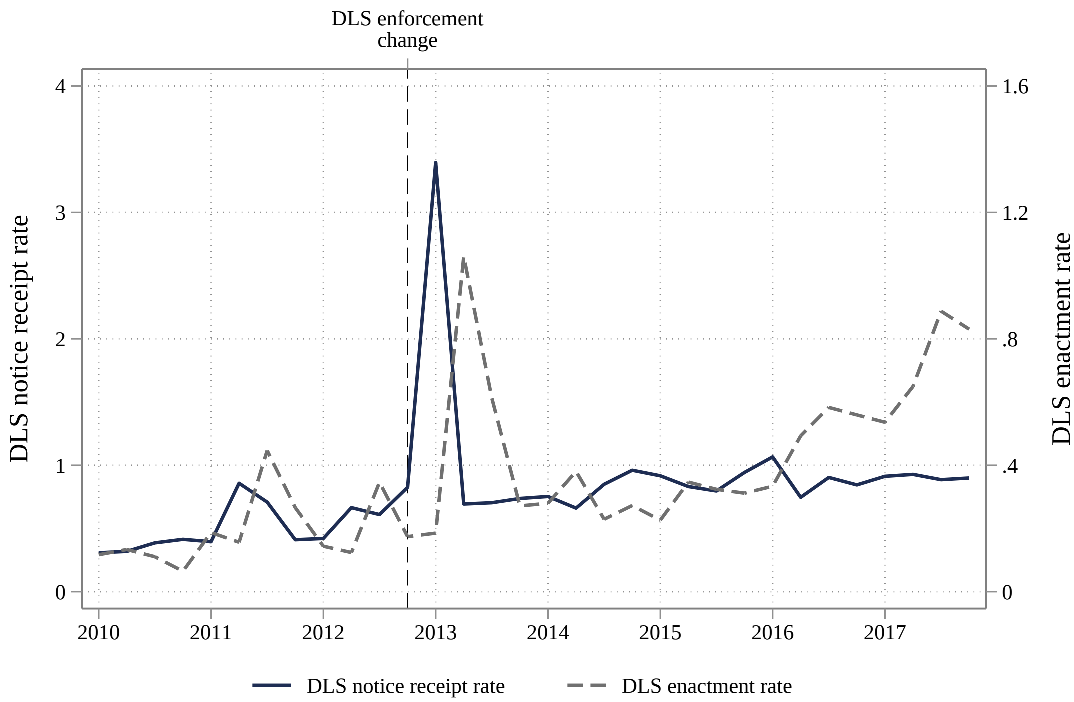
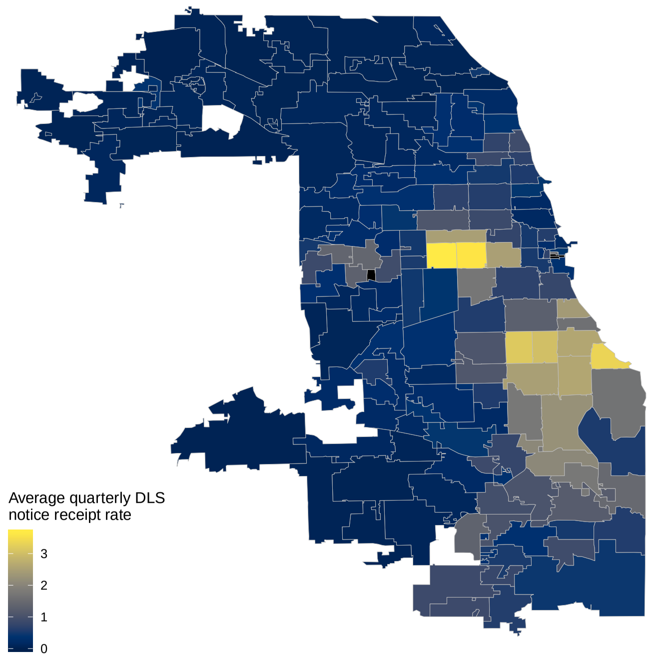
Figure 1: Evolution of notices of DLS and traffic-fine-related DLS enactments in Cook County, IL



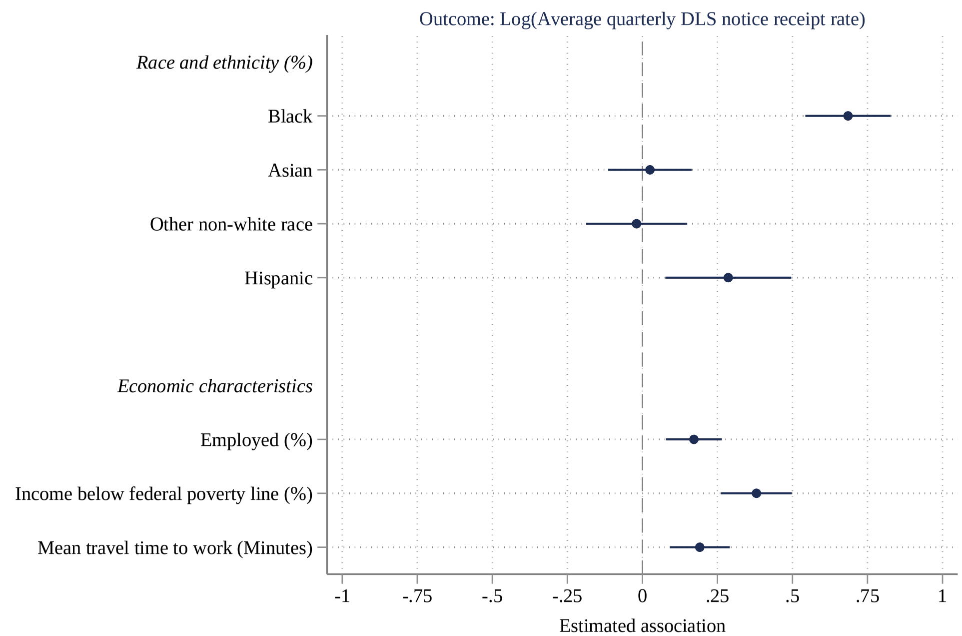

Notes: This figure shows the total number of notices of DLS and traffic-fine-related DLS enactments per 1000 residents across Cook County, IL ZIP Codes. I define a Cook County, IL ZIP Code as a ZIP Code with a plurality of its population in Cook County, IL as of the 2010 Census. I define a traffic-fine-related DLS enactment as a DLS for "failure to pay fines or penalties for 10 or more parking violations", "outstanding warrant for 10 or more parking violations" , or "failure to pay fines/penalties for 5 automated traffic violations". The unit of observation is a calendar quarter. The solid navy blue line shows the total number of notices of DLS per 1000 residents across Cook County, IL ZIP Codes in each calendar quarter (i.e., the DLS notice receipt rate). The dashed grey line shows the total number of traffic-fine-related DLS enactments per 1000 residents across Cook County, IL ZIP Codes in each calendar (i.e., the DLS enactment rate).

Figure 2: Location and area-level correlates of notices of DLS in Cook County, IL

*Panel A: Location of notices of DLS*



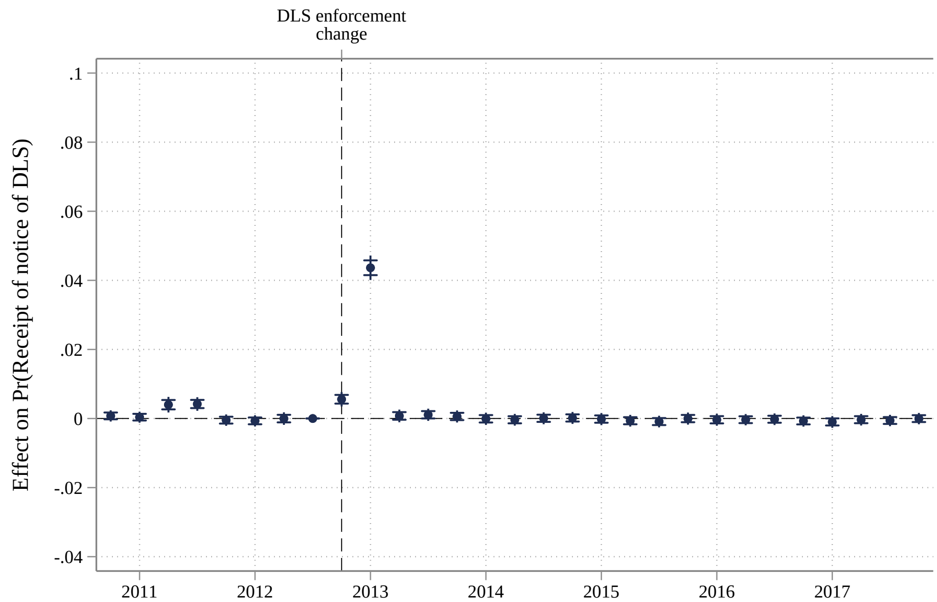

*Panel B: Area-level correlates of notices of DLS*



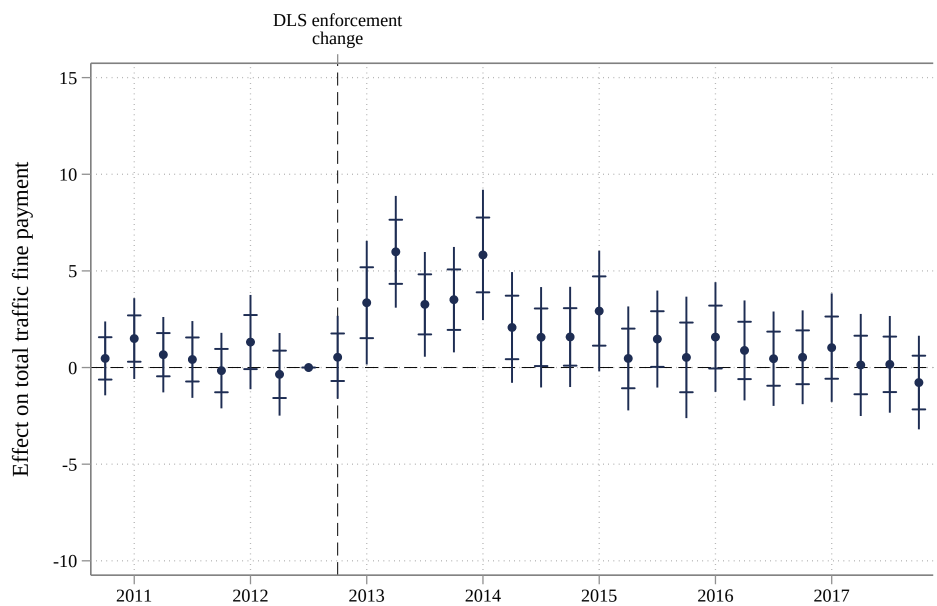

Notes: The figure shows the location and area-level correlates of notices of DLS across Cook County, IL ZIP Codes. I define a Cook County, IL ZIP Code as a ZIP Code with a plurality of its population in Cook County, IL as of the 2010 Census. The unit of observation is a ZIP Code. In both plots, the average quarterly DLS notice receipt rate is defined as the average number of notices of DLS sent by the city in calendar quarters between 2010 and 2017 divided by the resident population of the ZIP Code (in 1000s). Panel A shows the distribution of average quarterly DLS notice receipt rates across ZIP Codes. ZIP Codes with fewer than 500 residents are shaded black regardless of their DLS notice receipt rate. Panel B shows the estimated coefficients from an OLS regression of the log of average quarterly DLS notice receipt rate on a vector of ZIP Code characteristics. The ZIP Code characteristics are standardized to have a mean of zero and a standard deviation of one. The regression is weighted by the resident population of each ZIP Code. Error bars represent 95 percent confidence intervals. Confidence intervals are robust to heteroskedasticity.

Figure 3: Evolution of notices of DLS and total traffic fine payment

*Panel A: Notice of DLS*

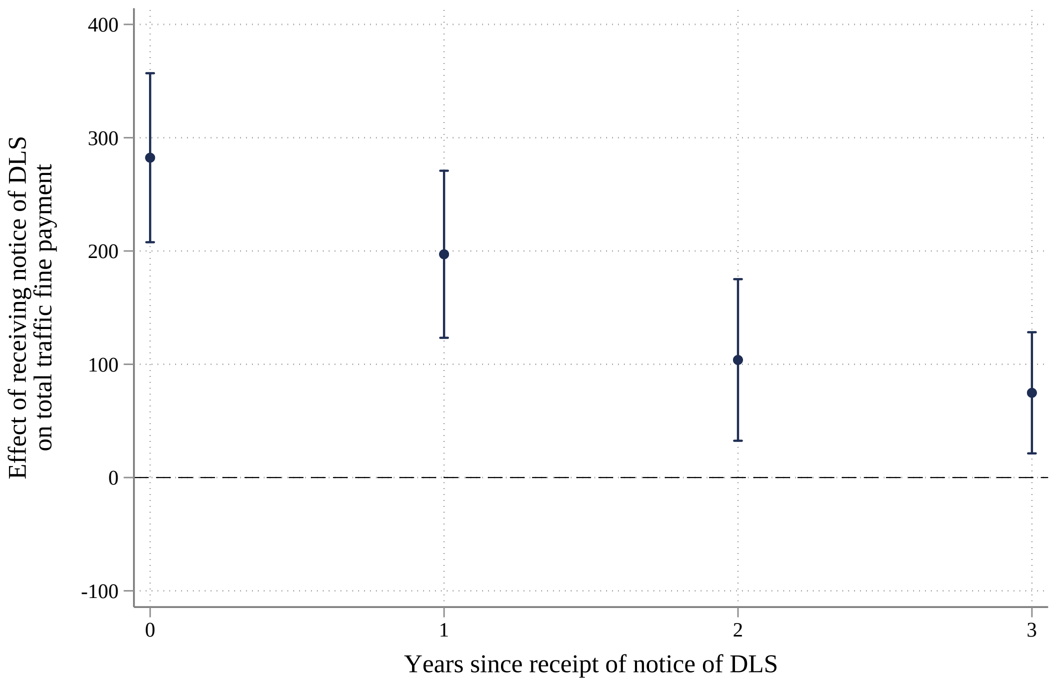



*Panel B: Total traffic fine payment*




Notes: The figure shows the evolution of the likelihood of receiving a notice of DLS and total traffic fine payment around the change in enforcement in DLS policy. The unit of observation is a driver-quarter. The sample is the primary sample defined in section 3.2. Each figure presents estimates of the coefficients $\gamma^k$ on the interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008 from an ordinary least squares (OLS) regression of the outcome on interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008, interactions between calendar quarter indicators and the number of focal traffic fines, and driver and calendar quarter fixed effects. In panel A, the outcome is an indicator for receipt of a notice of DLS. In panel B, the outcome is total traffic fine payment. The inner error bars represent 95 percent pointwise confidence intervals based on asymptotic standard errors clustered by driver. The outer error bars represent 95 percent uniform sup-$t$ confidence intervals computed as outlined in Montiel Olea and Plagborg-Møller (2019) based on an asymptotic variance-covariance matrix clustered by driver.

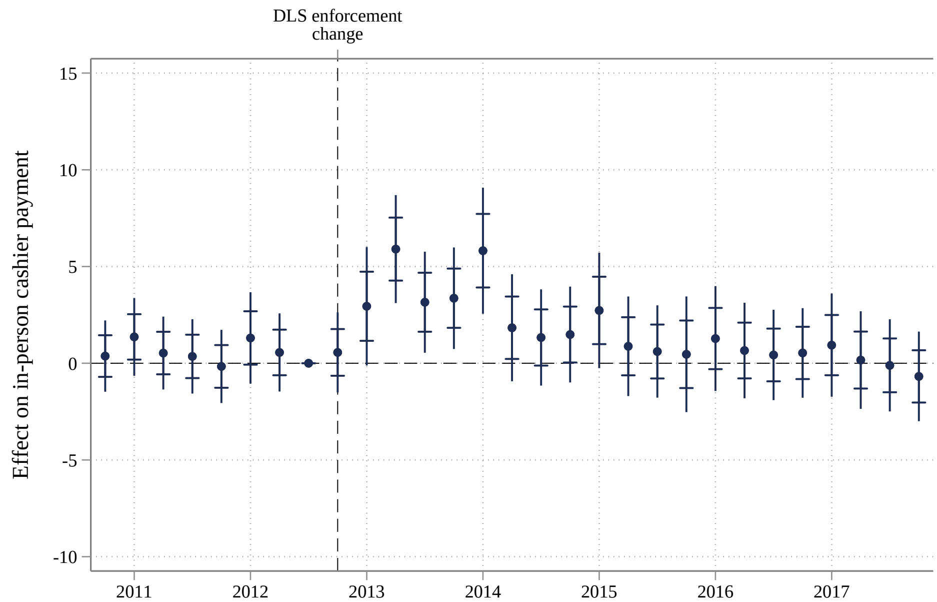
Figure 4: Dynamic effects of DLS notice receipt on total traffic fine payment



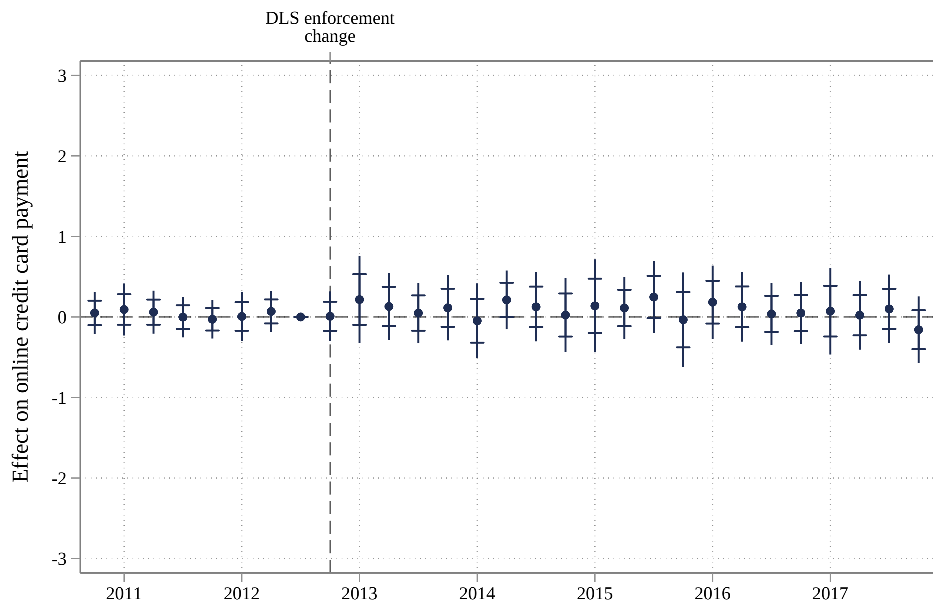

Notes: The figure shows estimates of the effect of receiving a notice of DLS on total traffic fine payment by year since receipt of the notice. The unit of observation is a driver-quarter. The sample is the primary sample defined in section 3.2. The figure presents estimates $\sum_{k=y}^{y+3} \hat{\beta}^k$ for $y \in \{0, 4, 8, 12\}$ from a two-stage least squares (2SLS) regression of total traffic fine payment on contemporaneous and lagged indicators for DLS notice receipt and driver and calendar quarter fixed effects, with the contemporaneous and corresponding lagged values of an interaction between an indicator for whether the calendar quarter is Q1 2013 and the share of focal traffic fines issued in 2008 as excluded instruments and a full set of interactions between calendar quarter indicators and the number of focal traffic fines as exogenous controls. The error bars represent 95 percent pointwise confidence intervals based on asymptotic standard errors clustered by driver.

Figure 5: Evolution of traffic fine payment by mode of payment

*Panel A: In-person payment*



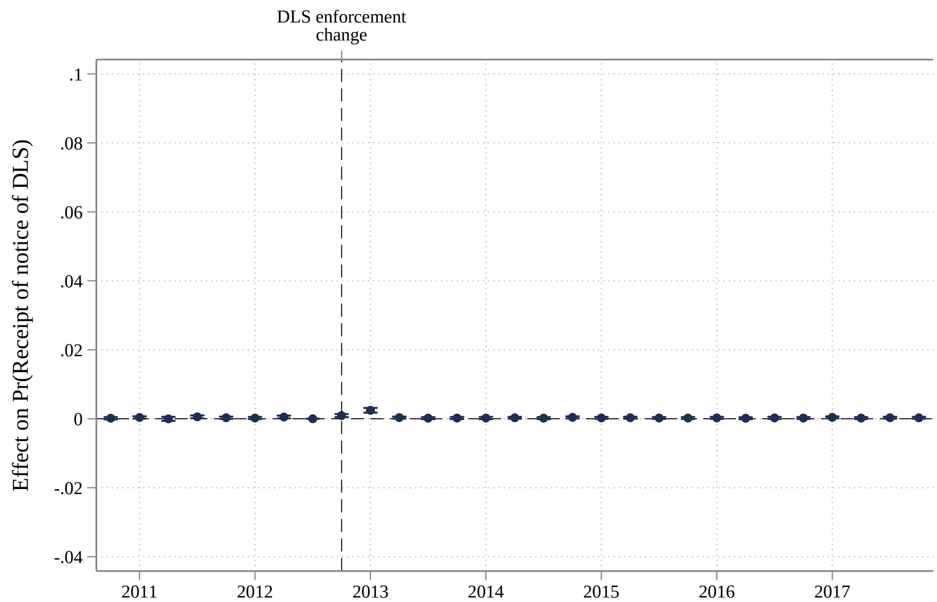

*Panel B: Online credit card payment*



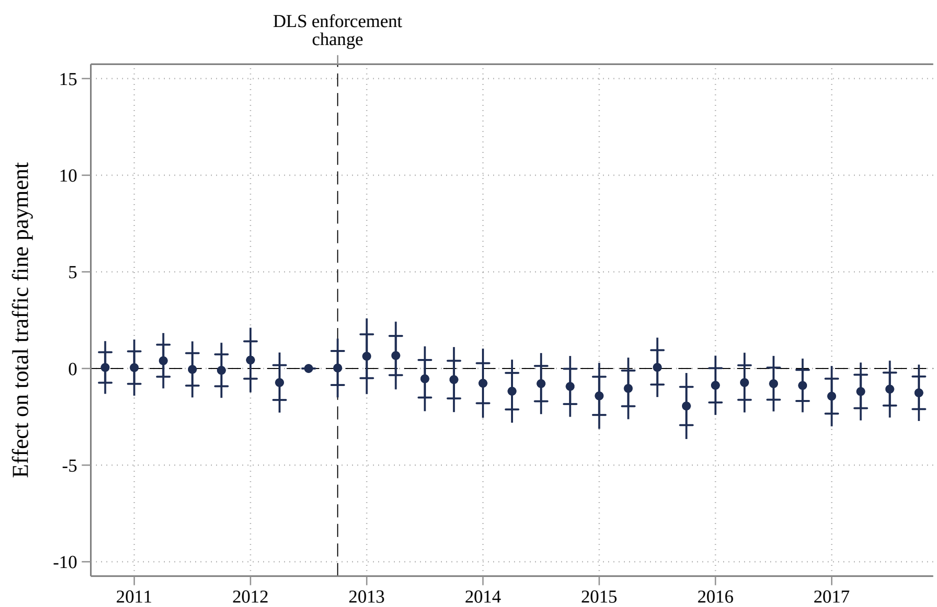

Notes: The figure shows the evolution of in-person and online credit card traffic fine payment around the change in enforcement in DLS policy. The unit of observation is a driver-quarter. The sample is the primary sample defined in section 3.2. Each figure presents estimates of the coefficients $\gamma^k$ on the interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008 from an ordinary least squares (OLS) regression of the outcome on interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008, interactions between calendar quarter indicators and the number of focal traffic fines, and driver and calendar quarter fixed effects. In panel A, the outcome is in-person traffic fine payment. In panel B, the outcome is online credit card traffic fine payment. The inner error bars represent 95 percent pointwise confidence intervals based on asymptotic standard errors clustered by driver. The outer error bars represent 95 percent uniform sup-$t$ confidence intervals computed as outlined in Montiel Olea and Plagborg-Møller (2019) based on an asymptotic variance-covariance matrix clustered by driver.

Figure 6: Evolution of notices of DLS and total traffic fine payment among drivers ineligible for DLS

*Panel A: Notice of DLS*



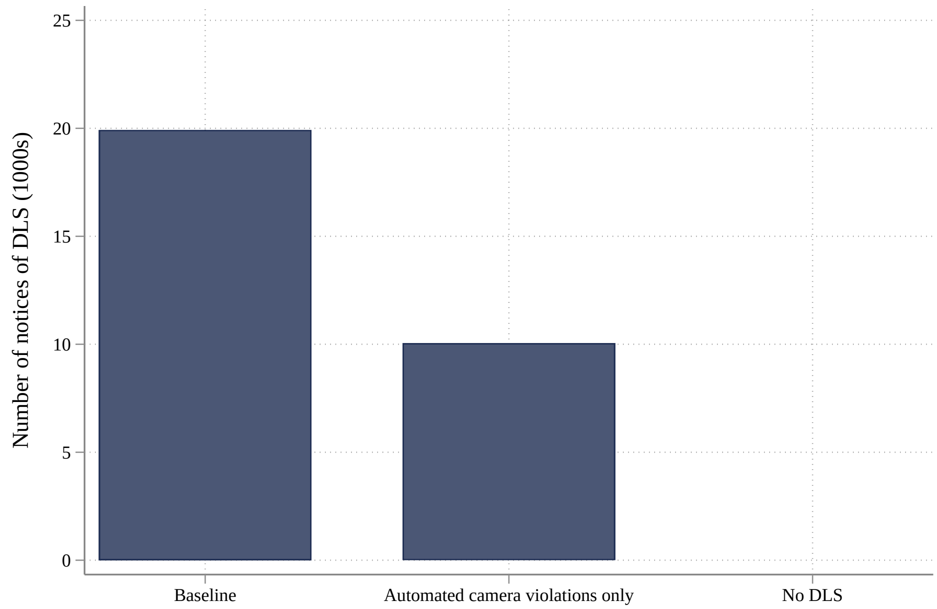

*Panel B: Total traffic fine payment*



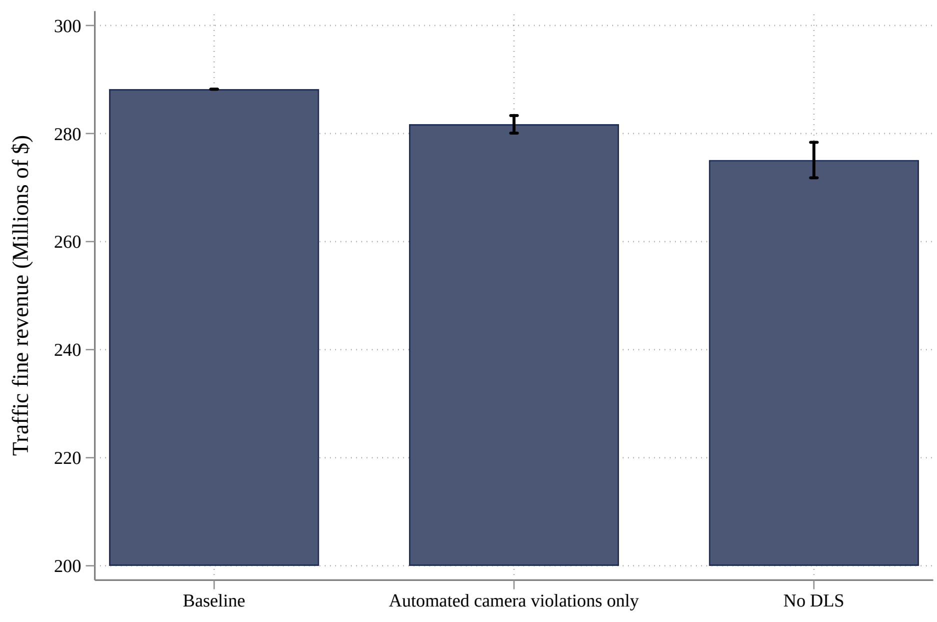

Notes: The figure shows the evolution of the likelihood of receiving a notice of DLS and total traffic fine payment around the change in enforcement in DLS policy. The unit of observation is a driver-quarter. The sample is the subset of drivers in the primary sample defined in section 3.2 who have fewer than 10 unpaid traffic fines for parking or compliance violations and 5 unpaid traffic fines for automated camera violations as of December 1, 2012. Each figure presents estimates of the coefficients $\gamma^k$ on the interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008 from an ordinary least squares (OLS) regression of the outcome on interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008, interactions between calendar quarter indicators and the number of focal traffic fines, and driver and calendar quarter fixed effects. In panel A, the outcome is an indicator for receipt of a notice of DLS. In panel B, the outcome is total traffic fine payment. The inner error bars represent 95 percent pointwise confidence intervals based on asymptotic standard errors clustered by driver. The outer error bars represent 95 percent uniform sup-*t* confidence intervals computed as outlined in Montiel Olea and Plagborg-Møller (2019) based on an asymptotic variance-covariance matrix clustered by driver.

Figure 7: Annual traffic fine revenue under counterfactual DLS policies

*Panel A: Notice of DLS*




*Panel B: Traffic fine revenue*




Notes: This figure presents estimates of annual traffic fine revenue under counterfactual DLS policies. Panel A presents the number of notices of DLS under each counterfactual DLS policy. The "baseline" bar represents the average number of notices sent by the city between 2013 and 2017. The "automated camera violations only" bar reflects the share of the baseline number of notices of DLS sent per year associated with drivers with at least 5 unpaid automated camera fines as of the notice date. The "no DLS" bar represents the zero notices of DLS that would be sent if the city were to stop using DLS to compel payment of traffic fines. Panel B presents annual traffic fine revenue under each counterfactual DLS policy. The "baseline" bar reflects the average annual traffic fine revenue between 2013 and 2017. The "automated camera violations only" and "no DLS" bars reflect estimates of average annual traffic fine revenue under the given counterfactual DLS policy. For each counterfactual, I estimate counterfactual annual traffic fine revenue as baseline annual traffic fine revenue plus the cumulative effect of DLS notice receipt on total traffic fine payment times the change in the number of notices of DLS under the given counterfactual. I set the cumulative effect of DLS notice receipt on total traffic fine payment equal to the estimate reported in the second row and second column of table 2. The error bars in panel B represent $\pm$ 1.96 standard errors. Standard errors take into account only the statistical uncertainty in the estimate of the cumulative effect of DLS notice receipt on total traffic fine payment.

Table 1: Summary statistics

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Fraction of focal traffic fines issued in 2008: | | |
| | Overall | Below median | Above median | Difference |
| Number of focal traffic fines | 2.758 | 2.779 | 2.736 | -0.0437 |
| | (3.544) | (3.507) | (3.581) | (0.0194) |
| Share of focal traffic fines issued in 2008 | 0.503 | 0.046 | 0.976 | 0.9300 |
| | (0.478) | (0.131) | (0.083) | (0.0006) |
| Traffic fine debt (1000s) | 1.659 | 1.627 | 1.693 | 0.0653 |
| | (2.381) | (2.326) | (2.436) | (0.0131) |
| Average quarterly notice of DLS receipt | 0.006 | 0.005 | 0.007 | 0.0017 |
| | (0.029) | (0.027) | (0.031) | (0.0002) |
| Average quarterly traffic fine payments: | | | | |
| Total | 8.160 | 7.351 | 8.997 | 1.6466 |
| | (39.847) | (37.872) | (41.775) | (0.2189) |
| In person | 7.385 | 6.552 | 8.247 | 1.6941 |
| | (38.971) | (36.888) | (40.996) | (0.2141) |
| Online credit card | 0.422 | 0.380 | 0.466 | 0.0867 |
| | (4.524) | (4.278) | (4.764) | (0.0249) |
| Number of drivers | 132983 | 67603 | 65380 | 132983 |

Notes: This table presents summary statistics for select variables among drivers in the primary sample defined in section 3.2. Columns (1) through (3) report estimates of the mean and standard deviation (in parentheses) of each variable across different subsets of the primary sample of drivers. Column (4) reports an estimate of the difference in means in each variable across drivers with below- and above-median shares of focal traffic fines issued in 2008. Heteroskedasticity-robust standard errors are reported in parentheses. In column (1) the sample is all drivers in the primary sample. In columns (2) and (3) the samples are drivers in the primary sample with a below- and above-median shares of focal traffic fines issued in 2008, respectively. In column (4) the sample is all drivers in the primary sample. In all columns, the unit of observation is a driver. Traffic fine debt is computed as December 1, 2012. Average quarterly notice of DLS receipt and average quarterly traffic fine payments are computed across calendar quarters between Q4 2010 and Q3 2012.

Table 2: Cumulative effect of DLS notice receipt on traffic fine payment

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | | Traffic fine payment: | |
| | Notice of DLS | Total | In person | Online credit card |
| Cumulative effect of exposure $\left(\sum_{k=0}^{15} \hat{\gamma}^k\right)$ | 0.049 | 35.6 | 33.0 | 1.6 |
| | (0.006) | (7.9) | (7.7) | (1.0) |
| Cumulative effect of DLS notice receipt $\left(\sum_{k=0}^{15} \hat{\beta}^k\right)$ | | 658.1 | 603.6 | 25.3 |
| | | (84.1) | (81.9) | (12.5) |
| Average traffic fine debt | 1658.7 | 1658.7 | 1658.7 | 1658.7 |
| Number of drivers | 132983 | 132983 | 132983 | 132983 |
| Number of driver-quarters | 3856122 | 3856122 | 3856122 | 3856122 |

Notes: This table presents estimates of four-year effects of DLS notice receipt on traffic fine payment. In all columns, the unit of observation is a driver-quarter. The sample is the primary sample defined in section 3.2. The first row reports estimates of the four-year effect of exposure to the change in DLS policy enforcement on the given outcome obtained via an ordinary least squares (OLS) regression of the outcome on interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008, interactions between calendar quarter indicators and the number of focal traffic fines, and driver and calendar quarter fixed effects. The second row reports estimates of the four-year effect of DLS notice receipt on the given outcome obtained via a two-stage least squares (2SLS) regression of the outcome on lagged indicators for DLS notice receipt and driver and calendar quarter fixed effects, with the contemporaneous and corresponding lagged values of an interaction between an indicator for whether the calendar quarter is Q1 2013 and the share of focal traffic fines issued in 2008 as excluded instruments and a full set of interactions between calendar quarter indicators and the number of focal traffic fines as exogenous controls. In both rows, standard errors clustered by driver are reported in parentheses. In column (1) the outcome is an indicator for receipt of a notice of DLS. In column (2) the outcome is total traffic fine payments. In columns (3) and (4) the outcomes are in-person and online credit card traffic fine payments, respectively.

Table 3: Cumulative effects of exposure to change in DLS policy enforcement by DLS eligibility

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Notice of DLS | | | Total traffic fine payment | |
| | All | DLS ineligible | Difference | All | DLS ineligible | Difference |
| Cumulative effect of exposure $\left(\sum_{k=0}^{15} \hat{\gamma}^k\right)$ | 0.049 | 0.007 | 0.042 | 35.6 | -9.3 | 44.9 |
| | (0.006) | (0.002) | (0.006) | (7.9) | (5.3) | (5.4) |
| Average traffic fine debt | 1658.7 | 807.9 | 1658.7 | 1658.7 | 807.9 | 1658.7 |
| Number of drivers | 132983 | 105609 | 132983 | 132983 | 105609 | 132983 |
| Number of driver-quarters | 3856122 | 3062642 | 3856122 | 3856122 | 3062642 | 3856122 |

Notes: This table presents estimates of four-year effects of exposure to the change in DLS policy enforcement by DLS eligibility. In all columns, the unit of observation is a driver-quarter. In columns (1), (3), (4), and (6) the sample is the primary sample defined in section 3.2. In columns (2) and (5) the sample is the subset of drivers in the primary sample who have fewer than 10 unpaid traffic fines for parking or compliance violations and 5 unpaid traffic fines for automated camera violations as of December 1, 2012. Columns (1), (2), (4), and (5) present estimates of the four-year effect of exposure to the change in DLS policy enforcement on the given outcome obtained via an ordinary least squares (OLS) regression of the outcome on interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008, interactions between calendar quarter indicators and the number of focal traffic fines, and driver and calendar quarter fixed effects. Standard errors clustered by driver are reported in parentheses. Column (3) presents an estimate of the difference between the estimates in columns (1) and (2). Column (6) presents an estimate of the difference between the estimates in columns (4) and (5). In both columns (3) and (6), standard errors estimated via a non-parametric bootstrap with 30 replicates and sampling done by driver with replacement are reported in parentheses. In columns (1)-(3), the outcome is an indicator for receipt a notice of DLS. In columns (4)-(6), the outcome is total traffic fine payments.

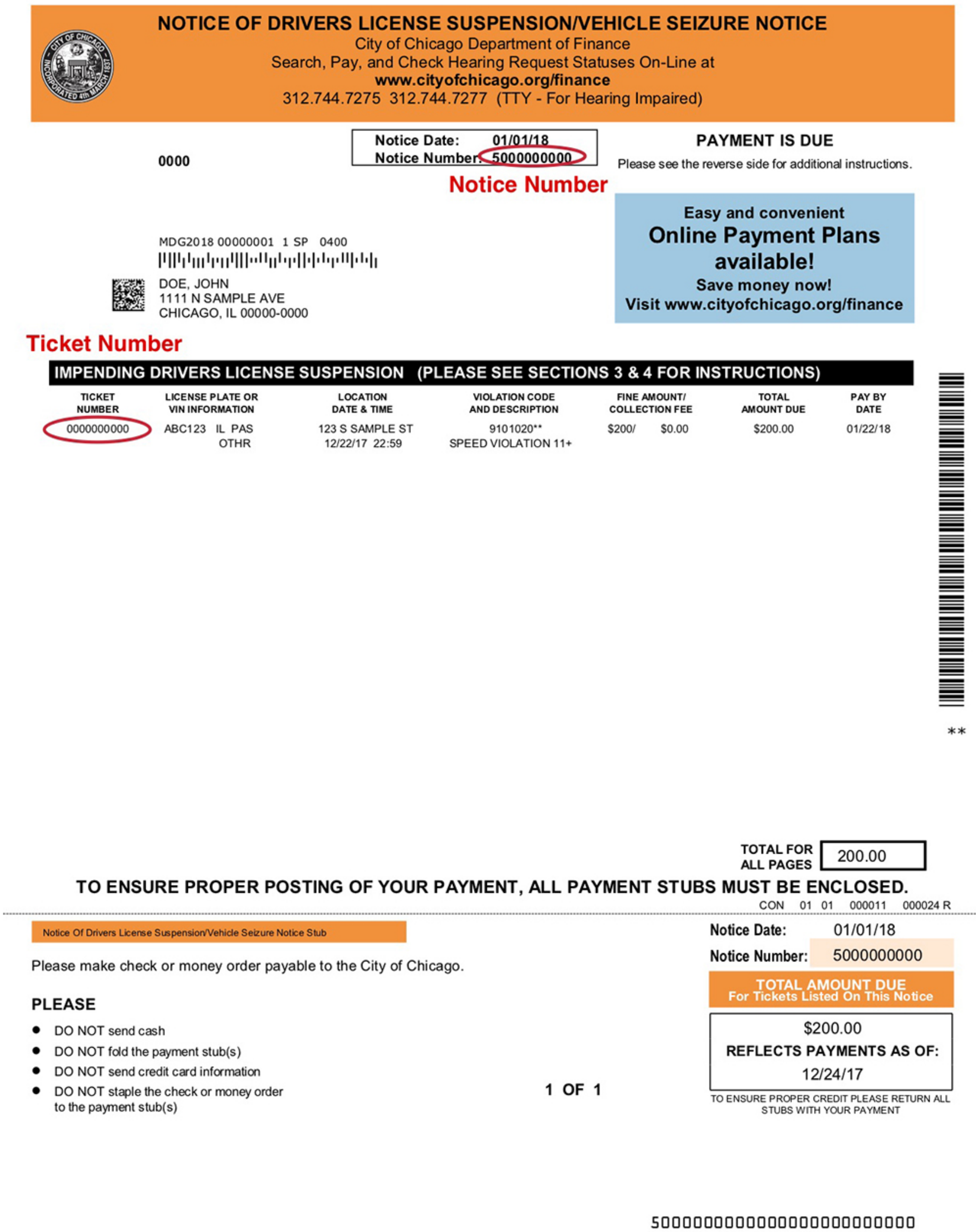
Table 4: Heterogeneity in cumulative effect of DLS notice receipt

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Driver ZIP Code characteristic: | | Difference: | |
| | Below median | Above median | Level | Share of debt |
| (1) Share with income below federal poverty line | 878.3 | 507.2 | -371.1 | -0.423 |
| | (130.3) | (110.8) | (175.7) | (0.107) |
| | [1315.0] | [2070.1] | | |
| (2) Share black | 804.9 | 565.8 | -239.0 | -0.348 |
| | (128.1) | (113.1) | (196.0) | (0.125) |
| | [1293.6] | [2060.6] | | |
| (3) Share hispanic | 678.4 | 639.0 | -39.4 | 0.065 |
| | (113.9) | (128.0) | (134.0) | (0.082) |
| | [1842.5] | [1475.8] | | |

Notes: This table presents estimates of the four-year effect of DLS notice receipt on total traffic fine payment by driver ZIP code characteristics. In all columns, the unit of observation is a driver-quarter. For each driver ZIP Code characteristic, column (1) and (2) present estimates of the four-year effect of DLS notice receipt on total traffic fine payment among drivers with below- and above-median values of the characteristic, respectively. The estimates are obtained via a two-stage least squares (2SLS) regression of total traffic fine payment on lagged indicators for DLS notice receipt and driver and calendar quarter fixed effects, with the contemporaneous and corresponding lagged values of an interaction between an indicator for whether the calendar quarter is Q1 2013 and the share of focal traffic fines issued in 2008 as excluded instruments and a full set of interactions between calendar quarter indicators and the number of focal traffic fines as exogenous controls. Standard errors clustered by driver are reported in parentheses. The average traffic fine debt within the sample is reported in brackets. Columns (3) presents estimates of the differences between the estimates in columns (2) and (1). Column (4) presents estimates of the same differences, where the estimates in columns (2) and (1) are expressed relative to the average traffic fine debt in their respective samples. In both columns (3) and (4), standard errors estimated via a non-parametric bootstrap with 30 replicates and sampling done by driver with replacement are reported in parentheses. In row (1), the driver ZIP Code characteristic is the share of residents with income below the federal poverty line. In row (2), the driver ZIP Code characteristic is the share of residents who are black. In row (3), the driver ZIP Code characteristic is the share of residents who are hispanic.

# A Supplemental Tables and Figures

Figure A1: Example notice of driver's license suspension and vehicle seizure



**NOTICE OF DRIVERS LICENSE SUSPENSION/VEHICLE SEIZURE NOTICE**
City of Chicago Department of Finance
Search, Pay, and Check Hearing Request Statuses On-Line at
**www.cityofchicago.org/finance**
312.744.7275 312.744.7277 (TTY - For Hearing Impaired)

**0000**

Notice Date: 01/01/18
Notice Number: 5000000000
Notice Number

**PAYMENT IS DUE**
Please see the reverse side for additional instructions.

Easy and convenient
**Online Payment Plans available!**
Save money now!
Visit www.cityofchicago.org/finance

MDG2018 00000001 1 SP 0400
DOE, JOHN
1111 N SAMPLE AVE
CHICAGO, IL 00000-0000

Ticket Number

**IMPENDING DRIVERS LICENSE SUSPENSION (PLEASE SEE SECTIONS 3 & 4 FOR INSTRUCTIONS)**

| TICKET NUMBER | LICENSE PLATE OR VIN INFORMATION | LOCATION DATE & TIME | VIOLATION CODE AND DESCRIPTION | FINE AMOUNT/ COLLECTION FEE | TOTAL AMOUNT DUE | PAY BY DATE |
|---|---|---|---|---|---|---|
| 0000000000 | ABC123 IL PAS OTHR | 123 S SAMPLE ST 12/22/17 22:59 | 9101020** SPEED VIOLATION 11+ | $200/ $0.00 | $200.00 | 01/22/18 |

**

TOTAL FOR ALL PAGES 200.00

**TO ENSURE PROPER POSTING OF YOUR PAYMENT, ALL PAYMENT STUBS MUST BE ENCLOSED.**
CON 01 01 000011 000024 R

Notice Of Drivers License Suspension/Vehicle Seizure Notice Stub

Please make check or money order payable to the City of Chicago.

**PLEASE**

- DO NOT send cash
- DO NOT fold the payment stub(s)
- DO NOT send credit card information
- DO NOT staple the check or money order to the payment stub(s)

1 OF 1

Notice Date: 01/01/18
Notice Number: 5000000000
TOTAL AMOUNT DUE
For Tickets Listed On This Notice
$200.00
REFLECTS PAYMENTS AS OF:
12/24/17
TO ENSURE PROPER CREDIT PLEASE RETURN ALL STUBS WITH YOUR PAYMENT

5000000000000000000000000000

Notes: This figure shows an example notice of driver's license suspension and vehicle seizure from the City of Chicago. The image was captured from `https://pay.chicago.gov/findticketimage#notices` on September 2, 2019.

Figure A2: Details regarding City of Chicago traffic fine payment plans

*Panel A: Payment plan parameters*

| | Online Payment Plans | | In-Person Payment Plans | |
|---|---|---|---|---|
| | Early | Standard | Standard | Hardship |
| Eligible Violations | Violations in Violation or Determination Status | Violations in Final, Seizure, Suspension Status | Violations in Final, Seizure, Suspension Status | Violations in Final, Seizure, Suspension Status |
| Restrictions | Not eligible if vehicle booted or driver's license is suspended, have unpaid fees or violations are in a judgment or protected by bankruptcy. | Not eligible if vehicle booted or driver's license is suspended, have unpaid fees or violations are in a judgment or protected by bankruptcy. | No | Must meet Hardship Qualifications |
| Term | 3 Months | Up to 24 Months | Up to 24 Months | Up to 36 Months |
| Down Payment | Payment equal to first equal monthly installment payment | Payment equal to first equal monthly installment payment | *Payment equal to first equal monthly installment payment + payment of all outstanding fees (boot, tow, storage, etc.) in full<br>*If booted or driver's license suspended - 50% of ticket debt, plus payment of all outstanding fees (boot, tow, storage, etc.) in full | *Payment equal to first equal monthly installment payment + payment of all outstanding fees (boot, tow, storage, etc.) in full<br>*If booted or driver's license suspended - 25% of ticket debt, plus payment of all outstanding fees (boot, tow, storage, etc.) in full |
| Multiple Payment Plans | Yes | No | No | No |
| Add Additional Tickets to Existing Plan? | No | Yes | Yes, with additional down payment | Yes, with additional down payment |
| Default Fee | None. However, motorist is prohibited from another early payment plan for 12 months. | $100 | $100 | $100 |
| Additional Benefit | No Penalty Assessed | 22% Collection Costs Waived | No | Must meet Hardship Qualifications |

*Panel B: Hardship payment plan eligibility*

**Individuals that meet at least one of the following qualifications are eligible for a hardship payment plan:**

- Student (currently attending college or high, trade or vocational school) with a valid student ID card;
- Senior citizen (65 and older);
- Active military (including reservists and national guard);
- Recently inactive military (discharged from the military in the last 180 days);
- Foreclosure (received a notice of foreclosure, entered into a consent foreclosure, gave a deed in lieu of foreclosure, or had a judgment of foreclosure entered on primary residence within last three years);
- Bankruptcy (liability for fines and penalties remain after obtaining a bankruptcy discharge);
- Claimed Earned Income Tax Credit (on state or federal individual income tax return for the most recent tax year); or
- Participation in any of the following programs:

• Government Issued Unemployment Compensation

• Low income home energy assistance program (LIHEAP)

• Federal Public Housing/ Section 8

• Food Stamps

• Medicaid or Supplemental Security Income (SSI)

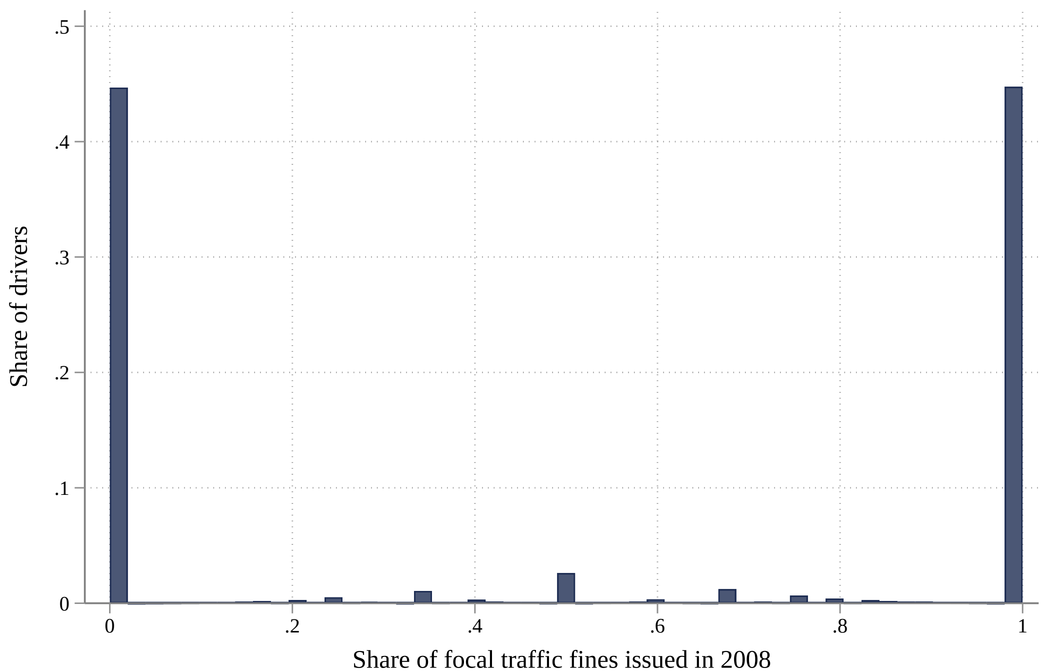
• Temporary Assistance for Needy Families (TANF) program administered by the U.S. Department of Health and Human Services. Program information available on-line at www.hhs.gov;

• Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) administered by the U.S. Department of Agriculture. Program information available on-line at www.usda.gov;

• Worker's compensation income benefits. Program information available on-line at www.iwcc.il.gov.

Notes: This figure presents details regarding traffic fine payment plans offered by the City of Chicago. Panel A provides an overview of all available payment plans. Panel B presents details regarding eligibility for the hardship payment plan. Both images were captured from `https://www.chicago.gov/city/en/depts/fin/supp_info/revenue/parking_and_red-lightticketpaymentplans.html` on January 9, 2020.

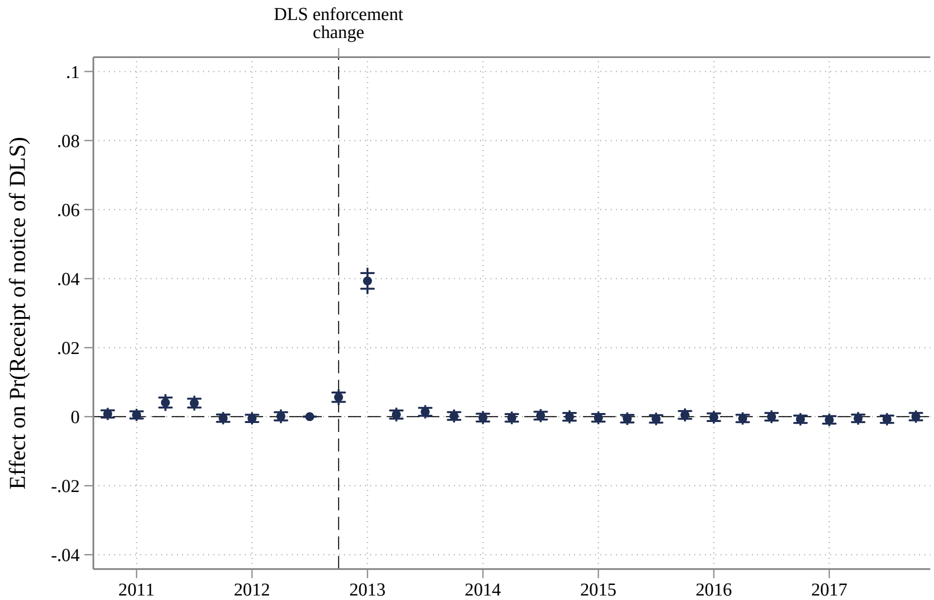
Figure A3: Distribution of share of focal traffic fines issued in 2008 among drivers in primary sample



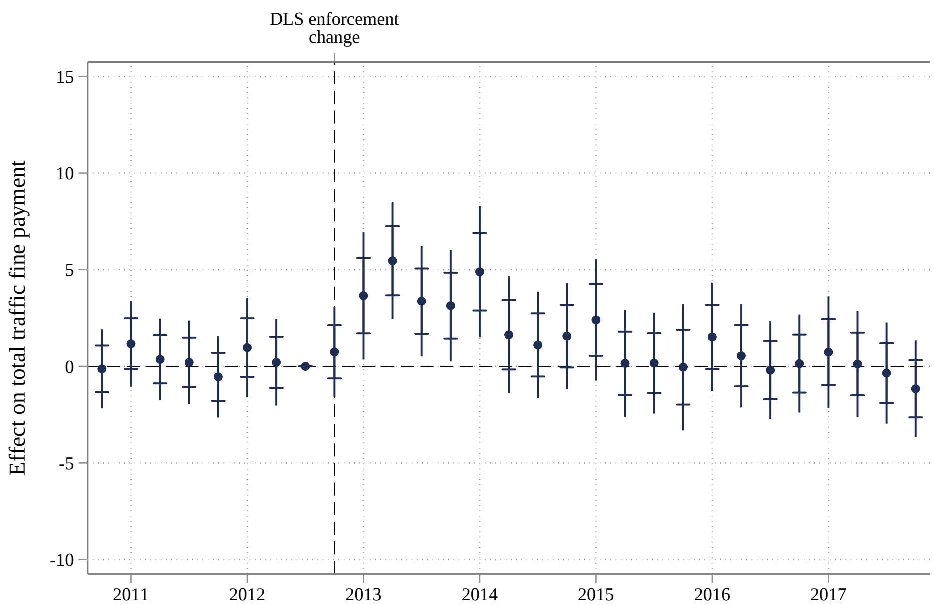

Notes: This figure shows the distribution of the share of focal traffic fines issued in 2008 across drivers in the primary sample defined in section 3.2. The unit of observation is a driver.

Figure A4: Evolution of notices of DLS and total traffic fine payment among drivers never garnished

*Panel A: Notice of DLS*




*Panel B: Total traffic fine payment*




Notes: The figure shows the evolution of the likelihood of receiving a notice of DLS and total traffic fine payment around the change in enforcement in DLS policy. The unit of observation is a driver-quarter. The sample is the primary sample defined in section 3.2, excluding drivers with any traffic fine payment to the city via state payment garnishment. Each figure presents estimates of the coefficients $\gamma^k$ on the interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008 from an ordinary least squares (OLS) regression of the outcome on interactions between calendar quarter indicators and the share of focal traffic fines issued in 2008, interactions between calendar quarter indicators and the number of focal traffic fines, and driver and calendar quarter fixed effects. In panel A, the outcome is an indicator for receipt of a notice of DLS. In panel B, the outcome is total traffic fine payment. The inner error bars represent 95 percent pointwise confidence intervals based on asymptotic standard errors clustered by driver. The outer error bars represent 95 percent uniform sup-*t* confidence intervals computed as outlined in Montiel Olea and Plagborg-Møller (2019) based on an asymptotic variance-covariance matrix clustered by driver.

Table A1: Focal traffic fines and traffic fines affected by change in enforcement of DLS policy

| Violation code | Violation description | Focal traffic fines (Issued 2007-2008) | Total affected traffic fines (Issued 2008-2012) |
|---|---|---|---|
| 0976160F | EXPIRED PLATES OR TEMPORARY REGISTRATION | 161983 | 476309 |
| 0964125 | NO CITY STICKER OR IMPROPER DISPLAY | 133453 | 281935 |
| 0976160A | REAR AND FRONT PLATE REQUIRED | 55615 | 156073 |
| 0964125B | NO CITY STICKER VEHICLE UNDER/EQUAL TO 16,000 LBS. | 0 | 93956 |
| 0976220B | SMOKED/TINTED WINDOWS PARKED/STANDING | 5911 | 17903 |
| 0976160D | NONCOMPLIANT PLATE(S) | 6713 | 14940 |
| 0976210B | WINDOWS MISSING OR CRACKED BEYOND NUM INCH | 2386 | 6408 |
| 0976220A | OBSTRUCTED OR IMPROPERLY TINTED WINDOWS | 1016 | 3359 |
| 0976050B | TWO HEAD LAMPS REQUIRED VISIBLE 1000' | 382 | 1965 |
| 0964125D | IMPROPER DISPLAY OF CITY STICKER | 0 | 1006 |
| 0976210A | LAMPS BROKEN OR INOPERABLE | 278 | 982 |
| 0976050D | REAR PLATE LIT AND LEGIBLE FOR 50' | 110 | 788 |
| 0964125C | NO CITY STICKER VEHICLE OVER 16,000 LBS. | 0 | 672 |
| 0976050C | RED REAR LAMP REQUIRED VISIBLE 500' | 202 | 665 |
| 0940080 | PARKED/STANDING UNATTENDED W/MOTOR RUNNI | 272 | 584 |
| 0940170 | UNSAFE CONDITION | 206 | 483 |
| 0976120 | REAR VIEW MIRROR REQUIRED | 173 | 398 |
| 0976110A | PROPER FRONT AND REAR BUMPERS REQUIRED | 87 | 201 |
| 0976160C | FRONT PLATE REQUIRED FOR TRUCK TRACTORS | 95 | 177 |
| 0976160B | REAR PLATE REQUIRED MOTORCYCLE/TRAILER | 57 | 148 |
| 0940220 | NO OPERATOR SIGNAL | 30 | 136 |
| 0976140A | NO OR IMPROPER MUFFLER | 52 | 113 |
| 0976140B | EXCESS FUMES/SMOKE DURING OPERATION | 10 | 85 |
| 0976080 | IMPROPER LAMPS NON-MOTOR VEHICLE | 18 | 64 |
| 0976040B | USE OF SIREN/BELL/WHISTLE PROHIBITED | 16 | 62 |
| 0976090C | DEPR./DIMMED LAMPS | 7 | 58 |
| 0976090B | IMPROPER LAMP FOR PARKED VEH ON UNLIT ST | 8 | 39 |
| 0976050E | 2 REAR TRAILER LAMPS REQ'D VISIBLE 500' | 8 | 39 |
| 0976050A | MOTORCYCLE HEAD LAMP VISIBLE 500' | 15 | 37 |
| 0976100A | SUSPENSION MODIFIED BEYOND NUM INCH | 8 | 32 |
| 0976200B | PROJECTING LOAD (REAR) | 10 | 31 |
| 0976020B | HAND BRAKES:PROPER STOPPING CAPABILITY | 7 | 25 |
| 0976200A | PROJECTING LOAD (LEFT OR RIGHT SIDE) | 16 | 24 |
| 0976020A | SERVICE BRAKES:STOPPING CAPABILITY | 11 | 24 |
| 0976020E | BRAKES REQUIRED IN GOOD WORKING ORDER | 2 | 13 |
| 0976070A | IMPROPER SIDE COWL/FENDER LAMPS | 4 | 12 |
| 0976030 | WINDSHIELD WIPERS REQUIRED | 4 | 10 |
| 0976060A | MORE THAN ONE OR IMPROPER SPOT LAMP | 0 | 7 |
| 0976060B | MORE THAN THREE OR IMPROPER AUX LAMP | 1 | 5 |
| 0976040A | HORN REQUIRED DURING OPERATION | 1 | 3 |
| 0976130 | TWO RED REAR TRAILER REFLECTORS REQUIRED | 1 | 3 |
| 0976010A | BRAKES REQUIRED DURING OPERATION | 0 | 3 |
| 0976070D | MORE THAN FOUR FRONT MOUNTED LAMPS | 0 | 1 |
| 0976200C | SAFETY CHAINS REQUIRED | 0 | 1 |
| 0976190 | COMMERCIAL IDENTIFICATION ETC. REQUIRED | 0 | 1 |
| 0976070C | BACK-UP LAMP LIT DURING OPERATION | 0 | 1 |
| 0976020C | ANTIQ VEH BRAKES:STOPPING CAPABILITY | 0 | 1 |
| 0976010B | MOTORCYCLE BRAKES REQ'D DURING OPERATION | 1 | 1 |
| Number of traffic fines | | 369169 | 1059783 |
| Number of drivers | | 133107 | 372949 |

Notes: This table presents the number of focal traffic fines and the number of traffic fines affected by the change in enforcement of DLS policy by violation code. A focal traffic fine is a traffic fine issued for a compliance violation over the course of 2007 and 2008 that was left unpaid as of December 1, 2012. A fine affected by the change in enforcement of DLS policy is a traffic fine issued for a compliance violation over the course of 2008 and 2012 that was left unpaid as of December 1, 2012.

Table A2: Results for alternative samples and specifications

| | (1) Cumulative effect of DLS notice receipt on traffic fine payment (Std. error) | (2) Number of driver-quarters (Drivers) |
|---|---|---|
| (1) Baseline | 658.1 | 3856122 |
| | (84.1) | (132983) |
| (2) Excluding drivers with state payment garnishment | 673.2 | 3168380 |
| | (98.0) | (109265) |
| (3) Excluding drivers with one relevant traffic fine | 573.0 | 1930230 |
| | (79.3) | (66571) |
| (4) Not excluding top 0.1 percent of driver-quarters | 728.3 | 3856507 |
| | (89.3) | (132983) |
| (5) Using $z_{it} = \mathbb{1}(c_i \geq 0.5) \times \mathbb{1}(t = t^* + 1)$ | 681.4 | 3856122 |
| | (84.7) | (132983) |
| (6) Five-year cumulative effect ($L = 19$) | 821.9 | 3324195 |
| | (110.9) | (132983) |
| (7) No time-varying controls | 653.9 | 3856122 |
| | (85.1) | (132983) |

Notes: This table presents estimates of the cumulative effect of receiving a notice of DLS on total traffic fine payment under alternative samples and model specifications. Column (1) presents estimates of the cumulative effect of receiving a notice of DLS on traffic fine payment, with the corresponding standard error in parentheses. Column (2) presents the number of driver-quarters and drivers used in estimation. Specification (1) repeats the estimates presented in the second row and second column of table 2. Specification (2) repeats specification (1) excluding drivers with any traffic fine payment to the city via state payment garnishment from estimation. Specification (3) repeats specification (1) excluding drivers with only one focal traffic fine from estimation. Specification (4) repeats specification (1) not excluding driver-quarters in the top 0.1 percent of the total traffic fine payments distribution from estimation. Specification (5) repeats specification (1) with the instruments defined using an indicator for whether the share of focal traffic fines is at least 0.5 rather than the share of focal traffic fines itself. Specification (6) repeats specification (1) with the cumulative effect defined over 5 years (i.e., $L = 19$). Specification (7) repeats specification (1) without any time-varying controls.