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Escaping the long arm of the law? Racial disparities in the effect of drivers' licence suspensions of offence probabilities

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Abstract

This paper studies the unintended consequences of failure-to-pay (FTP) driver's license suspensions. Unlike other traffic enforcement papers which focus on the public benefit to increases in enforcement we focus on the private returns. Drawing on a unique administrative dataset and institutional features that result in as-good-as random assignment of FTP suspension we estimate the effect of these suspensions on the probability a driver receives additional tickets. We find that financial penalties and FTP suspensions reduce the probability of reoffence for White drivers. However, among Black drivers' financial penalties have no effect and FTP suspension increases the probability of reoffence by six to nine percentage points. A series of additional analyses fail to produce evidence of racial differences in driver's response to FTP suspension, leading us to conclude that following suspension drivers make behavioral adjustments to minimize the probability of future tickets. However, these behavioral adjustments are only effective for White drivers.

JEL Codes: K1, K40, K42, J15

Keywords: Drivers' license suspensions, traffic stops, racial discrimination

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1. Introduction

Drivers' license suspensions are a ubiquitous policy tool, used in states across the US as punishment for a wide range of behaviors such as drug-related offences, truancy, outstanding child support, and failure-to-pay a traffic ticket (FTP suspensions henceforth). The latter is by far the most common reason for license suspension. As of 2016, at least seven million Americans' had a suspended license for failing to pay a court debt. In three states more than nine percent of the over-18 population had active license suspensions for this reason (Moyer, 2018).[1] This issue has received a substantial amount of attention in popular media in recent years with concerns raised over the disparate impacts of these policies on the poor and on people of color (Grabar, 2017; Sanchez, 2018; Coleman, 2020; Lopez, 2020). This concern has grown so large many states are proposing and passing legislation to end or restrict their use (Pedraza, 2020; Hood, 2020; Cap News Services, 2020; Ward, 2020).

FTP suspensions are controversial because rather than being a tool designed to protect public safety their primary purpose is revenue collection, described as "perhaps the most valuable tool available to the municipal courts for inducing payment on past due accounts" (Pawasarat and Quinn, 2014, p. 1). However, it is unlikely that the effect of FTP policies is limited to the budgetary realm. FTP suspensions may have a deterrent effect, producing a positive externality by inducing safer driving behavior (Markowsky and Stratmann, 2011; Gehrsitz, 2017). However, they likely also have negative, unintended consequences. By limiting access to employment while simultaneously demanding payment, drivers' license suspension likely has an outsized impact on an individual's economic position. Studying the impact financial penalties from minor traffic violations have on a variety of financial health outcomes, Mello (2018) finds that minor traffic fines increase financial distress in financially fragile households, resulting in a welfare loss of approximately \$500. Other evidence suggests drivers belonging to racial minority groups will be disproportionately affected. This may occur because cities with larger Black populations are more reliant on fine and fee revenue (Sances and You, 2017; Kopf, 2016). It may also be a result of the over-policing of minority individuals and minority communities (Epp et al., 20176). In California drivers of color are up to sixteen times more likely to be arrested and jailed for failing to pay a fine than their white counterparts (Bingham et al., 2017).

There are also legal consequences that flow from license suspension. On the extensive margin, individuals may continue to drive after their license is suspended, raising the possibility of escalating punishments. On the intensive margin, by adding to a driver's traffic offence history, FTP suspension may increase the likelihood of receiving a future ticket if it leads to less lenient treatment by law enforcement officers. A large body of empirical literature on racial discrimination in traffic stops (for example Goncalves and Mello (2020) find that officers ticket Black drivers more severely than their White counterparts) suggests that these negative consequences will be borne disproportionately by Black drivers.

In this paper, we provide evidence of the unintended consequences of FTP suspensions and how they vary by race by asking two questions. First, does FTP suspension affect an individual's probability of receiving a future traffic ticket? Second, does this effect depend on the race of the driver? To answer these questions, using the universe of traffic tickets filed in Marion County, Indiana (home to the city of Indianapolis), we employ a similar identification strategy to Gehrsitz (2017) in which we leverage an automatic suspension process and a driver information deficit that together result in as-good-as random assignment of FTP suspension.

In Marion County, if a ticket is not paid or contested within 72 days of the date it was issued, the individual's license is automatically suspended for failure to pay. Importantly, drivers appear to be unaware of this deadline as information on the ticket indicates drivers have 60 days to pay the fine. We take advantage of this institutional feature, as well as lags in processing time and court reporting, to identify a three-day window immediately following the 72 day deadline in which FTP suspension is good-as-randomly assigned, about 50 percent of drivers happened to pay their ticket just before the deadline while the other half just missed the 72 day cutoff. Henceforth, we refer to tickets paid within this short window as "window tickets". Limiting our analysis to these tickets allows us to account for systematic differences between individuals inclined to pay early and those inclined to pay late and produce causal estimates of the effect of license suspension on the likelihood that an individual receives an additional ticket within two years of the initial ticket.

Our initial analysis of window tickets detects no evidence of changes in the probability of incurring future tickets. However, after allowing for race-specific treatment effects we find that White drivers experience a 2.8 percentage point ($p < .1$) decrease in their probability of receiving a future ticket. Consistent with the literature on the public returns to ticketing in the sample of White drivers, the size of the financial penalty is inversely related to the probability of future ticket receipt ($p < .01$), suggesting that drivers adopt safer driving behavior in order to minimize the chance of incurring more costly tickets in the future. For Black drivers, the other hand, FTP suspension increases the probability of receiving a future ticket by between 6.3 and 8.2 percentage points ($p < .05$). Moreover, the financial penalty associated with the window ticket has a negative but statistically insignificant effect on future outcomes. These results are robust to the inclusion of control variables and neighborhood fixed effects, meaning that geographic variation in policing practices does not explain our results.

A possible explanation is that there are unobservable differences in the underlying behavior of the groups that lead them to respond differently to FTP suspension. To explore this possibility, we run a series of models looking for racial differences in driving behavior. Specifically, we test whether White and Black drivers engage in different amounts of risky driving, if White and Black drivers exhibit different levels of financial responsibility and finally, if White and Black drivers regain their license following suspension at different rates. These tests fail to find any significant or substantive differences in driving behavior between the two groups that could explain our main result, leading us to conclude that drivers of both races act to minimize the probability of incurring additional tickets, however these behavioral adjustments are only effective for White drivers.

We argue that taken together our results suggest that regardless of driving behavior Black drivers are more likely to be stopped by the police and thus the FTP suspension is more likely to come to the attention of the officer. However, we cannot rule out a role for officer leniency in the ticketing decision; it is possible that once stopped police officers are more likely to extend lenient treatment to the marginal White driver but not to the marginal Black driver. Nevertheless, this paper makes several important contributions. It is the first quasi-experimental paper studying the effects of FTP license suspension, a common and understudied policy, in the US and contributes to a growing literature on the effects of enforcement on future behavior (Markowsky and Stratmann, 2011; Harper et al., 2014; Luca, 2015; Gehrsitz, 2017, Mello, 2018). By demonstrating the size of the financial penalty impacts future outcomes we contribute to existing literature on the shared benefits of safer driving while building on this literature by estimating private returns to traffic enforcement, finding they accrue to White, but not to Black, drivers.

This paper also makes additional contributions to a growing literature on the financial determinants of law enforcement behavior. Makowsky and Stratmann (2009, 2011), Garrett & Wagner (2009) and Su (2019) study the effect of revenue shortages on ticketing activity while Holcomb et al. (2018) and Mughan et al. (2019) explore how financial incentives increase levels of asset forfeiture. We extend the literature on revenue-generating policies in criminal justice systems by studying how a revenue-orientated policy impacts individual outcomes.

The remainder of the paper is organized as follows. Section 2 briefly discusses the mechanisms through which suspensions are likely to impact driver behavior and future outcomes. Section 3 explains the Marion County FTP policy and how it results in random assignment of FTP suspension. Section 4 describes our data and defines our sample and the following section details our empirical approach. We discuss our results in Section 6 and Section 7 concludes.

2. Mechanisms and Literature Review

In a rational choice model of crime an actor's decision to break the law is based on the expected benefits—financial gains, convenience, and so on—and the expected costs—probability of arrest, financial penalties, time spent in jail (Becker, 1968; Lee, 1985). This model predicts that FTP suspensions lead individuals to drive more cautiously if FTP suspensions increase the cost of future tickets. In addition to escalating fines resulting from repeat offending, FTP suspensions do this by altering driver expectations regarding treatment by law enforcement. For example, a driver may calculate that when a police officer sees a history of traffic offences *and* license suspension(s) the officer will interpret this as evidence of prior bad behavior and dole out harsher punishments.

A similar logic motivates studies on the relationship between traffic enforcement and traffic events such as crashes, tickets, fatalities. By increasing the perceived cost of offending, enforcement is hypothesized to result in a reduction in traffic incidents (Makowsky and Stratmann, 2011; Luca, 2015). Empirical evidence bears out this prediction. Using a panel of municipality-level monthly traffic accident and traffic stop data in Massachusetts, Makowsky and Stratmann (2011) find that an increase in traffic tickets issued reduces the number of accidents and accident-related injuries. Also using data from Massachusetts, Luca (2015) exploits an exogenous increase in ticketing resulting from a "Click-it-or-Ticket" campaign. Specifically, the study focuses on the part of the campaign that deliberately increased the rate of ticket issuance for one to two-week periods, finding that a one percent increase in ticketing leads to a 0.28 percent decrease in motor vehicle accidents. In a literature review of empirical studies on the effect of enforcement Soole et al. (2013) conclude that available evidence suggests a significant decrease in crash rates in response to increases in enforcement.

We are aware of one other quasi-experimental paper studying the effect of license suspensions on driver behavior.[2] Gehrsitz (2017) exploits a German law governing temporary license suspensions. He utilizes a regression discontinuity design and asserts the policy is sufficiently complex as to prevent individuals sorting themselves out of treatment. He finds that a one-month license suspension leads individuals to drive more cautiously in the following year, reducing their probability of receiving a second ticket by 20 percent. However, this finding is not easily generalizable to the American context because, unlike the tickets in Gehrsitz's data, which are enforced with cameras, ticking outcomes in the US are a result of choices made by drivers *and* choices made by police officers.[3]

This raises the possibility that any behavioral adjustment made by drivers is offset by FTP-suspension-induced changes in officer decision making. For example, after stopping a driver, the officer may be inclined to let them off with a warning. However, looking at their driving history the officer sees a past suspension and decides to issue a citation. Leniency is an ever-present factor in traffic stops because officers have a high level of discretion in initiating a traffic stop and in the ticketing decisions. Anbarci and Lee suggest leniency in these minor interactions may even be encouraged: "…officers who are lenient in vehicle searches could be accused of abandoning their duty, while leniency in issuing speeding tickets could even be considered 'humane' in cases involving first time offenders and motorists with seemingly limited financial means (2014, p. 13)." As such, while we expect FTP suspension to decrease the probability of receiving future tickets due to behavioral adjustments by drivers, *once a driver is pulled over* an FTP suspension is expected to increase the probability a driver receives a ticket.[4]

Additionally, previous literature suggests policing patterns may account for a large proportion of racial differences in low-level criminal justice outcomes because low-income neighborhoods, where minorities are overrepresented, are more likely to be over policed (Mullainathan, 2015). As a result, Black and minority individuals have greater exposure to law enforcement. They are more likely to encounter police officers and thus log higher rates of the consequences of those interactions. For example, in studying racial disparities in policing under the stop-and-frisk regime in New York, Goel et al. (2016) find that differences in policing across precincts accounts for nearly half of the racial differential in "hit rates", the likelihood of finding a weapon in searches of people suspected of criminal possession of a weapon. However, the racial differential in hit rates is also explained by lower stop thresholds for Blacks; officers would stop a Black person, but not a similarly situated White person.

Epp et al. (2017) produce similar findings. In an analysis of survey data from Kansas City drivers, the authors find no racial disparity in stops where officers are enforcing traffic safety laws. However, Black drivers were 2.7 times more likely than White drivers to experience an "investigatory stop", a distinct type of traffic stop in which the primary purpose is to check out people who are deemed to look suspicious. This is consistent with earlier work showing that young, Black men were more likely to be issued a warning, but less likely to be issued a citation after they were stopped by police (Tillyer and Engel, 2013). Taken together these findings imply officers have a lower threshold for stopping Black motorists.

Because an enormous body of evidence suggests discrimination against Black drivers by police officers (Goncalves and Mello, 2020; Tillyer and Engel, 2013; Anbarci and Lee, 2014; Lytle, 2014) we estimate treatment effects for White and Black drivers. It is important to allow for racially heterogeneous effects as this also allows us to speak to the effectiveness of behavior adjustments made by drivers. For example, all-else-equal, if FTP suspension reduces the probability of recidivism for White drivers only, we can infer that it is due to differences in treatment from police officers along racial lines.[5] We do not attempt to provide definitive evidence on the source of such differentials. They may stem from individual bias on the part of officers and/or from specific policies that increase the frequency with which Black citizens come into contact with the police. Examples of such policies include "stop and frisk" (Goel et al., 2016), broken windows policing (Golub et al., 2007), and investigatory traffic stops (Epp et al., 2017). However, we argue that our evidence is suggestive of the latter.

3. FTP Suspension and Random Assignment

License suspensions in Marion County Indiana (home to the city of Indianapolis) work as follows: Every ticket informs the driver they have 60 days to pay or contest the ticket. The vast majority of traffic infractions do not require a court appearance and thus payment can be made in person at the courthouse, by mail, over the telephone, or online. If the ticket is not paid or contested within 72 days of receiving the ticket, the court instructs the Bureau of Motor Vehicles (BMV) to suspend the defendant's drivers' license. The BMV suspends the license and notifies the driver of the suspension by sending a letter to the most recent address listed in the Bureau's records.[6] The license remains suspended until the ticket is paid, at which point the driver is eligible to reinstate their license—conditional on satisfying any other attached conditions, for example completing a driver safety program. At a minimum, reinstatement involves paying a fee ranging from $250 to $1000.[7]

Marion County is unique in that this suspension process is automatic. In other Indiana counties FTP issuance is a discretionary choice made by a judge. This is key to our identification strategy as it precludes the possibility of judges extending special treatment to certain individuals or groups. This feature of the suspension process is illustrated in Figure 1 depicting the interquartile range of the number of days between the date the ticket was received and the date the FTP suspension was issued.

FIGURE 1 ABOUT HERE

Marion County is represented by the black line, which admittedly looks more like a dot, while the other counties are shown in gray. Unlike other counties, almost all of the suspensions in Marion County occur in the span of a few days, providing evidence of an automatic suspension process.

In addition to automatic suspension our identification strategy rests on the assumption that drivers are unaware of the real payment deadline. Several observations support this assumption. The deadline is not advertised on the ticket. The BMV website does not advertise this deadline and neither does the Marion County website. Furthermore, if individuals are aware of the 72-day deadline we would expect a spike in payments right before this day. According to Panel A of Figure 2, depicting the distribution of the number of days between when a ticket is incurred and when it is paid, there is no such spike.

FIGURE 2 ABOUT HERE

There is, however, a steep increase around 60 days, behavior that is consistent with the information the driver receives from the ticket. A closer view of the 72-day mark is given in Panel B. Payment rates stay essentially flat, indicating that individuals did not anticipate this deadline and adjust their behavior accordingly. There is a slight rise in payments made around the 80-day mark, likely a response to the suspension notifications sent by mail.

Although there is a hard payment deadline of 72 days, court records show that 82 percent of suspensions are issued between 73 and 75 days after ticket issuance.[8] However, roughly 46 percent of tickets paid on these days do not receive a suspension. This is due to the fact that court records, the data used in this analysis, do not report the day a payment is made, but rather the day a payment is processed. This means that a payment received by the 72nd day (thus not receiving an FTP suspension) may be recorded as being made on the 73rd or even 75th day. For example, Person A makes a payment in person on the 71st day, but it is near the end of closing on a Friday. The payment is received on the 71st day, but the clerks do not process it until the following Monday. Person A does not receive a suspension, but their payment is recorded as being made on the 74th day. Person B pays their ticket on a Thursday, 74 days after receiving the ticket. Their payment is made and recorded as occurring on the 74th day and the driver's license is suspended.

The online and phone payment systems further complicate payment timing. The online portal for ticket payments in Indiana states that online and over the phone payments must be made at least 48 hours prior to the ticket deadline. When you click through to make an online payment you are greeted with the warning, "Any payments made through this system after the 48-hour deadline *may* still result in a judgement and legal action."[9] Thus, Person C may go online to pay their ticket on the 71st day, only to discover that their payment may not be received for two more days.

The lag in payment receipt and the recording process creates a series of payment days, 73-75, in court records where some individuals receive a suspension and some individuals do not receive a suspension. We refer to this three-day series as the "payment window" and refer to tickets paid within this window as "window tickets." We argue that FTP suspension is randomly assigned to drivers who pay within this payment window. The automatic nature of the suspension means that court and administrative officials are not systematically selecting individuals for suspension. The fact that individuals are unaware of the deadline means that drivers are not adjusting their behavior in order to avoid the suspension. Taken together these features suggest that rules surrounding payment and FTP are complex and opaque enough that assignment to suspension is random within the payment window. We further support this claim with a series of tests verifying random assignment within the payment window in Section 4.3.

4. DATA & SAMPLE DEFINITION

4.1. Data

The data used in this analysis was obtained from the Indiana State Court Administration and includes infractions filed 1 January 2011 through 30 November 2017 in Marion County Circuit Court. There is comprehensive data on each case, which can be grouped as belonging to one of two categories: driver and ticket. Driver variables include age, sex, race and address while case data contains detailed information on each case including, but not limited to, the offence date, date the case was filed, the filed charge, charge severity—ranging from the most serious class-A infractions to the least serious class-D infractions—and all case events—for example, initial hearings, pleas entered, payments received, suspension and payment outcome. Unfortunately, the data does not contain the financial penalty associated with the ticket. Fortunately, using the driver information in our data we were able to collect this information by looking up individual cases in Indiana's records of non-confidential cases. We collect two variables, court costs and fine. Court costs are the fees associated with a given case and are largely non-discretionary as they are set by state law. For a given offence category state law sets a maximum value fines may take, giving officers have more discretion in issuing fines.[10]

Cases are filed under 128 unique statutes in the dataset. Over 99 percent of the cases are related to driving, however, a tiny fraction of the data consists of non-driving infractions, for example littering and failure to possess a hunting license while hunting. Speeding and failing to wear a seatbelt are the most frequent offences, appearing in 37 and 23 percent of cases respectively. Variations on a speeding charge—for example speeding in a school zone or a construction zone—account for a further eight percent of cases, while driving with a suspended license charges account for nine percent and expired plate charges account for seven percent or cases.

To account for spatial differences in policing we mapped 2015 data from the American Community Survey onto an Indiana block group shapefile, both published by the Census Bureau.[11] The ticket data is geocoded using the defendant's address as recorded by the officer writing the ticket and matched with the Census block group data using GIS mapping software. This process results in three variables: average block group income, the proportion of workers over the age of 16 in a block group area who drive to work (used as a proxy for individual's willingness-to-pay), and a binary variable indicating if a driver resides in Marion County. A map of block groups in Marion County (Figure S1) as well as a table showing the number of drivers living in each block group (Table S1) can be found in the Appendix.

4.2. Sample Definition

Because our identification strategy relies on the unique institutional features of suspension in Marion County, the sample is limited to individuals who received a ticket between January 2011 and January 2016 and paid the ticket within the payment window. We follow these individuals for two years and observe whether they receive a ticket during this future period. This two-year post-treatment time period allows us to account for effects that may diminish over time, for example tickets received five years ago may receive little weight in an officer's decision calculus.

To avoid misidentification, we further refine our sample in a number of ways. First, we drop all individuals who received an FTP suspension prior to their window ticket as their inclusion may confound our random assignment as they may be aware of the 72 day deadline. Second, we drop all individuals who were involved in a trial or deferral program as these alter the suspension time frame our identification strategy relies upon, resulting in 301 dropped observations.[12] Third, because FTP suspension increases the probability a driver will be violating the law in the future by driving without a license we drop 51 drivers who received a second ticket for driving without a valid license. Finally, we limit our analysis to the impact of suspension on receiving a *second* ticket within two years. Random assignment of suspension allows for causal analysis of the effect of suspension on future outcomes. However, once you look beyond the second ticket additional factors are introduced that may confound further analysis.

The result is a sample of 2,435 tickets, issued to 2,178 unique individuals *who paid their ticket during the payment window*. Of these drivers, 1,145 (52.57 percent) received an FTP suspension on their window ticket, while 1,033 (47.43 percent) did not, and a total of 257 drivers received a second ticket within two years of the initial window ticket. Table 1 reports summary statistics by FTP status for the final sample.

TABLE 1 ABOUT HERE

The variable *highest charge* is a factor variable with four levels ranging from class A, consisting of the most severe offences, to a class D. Every class D offence is for failure to wear a seat belt, while a variety of high-level infractions such as driving while suspended and driving without car insurance make up Class A offences. Speeding, the most common infraction, is a class C offence. *Financial penalty* is the total monetary amount associated with a ticket, the average ticket costs $153 in fines and court costs.

4.3. Tests for Random Assignment

To substantiate our random assignment claim, we run a series of t-tests comparing the difference in means of a variety of observable characteristics in the suspension and no-suspension groups of our final sample. Our primary interest lies in comparing group means in characteristics of drivers who paid their tickets within the payment window and received a suspension to those who paid in the window and did not receive a suspension. Results from the t-tests are presented in Panel A of Table 2. For comparison, Panel B presents equivalent statistics for tickets not paid within the payment window.

TABLE 2 ABOUT HERE

In general, results reveal no statistical difference in driver characteristics across suspension status among drivers who paid during the payment window. The exception is age, where we observe a statistically (though not substantively) significant difference in group means.[13] It is, perhaps, possible that younger drivers are more careless with their driving and financial responsibilities and thus experience future tickets at slightly higher rates, leading to endogeneity within the model. However, this difference appears to be driven by a slight over representation of elderly individuals in the No FTP group rather than a large number of young individuals in the FTP group. This can be seen in the dummy variables *Under 24* and *Over 60*. These show a balanced number of drivers under the age of 24 between the treatment and control group and a slightly larger number of drivers over the age of 60 in the control group. However, given that 60+ drivers make up less than three percent of our sample, the difference in mean age is substantively insignificant, and the similarity of the means of other variables across FTP status—a similarity that is striking when contrasted with the same statistics in the general ticket population—we are inclined to accept the latter explanation. However, we cannot completely rule out the possibility of endogeneity in FTP status.[14]

5. Empirical Approach

Capitalizing on the as-good-as-random FTP suspension assignment we use OLS model and fixed effect models to estimate the impact of suspension on future ticket probability, allowing for treatment effect to vary by race. This strategy leads to the following model:

$$SecondTicket_i = \beta_0 + \beta_1 FTP_{iw} + \beta_2 Black_i + \beta_3 (FTP_{iw} * Black_i) + \delta D_i + \gamma C_w + \vartheta BG + \varepsilon_i \tag{1}$$

The unit of observation, *i*, is the defendant. The dependent variable, *SecondTicket*, is equal to one if the defendant received an additional ticket within two years of their window ticket and zero otherwise. The *FTP* variable measures whether individual *i* received an FTP suspension on their widow ticket *w*, *Black* is measured using a binary variable equal to one if the defendant is Black and zero otherwise. The interaction term between *FTP* and *Black* captures the differential effects of FTP suspension by race. *C* is a vector containing characteristics of the window ticket and includes the number of charges on the ticket and the amount of the financial penalty associated with the window ticket. If larger monetary sanctions are more effective in deterring illegal driving, the probability of receiving a second ticket will decrease as the size of the penalty increases. Finally, Uber began operating in Marion County in June of 2014 (Brazil and Kirk 2016). By providing an alternative transportation option, Uber may reduce the probability that a driver receives future tickets. Moreover, there may be racially specific ramifications for receiving a second ticket probability if, for example, Black drivers are less likely to use Uber's services than are White drivers. Therefore, *Pre-Uber Introduction*, a binary variable equal to one if a driver received their window ticket *and* their second ticket before Uber began operating in Indianapolis is included in *C*.[15]

Driver characteristics, gender, race, age, residency, as well as the proxies for likelihood of driving to work and block group income are included in *D*, a vector containing driver characteristics. The residency variable is an indicator equal to one if the driver lives in Marion County. The likelihood a defendant drives to work is included because FTP suspension may have a disproportionate, negative effect on those relying on a car for employment. It may also increase their willingness to drive without a valid license. Average block group income is added for two primary reasons. First, the police often have a greater presence in lower income areas. Second, these areas tend to have larger populations of racial minorities (La Vigne, Fontaine and Dwivdei 2017).

In some specifications we also include block group fixed effects. Basing estimates on within-neighborhood variation enables us to exclude spatial differences in policing practices that are correlated with income and race (Goel et al. 2016). For example, Black drivers may be more likely to live in areas where minor infractions are aggressively enforced and are thus more likely to receive multiple tickets over time, all-else-equal. Fixed effects are also used to control for unobservable, time-invariant characteristics of drivers that are tied to the area where drivers live, for example attitudes towards the police and justice system. However, the OLS models are our preferred models as there is little variation in many of our block groups (20.71 percent of observations in our sample are the only observation in their block group), meaning that they drop out of the fixed effects model.

6. Results

6.1. Main Results

Table 3 presents our main results.

TABLE 3 ABOUT HERE

Column 1 reports our baseline results, prior to the introduction of control variables. For White drivers, the estimated effect of receiving an FTP suspension is a statistically insignificant decrease in the probability of a second ticket of 2.4 percentage points. For Black drivers, FTP increases this probability by approximately nine percentage points ($p < .01$). Additionally, those who have previous observable tickets on their record, captured by *Driver has past traffic ticket*, are more likely to receive a future ticket ($p < .01$). Another important finding is that the coefficient on *Black*, the change in the probability of second ticket receipt explained solely by the race of the driver, is substantively and statistically insignificant, race on its own has little explanatory power. Furthermore, the F-test suggests prior driving history has a larger impact on the future outcomes for Black, relative to White, drivers ($p < .01$), suggesting a role of officer leniency in ticketing.

The inclusion of control variables, shown in Column 2, does not substantively alter the direction or magnitude of the effect of *FTP* suspension for Black or White drivers, however the point estimate for White drivers is now marginally significant (it remains highly significant for Black drivers).; for White drivers FTP suspension decreases the probability of incurring another ticket by 2.8 percentage points ($p < .1$). The control variables have the directional effects anticipated based on previous empirical findings. Females and older drivers are less likely to receive a future ticket. Those who live in block groups with more people who drive to work have an increased likelihood of a second ticket. This makes sense as these individuals are more likely to drive, in general, which puts them at greater risk of experiencing a traffic stop. Finally, consistent with previous literature, a negative relationship between the probability of receiving a second ticket and the size of the financial penalty on the window ticket ($p < .01$) suggests that financial penalties have a deterrent effect.

Estimates are also robust to the inclusion of block group fixed effects, reported in Column 3. Although the OLS model is our preferred model we present the fixed effects results to show that the OLS results are consistent with estimates based on within-neighborhood variation.[16] This is important because it rules out differential effects induced by differences in policing strategies across neighborhoods. One serious concern is that racial minority majority neighborhoods experience higher levels of policing, making Black residents more likely to come into contact with police. These within-block-group estimates assuage that fear.

In the final two columns we present results after splitting the sample by race. Doing so allows for all covariates to have different effects across race. As seen in Columns 4 and 5 the sample, the point estimates on FTP suspension are largely unchanged as is the statistical significance of those estimates. In addition, most covariates have the same directional effect. Two control variables are of particular interest, *Driver has past traffic ticket* and *Financial penalty on window ticket*. Regardless of race, the former is highly significant however, the effect is approximately four percentage points larger for Black drivers. The latter has the expected negative sign; however, it is only statistically significant ($p < .01$) for White drivers.

Since the block group fixed effects ruled out neighborhood specific policing tactics as the driver of the differential effects of FTP suspensions, this leaves us with two explanations: Black drivers are treated differently by law enforcement and/or there are unobserved, systematic differences between the behavior of White and Black drivers. Our findings on the effect of driving to work are indicative of the former explanation. The interactive model (Column 2) shows that a one point increase in the percentage of people driving to work in a driver's block group increases the probability of receiving a second ticket by 26.6 percentage points ($p < .01$). No other variable effect comes close to this magnitude. While we have already stated that this is likely a product of being on the road more, thus exposing yourself to more chances of offending or interacting with the police, it is important to notice the difference in the magnitude of this coefficient in the split models. This effect is significant at the 95% confidence level in Columns 4 and 5, but for White drivers (Column 4) the magnitude decreases to 22 percentage points, while for Black drivers (Column 5) it increases to 34 percentage points, a 12 percentage point difference.

Additionally, two features of our research design go a long way to mitigate the possibility racial differences in driving behavior explain the racial gap in second ticket probability. First, we know that drivers are selected into our sample based in-part on a latent measure of responsibility- they all paid their ticket around the same time. This self-selection suggests that drivers in our sample are comparable along margins beyond FTP status. Second, within racial groups, FTP suspension is randomly assigned and absent discrimination, there is no reason to expect FTP suspension to have opposite directional effects on the behavior of Black and White drivers. Exploiting these sample features we conduct a series of tests exploring systematic racial differences in driving behavior as a potential cause. The results of these tests are explained in detail below.

6.2. Racial Differences in Behavior

To establish the comparability of drivers across race we explore three questions concerning potential differences in driving behavior that would impact future ticket receipt: (1) Do White and Black drivers engage in different degrees of risky driving? (2) Do White and Black drivers exhibit different levels of financial responsibility? (3) Do White and Black drivers regain their license following suspension at different rates?

6.2.1. Question 1: Do White and Black drivers engage in different amounts of risky driving?

If Black and White drivers exhibit similar driving patterns we would expect there to be little to no difference on key characteristics of their window ticket, the number of charges, severity of the charges and the financial penalty. We study the window ticket, rather than any ticket that comes after it, because those future tickets will reflect driving behavior *plus* potential racial differentials in leniency resulting from officer discretion. We test this expectation by conducting differences-in-means tests across race in the previously mentioned variables, breaking financial penalty into its component parts.[17] The results of these tests are presented in Table 4.

TABLE 4 ABOUT HERE

The only characteristics where we find a statistically significant difference is the severity of the charge ($p < .01$), on average tickets issued to Black drivers are for more severe offences than those issued to White drivers. However, this result comes with two crucial caveats. First, while this result is highly statistically significant substantively it is not economically significant. Second, as is the case with all characteristics in Table 4, it is possible differences in group means are driven by differential treatment by officers rather than the behavior of the driver. A larger difference in group means in the more discretionary fine measure relative to the less discretionary court costs measure lends some support to this interpretation. Ideally, to avoid this ambiguity we would study outcomes that are solely determined by the driver (i.e. are not directly impacted by the choices of the issuing officer). This is what we do in the remaining sub-sections.

6.2.2. Claim 2: Do White and Black drivers exhibit different levels of financial responsibility?

Black drivers may be more likely to receive future tickets if they have lower incomes, have access to fewer resources and/or exhibit lower levels of financial literacy or responsibility. This is due to the fact that many offences are related to the solvency of the driver themselves, for example drivers may be ticketed for driving with a broken taillight or driving without a license or insurance. Because inclusion in the sample is contingent on payment of the initial ticket we estimate the effect of race on the probability of paying the future ticket. The relationship between race and financial responsibility is modeled as:

$$PaidSecondTicket_i = \beta_0 + \beta_1 FTP_{iw} + \beta_2 Black_i + \delta D_i + \gamma C_w + \vartheta BG + \varepsilon_i \qquad (2)$$

Where the dependent variable is equal to one if driver *i* paid their second ticket and zero otherwise and Black is the main variable of interest. As indicated by the subscript *w*, all ticket variables are attributable to the window ticket to account for detectable characteristics of driving behavior that may affect future ticket outcomes. These results are presented in Table 5.

TABLE 5 ABOUT HERE

Results from the OLS model with a full set of controls (Column 2) suggest there is substantively no racial gap in payment likelihood. Interestingly, the inclusion of block group fixed effects alters estimates significantly, when estimating purely off within neighborhood variation, Black drivers are around eight percentage points *more* likely to repay their second ticket (Column 3, $p < .1$). Continuing with the fixed effects approach, point estimates from the interaction model (Column 4) do suggest that the effect of FTP suspension on payment is constant across racial groups. In short, the analysis fails to provide evidence that Black drivers are less financially responsible than their White counterparts and thus more likely to reoffend. The analysis does, however, provide weak evidence that FTP suspension increases the probability of payment, suggesting that the suspensions are somewhat effective in collecting outstanding debts.

6.2.3. Claim 3: Do White and Black drivers regain their license at different rates?

One of the biggest shortcomings of our data is a lack of information on license reinstatement. We cannot rule out the possibility that Black and White drivers go to the BMV and reinstate their drivers' license following FTP suspension at different rates. However, we can speak to this question by estimating whether Black drivers are more or less likely than White motorists to be ticketed for driving with a suspended license.[18] Drivers may receive a DWS ticket for a few reasons, accumulating points on a drivers' license or committing an offence where license suspension is the recommended punishment. FTP increases the likelihood of the latter as it not every driver receiving an FTP suspension visits the BMV and pays upwards of $250 to reinstate their license. If Black drivers are more likely to be ticketed for driving without a license following an FTP suspension, we can infer that they are less likely than Whites to reinstate their license. If this is the case it could explain the racial differential in our main result as this group would be more likely to be committing a traffic offence overall and would be less likely to experience leniency from officers.

Out of the 308 individuals in our sample who received a second ticket, 51 people were ticketed for driving without a valid drivers' license. The following model is used to test the relationship between race, suspension, and driving while lacking the right to drive:

$$DWS_i = \beta_0 + \beta_1 FTP_{iw} + \beta_2 Black_i + \beta_3 (FTP_{iw} * Black_i) + \delta D_i + \gamma C_w + \vartheta BG + \varepsilon_i \qquad (3)$$

DWS indicates that person *i* received a second ticket for driving with a suspended license and indicates whether person *i* was randomly assigned into FTP suspension on their initial ticket. The interaction with race allows for the possibility that Black drivers are more likely to be driving with a suspended license following the FTP suspension. Results from equation 4 are presented in Table 6.

TABLE 6 ABOUT HERE

Across all specifications, FTP suspension has the expected positive effect for White drivers, increasing the probability of being ticketed by 14 percentage points (p <.05). We find no effect among Black drivers, where point estimates are consistently negative as well as statistically and economically insignificant. Taken together, these findings suggest that, at the very least, Black drivers are no more likely than their White counterparts to reinstate their drivers' license following FTP suspension. This result is consistent with theory, which would predict larger behavioral changes from Black drivers if the expected cost of a second interaction with police is higher because Black drivers expect less lenient treatment.

To summarize our results, we find that FTP suspension has opposite effects on the downstream outcomes of Black and White drivers, increasing the probability of future tickets for Blacks while decreasing that same probability for Whites. For reasons described above, our research design ensures that Black and White drivers in our sample are roughly comparable and additional tests fail to detect racial differences in driving behavior. Results are also robust to the inclusion of control variables and block group fixed effects. The latter is a vital point as the small geographic area of a block group goes a long way to exclude spatial policing patterns as a possible explanation of our results. We are left to conclude that differential treatment of Black drivers by law enforcement officers is the primary driver of the racial differentials in downstream outcomes caused by FTP drivers' license suspensions.

We do not seek to provide definitive evidence on the source of differential treatment. However, our results allow us to make some inferences. If individual bias—in the sense that police officers gain utility from treating Black drivers harshly—was responsible for our findings we would expect a racial gap in future ticket probability among drivers who received a ticket but no suspension (Table 3) because officers would be more likely to ticket Black drivers regardless of FTP status. We would also expect to see more charges levied and more serious charges against Black drivers (Table 4). According to our analysis, neither of these expectations hold. A more compelling explanation is that, as suggested by the negative sign on the financial penalty variable, White drivers are able to minimize the probability of being pulled over by altering their driving behavior. These adjustments are not effective for Black drivers because their stop outcome is only partially predicted by their driving. Because police adopt a lower stopping threshold for Black drivers (Goel et al. 2016) (or in the language of Epps et al. (2017) are more likely to perform an investigatory stop) FTP suspensions (as well as past tickets) are more likely to come to the attention of officers, who interpret them as evidence of a history of dangerous driving and become more likely to issue a ticket.

One final note is that, to this point, we have avoided using the terms "racial bias" and "statistical" or "taste-based" discrimination. One reason for this is that lack of data on the ticketing officers or details of the stop makes identification challenging, but more importantly, we believe it is not a particularly useful framing for the effects of FTP license suspensions. As Goel et al. point out "With statistical discrimination, officers may genuinely believe that blacks are more likely to carry weapons than the data suggest, perhaps due to faulty heuristics or limited opportunity to estimate event probabilities. For example, an object that is considered 'suspicious' on a black individual may not be considered 'suspicious' on a white person (2016, p. 280)." While the economist might not consider this racial bias, the Black driver surely would. Moreover, the outcome is the same, methods of policing inflict a disproportionate amount of harm on Black individuals in those communities.

7. Discussion and Conclusion

By demonstrating that higher financial penalties on traffic tickets can be a useful tool in deterring unsafe driving, this paper builds on existing literature that estimates the public returns to police policies designed to improve traffic safety. However, we also show that these effects are small and adjusting driving behavior to reduce the likelihood of receiving a ticket is only effective for White drivers. This is an important finding as it highlights inequities in the distribution of the private returns to safer driving.

This paper also expands the traffic enforcement literature by estimating the private returns to a common traffic policy, drivers' license suspensions for failing to pay a traffic ticket. Analyzing a sample of tickets issued in Marion County, Indiana in which FTP suspension is randomly assigned we show that FTP suspension decreases the probability of receiving a second ticket for White drivers while increasing the same probability for Black drivers by up to nine percentage points. While we cannot provide definitive evidence on how or why Black drivers are treated differently (our inability to demonstrate higher pull-over rates for Black drivers is certainly a shortcoming of this paper) we do show that FTP suspensions have a large negative effect on the future outcomes of Black, but not White, drivers and that this does not appear to be caused by behavioral differences between racial groups.

The main argument in this paper is that FTP suspensions act on future ticket probability via the driving record mechanism. There are several potential policy options that could address this issue specifically. Perhaps the most direct option is to remove the FTP suspension from the driving record once the financial obligations are met. A second option is the elimination of FTP suspensions all together. To the extent that FTP suspensions serve as an effective deterrent to non-payment this may reduce payment rates. However, it is also possible that replacing FTP suspensions with less punitive measures will have the opposite effect. The nine states that have eliminated FTP suspensions adopted a variety of reforms designed to assist low-income drivers. One example is incorporating ability-to-pay considerations into sentencing, if individuals are determined to be insolvent, a community service sentence can be used as an alternative to a monetary penalty. Another popular option is the adoption of flexible payment plans. Once adopted these plans could also be made to be more salient to ticketed drivers, easier to enroll in (often payment plans include an upfront payment plan fee and are subject to a minimum payment amount) and more difficult to be expelled from (often drivers are removed from payment plans after missing a payment).

While these reforms mitigate the disproportionate harm FTP suspensions have on Black drivers, they do not address the source of this racial differential which originates in the officer-driver interaction. As such this paper contributes to a growing number of studies highlighting the detrimental effect supposedly racially neutral policies, in our case automatic license suspension, have on people and communities of color (see for example Makowsky et al., 2019; Epp et al., 2017). The broad conclusion that can be drawn from this evidence is that implementing a race-neutral policy in a system that has been shown to exhibit racial bias is ineffective at producing non-racially biased outcomes.

In the end policy makers must balance the need for road safety with the long-term damage caused by FTP suspensions and the need for racial equity. Given the pervasiveness of FTP suspensions, it is important for policy makers and the broader public to have a better understanding of their use and consequences. This paper is a step in that direction, but more work needs to be done. Next steps include finding data to obtain a cleaner estimate of behavioral responses to license suspensions as well as extending the research program on downstream effects of license suspension and other low-level offences on employment and financial outcomes, particularly in low income and/or minority communities. Given the recent removal of FTP suspensions in certain states an evaluation of the road safety effects of those policies would be useful as well. These are all promising areas for future research.

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Endnotes

[1] This is according to data collected by the Washington Post. The actual number of people with suspended licenses is higher as eight states could not or would not provide suspension data.

[2] Garrett and Crozier (2019) use a random effects model to estimate the relationship between license suspensions for non-driving related reasons, poverty and race in North Carolina.

[3] While there are both red-light and speed cameras in the US, as of 2011 only twenty-five states had used red-light cameras and only twelve had used speed cameras. The Center for Disease Control provides a useful review of the various means of automated traffic enforcement. It can be found at https://www.cdc.gov/motorvehiclesafety/calculator/factsheet/.

[4] In Indiana driving records do not specify FTP as the reason for license suspension.

[5] Our underlying assumption is that directionality of the behavioral response is constant across racial groups. We acknowledge the possibility of racial differences in the magnitude of the response however we would point out that theory predicts a larger response from Black drivers as on average they likely assign a higher cost to potential interactions with law enforcement.

[6] IC § 9-30-3-8. If the defendant lives out of state the notice is sent to the address given to the ticketing officer by the driver.

[7] In Indiana, the reinstatement fee following one suspension is $250, $500 after a second suspension and $1,000 for any subsequent suspension. IC§ 9-29-10-1.

[8] If the time window is extended one day to include the 76th day it includes 90.37 percent of suspensions. Only 1.13 percent of suspensions occur prior to 73 days after ticket issuance.

[9] https://pay.indy.gov/traffic_tickets

[10] Fees are monetary payments associated with use of the court services whereas fines are financial penalties for breaking the law. The following are the maximum fines for infraction classes: Class A infraction ($10,000), Class B infraction ($1,000), Class C infraction ($500), Class D infraction ($25) § IC 34-28-5-4.

[11] A block group is the smallest unit the Census Bureau publishes data on and usually contains between 600 and 3,000 individuals.

[12] In the deferral program eligible drivers' pay a one-time fee of $226 and agree to not incur any new traffic violations for six months. If they satisfy these conditions the ticket is dismissed and will not appear of the driver's record, if the driver receives another ticket they are dismissed from the program and required to pay the costs associated with the original ticket. These restrictions do not alter the finding of as-good-as random assignment into suspension.

[13] The amount of the financial penalty is not included in the Table 2 because the values for tickets with an FTP suspension include late fees that we are unable to isolate. As a result, tickets with an FTP will be systematically larger than tickets with no suspension.

[14] In another test of random assignment, we rerun the balance test in regression form. The results are consistent with those in Table 2 and can be found in Table S2 in the Appendix to this paper.

[15] The severity of the charge is not included in C because it is highly correlated with the size of the financial penalty.

[16] We prefer the OLS estimates because there is little to no variation in many of the block groups in our sample, this is evidenced by the larger standard errors in the fixed effects specification.

[17] A regression analysis where we control for additional driver and ticket characteristics produces similar results. These estimates are not included here but are available upon request.

[18] This analysis includes the 51 observations that are dropped from the main analysis.

Tables

Table 1: Summary Statistics

	Mean	SD	Min	Max	N
Black	0.337	0.473	0	1	2,178
Female	0.384	0.487	0	1	2,178
Age	35.134	12.207	13.373	96.181	2,178
Under 24	0.202	0.402	0	1	2,178
Over 60	0.030	0.171	0	1	2,178
Marion county resident	0.648	0.478	0	1	2,178
Financial penalty (window ticket)	153	78	25	630	2,161
Highest charge (window ticket)	2.995	0.734	1	4	2,178
Number of charges (window ticket)	1.200	0.554	1	9	2,178
Receives 2nd ticket	0.118	0.323	0	1	2,178
Past traffic ticket	0.092	0.289	0	1	2,178
Median income	50,258	24,246	8,357	179,079	2,154
Drive to work (%)	0.920	0.076	.246	1	2,061
Uber in Operation	0.271	0.445	0	1	2,178

Notes: Highest charge is a categorical variable with 1 indicating the most serious offence and 4 the least. Approximately 72 percent of observations have a value of 3, representing a speeding offence.

Table 2: Balancing Test, Comparison of Group Means

	Panel A: Ticket Paid Inside Payment Window			**Panel B: Ticket Paid Outside Payment Window**		
	No FTP	FTP	*p*-value	No FTP	FTP	*p*-value
Black	0.342	0.333	0.658	0.194	0.468	.000***
Female	0.393	0.376	0.426	0.336	0.383	.000***
Age	35.872	34.469	0.007***	37.851	32.612	.000***
Under 24	0.204	0.200	0.805	0.191	0.275	.000***
Over 60	0.037	0.024	0.093*	0.077	0.025	.000***
Highest charge	3.028	2.966	0.049**	3.006	2.626	.000***
Number of charges	1.199	1.194	0.816	1.159	1.427	.000***
Marion county resident	0.654	0.643	0.571	0.542	0.757	.000***
Log median income (BG)	50,242	50,271	0.897	54,859	43,887	.000***
Log percent of workers driving to work (BG)	0.922	0.919	0.264	0.919	0.913	.000***
Past traffic ticket	0.086	0.098	0.348	.	.	.

Notes: Panel A presents group means for characteristics associated with tickets paid inside of the payment window where we argue FTP suspensions are randomly assigned. For comparison, Panel B presents these statistics for the remaining tickets in our sample where there is no random assignment. "BG" is short for Block group and indicates the variable is measured as the Census block group level. Past traffic tickets captures the driving history of drivers in our subsample where FTP suspension is randomly assigned, it is not available for the larger sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Racial Differential in the Effect of Suspension on Recidivism

	Full Sample			White Drivers	Black Drivers
	(1)	(2)	(3)	(4)	(5)
FTP suspension	-0.024	-0.027*	-0.023	-0.028*	0.063**
	(0.016)	(0.016)	(0.022)	(0.016)	(0.029)
Black	0.010	0.004	0.035	.	.
	(0.022)	(0.023)	(0.032)		
FTP * black	0.090***	0.092***	0.082**	.	.
	(0.031)	(0.032)	(0.036)		
Driver has past traffic ticket	0.117***	0.104***	0.075*	0.104***	0.140***
	(0.038)	(0.038)	(0.039)	(0.038)	(0.053)
Past traffic * black	0.037	0.042	0.067	.	.
	(0.063)	(0.064)	(0.071)		
Financial penalty on window ticket (log)	.	-0.031***	-0.039***	-0.037***	-0.024
		(0.010)	(0.013)	(0.012)	(0.017)
Female	.	-0.032**	-0.032**	-0.033**	-0.030
		(0.014)	(0.015)	(0.016)	(0.028)
Age (log)	.	-0.112***	-0.125***	-0.084***	-0.168***
		(0.021)	(0.022)	(0.025)	(0.039)
Marion county resident (binary)	.	0.043***	.	0.041**	0.044
		(0.016)		(0.017)	(0.039)
# of charges on window ticket					
2	.	-0.028	-0.036	-0.013	-0.048
		(0.022)	(0.025)	(0.026)	(0.037)
3	.	-0.041	-0.052	-0.022	-0.072
		(0.040)	(0.038)	(0.047)	(0.069)
4 or more	.	-0.030	-0.013	-0.081***	0.055
		(0.072)	(0.095)	(0.023)	(0.182)

Income (block group, log)	.	0.011	.	0.010	0.018
		(0.015)		(0.016)	(0.031)
% driving to work (block group)	.	0.266***	.	0.217**	0.338**
		(0.079)		(0.093)	(0.145)
Uber in Operation	.	-0.033**	-0.051***	-0.049***	-0.002
		(0.016)	(0.018)	(0.017)	(0.032)
Constant	0.100***	0.310*	0.779***	0.306	0.321
	(0.012)	(0.179)	(0.113)	(0.197)	(0.358)
F-test (*Black + (FTP * black) =0; p-values in parentheses*)	6.09***	5.46**	4.01**	.	.
	(0.014)	(0.020)	(0.046)		
F-test (*Black + (past ticket * black) =0; p-values in parentheses*)	9.11***	7.91***	7.39***	.	.
	(0.003)	(0.005)	(0.007)		
Block group fixed effects	No	No	Yes	No	No
N	2,178	2,053	2,147	1,357	696

Notes: The outcome variable is a binary measure of future tickets, equal to one if driver i received a second ticket and zero otherwise. The number of charges on the window ticket is a categorical variable, the base category is one charge. Robust standard errors are included in parentheses unless otherwise indicated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Assessing Driving Behavior: Balancing Test, Comparison of Group Means on Window Ticket by Drive Race

	White	Black	*p*-value
Number of charges	1.184	1.219	0.170
Severity of charge	3.026	2.935	0.006^{***}
Court cost amount	98.946	99.940	0.655
Fine amount	51.623	54.400	0.210

Notes: White and Black columns present means for the given variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Assessing Financial Responsibility: Differences in Likelihood of Paying Second Ticket

	(1)	(2)	(3)	(4)
Black	-0.022	0.007	0.089*	0.078
	(0.035)	(0.040)	(0.046)	(0.076)
FTP suspension	0.049	0.043	0.074*	0.065
	(0.036)	(0.036)	(0.039)	(0.045)
FTP * black	.	.	.	0.018
				(0.077)
Past traffic ticket (1 for yes, 0 otherwise)	.	0.004	-0.033	-0.036
		(0.044)	(0.030)	(0.031)
Female	.	-0.053	-0.083	-0.083*
		(0.038)	(0.050)	(0.050)
Age (log)	.	0.035	0.054	0.055
		(0.051)	(0.065)	(0.065)
Marion county resident (binary)	.	-0.022	.	.
		(0.046)		
Charge on Second Ticket				
Class B offence	.	0.148	0.206	0.205
		(0.199)	(0.147)	(0.146)
Class C offence	.	0.198	0.064	0.061
		(0.157)	(0.093)	(0.090)
Class D offence	.	0.286*	0.106	0.103
		(0.161)	(0.103)	(0.099)
# Charges on Second Ticket				
2	.	0.089**	-0.030	-0.031
		(0.041)	(0.048)	(0.046)
3	.	-0.074	-0.321	-0.323
		(0.178)	(0.346)	(0.348)
4 or more	.	0.072	.	.

		(0.054)		
Income (block group, logged)	.	0.053	.	.
		(0.047)		
Pct Driving to Work (block group)	.	-0.545**	.	.
		(0.255)		
Financial penalty on window ticket (log)	.	0.051**	0.049	0.049
		(0.025)	(0.033)	(0.033)
Uber in Operation	.	-0.104*	-0.198***	-0.198***
		(0.053)	(0.062)	(0.062)
Constant	0.898***	0.274	0.404	0.412
	(0.032)	(0.653)	(0.358)	(0.360)
Block group fixed effects	No	No	Yes	Yes
N	257	257	257	257

Notes: The outcome variable is a binary measure of future ticket receipt, equal to one if driver i received a second ticket and zero otherwise. The OLS models are our preferred models as 20.71 percent of our observations in our sample are the only observation in their block group, meaning that they drop out of the fixed effects model. Robust standard errors are included in parentheses unless otherwise indicated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Assessing License Reinstatement: Does FTP Suspension Increase the Probability a Second Ticket for Driving Without a License?

	(1)	(2)	(3)
FTP suspension	0.014**	0.013**	0.014**
	(0.006)	(0.006)	(0.007)
Black	0.026***	0.020*	0.034***
	(0.010)	(0.011)	(0.012)
FTP * black	-0.005	-0.007	-0.017
	(0.015)	(0.016)	(0.015)
Constant	0.007**	0.051	0.105*
	(0.003)	(0.087)	(0.061)
Controls	No	Yes	Yes
Block group fixed effects	No	No	Yes
N	2,229	2,110	2,204

Notes: Dependent variable is binary, equal to 1 if the second ticket was for driving with a suspended license and 0 otherwise. Robust standard errors in parentheses unless otherwise indicated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 1:

Figure 1: Is Suspension Automatic? Interquartile Range of the Number of Days Between Offence and Suspension

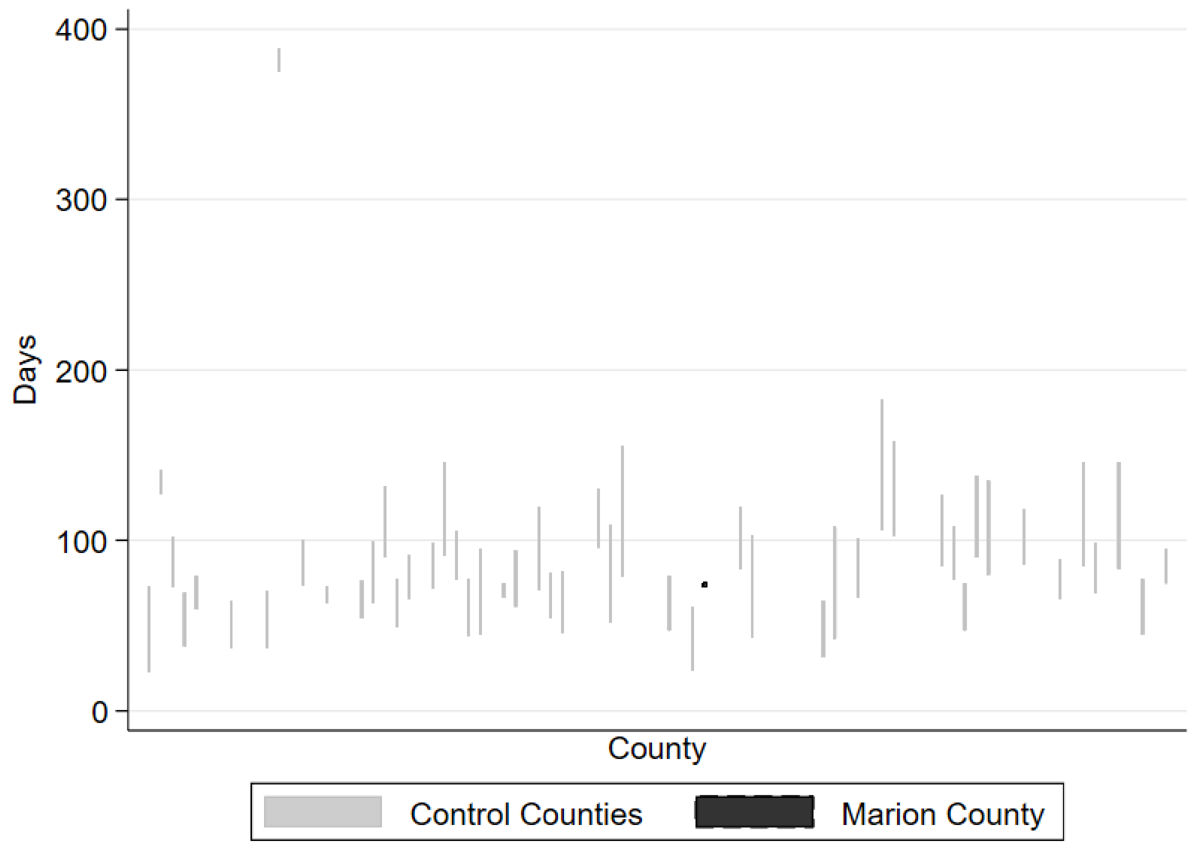
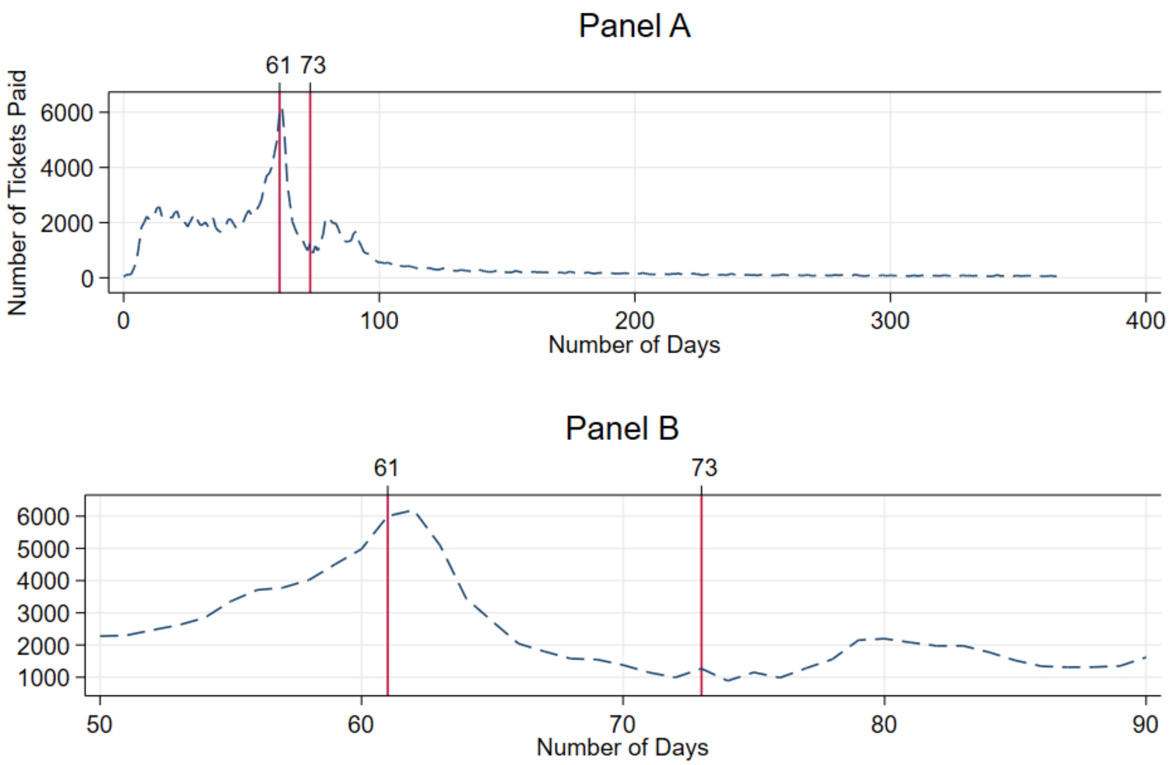


Figure 2:

Figure 2: Distribution of the Number of Days Between Ticket Receipt and Ticket Payment



Note: 60 days is the stated number of days people have to pay a ticket 72 days is the last day before suspension occurs. Panel A shows the entire distribution, Panel B zooms in on the time period of interest.

Appendix

Figure S1: Marion County Block Group Map

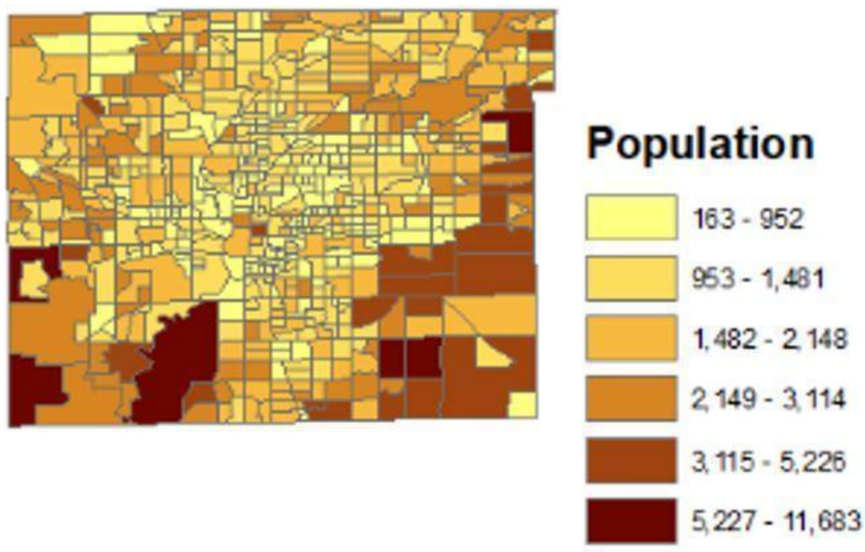


Table S1: Distribution of Drivers Across Block Groups

# Drives in the BG	Frequency	Percent
1	454	20.84
2	170	7.81
3	114	5.23
4	104	4.78
5	60	2.75
6	12	0.55
7	35	1.61
8	56	2.57
9	27	1.24
10	20	0.92
12	24	1.1
13	26	1.19
14	28	1.29
15	30	1.38
16	48	2.2
17	17	0.78
18	18	0.83
19	19	0.87
22	22	1.01
24	72	3.31
26	26	1.19
27	27	1.24
29	29	1.33
31	31	1.42
33	33	1.52
34	34	1.56
35	105	4.82

37	74	3.4
38	38	1.74
40	40	1.84
44	44	2.02
53	106	4.87
56	112	5.14
59	59	2.71
64	64	2.94

Notes: BG is short for block group

Testing for Random Assignment

We rerun the balance test in regression form to get a more complete understanding of these differences. These results are reported in Table S2. The three specifications differ only in their treatment of age, which is included as a continuous measure (column 1), as a series of dummies (column 2) and omitted (column 3).

TABLE S2 ABOUT HERE

These results are consistent with those in Table 2, however, we can now see that the severity of the offence (as indicated by class of offence) is a significant predictor of license suspension. Compared to the most serious types of offences (Class A offence) individuals with a ticket for a Class C or D offence are between 9.1 and 10.8 percentage points less likely to receive a suspension on their window ticket. This is likely due to the severity of Class A offences and their infrequency in the final sample. Of the window tickets in the sample, 89.36 percent are Class D and C. Taken together, Wald tests indicate that defendant and ticket characteristics are not jointly significant predictors of FTP suspension status.

Table S2: Testing Covariate Balance for Random Assignment

	(1)	(2)	(3)
Black	-0.023	-0.019	-0.018
	(.025)	(.025)	(.025)
Female	-0.012	-0.012	-0.009
	(.023)	(.023)	(.023)
Age (Continuous, logged)	-0.084**	.	.
	(.033)		
Age (1 if < 24, 0 otherwise	.	-0.006	.
		(.027)	
Age (1 if > 60, 0 otherwise)	.	-0.133**	.
		(.065)	
Marion county resident	-0.006	-0.004	-0.005
	(.026)	(.026)	(.026)
Log median income (block group)	0.004	0.004	0.004
	(.024)	(.024)	(.024)
Log percent of workers driving to work (block group)	-0.148	-0.154	-0.152
	(.147)	(.147)	(.145)
Class B offence	-0.065	-0.072	-0.066
	(.093)	(.093)	(.093)
Class C offence	-0.088**	-0.088**	-0.086**
	(.042)	(.041)	(.042)
Class D offence	-0.095**	-0.098**	-0.097**
	(.048)	(.048)	(.048)
2 charges on ticket	-0.027	-0.023	-0.024
	(.036)	(.036)	(.036)
3 charges on ticket	-0.061	-0.055	-0.051
	(.078)	(.077)	(.077)
4 or more charges on ticket	0.014	0.024	0.028

	(.108)	(.108)	(.108)
Past traffic ticket (1 for yes, 0 otherwise)	0.043	0.043	0.043
	(.037)	(.037)	(.038)
Wald test for joint significance (*p-value in parentheses*)	1.17	0.87	0.68
	(.2983)	(.5815)	(.7759)
N	2,059	2,059	2,059

Notes: The specifications differ in the measure of age. Column 1 presents results when age is included as a continuous measure. Column 2 shows results when the age dummy variables are included and the specification in column 3 age is omitted. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$