Fines, Fees, Forfeitures and Disparities:
A Link Between Municipal Reliance on Fines and Racial Disparities in Policing

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Abstract

We investigate a possible linkage between municipal reliance on fines, fees, and forfeitures as a revenue source and policing behavior. With a dataset of four million traffic stops made by North Carolina municipalities, we demonstrate that a regular reliance on fines, fees, and forfeitures has powerful, predictable, and racially distinct impacts on black and white drivers, and that fiscal stress exacerbates these differences. A greater regular reliance on fines, fees, and forfeitures is linked to: a decrease in the probability of white, but not black, drivers being searched; and increased odds of finding contraband among those white drivers who are searched, but no such change for black drivers. We validate the North Carolina tests with aggregate analyses of municipalities across four states.

Keywords: race and policing, traffic stops, local government, budgeting, criminal justice

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The U.S. Department of Justice's (DOJ) investigation of the Ferguson (MO) Police Department in the aftermath of the protests that followed the killing of Michael Brown concluded that the Ferguson Police Department engaged in predatory policing, which is "the utilization of ordinary policing mechanisms, such as warrants, arrests, and citations, to generate revenue for municipalities and police departments…" (Carbado 2017, 552). The DOJ report stated that the local police department's practices were geared more toward raising revenue than maintaining public safety (DOJ 2015). Of course, these predatory practices were not racially neutral, the DOJ noted, and they most likely contributed to the catastrophic lack of public trust in the police. In this paper, we examine how common it is that local governments generate revenue by fining citizens, seizing their property, and collecting court fees. Further, we ask how this affects policing.

The causes and consequences of predatory policing are systematic and generalizable. Studies have shown that: (1) more municipal revenue is raised through fines, fees, and forfeitures in communities where a greater proportion of the population is black and where there is no black representation in local elected offices (Sances and You 2017), and (2) this greater focus on revenue raising compromises crime-solving efforts (Goldstein, Sances, and You 2018). At their roots, these racially disparate police practices signal to members of minority communities that they are not full citizens, that their voice will not be heard, and that their political leaders are willing to exploit them for financial gain. No wonder then that scholars have shown that negative interactions with the police and criminal justice system demobilize voters (Weaver and Lerman 2010, Lerman and Weaver 2014, White 2019).

We seek to understand what happens to police-citizen interactions when municipalities rely on the police to fill fiscal shortfalls. To do this, we focus on the routine traffic stop. Research has shown that police departments conduct more stops and issue more tickets when the associated

municipal government relies on the department for some of its revenue (e.g., Worrall 2001, Garrett and Wagner 2009, Makowsky and Stratmann 2009 and 2011, Baicker and Jacobson 2007, Holcomb et al 2018). As traffic stops, like many policing activities, have racially disparate outcomes (e.g., Engel and Calnon 2004, Knowles, Persico, and Todd 2001, Gelman, Fagan, and Kiss 2007), researchers have begun to question whether an increased reliance on fines, fees, and forfeitures may be associated with these disparities. Clearly, these relations can be complicated.

One recent study (Harris, Fagan, and Ash 2020) found that white drivers—often stereotyped as wealthier and who are less likely to have negative police encounters—are more likely to be ticketed (compared to black drivers) in municipalities that are facing fiscal shortfalls. The idea is that when faced with the goal of generating more revenue, officers increase their ticketing behavior and possibly expand the scope of who is policed. Harris, Fagan, and Ash (2020) make clear that their focus is on patterns of ticketing and the fines associated with them. However, the traffic code can also be used to enforce the wars on crime and drugs, which in turn can generate income in other ways – not just through fines. These different uses of the traffic code lead to different racial implications, as we make clear below. While white drivers may suffer from a focus on traffic tickets, black drivers are disadvantaged by more enforcement of other parts of the traffic code, particularly those potentially leading to a search for contraband. This leads to our central question: Does a greater reliance on fines, fees, and forfeitures accentuate racial disparities in who is searched?

We hypothesize that the answer is yes. This expectation builds from three observations. First, traffic stop outcomes, including searches, vary by driver race (e.g., Engel and Calnon 2004, Knowles, Persico, and Todd 2001, Epp, Maynard-Moody, and Haider Markel 2014, Simoiu, Corbett-Davies, and Goel 2017, or Baumgartner, Epp, and Shoub 2018). These disparities are

typically attributed to either officer bias (e.g., Eberhardt 2019) or institutional practices that inculcate racialized stereotypes (e.g., Epp, Maynard-Moody, and Haider-Markel 2014). Second, when under pressure from the municipal government, departments may alter their policies or priorities to raise revenue. This often means that traffic stops and citations increase (e.g., Garrett and Wagner 2009, Makowsky and Stratmann 2009 and 2011). Third, increased traffic stop activity may lead to differences in the outcomes that drivers are likely to experience based on their identity (e.g., Harris, Fagan, and Ash 2020, Baumgartner, Epp, and Shoub 2018). In particular, black and white drivers might have different odds of being stopped and searched depending on the fiscal situation of the surrounding municipality. Each of these in turn may influence the observed probability of being found with contraband as the base exposure rates and probabilities change.

Municipal reliance on fees may lead police departments to redirect officer attention to generating revenue by increasing traffic stops and ticketing, which can lead to a decline in other policing activities. Thus, we anticipate a reduction in searches when police departments are called upon to fill municipal coffers. Because white motorists are stereotypically seen as a) less suspicious and b) more likely to be able to pay a ticket, those drivers may be targeted for stops, but not searches. Stereotypes are just the opposite for black motorists. For black drivers, the logic of revenue-maximization is less applicable and officers may approach black drivers in much the same way regardless of budgetary context. It follows then that black drivers will be less likely to benefit from reductions in the search rate that occur for white drivers. Finally, if differential search patterns are observed and if it may be due to differential expectations for revenue generation, then this has implications for the discovery of contraband. If white motorists are searched only when they appear especially suspicious, then contraband hit rates should increase. This may not be the case for black motorists if they experience no reduction in search rates in the first place.

To test these expectations, we first use information on over 4 million individual traffic stops made by municipalities in North Carolina, predicting the likelihood that a driver will be subjected to a search during a police traffic stop. Our use of individual stop-level data allows us to control for factors that we know to be related to the outcome of a stop, such as why the driver was initially pulled over (e.g., speeding). We create three distinct measures of municipal reliance on revenue generated by the police, building on different ways previous studies have measured this concept. The first measure captures the *regular* reliance a municipality may have on fines, fees, and forfeitures. The second and third capture reliance in the face of a *short-term* shock, such as an increase in the deficit or revenue shortfall compared to the previous year. Results from these analyses show that a greater, regular reliance on fees: (1) decreases the probability of being searched significantly for white drivers, and to a much lesser extent for black drivers; (2) increases the racial disparities in who is searched; and (3) is related to a significant increase in the contraband hit rate for white drivers, but not for black drivers. Put another way, regular reliance on fines, fees, and forfeitures for revenue leads the police to conduct a slightly higher share of fruitless searches of black drivers, while leading them to conduct a substantially higher share of fruitful searches of white drivers. This finding is in line with previous scholarship that demonstrates the tradeoffs between high-contact policing (i.e. making a lot of stops) and effectiveness at locating contraband (Mummolo 2018; Epp and Erhardt 2020).

These micro-level analyses allow us to explore how a reliance on fines, fees, and forfeitures to fund municipalities changes the outcomes that individuals experience in their interactions with police officers and leads to troubling conclusions. In order to assess the aggregate impact of these patterns across entire populations, we create a municipal-level dataset featuring multiple years of traffic stop data from 39 cities across four states. With this database, we test whether higher

reliance on policing revenue influences racial disparities in search rates. In line with the individual-level analyses, we find that higher regular reliance on fines, fees, and forfeitures and greater fiscal stress correspond to increased racial disparities in who is searched following a traffic stop.

These analyses help clarify what happens when municipalities turn to their police departments for help in generating revenue. White drivers see an uptick in behavior we see as a "normal," if annoying, outcome from an interaction with local law enforcement: A ticket (Harris, Fagan, and Ash 2020). Black drivers see a much more intrusive and alienating outcome suggestive of criminal suspicion: A fruitless search of their vehicle. Predatory policing has distinct impacts on black and white community members.

Policing, Revenue, and Race

To better understand the way that fiscal pressures influence interactions between ordinary individuals and the police, we must understand two well-established relationships. First, regardless of fiscal pressure, policing does not affect communities in a color-blind way. Instead, black and brown people tend to experience harsher treatment by the police than their white counterparts (e.g. Alexander 2020, Christiani 2020, Weaver and Lerman 2010). Second, police departments are often compelled to generate revenue, whether to supplement their own funding or to contribute to the municipality (e.g. Baicker and Jacobson 2007, Harris, Fagan, and Ash 2020). These two phenomena are linked: departmental policies and priorities can shape officer behavior and thus, individual outcomes from police interactions. Here we delve into each of these points in greater detail and end by introducing our hypotheses.

First, policing has racially disparate outcomes – black people are stopped and searched more than white people during street stops (Gelman, Fagan, and Kiss 2007) and traffic stops (e.g., Epp, Maynard-Moody, and Haider-Markel 2014, Smith and Petrocelli 2001, Miller 2009, Moon

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and Corley 2007, Rojek, Rosenfeld, and Decker 2004, 2012, Pierson et al 2020). They are also more likely to be arrested (Sharp 2014), incarcerated (Alexander 2020), and to experience longer prison sentences (Rehavi and Starr 2014). The causal mechanism behind these racial disparities may be individually-held implicit and explicit racial biases that link black people with criminality (Gilliam and Iyengar 2000; Loury 2008; Muhammad 2010; Welch 2007) or institutionally taught and enforced practices that inculcate stereotypes that characterize black people as criminal (Eberhardt 2019, Fagan and Geller 2015). Even though racial profiling is illegal, a network of institutional practices tends to reproduce it (Epp, Maynard-Moody, and Haider-Markel 2014). Epp, Maynard-Moody, and Haider-Markel (2014) cite police training materials that state that while racial profiling is not legal, traditional profiles (which cast blacks as likely involved in the drug trade) still "correlate closely" with many drug couriers today (p. 40).

Mummolo (2018) demonstrates that contrary to much prior work, police officers are indeed responsive to policy change. The New York Police Department instituted a requirement that any stop an officer made must be accompanied by a narrative explaining their reason for the stop. Officers perceived this change as an increase in scrutiny and, as such, were more judicious in their stops. This resulted in fewer stops but a greater rate of uncovering of weapons in the stops that were made (Mummolo 2018). Policies and procedures can shape the actions of police officers on the ground.

Because of the racialized nature of policing, we may reasonably expect that policy changes may be felt differently across racial groups. For example, Makowsky, Stratman, and Tabarrok (2019) find that officers from municipalities with local deficits tend to make more arrests of black and Latinx people for drugs, driving under the influence (DUI), and prostitution, while whites' drug and DUI arrests are uncorrelated with these institutional pressures. In the case of traffic stops,

institutional pressures may also be felt differently by white and black drivers. Indeed, previous research shows that this is the case with respect to who is ticketed: in periods of increased reliance on police departments for revenue, white drivers see an increased probability of being ticketed, while black and Latinx drivers see no change in their probabilities of being ticketed following a stop (Harris, Fagan, and Ash 2020). Less is known about how pressuring police departments to raise revenue affects police searches, which is our focus here.

Sometimes, these institutional policies and imperatives may be shaped by fiscal pressures. There are two general reasons that police departments may need to raise revenue. First, they may have to fund themselves, such that they either generate revenue that is directly paid to the police department or that is essentially automatically returned to them in the municipal budget (e.g., Baicker and Jacobson 2007). An anecdote that Baicker and Jacobson (2007) pulled from a newspaper article run in the *Kansas City Star* (Dillon 2000, quoted in Baicker and Jacobson 2007) highlights this pressure: A San Jose city manager responded to the local police chief's inquiry about why the city was not providing funds for police equipment in the annual budget by saying, "Well, you guys seized $4 million last year." In the city manager's view, the police had plenty of funds, and the ability to raise more if they needed it, so the city could prioritize other budget categories, essentially using the police as a revenue source.

Second, the police department may have to assist in funding the municipality, either as a regularly relied upon revenue source or as one of the few avenues by which a municipality can augment their budget in the face of unexpected expenditures or shortfalls. As Mayor John Gwaltney of Edmundson, Missouri said in a memo to the municipal police department (sent on April 18, 2014): "…the tickets that you write do add to the revenue..." He then went on to drive the point home by concluding his memo with: "As budget time approaches, please make a self-

evaluation of your work habits and motivation, then make the changes that you see that will be fair to yourself and the city." Regardless of the mechanism (i.e., budget shortfalls, a regular reliance on this revenue, or a self-funding and offsetting model), this means that as reliance on revenue generated by the police increases, predatory policing practices likely increase. This is indeed what has been documented for traffic stops (Garrett and Wagner 2009, Harris, Fagan, and Ash 2020, Makowsky and Stratmann 2009, 2011) and asset seizure and forfeitures (e.g., Baicker and Jacobson 2007, Makowsky, Stratmann, and Tabarrok 2019).

When directed to raise revenue either to keep their own department afloat or to contribute to the municipal budget, police departments can do so through three linked means: fines, fees, and forfeitures. Each has a distinct manner in which it generates revenue: fines may be direct financial punishment for wrongdoing (i.e., a ticket for speeding), fees may be payment for the use of a service (i.e., court costs), and forfeiture is the seizure of assets for suspected criminal activity or suspected use in criminal activity (i.e., seizure of a car). However, all three are often explicitly or implicitly linked, and our data does not allow us to distinguish among them. For example, in the case of a traffic ticket, typically an individual must pay the fine itself and an administrative fee, such as either a court or processing fee. Generally speaking, fines through traffic tickets are the quickest and most reliable way for a police department to raise revenue. Thus, a primary way that many police departments raise revenue is through an uptick in traffic stops (Makwosky and Stratmann 2009; Garrett and Wagner 2009; Baicker and Jacobson 2007). Methodologically, because the collected budgetary data does not allow us to distinguish among these three revenue sources, we analyze their collective totals.

Hypotheses

Our review of the literature suggests several possible links between reliance on fines, fees, and forfeitures and racially disparate policing. When the police are tasked with raising money, they conduct more stops and/or write more tickets. This behavior is targeted at white drivers, who are presumed to be better able to pay, compared to black drivers. The focus on writing tickets leads to a reduction in other activities, including searches. This, however, is racially disparate as well: white drivers benefit from this reduction more than black drivers. This, in turn, leads officers to use a higher threshold of suspicion when deciding whether or not to search white drivers. Thus, contraband hit rates will likely be higher for those white drivers who are searched, with no corresponding shift for black drivers, since they do not see the same reduction in search rates.[3] We hypothesize:

(H1) *Greater reliance on revenue generated by the police department is linked to lower search rates for both black and white drivers.*

(H2) *Greater reliance on revenue generated by the police department is linked to a bigger reduction in search rates for white drivers than for black drivers.*

(H3) *Greater reliance on revenue generated by the police department is linked to an increase in the contraband hit rate for white drivers but not for black drivers.*

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[3] In addition to changes in search rates potentially shaping the rate at which contraband is found, previous studies have also shown that contraband is found on drivers or in their cars at differential rates by race (e.g., Tillyer and Klahm 2011, Pierson et al 2020, and Baumgartner, Epp, and Shoub 2018).

Data from North Carolina Municipalities

In our first test, we turn to data on individual traffic stops. Looking at individual stops allows us to better control for other contextual factors that have been shown to matter in predicting and explaining who is searched, such as driver characteristics (e.g., driver gender and age) and stop characteristics (e.g., time of day and stop purpose). However, data on individual stops conducted by municipal police departments are not widely available. Further, areas where publicly available municipal budget information co-occurs with publicly available policing data is even rarer. Fortunately, the state of North Carolina makes both available.

More generally, North Carolina is a good case with which to test our hypotheses, because the state is close to the US average in terms of population, inequality, and crime rates. Our initial focus is on North Carolina municipalities, which exhibit substantial variation in their composition (racial, socioeconomic, and degree of urbanization). That being said, we expand our analysis to focus on multiple states to test whether our results are robust in the second set of analyses. In that analysis, we examine aggregate municipal information rather than individual stop outcomes.

To create the North Carolina dataset, we merge information from two sources. The first is information on individual traffic stops conducted in municipalities. In North Carolina, officers from almost every jurisdiction in the state must record their traffic stops using the SBI 122 form (Figure 1). This data is made publicly available by the state's Bureau of Investigation (for additional information see Baumgartner, Epp, and Shoub 2018); we focus on municipal police departments. This record of traffic stops is combined with municipal budget data reported to and made public by the state treasurer's office from the fiscal year 2008 onward. The resulting merged dataset has 4,900,339 traffic stops made across 126 municipal police departments.

[[Insert Figure 1 about here.]]

To ensure that our data has sufficient information to produce reliable estimates, we restrict our dataset to stops made in municipalities where: (1) the department made at least 50 stops of white, black, and Latinx drivers each, and (2) there are multiple years of data for that municipality.[4] In a similar vein, we drop stops occurring in municipalities in years where: (1) a municipality reported no revenue in either the current or previous year, as we assume these were either clerical errors or that no actual data was reported to the state, or (2) reported values for our key independent variables appear as extreme outliers, which is discussed in greater detail below. Finally, we exclude stops of other race drivers (i.e., not white, black, or Latinx drivers), as there are not sufficient observations to produce reliable estimates across municipalities, and stops that include a mandatory search (i.e., warrant searches, protective frisk searches, and incident to arrest searches. Our theoretical expectations depend on officers having discretion, but these types of search are largely procedural. Subsequent analyses look only at consent and probable cause searches, which offer officers much greater leeway in deciding who should be searched.[5] The resulting data set

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[4] Before this point, passengers and drivers stopped as a part of a check point stop have been dropped from the data set. This is because passengers are only required to be recorded if a search is conducted, and check point stops are only required to be recorded if a search is conducted. As a result, inclusion of either would bias the estimation or make estimation impossible.

[5] Altogether, we exclude 320,868 stops. Of these, 179,719 stops are excluded due to driver conditions, 132,408 stops are excluded due to one of the municipal or municipal-year conditions, and 8,741 stops are excluded that meet both conditions. Outliers with respect to revenue reliance are dropped at the conclusion of this process, which results in an additional 37,814 stops being dropped. If outliers are included, the sign and significance of the coefficients do not change and

runs from 2010 through 2016, spans 126 municipal police departments, and contains 4,579,471 stops. For additional information on which municipalities are and are not included, see the online appendix.

From the data on individual stops, we construct two dependent variables: whether a driver is searched (167,766 searches conducted), which allows us to test our first and second hypotheses, and whether contraband is found if the driver is searched (62,425 searches that yielded contraband). In addition, the SBI-122 form also provides one of our key independent variables: driver race and ethnicity. The mutually exclusive race-ethnicity categories are: non-Latinx white (2,224,398), non-Latinx black (1,940,725), and Latinx (376,534). Drivers of other races and ethnicities are excluded from this analysis.

Our second set of key independent variables are constructed using the municipal budget data. From these datasets, we extract information both on the total amount of revenue raised and the total raised through fees[6]. Of the 553 entities reporting to the state treasurer, 161 have a

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the evaluation of the hypotheses does not change. In total, these exclusions amount to 7.32 percent of the initial dataset.

[6] This information is taken from the North Carolina State Treasurer's Office website, which can be found by using this link: https://www.nctreasurer.com/slg/lfm/financial-analysis/Pages/Analysis-by-Population.aspx. We operationalize revenue from "fines, fees, and forfeitures" from the justice system in North Carolina as revenue reported in the following categories, which do not differentiate types of fundraising: (1) "Public Safety-Clerk of Superior Court facility fees, arrest fees & other court cost" collected by "Federal Intergov. Revenues," "State Intergovernmental Revenues," and "Local Intergov. Revenues," (2) "All other Public Safety

corresponding police department in the traffic stops data set, and 126 municipalities have multiple years of data that meet our criteria. The discrepancy is born from the fact that not every municipality maintains its own police force, not every police department must report traffic stop information to the state, a small number of municipalities are excluded for not having stopped a sufficient number of drivers for this analysis, and some municipalities that only reported one year of data. Among the 126 municipalities included in our analysis, the total revenue per capita raised in the previous fiscal year ranges from approximately $254.70 to $17,483.10 with a mean of $2,172.20, while the total expenditures per capita the previous fiscal year ranges from approximately $343.50 to $17,211.40 with a mean of $2131.20. The total revenue from fines, fees, and forfeitures raised in the previous fiscal year ranges from approximately $0 to $1,218.18 with a mean of $23.91.

Using this data, we create three measures of ways that a municipality may rely on revenue generated by the justice system. First, the municipality may regularly rely on fines, fees, and forfeitures to fund the government, just as it regularly relies on other sources of revenue such as taxes. To operationalize this concept, we calculate the proportion of the municipality's total revenue that comes from fines, fees, and forfeitures. This measure captures the extent to which a municipality's budget is dependent on these revenue streams and is constructed in the same way as the measure used by Sances and You (2017). The logic behind this measure is that, on average, budgets and revenue streams vary little from year to year. As such, we assume that if the local

fees- Excluding Unauthorized substance tax and clerk of court facility fees" collected by "Federal Intergov. Revenues," "State Intergovernmental Revenues," and "Local Intergov. Revenues," and (3) revenue from "Public Safety" from "Sales & Service."

criminal justice system raised 1 percent of the overall revenue for the municipality the previous budget cycle, the community would expect that about 1 percent of the overall revenue for the current budget cycle would also come from the local criminal justice system or police. This variable ranges from 0.00 percent to 7.50 percent, with a mean of 1.15 percent. This captures a regular reliance on fines, fees, and forfeitures for revenue.

A second way that municipalities may come to rely on such revenue is in the face of fiscal stress. Municipalities with temporary budget shortfalls may turn to fines, fees, and forfeitures as a stop-gap measure to make up for lost revenue. Here, the reliance on these streams of revenue may change year to year. To measure this concept, we generate two separate variables. The first is the difference in revenue between the current and previous budget cycle, not counting revenue generated by fines, fees, and forfeitures. Harris, Fagan, and Ash (2020) use the same measure of fiscal stress. Negative values indicate a decline in revenue from other sources. This is calculated by differencing the current year's total revenue per capita and the previous year's revenue per capita. This ranges from -$1763.68 to $1812.10, with a mean of -$1.38. Our second measure of fiscal stress is the difference between municipal revenue and expenditures per capita in the previous year. This ranges from -$1,557.08 to $1,565.52, with a mean of $41.01. This captures the extent to which the municipality is operating in surplus or deficit mode.

For each of the three key fiscal independent variables described in this section, we drop extreme outliers.[7] Further, for each measure of revenue reliance we use lagged budget information.

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[7] Outliers are values lying outside six times the interquartile range added to or subtracted from the interquartile range, which we identify outliers for each of the measures. This results in 37,814

By using the budget revenue amounts from the previous year, we ensure that the recorded stops that took place cannot affect the revenue totals used to construct the variables. Additionally, we use lagged budget information to address endogeneity concerns stemming from simultaneous measurement if we were to use measures constructed using the current year's information. The last thing to note about these measures is they are not highly correlated with each other, lending evidence to the notion that they do indeed capture different ways that a municipality may experience fiscal stress.[8]

With all three of these measures, we are able to better understand not only *if* a municipality responds to fiscal stress with a change in policing, but whether certain types of stress generate certain policing outcomes. That is, it could be that when a municipality regularly relies on fines, fees, and forfeitures, the police department is regularly expected to play an important role in generating revenue. On the other hand, it could be that the police are only called upon to help raise revenue as a stop-gap measure. Separating these out, both conceptually and methodologically, allows for an understanding of the types of fiscal stress that may lead to a change in police behavior. Theoretically, we do not have separate expectations for the two types of fiscal stress but instead expect that any kind of fiscal stress will lead to more reliance on the police for revenue.

In addition to the two key sets of independent variables—driver race and municipal reliance on revenues generated by the criminal justice system—we include a number of standard control variables based on previous studies (Baumgartner, Epp, and Shoub 2018). These are: driver

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stops being excluded. If outliers are included, the sign and significance of the coefficients do not change, and the evaluation of the hypotheses does not change.

[8] None of the correlations is greater than 0.27 or less than -0.27.

gender, hour of day, day of week, and initial stop purpose. Additionally, we include fixed effects for municipalities to capture unexplainable differences between agencies and municipalities.

Analysis of North Carolinian Municipal Traffic Stops

We estimate two logistic regressions: whether the driver was searched (model 1) and whether the search led to the discovery of contraband (model 2).[9] The first of these models allows us to test our first and second hypotheses, while the second model allows us to evaluate our third hypothesis. In each, the key independent variables of interest are driver race, the proportion of revenue from fines, fees, and forfeitures, and our two measures of fiscal stress. Further, we include interactions between driver race and our three variables capturing reliance on policing revenue. Table 1 shows the results.

[[Insert Table 1 about here.]]

Hypothesis 1 focused on fee reliance generally. Necessary but not sufficient support for this would be seen if the coefficient associated with the proportion of revenue variable is negative and statistically significant, while the two measures of fiscal stress should be positive and statistically significant. This is precisely what we see across all three measures. Further, for the

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[9] The first of these regressions can be summarized as: $S_{i,j,t}$ = Driver Race$_{i,j,t}$ * Revenue Reliance$_{j,t}$ + Controls$_{i,j,t}$ + Municipality$_j$ + Year$_t$, where i indicates the stop, j indicates the municipality, t indicates the year, and S is whether a search occurred during the specified stop. The first of these regressions is conditional on a search occurring and can be summarized as: $C_{i,j,t}$ = Driver Race$_{i,j,t}$ * Revenue Reliance$_{j,t}$ + Controls$_{i,j,t}$ + Municipality$_j$ + Year$_t$, where i indicates the stop, j indicates the municipality, t indicates the year, and C is whether a contraband is found following a search. In each, a logistic regression is fit.

interactive hypothesis (2) to see support, the interaction term must be statistically significant. We once again see this across all three measures and their interaction with race. To further evaluate these hypotheses, we turn to predicted probability plots and a consideration of how the coefficients interact.

Figure 2 shows the predicted probability of being searched across the observed range of values for the regular fee reliance variable—the proportion of revenue from fines, fees, and forfeitures. All other values are held to their mean or mode, and the municipality is assigned to be Charlotte, the largest city in the dataset. The x-axis shows revenue reliance across the observed range of values, while the y-axis shows the predicted probability of being searched. The solid line indicates the predicted probability for white drivers, while the dashed line indicates the predicted probability for black drivers. The shaded area indicates the 95 percent confidence interval.

[[Insert Figure 2 about here.]]

Regarding reliance on fees and search rates for black and white drivers, Figure 2a clearly shows that there is no impact for black drivers, but higher reliance on fines, fees, and forfeitures correlates with a sharp reduction in searches for white drivers. Regarding fiscal stress Figure 2b, shows a modest increase in the odds of search for white drivers, but a sharp increase for blacks. (We do not show the figure depicting the predicted probabilities across the range of changes in revenue between the current and previous year, as the same patterns are observed for this as are shown in Figure 2b.) Thus, we see support for H1 and see the opposite of what is expected in H2.

One implication here is that the racial disparity in search rates *grow* in the face of regular reliance on fines, fees, and forfeitures, but, conversely, also grow during years of budgetary surplus. This can be more clearly seen if we plot the expected difference, as we do in Figure 3. In Figure 3, we plot the change in the predicted search rate ratio, which is calculated by dividing the

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probability of a black driver being searched by the probability of a white driver being searched. Values greater than one indicate that black drivers are more likely to be searched, values of one mean white and black drivers are equally likely, and values below one indicate that white drivers are more likely to be searched.

[[Insert Figure 3 about here.]]

Figure 3 reveals that racial disparities in who is searched following a traffic stop increase between those places that do not regularly rely on fines, fees, and forfeitures—measured as the proportion of revenue from fines, fees, and forfeitures—and those that do. Conversely, going from a high deficit (greater reliance) to a high surplus (less reliance) increases the search rate ratio: short-term reliance is related to a decrease in disparities. Additionally, black drivers are always searched at higher rates given these parameters. On balance, this indicates that greater reliance may be linked to more disparate treatment of black and white drivers.

Finally, we evaluate H3: as reliance on fees increases, and searches of whites decline, we should observe an increased probability of finding contraband following those searches of white drivers that do occur. Black drivers, seeing no reduction in search rates, should see no change in contraband hit rates. As with the other hypotheses evaluated, this too is conditional and we approach evaluation in the same way: first, we evaluate whether either interaction term is statistically significant, which is a necessary condition of finding support for the hypothesis, and, if it is, we evaluate whether the observed predicted probabilities show the hypothesized pattern. Looking at Model 2 of Table 1, we see that the interaction between regular fee reliance or the proportion of revenue from fines, fees, and forfeitures and driver race reaches statistical significance. However, the interactions with our fiscal stress measures do not. As such, we now

turn to evaluating whether the posited relationship is observed by plotting the predicted probabilities of finding contraband.

Figure 4 shows the predicted probabilities of finding contraband following a discretionary search (y-axis) by driver race and across the observed range of values for regular reliance or the proportion of revenue from fines, fees, and forfeitures (x-axis). As in previous figures, the solid line indicates black drivers, while the dashed line indicates white drivers. The gray shaded area around each line indicates the 95 percent confidence interval. All other values are held to their mean or mode, and the city is assumed to be Charlotte.

[[Insert Figure 4 about here.]]

In Figure 4, we see precisely what we predicted based on our hypothesis: the probability that a black driver will be found with contraband is largely flat as reliance on fees increases, and the probability that a white driver will be found with contraband significantly increases, supporting H3. This highlights a potential benefit of conducting fewer searches as the higher hit rates suggest that officers are eliminating lower-quality searches that are more likely to turn up empty. Thus, officers can operate more efficiently and motorists can find relief from intrusive police scrutiny. All in all, increased reliance on fees affects white and black drivers in different ways. The next section asks whether these findings generalize to other municipalities across the United States and explicitly tests changes in the search disparity.

Because the available data on municipal budgets does not allow separate analyses of fines, fees, and forfeitures, we are unable consistently to break apart these parts of the process. However, we can assess directly whether property is seized, and we do so in the appendix. First, we predict whether any property is seized as a part of the traffic stop if a search is conducted. This more directly links to the concept of forfeitures. Here the same hypotheses would be tested

as with contraband: as reliance on fees increases and searches of whites decline, we should observe an increased probability of property being seized following those searches of white drivers but not of black drivers. This is observed. Second, we re-estimate the contraband and seizure regressions such that they are not conditional on a search occurring. In this case, if white drivers see disproportionally lighter outcomes when there is increased revenue reliance, then we should observe the sign on driver race and the associated interaction terms reverse. Once again, this is observed. For this analysis and longer discussion, see the appendix.

Aggregate Tests for Racial Disparities

We now turn to aggregate tests, which allow us to test the implied connection between reliance on fines, fees, and forfeitures and racial disparities. To so, we look at racial disparities in searches by year across 39 municipalities in 4 states. Additionally, we test a slightly different hypothesis here:

(H4) Greater fee reliance is linked to higher Black:White Search Rate Ratios.

For this analysis, we draw on four data sources: (1) the Annual Survey of State and Local Government Finances administered by the Census (for revenue information), (2) traffic stop information made public by select states and municipalities collected by Baumgartner et al. (2017), (3) the US Census and American Community Survey (for population estimates), and (4) the FBI's Universal Crime Reporting statistics. With this, we produce a new data set with 216 observations spanning 39 cities across 4 states across a varying number of years for each (between one and seven years). We leverage the longitudinal element of this data by relying on a lagged structure of the revenue reliance to mitigate concerns about simultaneity bias. Table 2 provides a summary of the data set.

[[Insert Table 2 About Here.]]

Whereas in the previous section we compared relative probabilities of being searched for white and black drivers to test whether the disparity in search rates grows or shrinks, here we estimate the disparity by agency and year. To measure racial disparities, we calculate a Black:White search rate ratio (SRR), as shown in Figure 3 above. Values of 1 indicate equal search rates, while values greater than 1 indicate that black drivers are searched at a higher rate than whites. All agencies have an SRR greater than 1, and most have an SRR greater than 2. The measure ranges from 1.08 to approximately 7.96. This is clear in Table 1, where the average is 2.88. Below we show that if outliers are excluded, the results remain the same. The Black:White SRR is a robust measure: when compared to logistic odds ratios generated by regressions controlling for possible confounding variables—such as those controlled for in the previous analysis—they correlate at 0.98. For this analysis, see the appendix.

One concern with using a ratio to measure disparities is that when there are few observations—in this case when few stops are made—small changes in the number of searches conducted can produce large differences in the ratio. In other words, it may result in a volatile and unreliable measure. To address this, we only include agencies and time periods with at least 10,000 traffic stops, including 100 stops each of white and black drivers, and where at least 1 white driver and 1 black driver were searched. To maximize the number of municipalities in the analysis, if these stop thresholds are not met in a single year, information across years are combined until thresholds are met. All related data are tied to the first year in the window. For more information, see the online appendix. In a robustness check discussed and presented below, we show that narrowing the data used to only observations where one year's worth of data is used does not change the results.

Once again, the primary concept of interest is reliance on revenue generated by the police. Here we use information recorded by the Census Bureau in their database on individual local government finances. We draw from two of the reported fields: the total revenue reported and the revenue raised from fines, fees, and forfeitures.[10] This data is drawn from a periodic survey of local governments, which the Census has been conducting since 1967. However, in most years the survey is not comprehensive and the participation of individual municipalities varies. Starting in 2005, data on the same set of municipalities becomes consistently available through 2012, so this window of time is the focus of our analysis.

Furthermore, while the data provides a reliable measure of spending in different areas of municipal governance, it does not serve the same function as an accounting statement so the associated Census-issued codebook warns against calculating a deficit or surplus by comparing aggregate expenditures and revenues. This makes it impossible to recreate our measure of fiscal stress, but we still are able to replicate our other measures of reliance on fees. First, we again calculate the proportion of total revenue from fines, fees, and forfeitures to capture regular reliance as reported by the municipality in response to the census of local governments. This variable ranges from 0 to 0.09, with a mean of 0.01. Second, we again calculate the difference in per capita revenue

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[10] The census of governments asks municipalities how much revenue they collect collectively from "penalties imposed for violation of law; civil penalties (e.g., for violating court orders); court fees if levied upon conviction of a crime or violation . . . and forfeits of deposits held for performance guarantees or against loss or damage (such as forfeited bail and collateral)" (https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html). We use responses from this question to operationalize revenue raised from fines, fees, and forfeitures.

omitting revenue from fines, fees, and forfeitures raised between the current and previous year, which captures short-term reliance. Negative values indicate that there is a revenue shortfall. This variable ranges from -$1.85 to $2.49, with a mean of $0.06. These measures mirror what is used in the previous section and test. One concern with these variables, as in the previous analysis, is that outliers in either variable will bias the results. Below we show that if outliers are excluded, the results hold.

In addition to our key variables of interest, we consistently account for variation over time and across municipality. To the first, we include fixed effects for each year, as this period spans the great recession, and there was variable national attention on traffic stops during this period. To the second, we include random intercepts by municipality because local funding structures and traffic stops conventions differ by state. We choose to include random intercepts rather than fixed effects as there is minimal variation or very few observations over time for some municipalities. Due to the inclusion of intercepts by municipality, the data set is restricted to those municipalities and departments that occur multiple times within the data set.

In one robustness check, which we present and discuss below, we also control for a number of additional and alternative explanations. Specifically, these are: the proportion of the population that is black, the proportion of the community with less than a high school degree, the proportion below the poverty line, and the overall crime rate. While this set of controls does not account for every possible explanation, many other potential variables of interest are either inconsistent across cities or are only available by county. For example, most city councils are nonpartisan, and partisan voting data is most commonly available at the county level. This means that controlling for partisanship is not possible with existing data.

Analysis

Using this data set, we test whether policing disparities, measured by the Black:White Search Rate Ratio (SRR), are statistically linked to a city generating more or less revenue from fines, fees, and forfeitures. We do this by estimating a series of regressions, where our primary model is a hierarchal linear model and includes only a lag of the dependent variable, our revenue reliance measures, and controls for year and municipality (Model 1 in Table 3).[11] We include a lag of the dependent variable as the SRR in the current year may be linked to its past level either due to institutional or contextual factors. Next, we show that regardless of specification, our results hold (Models 2-5 in Table 3). Each of these is discussed in greater detail below. Finally, we test whether a reverse causal relationship is additionally or alternatively observed by leveraging the temporal aspect of these data: in this case, the proportion of local revenue from fees is predicted (Model 6 in Table 3). Table 3 presents these regressions.

[[Insert Table 3 about here.]]

Using these regressions, we can test our fourth hypothesis, which posits that there will be an increase in search disparities as reliance on policing revenue increases. Support for this

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[11] Models 1 through 5 have the same basic specification, but each includes different control variables. These regressions can be summarized as follows: $SRR_{j,t}$ = Revenue Reliance$_{j,t}$ + Controls$_{j,t}$, where j indicates the municipality, t indicates the year, and *SRR* is the Black:White Search Rate Ratio of a municipality in a given year. Model 6 can be summarized as: $FFF_{j,t}$ = SRR_{t-1} + Controls$_{j,t}$ + Municipality$_j$ + Year$_t$, where j indicates the municipality, t indicates the year, SRR indicates the Black:White Search Rate Ratio of municipality j in from year t-1, and *FFF* is the proportion of revenue from fines, fees, and forfeitures from the current year t.

hypothesis would be seen if the coefficients associated with the proportion of revenue from fines, fees, and forfeitures are positive and statistically significant in Model 1 in Table 3, but the coefficients associated with the difference in revenue are negative and statistically significant. We see mixed support for our hypothesis. Regular reliance on fines, fees, and forfeitures, as measured by the proportion of revenue generated by fines, fees, and forfeitures appears to increase the Black:White SRR. However, there appears to be no relationship between short term reliance on revenue, as measured by the difference in the current and previous year's revenue, and the Black:White SRR --the associated coefficients fail to reach statistical significance but do point in the expected direction.

Before turning to a substantive interpretation of these results, we question whether this finding is an artifact of how we chose to construct the dataset and fit our regression. To address this concern, we re-estimate the model in four ways (models 2-5 in Table 3) and find support for our initial findings each time. First, we test whether the inclusion of the lag of the dependent variable alters our results (Model 2 in Table 3). It does not, and the substantive relationship actually greatly increases. Next, we test whether our choice of random rather than fixed effects influenced our results using OLS rather than HLM (Model 3 in Table 3). Once again, it does not. Third, we include additional contextual controls about the municipality, which are discussed above (Model 4 in Table 3). Again, the relationships hold, and in this case, see a modest increase in the substantive relationship. Finally, we test whether our decision to include outliers and municipalities that use more than one year of data to construct an estimate of the SRR alters our results (Model 5 in Table 3). By excluding observations that do not meet this criterion, we lose 66 observations and 9 municipalities. Even in this case, the results hold – and we see a modestly larger substantive connection between long term reliance or the proportion of revenue from fines, fees,

and forfeitures and the Black:White Search Rate Ratio. In sum, we find support for our hypothesis regardless of specification, and demonstrate that if there is any change to the relationship, it is that we may be underestimating the relationship with our chosen specification and construction of the data set.

With a better understanding of how our modeling and measurement choices relate to our results—namely that they hold across specification—we take a closer look at the substantive relationship between the Black:White SRR and the proportion of revenue from fines, fees, and forfeitures as shown in the first model. To do so, we calculate the expected value for the Black:White SRR across the observed range of values for the proportion of revenue. In doing so, we use the estimates from Model 1 in Table 3. We hold other variables at their means or mode and hold the municipality to be Illinois' capital: Springfield. The expected values are shown in Figure 5, where the expected values are shown along the y-axis and the revenue proportion is shown along the x-axis. The black line indicates the expected value of the Black:White SRR, while the light grey shared area surrounding it indicates the 95 percent confidence interval. Additionally, the points in grey show the observed values. As a reminder, a value of one indicates that the black and white drivers are searched at an equal rate, while values above one indicates that black drivers are searched at a higher rate.

[[Insert Figure 5 about here.]]

Figure 5 reveals that across the range of observed values for the proportion of revenue from fines, fees, and forfeitures, the expected value for the Black:White Search Rate Ratio increases by 1.38, which is more than one standard deviation of the Black:White SRR. This indicates that, in addition to there being a statistical relationship between the two variables, there is a strong

substantive relationship between the Black:White SRR and the proportion of municipal budget revenue from fines, fees, and forfeitures.

Finally, we ask and test whether the relationship between proportion of revenue and the SRR we identify here is actually caused by the reverse process: agencies that have higher disparities in search rates may, as a result, generate more revenue from fines, fees, and forfeitures. This may be the case if black drivers are more likely to have contraband on them, more likely to go be arrested following a traffic stop, and/or more likely to meet the requirements of civil forfeiture, such that their property can be possessed. If such a world existed, then the proportion of the municipal budget generated through fines, fees, and forfeitures should increase. However, this is not what the final model shows in Table 3. Rather, the last model in Table 3 suggests that revenue shortfalls in one-year lead to increased reliance on fines, fees, and forfeiture in the following year.

Model 6 in Table 3 shows that there is no statistically significant relationship between the Black:White SRR and proportion of revenue from fees. However, the coefficient (0.0004) does point in the expected direction. This holds even if the model is re-specified to exclude the lagged dependent variable or with fixed rather than random effects. Further, we do observe the expected relationship between a lagged dependent variable and the dependent variable (the coefficient is positive and statistically significant) *and* the difference in revenue with the proportion of revenue (the coefficient is negative and statistically significant). In line with previous studies, we see that in periods of greater fiscal stress—if the difference in revenue is negative indicating a revenue shortfall—then there is an increase in the proportion of revenue generated from fines, fees, and forfeitures. Thus, the degree to which there is a revenue shortfall in a municipality appears related to the proportion of revenue, but the previous year's Black:White SRR does not appear related to

the current proportion of revenue generated from fines, fees, and forfeitures. This lends support to the idea that the posited relationship—and that greater, regular reliance on fees increases search disparities—exists and in the proposed direction. Additionally, this corroborates what previous studies, which have typically been qualitative or anecdotal, show: greater fiscal stress is linked to an increase in the proportion of revenue drawn from fines, fees, and forfeitures.

In sum, this analysis shows support for the hypothesis that for municipalities where a greater proportion of revenue comes from the justice system, there will be greater disparities in policing. It does so using a range of different model specifications and by showing that the Black:White Search Rate Ratio does not appear to be driving the proportion of revenue that comes from fines, fees, and forfeitures (i.e., no evidence of reverse causality).

Discussion

We have assessed the relationship between policing, race, and municipal revenues, with a focus on the searches that result from traffic stops. Several important substantive consequences ensue when cities rely more heavily on fines, fees, and forfeitures. First, search rates decline, but only for white drivers. Thus, as a consequence, the racial disparity in searches increases: black drivers are searched at the same rate, but the rate for white drivers declines, leading to higher disparities, as reliance on fees increases. Second, white drivers are subjected to search only when they appear particularly suspicious; this is reflected in the fact that contraband hit-rates increase sharply for whites as a reliance on fees increases, but not for blacks. Because black drivers are subjected to an equal chance of search as when reliance on fees is low, an equal share of the searches are, in retrospect, unjustified. For white drivers, fewer unjustified searches occur, resulting in an increase in racial disparities are the reliance on fees increase.

While we contribute to the ongoing discussions of what informs policing patterns generally and how revenue reliance shapes those patterns specifically, a number of lingering questions remain that should be studied in the future. First, our findings are consistent with regards to a municipality's regular reliance on revenue raised by the justice system, but they were mixed with regards to the role of fiscal stress. One reason for these mixed findings may relate to problems in measurement: we cannot differentiate among fines, fees, and forfeitures. Different types of police behaviors may be related to these three types of revenue sources, but the available data do not allow us to distinguish among them. However, these mixed findings—consistent support for a connection between a regular reliance and disparities but mixed with regards to a short-term reliance—may not be mere measurement artifacts. One explanation for this might be that the police behaviors we are analyzing do not turn on a dime. These may be long-standing practices that differ more by the culture of the local municipality, generating long-term expectations. As such, future research should explore both how the differential ways revenue may be generated connect to police behavior by turning to other sources of data and continue to explore differences in the connections between regular and short-term reliance on revenue generation for policing behavior.

Second, a related concern is that we do not differentiate between how revenue is used, distributed, and generated: Does it go directly to the department who then uses those funds; Is it transferred to the municipality; Is revenue garnered directly from the public; Is revenue generated via a transfer from the state or federal governments as payment for participation in a program or for services rendered; Does a mixture occur? Answers to these questions are important, because the way that revenue is used, distributed, and generated may modify how reactive a department is to revenue needs and in what ways they respond. For example, recent calls by organizations aimed at police reform have included proposals to redirect some funds typically allocated for police

departments for services that more directly address the root causes of poverty and crime. However, this may only be an effective strategy in municipalities where a significant amount of the policing budget comes from municipal funds rather than by directly raising and keeping funds.

Finally, in this study, our focus is on the connection between reliance on revenue generated by the justice system and officer search patterns as a part of a traffic stop. This is only one part of a traffic stop and one type of police activity. In related research, others have looked at how revenue reliance informs traffic ticketing patterns. Harris, Fagan, and Ash (2020) have shown that white drivers are subjected to revenue extraction by other means: stops followed by tickets. In the future, researchers should take a holistic look at the traffic stop encounter to evaluate and understand what aspects are altered when revenue generation is part of the goal of the stop.

In sum, our analyses have used large datasets from many states to demonstrate that when municipalities rely on their police department for revenue, racial disparities in traffic stop searches increase and black drivers are subject to more fruitless searches. While the findings do not answer every question that one might have, they consistently point to the idea that where policing is concerned, any change in policy can be expected to have distinct impacts on the white and black communities served. Predatory policing driven by municipal reliance on fines and fees may inconvenience white drivers and subject them to a greater number of tickets. For black drivers, however, it exacerbates the racial disparities in much harsher police behaviors associated with being treated like a criminal suspect.

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Figures

Figure 1. SBI 122 Form

TRAFFIC STOP REPORT

Agency Name

Date (Month/Day/Year)   Time

County of Stop

Officer ID Number

City of Stop

Part I

Initial Purpose of Traffic Stop *(check only one)*

☐ Checkpoint
☐ Driving While Impaired
☐ Investigation
☐ Other Motor Vehicle Violation
☐ Safe Movement Violation
☐ Seat Belt Violation
☐ Speed Limit Violation
☐ Stop Light / Sign Violation
☐ Vehicle Equipment Violation
☐ Vehicle Regulatory Violation

Vehicle Driver Information

Driver's Age _____ Driver's Race ☐ White ☐ Black ☐ Native American ☐ Asian ☐ Other

Driver's Sex ☐ Male ☐ Female

Driver's Ethnicity ☐ Non-Hispanic ☐ Hispanic *(Person of Mexican, Puerto Rican, Cuban, Central or South American, or other Spanish Culture)*

Enforcement Action Taken as a Result of the Traffic Stop *(check only one)*

☐ Citation Issued
☐ No Action Taken
☐ On-View Arrest → If arrest made, who was arrested?
☐ Verbal Warning
☐ Written Warning
☐ Driver
☐ Passenger(s)

Physical Resistance Encountered

Did Officer(s) encounter any physical resistance from Driver and/or Passenger(s)? ☐ Yes ☐ No
Did Officer(s) engage in the use of force against the Driver and/or Passenger(s)? ☐ Yes ☐ No
Did injuries occur to the Officer(s) as a result of the stop? ☐ Yes ☐ No
Did injuries occur to the Driver as a result of the stop? ☐ Yes ☐ No
Did injuries occur to the Passenger(s) as a result of the stop? ☐ Yes ☐ No

Vehicle/Driver/Passenger(s) Search

Was a search initiated subsequent to the traffic stop? ☐ Yes* ☐ No
*If search was initiated, complete Part II

SBI-122 (Rev. 12/09)

Traffic Stop Report

Part II

Type of Search *(check only one)*

☐ Consent ☐ Search Warrant ☐ Probable Cause ☐ Search Incident to Arrest ☐ Protective Frisk

Basis for Search

☐ Erratic/Suspicious Behavior ☐ Observation of Suspected Contraband ☐ Suspicious Movement
☐ Informant's Tip ☐ Other Official Information ☐ Witness Observation

Person(s)/Vehicle Searched

Was the Vehicle Searched? ☐ Yes ☐ No
Was the Driver Searched? ☐ Yes ☐ No
Was a Passenger(s) Searched? ☐ Yes ☐ No
Were the Personal Effects of the Driver and/or Passenger(s) Searched? ☐ Yes ☐ No

Identify the sex, race, and ethnicity of each passenger searched

	Age	Sex		Race					Ethnicity	
		Male	Female	White	Black	Native American	Asian	Other	Hispanic	Non-Hispanic
Passenger 1										
Passenger 2										
Passenger 3										
Passenger 4										

Contraband Found

Contraband found as a result of the search: ☐ None   **OR** complete the following:

☐ Drugs _____ Ounces _____ Pounds _____ Dosages _____ Grams _____ Kilos
☐ Alcohol _____ Pints _____ Gallons
☐ Money _____ Dollar Amount
☐ Weapons _____ Number of Weapons
☐ Other _____ Dollar Amount

Property Seized

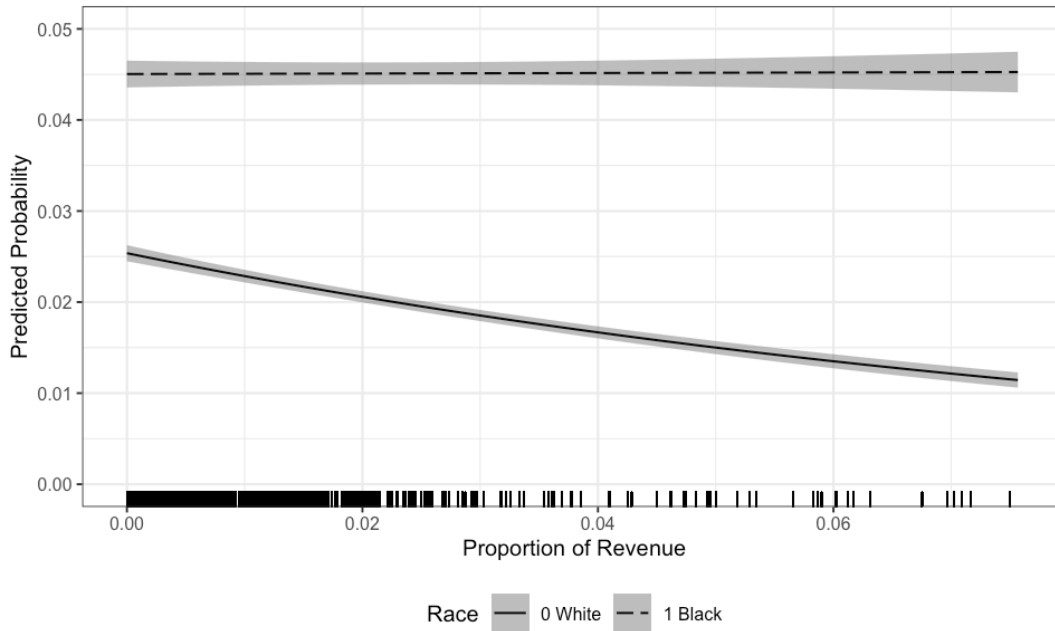Property seized as a result of the search: ☐ None   **OR** complete the following:

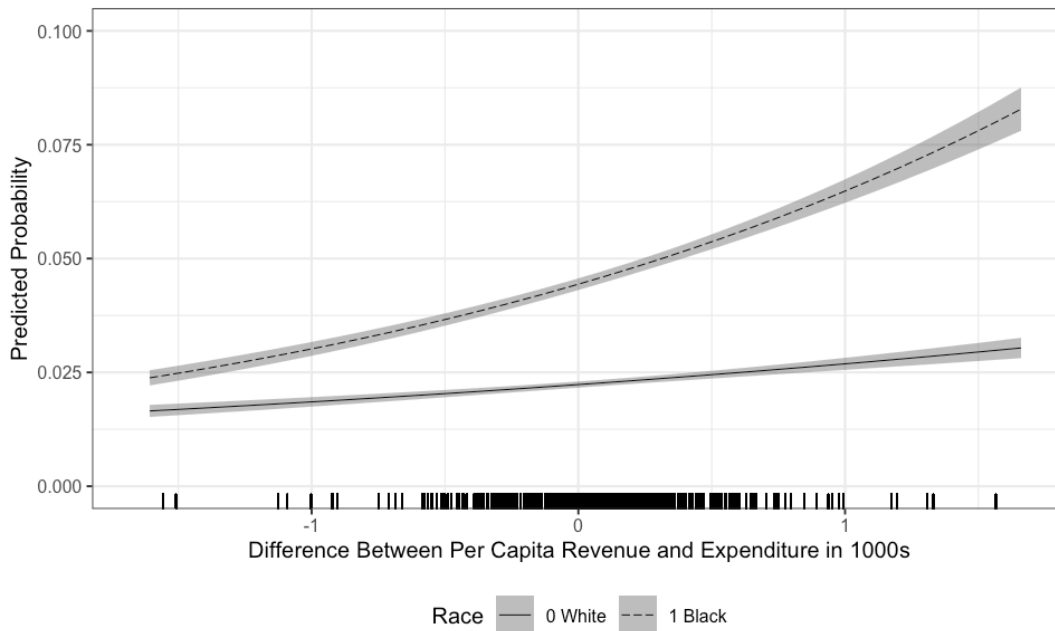☐ Motor Vehicle ☐ Personal Property ☐ Other Property

Office Use Only	Date	Initials
Reviewed		
Entered		

SBI-122 (Rev. 12/09)

Figure 2. Probability of Being Searched by Revenue Reliance and Driver Race
a. Proportion of Revenue from Fines, Fees, and Forfeitures, Previous Year

b. Difference Between Per Capita Revenue and Expenditures

Note: All other values held to their mean or mode, the municipality is Charlotte, NC, and as in the regressions extreme outliers are excluded. Similar patterns are seen when looking at the predicted probabilities of the difference between per capita revenue and expenditures and the change in per capita revenue.

Figure 3. Racial Disparities in the Probability of Being Searched Across the Observed Range of Values of the Proportion of Revenue from Fines, Fees, and Forfeitures (or Regular Reliance)
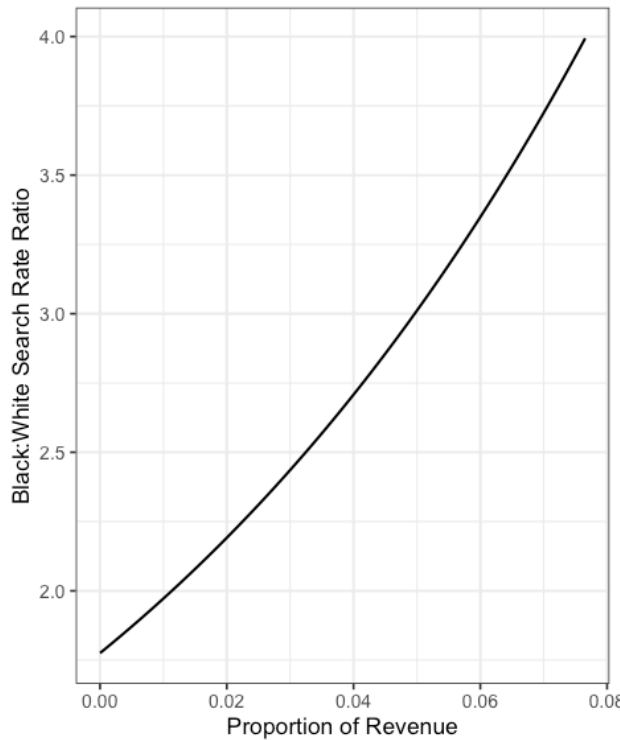
a. Propotion of Revenue   b. Change in Revenue
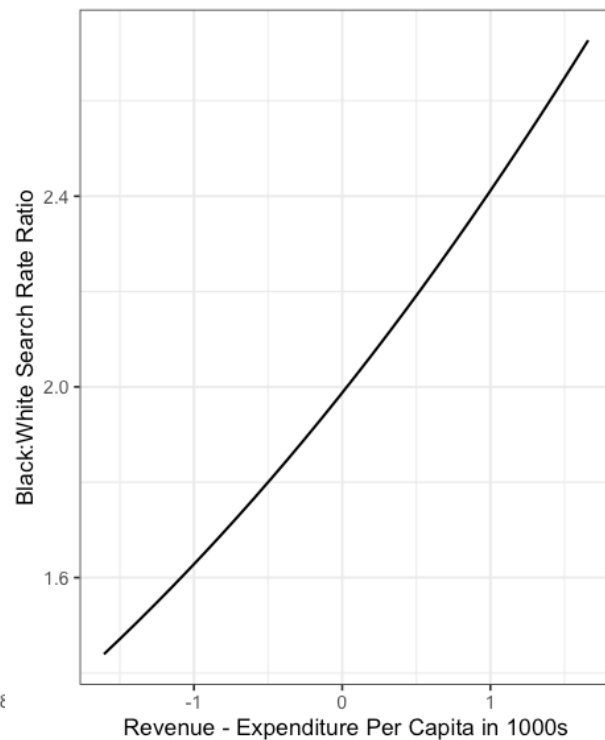
Note: The Black:White Search Rate Ratio is calcualted by dividing the predicted probability of a black driver being searched by the predicted probability of a white driver being searched across the approximate range of observed values excluding extreme outliers. This means values over 1 mean a black driver is more likely to be searched. Predicted probabilities are the same as those shown in Figure 3, where other variables are held to their means or modes. Patterns shown in 3b hold when looking at the change in revenue.

Figure 4. Probability of Being Found with Contraband by Driver Race and Proportion of Revenue from Fines, Fees, and Forfeitures in the Previous Year
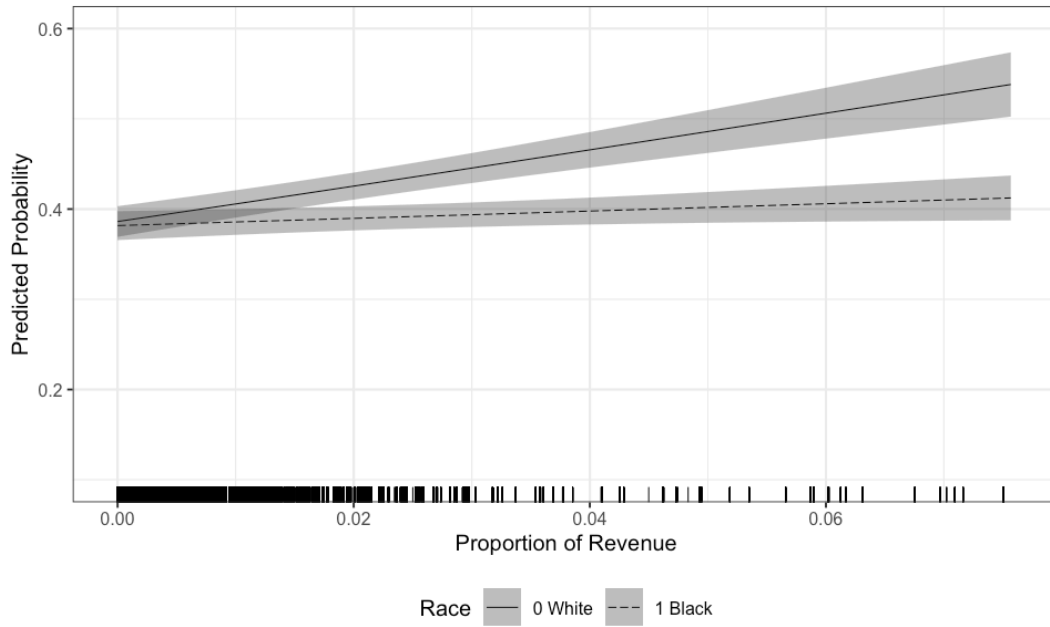
Note: All other values held to their mean or mode, the municipality is Charlotte, NC, and as in the regressions extreme outliers are excluded. Similar patterns are seen when looking at the predicted probabilities of the difference between per capita revenue and expenditures and the change in per capita revenue.

Figure 5. Expected Values for the Black:White Search Rate Ratio Across a Range of Values for the Proportion of Revenue from Fines, Fees, and Forfeitures
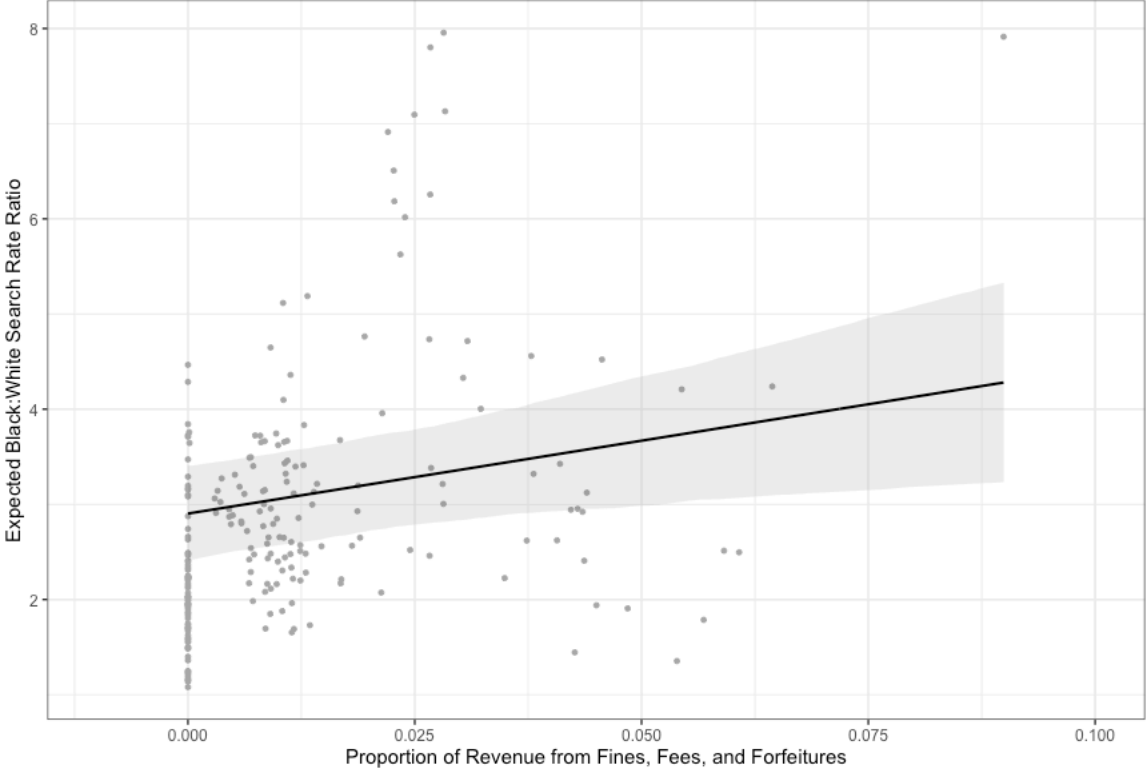
Note: Estimates of expected values calculated using the coefficient estimates from model one in Table 3. The mean or mode of all other variables are used to produce predictions and are held constant. The capital of Illinois (Springfield) is specified as the municipality. The SRR increases by 1.38, which is more than a standard deviation of the SRR variable.

Tables

Table 1. Explaining Individual Driver Stop Outcomes

	(1) Search	(2) Contraband | Search
Intercept	-5.65**	0.56
	(0.27)	(0.56)
Black Driver	0.59**	-0.02
	(0.01)	(0.02)
Proportion of Total Revenue from FFF	-10.71**	8.14**
	(0.60)	(1.13)
Difference in Total Revenue (sans FFF)	0.14**	0.05
	(0.02)	(0.03)
Revenue & Expenditures Difference	0.19**	0.14**
	(0.02)	(0.05)
Black * Prop. of Total Revenue from FFF	10.78**	-6.45**
	(0.61)	(1.16)
Black * Diff. in Total Revenue (sans FFF)	0.09**	0.04
	(0.02)	(0.04)
Black * Diff. b/t Revenue & Expenditures	0.21**	-0.10
	(0.03)	(0.06)
Male Driver	1.11**	0.02
	(0.01)	(0.01)
Driver Age	-0.04**	-0.01**
	(<0.01)	(<0.01)
Latinx Drivers & Interactions	Yes	Yes
Other Controls	Yes	Yes
Municipal Fixed Effects	Yes	Yes
AIC	1,169,314	209,106
BIC	1,171,692	210,816
Log Likelihood	-584,485	-104,382
Num. obs.	4,410,023	162,752

Note: ** indicates p < 0.01 and * indicates p < 0.05. Entries are coefficients from a logistic regression, with standard errors in parentheses below. FFF stands for "fines, fees, and forfeitures." "Other controls" are: initial stop purpose, month of stop, day of week of the stop, year of stop, and hour of stop. Heteroskedastic consistent standard errors (HC0) are shown, which correct for possible issues induced by the clustered nature of the data (i.e., clustered by municipality). When refit with HC3 heteroskedastic consistent standard errors, the results do not change.

Table 2. Data Overview of the Merged Data Set of Information on Traffic Stops and the Annual Survey of State and Local Government Finances

State	N	Municipalities	Stops	Mean SRR	Mean Difference in Revenue per Capita	Mean Revenue Proportion$_{t-1}$
IL	141	26	3,439,947	3.29	$0.06	0.0179
NC	65	11	1,960,441	2.00	$0.02	0.0000
OR	7	1	391,850	2.52	$0.10	0.0001
TX	3	1	561,730	3.17	$0.41	0.0094
Overall	216	39	6,353,968	2.88	$0.06	0.0118

Table 3. Relating Revenue Raised from Fines and Fees to Traffic Stop Search Disparities

	Black:White Search Rate Ratio					FFF Prop.
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	1.1395*	2.2140*	-0.0616	0.3784	0.6502*	0.0007
	(0.2090)	(0.2120)	(0.7370)	(1.4928)	(0.1927)	(0.0011)
B:W SRR, *t-1*	0.4566*		0.1627	0.4449*	0.6618*	0.0004
	(0.0594)		(0.0955)	(0.0609)	(0.0668)	(0.0003)
Prop. from FFF, *t-1*	15.3188*	26.8397*	25.3242*	18.4186*	16.5708*	0.9488*
	(5.7713)	(7.5808)	(12.6609)	(6.2056)	(7.8521)	(0.0254)
Change in Revenue	-0.1463	-0.2434	-0.2444	-0.1816	0.0003	-0.0191*
	(0.1629)	(0.1707)	(0.1821)	(0.1696)	(0.3674)	(0.0012)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	No	No	No
Controls	No	No	No	Yes	No	No
AIC	489.613	512.08		499.95	255.09	-1554.88
BIC	530.11	549.21		560.70	291.22	-1514.38
Log Likelihood	-232.80	-245.04		-231.97	-115.55	789.44
Observations	216	216	216	216	150	216
Municipalities	39	39		39	30	39
Intercept Var.	0.29	0.95		0.28	0.02	0.00
R^2			0.84			
Adj. R^2			0.79			
RMSE			0.58			

Note: * indicates that $p < 0.05$. B:W SRR stands for the Black:White search rate ratio. Models 1-5 predict the current Black:White SRR, while model 6 predicts the current proportion of revenue from fines, fees, and forfeitures (FFF). Model 1 presents the cleanest regression and only includes the variables of interest and controls for variation over time (year fixed effects) and across municipalities (municipal random intercepts). Models 2-5 present alternative specifications of model 1 to test whether results are robust. In Model 5, all outliers (based on the DV and revenue reliance variables) are excluded, and only municipalities that do not aggregate across years (i.e., use one year of data to estimate the SRR) are included. If Model 6 is refit exclude a lagged dependent variable or with fixed effects, the results hold. Models 1, 2, 4, 5, and 6 show bootstrapped standard errors, and Model 3 shows heteroskedastic consistent standard errors (HCO) in parentheses below coefficient estimates to correct for possible bias introduced by the clustered nature of the data.