Essays in Policing and Recidivism

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University
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Abstract

This dissertation consists of three chapters in public economics, with a particular focus on the factors that influence officials in the justice system and the role of deterrence. All three chapters assess, in part, the extent to which traffic penalties influence the behavior of drivers, though with substantial variation in their approach.

The first utilizes daily variation in officer-level lenience, exploiting variation in pollen levels and officer sensitivity to pollen. I find that just under 20 percent of Florida Highway Patrol officers substantially alter their behavior when pollen levels are high, with most becoming less lenient. I further find that drivers that receive a citation, rather than a warning, are substantially less likely to be involved in a traffic accident in the following year.

In the second chapter, I examine the relationship between local financial incentives and police activity. Following the Florida legislature's imposition of limits on municipal revenue generation from fines levied on the public, I find several municipalities greatly reduced their focus on traffic enforcement. I then show that that this reduction in enforcement led to an increase in traffic accidents, with analysis at both the municipal and driver level.

In the third chapter, I turn to data from Maryland's court system. I find that judges are less inclined to issue suspended sentences when the revenue associated with a citation would benefit a local government with a poor credit rating. I exploit overlapping jurisdictions on similar roads in many Maryland counties, and instances

in which judges hear cases outside of their usual court to support this conclusion. Unlike in previous chapters, judicial leniency here provides a direct incentive for safer driving, as probation is generally revoked if a further offence is committed. So, in line with expectations, I find that this reduction in leniency leads to a notable increase in traffic offenses among relevant drivers.

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1

Introduction

Over the past decade, concerns over the conduct of the U.S. justice system have become increasingly prominent. As technological change facilitated greater independent documentation of police interactions, videos depicting apparent police misconduct have frequently inspired public outrage. At the same time, researchers have taken a greater interest in empirical analyses of the justice system, assessing the extent to which high profile instances of misconduct represent systemic trends.

While police conduct surrounding use of force carries the most serious consequences, there is substantial public interest in the more routine interactions between the justice system and the public. Among these interactions, traffic enforcement is particularly prominent. Traffic enforcement is carried out by primarily by state and local authorities, accounting for tens of millions of interactions between police and the public in recent years. The substantial resources dedicated to traffic enforcement are justified, at least impart, by the public safety consequences associated with violations of traffic law.

While the link between traffic enforcement and safety has intuitive appeal, one may have concerns about less high-minded motivations influencing patterns of enforcement. Public officials may seek to supplement local revenue by increasing the intensity of enforcement, which may be less socially desirable than other means of satisfying fiscal constraints. Furthermore, the discretion afforded to individual police officers may also be a cause for concern, insofar as it may facilitate biased or capricious enforcement.

In the following three chapters, I assess various determinants of both police and judicial conduct. I find consistent support for the notion that drivers respond strongly to financial and administrative incentives, with future traffic violations clearly shifting based on the outcome of their interaction with law enforcement. In so doing, I find that some officers notably shift their conduct due to ambient factors unrelated to road safety, that revenue concerns can notably impact enforcement in some jurisdictions, and that judges seem to consider the impact of lenience on public finance.

2

Allergens, Enforcement, and Recidivism

Governments that oversee motor vehicle infrastructure are often tasked with encouraging safe driving by their residents. In the United States, this is generally the purview of state, county, and/or municipal governments. Local law enforcement agencies routinely dedicate some subset of their personnel to monitoring roadways, with the enforcement of speed limits being a frequent justification for law enforcement interaction with residents.

Enforcing traffic law is one of the most common interactions between law enforcement and residents in the US. Over 8 percent of drivers report being stopped in recent years, roughly equalling the number of citizens that reported a suspected crime.[1] The intensity of speed enforcement is motivated, at least in part, by the relative severity of traffic-related injuries and deaths. Traffic fatalities are most frequent cause of death by unintentional injury in the US, exceeding 35 thousand in 2019.[2] Insofar as drivers respond to the risk of judicial or administrative penalties, local governments can incentivize safer behavior with statutory sanctions and dedicated

[1] https://bjs.ojp.gov/content/pub/pdf/cbpp18st.pdf

[2] https://www.nhtsa.gov/press-releases/nhtsa-releases-2019-crash-fatality-data

police resources.

Traffic enforcement in Florida follows this general pattern. Florida law enforcement officials issue millions of non-criminal citations each year, with speeding citations generally accounting for over 500 thousand. Receiving a citation can be quite disruptive for the driver in question. Fines regularly exceed $100, and failure to pay can result in a suspended license, which itself caries the risk of criminal charges should the individual continue driving before clearing the suspension.

However, the consequences of a given detention on suspicion of a traffic offense can be influenced by the detaining officer. Florida officers are free to issue and record warnings for traffic offenses, alleviating all associated penalties. Alternatively, an officer could issue a citation while reporting a speed lower than that which was actually observed. The penalties associated with a speeding offense increase as the cited speed exceeds certain thresholds, meaning that this discounting would results in lessened financial penalties for the driver. In the former case, the only record of the interaction is internal within the relevant agency. In the latter, the charge and possible conviction will be recorded by both the court system and motor vehicle authority.

While lenience benefits the driver, more lenient regimes may run contrary to the objective of encouraging safer behavior among drivers. Existing work (Krumholz (2019), Makowsky and Stratmann (2011)) has found evidence of driver responses to changing enforcement patterns at the aggregate level. All such work must contend with the fact the intensity of traffic enforcement can be influenced by driver conduct, biasing ordinary least squares estimation.

Analysis focusing on individual-level outcomes faces similar concerns. Agents of the state, in deciding whether to exercise lenience, have access to notably more information than is generally captured in official records. If this information is somehow related to future outcomes, estimating the treatment effect of lenience is not straight forward. Existing work has exploited varying preferences for lenience between government officials (Dobbie et al. (2018), Goncalves and Mello (2017)) to estimate causal impacts on recidivism. While there is clear potential for outcomes involving a given judge, police officer, or similar to be correlated with unobservable characteristics of the accused, the match between accused individual and particular officials is often governed by happenstance. This variation could in principle, work as an instrument for the degree of leniency offered to a given defendant.

However, even granting this premise, it's often unclear if these assignments satisfy the monotonicity assumption required for straightforward interpretation of IV coefficients. Lenient officials may be uniformly more lenient than their counterparts, insofar as they would always offer treatment at least as lenient than their colleagues under like circumstances. There would, then, be no "defiers", which would be consistent with a monotonic instrument. On the other hand, varying degrees of aggregate lenience may result from completely different underlying preferences between officials. Seemingly more lenient officials may just be those that more frequently encounter individuals they find sympathetic or likely to respond well to leniency, rather than being more lenient to all individuals. Failure of the monotonicity assumption results in estimates that do not converge to the local average treatment effect (LATE), with the degree of bias increasing with the proportion of individuals for whom the monotonicity assumption fails and the degree to which their treatment effects diverge from the rest of the population (Angrist et al. (1996), Heckman and Vytlacil (2005), Huntington-Klein (2020)).

This analysis looks to limit this concern by exploiting officer-time variation in leniency. Intuitively, this shift is motivated by the idea that within-officer variation is more plausibly characterized by monotonic shifts than inter-officer differences in leniency. More specifically, I estimate officer charging decisions with an ordered probit model, allowing an officer's thresholds to vary across stops under certain conditions. This approach, however, requires the researcher to identify a time-varying determinant of leniency.

Ambient conditions have been a popular source of exogenous variation in many settings, including law enforcement conduct. Changes in ambient light, and therefore visibility, have been particularly popular in attempts to quantify discrimination in work inspired by Grogger and Ridgeway (2006).

This paper utilizes variation in allergen concentration across time and sensitivity to those conditions among officers as a source of variation in officer tendency towards lenience. Center for Disease Control (CDC) reports indicated that 7.7% of American adults have been diagnosed with hay fever (a common label for allergic rhinitis caused by seasonal allergens) over the preceding 12 months.[3] Even when not moderated by medication, symptoms of seasonal allergies are generally quite mild in comparison to most other ailments. Even so, one might expect an increased tendency towards mild or moderate discomfort to result in a decreased tendency towards leniency. Alternatively, fatigue and irritation might lead an officer to avoid the administrative hassle of filing citations when possible. Simple inspection of the data seems to lend some support to the former intuition. The median officer issues a warning for roughly 30 percent of their stops on days with relatively low pollen concentrations, compared to 27 percent on days with higher concentrations. Figure 2.1 displays the distribution of absolute changes in officer-level likelihood of issuing a warning conditional on initiating a traffic stop for speeding on relatively high pollen concentration days.

Of course, ambient allergen conditions are driven by other factors that may themselves influence officers preferences and driver behavior. Pollen density is determined largely by the reproduction cycle of local plant life, itself a function of temperature, sunlight, time of year, and other conditions. Moreover, the distribution and persistence of pollen in the air is moderated by local wind, precipitation, and other

[3] https://www.cdc.gov/nchs/fastats/allergies.htm

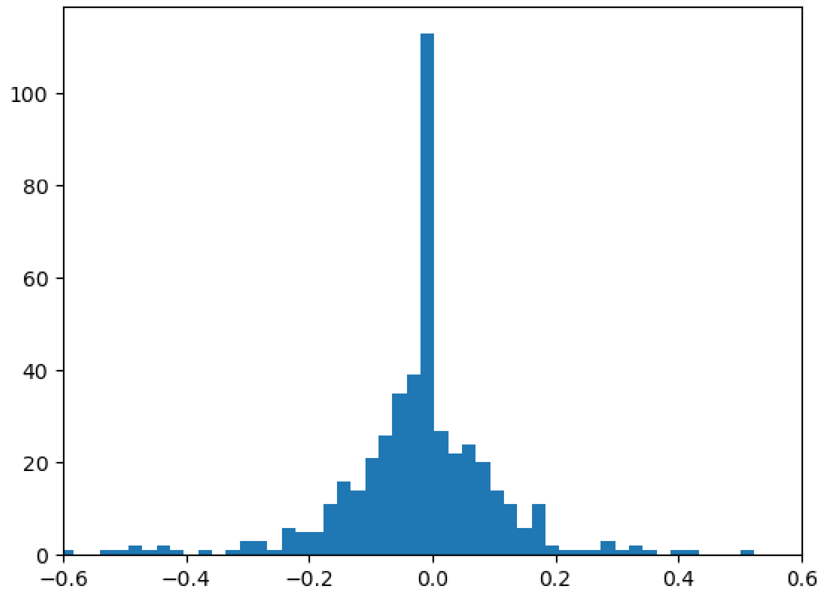


FIGURE 2.1: Empirical Shifts in Lenience with Pollen Levels

atmospheric factors. If the composition of offenses observed by police officers varies with these other ambient conditions, or if they impact the actual severity of otherwise similar offenses, failure to appropriately account for said conditions could bias estimation.

To model officer decision making and driver behavior, this paper estimates a model similar to that of Goncalves and Mello (2021), which allows driver conduct to vary with their location, personal driving history, demographic variables, and local weather conditions. I find that just under one in five officers vary their degree of leniency with local pollen conditions- with about 14 and 4 percent becoming notably less/more lenient, respectively.

The parameters of that model are used to estimate the shift in an officer's preference for leniency due to pollen conditions on the day of a given interaction. Using these values as an instrument, I find consistent evidence of driver responsiveness to non-lenient outcomes. In the year following a traffic stop, drivers that receive a warning are notably more likely to receive a speeding citation from a state police officer and to be involved in a traffic accident. Results are broadly consistent with those from specifications that utilize general officer leniency as an instrument.

Lastly, I consider the impact of driver's license suspension on earlier results. I repeat the analysis above while excluding drivers that likely had their license suspended after failing to comply with their citation. The results from this approach follow the same patterns found in the unrestricted sample.

2.1 Data

Stops initiated by the FHP are the unit of analysis for the bulk of this paper. FHP data represent the contents of Traffic Stop Data Reports (TSDR), covering all interactions between FHP officers and members of the public, whether they result in warnings or citations. These data include driver and officer demographic information, reason for the initial stop, offenses observed after the stop, and the outcome for each offense. FHP data begin in 2014 and end in 2019. There is a gap in this data set, such that driver identifiers are not available for the second half of 2015. Supplemental data on warnings issued by the FHP allow these stops to be linked to motor vehicle records from other sources.

The Florida Court Clerks and Comptrollers provided data on all Florida traffic citations and outcomes between 2010 and 2020. The provided data include all relevant driver demographic information, and the details of any citation that was issued as a result of the interaction. For issued citations, one can also discern whether the citation was challenged, paid, or unaddressed. In the case of citations not paid or contested within 30 days, drivers risk having their license suspended. While interactions that do not result in a citation are not included in this data set, data specific to the Florida Highway Patrol (FHP) are more broad.

Table 2.1 describes the subset of interest. Those cited for speeds other than 9 MPH (and thus, implicitly, did not receive a warning) are more likely to be male,

Table 2.1: Speeding Stop Outcomes

	No Leniency	Discount	Warning
Sex	0.68	0.65	0.61
Age	35.20	36.47	38.68
White	0.47	0.54	0.49
Cited Speed	22.32	9.00	0.00
Speeding Last Year	0.17	0.15	0.10
Crash Last Year	0.14	0.12	0.11
Speeding Next Year	0.15	0.15	0.11
Crash Next Year	0.15	0.15	0.15
High Pollen	0.29	0.29	0.27
Count	110543	25256	51684

Table 2.2: Stop Outcomes by Officer

	Warn %	Lenient %	Warn | Leni	avg Daily Stops
mean	0.33	0.44	0.81	2.80
min	0.00	0.00	0.00	1.25
25%	0.13	0.19	0.70	2.02
50%	0.29	0.42	0.99	2.51
75%	0.48	0.67	1.00	3.17
max	0.93	0.99	1.00	8.00

white, and young relative to those that receive leniency. Moreover, said drivers are more likely both to have had a speeding citation or crash involvement in the year preceding a focal citation, while all drivers have similar rates of crash involvement in the year following an FHP stop.

Table 2.2 shows differing levels of leniency across officers in the sample. Variation is substantial, with some officers giving warnings almost exclusively while others rarely exercise any degree of lenience.

Statewide data on motor vehicle crashes were also provided by the Florida Department of Transportation, covering 2010 through 2019. Crash data include information on all vehicles involved in the crash, as well as driver information.

Other data include local weather information, particularly hourly precipitation and visibility from NOAA and pollen counts for specific dates from two measurement locations. Precipitation is measured at various locations in each county and, in the case of Florida, almost always reflects rainfall. Visibility refers to the greatest horizontal distance visible from the recording station in at least half of the horizon. For most stations, the maximum reported distance is 10 miles. For stations that report greater values, values over 10 are censored in this analysis.

While many media outlets offer daily information on expected pollen counts, it is not clear how frequently these reports reflect direct measurement of airborne pollen. Archived reports from such outlets were considered as a data source, but preliminary inspection revealed frequent disagreements between sources. Therefore, this analysis relies on direct measurements of pollen counts at two Florida locations.

Central Florida pollen data is available roughly once a week from a station in Tampa from February 2016. South Florida data are more complete, reported in Miami two to three times a week from mid 2014 to present. These data reflect average levels detected over a 24 hour period and are generally reported relatively early in the day. Therefore, measurements for a given day are treated as reflecting both that day and the preceding one. These sites report measurements on various types of pollen, but analysis here will focus on tree pollen in particular. High tree pollen levels occur notably more frequently than the others, particularly in central Florida, where high levels of grass or weed pollen are rarely reported.

Of the millions of stops and citations present in the provided data, only a relatively small subset is of interest. First, only Florida drivers are considered, as it's more likely that their interactions with Florida's police reflect their general driving tendencies. Second, interactions with the FHP are the main object of interest. Citations issued by the FHP tend to be better documented than those of some other departments, and interactions that do not result in citations are only visible for the FHP. However, when constructing measures of a driver behavior before and after an

FHP interaction, all interactions with Florida law enforcement are considered. FHP interactions are included as observations whenever they result in a speeding citation with no associated crash or criminal citation, or when a warning is issued following a stop motivated by observed excessive speed.

Moreover, the use of pollen counts as an instrument restricts the sample to days with an associated pollen reading (meaning a reported pollen count on the day in question or the following day). Lastly, the estimation of officer level parameters requires restricting the data to officers with a sufficient number of citations. To be included in the analysis, an officer must have at least 20 stops/citations on both days with high pollen levels and those without.[4]

All together, this subset accounts for some 180 thousand citations issued by nearly 450 FHP officers between mid 2014 and late 2018. While some data do cover 2019, the influence of COVID-19 on traffic patterns in 2020 would likely confound interpretation of driver outcomes following a 2019 police interaction. While full TSDR data are not available for the second half of 2015, crash and citation reports from that period are not impacted. So while analysis will not include interactions from that period, one can still observe the future activity of drivers cited in early 2015 or 2014.

Table 2.3 displays basic order statistics for officer conduct across the sample period. There is substantial variation in leniency across officers. The median officer issues a warning in nearly one third of stops initiated on the basis of observed speed, and is lenient in general in just over 40 percent of interactions.

2.2 Strategy

The object of interest is the impact of penalties imposed on offending drivers on their future behavior. The data provide several straightforward outcomes of interest. First,

[4] In practice, the requirement that officers have 20 stops on low pollen days is never binding.

Table 2.3: Speeding Stops and Pollen Levels

	Medium/Low	High
Sex	0.66	0.66
Age	36.28	36.47
White	0.48	0.48
Speed | Citation	19.91	19.68
Warning	0.28	0.26
Precipitation	0.01	0.01
Visibility	8.40	8.65
Speeding Last Year	0.15	0.15
Crash Last Year	0.13	0.13
Speeding Next Year	0.14	0.14
Crash Next Year	0.15	0.15
Count	134114	53369

future interactions with Florida law enforcement following a particular interaction indicate continued speeding. These interactions consist of citations issued anywhere in Florida, and all stops made by the FHP regardless of outcome. Within law enforcement interactions, I separately considers interactions in general, those that result in speeding citations, and those that result in citations issued by non-FHP officers. The non-FHP specific outcome is of interest to account for the possibility that while warnings do not enter the driver's official record, FHP procedures indicate that warnings are tracked internally. Thus, past FHP warnings may be known to FHP officers initiating a future stop, but not officers of other departments. Lastly, involvement in a crash is used as a proxy for unsafe driving generally.

Three approaches to this problem will be discussed. Most straight forwardly, a standard OLS regression of interaction outcome and probability of future offending is included. The limitations of this approach are straightforward. Police officers interacting with a driver likely have access to information about the driver not easily captured in administrative data. Physically observing the offense or speaking with the driver may, for example, convey information about the likelihood of the individual to re-offend or respond to penalties. While these judgements may not always be accurate, or play a role in officer decisions, any aggregate effect here would bias estimation. Thus, OLS results will be contrasted with two instrumental variable regressions.

Interpreting IV results as an estimate of local average treatment effects is predicated upon assumed relevance (the instrument predicts the endogenous regressor), monotonicity (greater values of the instrument imply a monotonic shift in values of the endogenous regressor), and exclusion (the instrument is uncorrelated with unobserved determinants of the outcome of interest). While the first assumption is testable directly, the latter two are not. Even so, one can find suggestive evidence by considering underlying relationships that would violate either assumption and examining their testable implications.

A common concern in exploiting variation in lenience across agents is the possibility of non-monotonic variation across agent preferences. Differences in apparent aggregate lenience might result simply from agents having differing inclinations towards lenience for types of offenses, circumstances, or offending citizens. Researchers have often sought to assuage such concerns by demonstrating that one finds broadly similar results when restricting analysis to various subsets of their data.

In keeping with the typical means of constructing such an estimator, analysis will also consider "leave-out-one" average lenience of the officer as an instrument of the impact of lenience. That is, the share of the officer's other interactions that lead to a particular lenient outcome (a warning specifically or either a warning or discounted cited speed).

The last approach utilizes officer-specific shifts in leniency associated with varying pollen counts as an instrument. Specifically, I construct a model of officer and driver behavior building on Goncalves and Mello (2021) augmented to account for warnings issued by police officers and possible sensitivity to pollen levels and other ambient factors.

Estimation of the structural serves two purposes for the broader analysis. First, to establish whether and to what extent allergen conditions influence officer conduct. While inspection suggestions a connection with lenience, possible impacts on driver behavior or correlation with other ambient factors could bias estimation if not disentangled carefully. Second, if such a connection is identified, model parameters can be used to compute the shift in officer lenience under counter-factual conditions.

The appeal of this approach is the ability to exploit within-agent variation in leniency. By construction, one would expect time-varying shifts in officer leniency to be correlated with the probability of their interactions with citizens ending leniently. This will be empirically verified in the first stage regression for these instruments.

With respect to monotonicity in this setting, the assumption requires that an individual discounted by an officer would also have received a discount under more favorable counter-factual ambient conditions. As in other settings, this cannot be explicitly verified.

The exclusion restriction would fail if the pollen instrument influences recidivism through some means other than its impact on lenience. Of particular concern would be if a shifts in ambient conditions resulted in officers detaining a different collection of drivers. While the inclusion of citations give a more complete depiction of officer conduct than citation data, many detentions (particularly traffic stops) are initiated based largely on officer discretion. If the ambient conditions that induce greater leniency also result in officers stopping fewer minor offenders with a perceived lower propensity to re-offend, that could induce bias.

Table 2.4 examines the number of daily stops (on those days where at least one stop was made) by officers as a function of ambient conditions. While average daily rain is associated with fewer stops being made, neither visibility or pollen levels are. This is true of both the entire sample and the subset of officers with a

Table 2.4: Daily Stops and Pollen Counts

	All Officers	-Pollen Shift	+Pollen Shift
High Pollen	-0.019	0.026	-0.245
Rain	-0.729^{***}	-1.284^{***}	-0.284^{**}
Visibility	-0.011	-0.059	0.0259
const	2.912^{***}	3.385^{***}	2.717^{***}
Observations	64161	10596	3250

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
Includes controls for month
SE clustered at officer/pollen level

significant and negative (or positive) shift in leniency associated with higher pollen levels. Thus, there is little reason to think that the decision to initiate a traffic stop is being materially impacted by pollen levels, even among those officers with a detected sensitivity to pollen.

Other failures of the exclusion restriction would entail instrument values influencing future outcomes by some means other than officer disposition. Even if officer decisions surrounding initiating stops doesn't change with pollen, drivers stopped on higher pollen days may differ from for reasons other than officer conduct.

However, analysis presented thus far does not suggest violations of the exclusions restriction. Structural model estimates found no differences in mean speeds with pollen levels. Moreover, if driver conduct (other than speed) varied in some way relevant to police lenience decisions, one would expect to find changing officer conduct across a relatively broad subset of officers. Since the estimated pollen coefficients are close to zero for a large majority of officers, a broad shift towards (un)safe driving seems unlikely.

2.3 Modelling Officer Conduct

The framework here is similar to that of Goncalves and Mello (2021). Officer j observes driver i exceeding the posted speed limit by some amount $s*$. The true excess speed of driver i of race r in county c and daily pollen indicator k is drawn from a Poisson distribution with mean $\lambda_{rck} + \gamma Z^{(1)} + m$. Z contains information on driver gender, age, previous citations and accidents, month of year, and local hourly rain and visibility, and γ is a vector of coefficients relating those factors to excess speed. m is a county-invariant indicator for the month of the year, accounting for possible changes in driving behavior at different times of year.

Most encounters between a speeding driver and officer, in this setting, can be resolved in one of three ways. For drivers exceeding the speed limit by more than s_d (9 mph), the officer can choose to issue a warning, cite the driver at a discounted speed s_d, or report the observed speed s^*. For drivers observed exceeding the speed limit by some speed equal to or less than s^d, the officer chooses only between issuing a warning or reporting s^*.

The officer faces a cost of leniency $b_l \times s^* + W \times w_j$, where b_l captures the impact of true speed on discounting behavior given local weather conditions l and w_j is the officer-specific difference in 'cost' associated with issuing a warning rather than discounted ticket. w_j is assumed to be non-negative, so officers are face a greater threshold for issuing a warning than a discount. Three values for l are included: b_2 applies to stops that occur with more .2 inches of precipitation in the past hour or visibility of 5 miles or fewer, b_1 to stops with more favorable but still non-ideal values, and b_0 to ideal conditions- that is, perfect visibility and no rain. Severe, moderate, and ideal conditions describe roughly 16 percent, 24 percent, and 60 percent of observations, respectively.

These costs are compared to the officer's disposition towards leniency $t_{ijk} = t_{rj} + \alpha Z^{(2)}_{ik} + a_j \times p_k + \epsilon_{ij}$. t_{rj} is a constant that depends on officer identity and driver race, $Z^{(2)}$ captures the information in $Z^(1)$ and county racial makeup and the α is the FHP-wide sensitivity to those factors. a_j,p_k are officer-specific sensitivity and an indicator for local high pollen counts, respectively.

If the utility from leniency exceeds the cost of issuing a warning

$$b_l \times s^* + w_j < t_{rj} + \alpha Z_{ik}^{(2)} + +a_j \times p_k + \epsilon_{ij}$$

then a warning is issued, while a discounted citation is issued when the value falls between the threshold of a warning and that of issuing a discounted citation

$$b_l \times s^* + w_j > t_{rj} + \alpha Z_{ik}^{(2)} + a_j \times p_k + \epsilon_{ij}$$

$$b_l \times s^* < t_{rj} + \alpha Z_{ik}^{(2)} + a_j \times p_k + \epsilon_{ij}$$

and the true speed is reported otherwise.

In summary, the model allows pollen levels to influence both driver behavior through differing λ_{rck} values and officer-level thresholds for lenience through a_j. Rain and visibility both effect driver conduct, officer lenience thresholds, and officer sensitivity to excess speed.

Some patterns of officer-level data do not result in point identification. Officers that never report lenient interactions do not have well identified values for any of the officer-level parameters. Their t_k term tends towards infinity and changing p_j, w_j terms have no impact of likelihood. Even so, interpretation of these is still straightforward- such officers essentially have an arbitrarily large negative value from leniency, regardless of driver-level or ambient factors.

2.4 Model Results

Parameter estimates are presented in tables 2.5 and 2.6. Estimates suggest that male drivers, younger drivers, and those with citations or crashes in the previous year tend to drive more quickly than others, while cited speeds decrease with rain

Table 2.5: Model Estimates, Speed, Preferences

	(Speed)		(Preference)	
	μ	σ^2	μ	σ^2
Male	0.834	0.023	-0.142	0.007
log(Age)	-2.180	0.029	0.279	0.009
Prev Ticket	0.800	0.028	-0.216	0.009
Prev Crash	0.432	0.029	-0.082	0.010
Rain	-2.029	0.171	0.101	0.052
Visibility	-0.395	0.044	0.067	0.035
County Minority Share			0.047	0.065

Table 2.6: Model Estimates, Lenience

	μ	σ^2
b_0, ideal slope	0.289	
b_1, moderate slope	0.289	
b_2, impaired slope	0.268	
t, off. lenience (white)	-0.370	1.887
t, off. lenience (minority)	-0.391	1.687
q, off. warning premium	0.375	0.475
p, off. pollen shift	-0.133	0.729

or high visibility. Officer leniency largely follows an inverted pattern: officers are less lenient to males and those with recent citations or crashes, though somewhat more lenient in the presence of rain or high visibility. White drivers drive somewhat more slowly than others in most counties, while speeds do not vary substantially with pollen levels.

2.2 plots the distribution of officer-level warning premia. That is to say, the marginal cost to the officer for issuing a warning, conditional on meeting the threshold for issuing a discounted ticket. For the majority of officers, this threshold is quite low, consistent with the fact that for most officers warnings are issued quite frequently relative to discounted tickets. Lenience in general is governed by the officer-race-level parameters t_{rj}, shown in 2.3. Variation across officers is substantial, while correlation between an officer's lenience towards white and minority drivers is relatively strong.

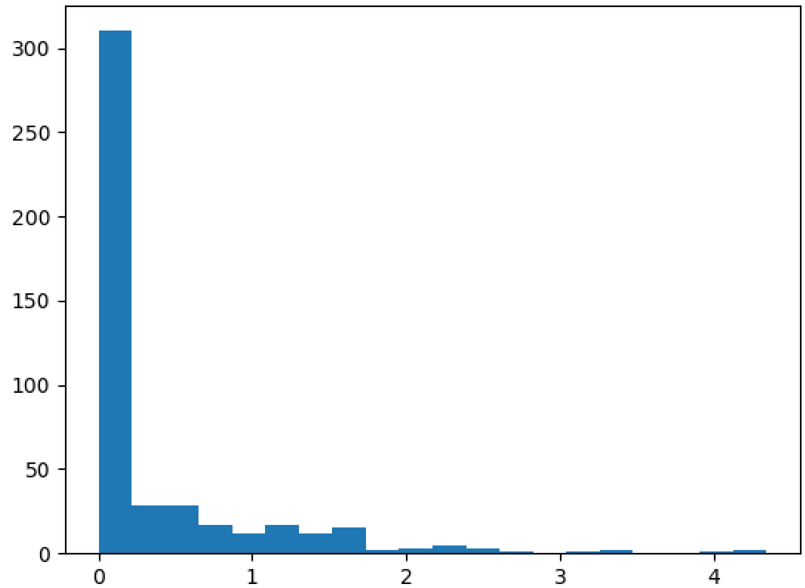


Figure 2.2: Distribution of Warning Premia

Figure 2.4 gives the distribution of officer-level parameters p, the shift in lenience associated with increased tree pollen levels. The vast majority of the mass is relatively close to zero, though with a notable leftward skew. So, while most officers do not exhibit substantial shifts in behavior associated with pollen, the subset that become notably less lenient with higher pollen counts is large relative to those that become more lenient.[5]

2.5 Penalties and Recidivism

The approach to estimation here relies on variation across officers and time in lenience. For each interaction, this instrument is equal to the change in the detaining officer's probability of offering any lenience (warning or discounted ticket) or a warn-

[5] More specifically, 42 officers have associated significant parameters at the 1 percent confidence level. Of these, 34 become less lenient with higher pollen counts while 8 become more lenient.

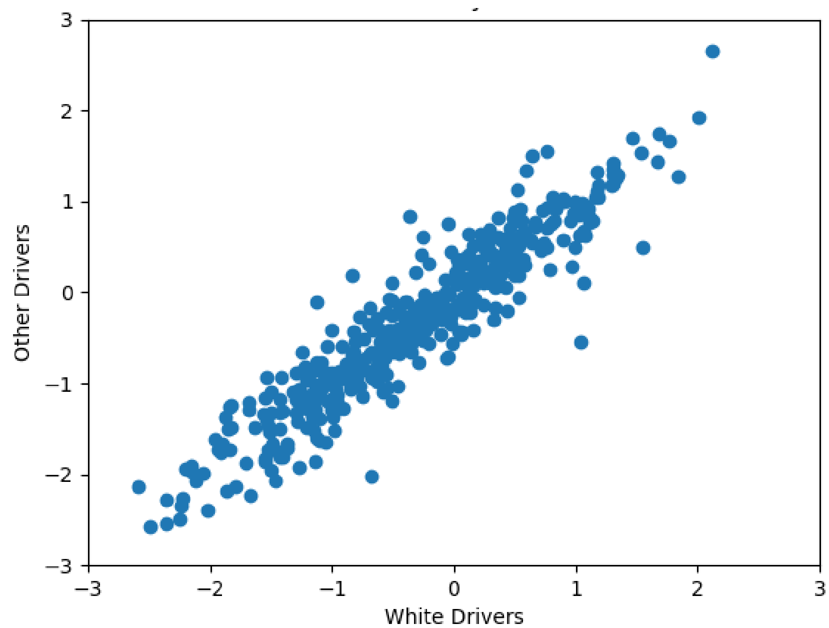


FIGURE 2.3: Distribution of Lenience Parameters

ing in particular associated with current pollen conditions. Specifically:

$$Z_{ijt,L} = \sum_{1}^{\bar{s}} P_\lambda(s = s^*)(P(L|s^*, p_k) - P(L|s^*, (1 - p_k))$$

$$Z_{ijt,W} = \sum_{1}^{\bar{s}} P_\lambda(s = s^*)(P(W|s^*, p_k) - P(W|s^*, (1 - p_k))$$

Intuitively, this instruments captures the change in a given officer's tendency towards lenience associated with that day's local allergen conditions, holding other factors constant.

The results from this estimation procedure are compared with those from OLS and IV estimates using officer-level mean tendency towards lenience in other interactions. In all regressions, standard errors are clustered at level of officer-pollen indicator interaction. Controls include driver demographic information and indicators for month of year and either county for the officer lenience IV or officer indicator for the OLS or pollen shift IV.

First stage results for both IVs indicate that both instruments are strongly asso-

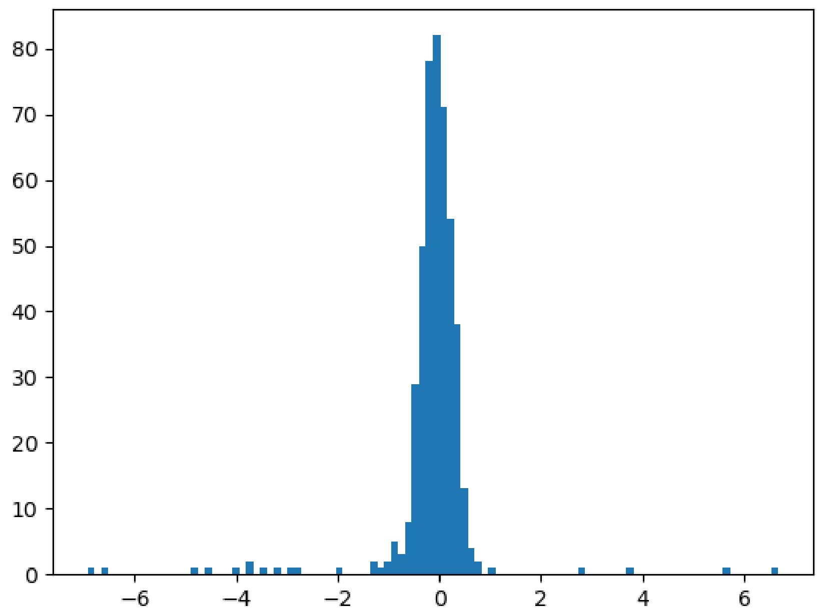


FIGURE 2.4: Distribution of Pollen Parameters

ciated with lenient outcomes. Both regressions include controls for month and driver demographic data, and the officer-level first stage includes controls for county while the pollen-IV includes indicator variables for the involved officer.These results are shown in 2.7

Table 2.8 assesses the link between leniency and the likelihood of crash involvement in the following year. Against a mean value of roughly 15 percent, all IV results find an increase of between 1.9 and 3.6 percentage points, while OLS coefficients show a 1.2 percentage point decline.

Table 2.9 relates degree of leniency and probability that an individual will be have any recorded interaction with the FHP in the year following the focal interaction. This outcome is of interest because, generally, officers only learn of a driver's history after initiating a stop. Hence, even if lenience in the focal interaction altered the outcome of future stops, officer discretion in initiating stops ought not be influenced. Only observations that occurred later than 2015 are included in this analysis, for

Table 2.7: First Stage Results

	(Pollen) Warning	(Officer) Warning	(Pollen) Lenience	(Officer) Lenience
Instrument	0.623***	1.218***	0.620***	1.094***
	(0.015)	(0.012)	(0.013)	(0.009)
Age	0.121***	0.120***	0.121***	0.121***
	(0.006)	(0.006)	(0.005)	(0.005)
Male	−0.059***	−0.058***	−0.060***	−0.059***
	(0.004)	(0.004)	(0.004)	(0.004)
White	0.004	0.000	0.015***	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
const	0.050**	−0.447***	0.254***	−0.430***
	(0.023)	(0.020)	(0.018)	(0.018)
Month V	*Y*	*Y*	*Y*	*Y*
County Ctrl	*Y*	*N*	*Y*	*N*
Officer Ctrl	*N*	*Y*	*N*	*Y*
Observations	187483	187483	187483	187483
R^2	0.342	0.325	0.401	0.383

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

which the involved officer had at least 20 interactions on both high and low pollen level days. For both treatments of interest, OLS analysis suggests that an individual that received leniency is just over two percentage points less likely to have a police interaction in the near future. Point estimates under both IV approaches are positive, significant, and of similar magnitude.

Table 2.10 assesses the probability of receiving a speeding ticket, and here all specifications suggest a negative treatment effect. However, it's possible that officer-discretion may be influencing these results. FHP warnings do not enter a driver's administrative records, and police may be more inclined to show leniency towards those with relatively clean recent records. If warnings issued by FHP officers are not visible to those of other departments, then coefficients in table 2.10 would represent the combined impact of leniency on driver behavior and the leniency decisions of

Table 2.8: Stop Outcome, Probability of a Crash Next Year

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	0.036**	0.036***	−0.012***			
	(0.018)	(0.006)	(0.003)			
Lenience				0.033**	0.019***	−0.012***
				(0.016)	(0.006)	(0.003)
Age	−0.083***	−0.086***	−0.077***	−0.083***	−0.084***	−0.077***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Male	0.016***	0.018***	0.013***	0.016***	0.017***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White	−0.028***	−0.037***	−0.028***	−0.029***	−0.038***	−0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
const	0.379***	0.448***	0.380***	0.372***	0.443***	0.382***
	(0.014)	(0.008)	(0.014)	(0.014)	(0.008)	(0.014)
Month Ctrl	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County Ctrl	*N*	*Y*	*N*	*Y*	*N*	*N*
Officer Ctrl	*Y*	*N*	*Y*	*N*	*Y*	*Y*
Observations	187483	187483	187483	187483	187483	187483
R^2	0.018	0.010	0.020	0.018	0.012	0.020

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at issuing-officer level

future officers.

Ideally, one might assess this problem by analyzing the tendency towards leniency for non-FHP interactions. However, limited data quality for said interactions in general and complete absence of information on interactions that don't result in citations generally inhibit that approach. Instead, table 2.11 assesses the relationship between leniency and future citations issued specifically by FHP officers. While OLS coefficients suggest a 1 percentage point decline from a mean of roughly 7 percent, both IV approaches find positive and significant increases from just under 1 percentage point to 2.7 percentage points.

The difference between tables 2.10 and 2.11 underlines an interesting facet of this

Table 2.9: Stop Outcome, Probability of an FHP Stop Next Year

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	0.028**	0.019**	−0.016***			
	(0.013)	(0.008)	(0.003)			
Lenience				0.023**	0.021***	−0.019***
				(0.013)	(0.006)	(0.003)
Age	−0.128***	−0.131***	−0.122***	−0.129***	−0.131***	−0.122***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Male	0.054***	0.056***	0.051***	0.054***	0.057***	0.051***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
White	−0.030***	−0.033***	−0.030***	−0.030***	−0.033***	−0.029***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
const	0.564***	0.630***	0.566***	0.556***	0.627***	0.571***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)	(0.014)
Mth Ctrl	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Cty Ctrl	*N*	*Y*	*N*	*Y*	*N*	*N*
Off Ctrl	*Y*	*N*	*Y*	*N*	*Y*	*Y*
Obs	134781	134781	134781	134781	134781	134781
R^2	0.029	0.021	0.031	0.028	0.021	0.031

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at issuing-officer level

setting. In addition to avoiding the immediate financial penalties associated with an offense, drivers that receive warnings can generally expect lesser penalties from future citations. Beyond the possible impact on leniency, particularly for non-FHP officers, drivers that receive warnings do not receive points on their license and thus face less risk of serious administrative penalties for future point accumulation. However, across most specifications the two treatments show broadly similar results.

While the link between lenience and recidivism is of interest, the specific impact on driver incentives can provide important context. In particular, Florida courts routinely suspend the licenses of drivers that fail to pay the penalties associated with traffic offenses. Insofar as such a suspension discourages driving in general,

Table 2.10: Stop Outcome, Probability of a Speeding Citation Next Year

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	−0.028	−0.035***	−0.029***			
	(0.017)	(0.007)	(0.002)			
Lenience				−0.016	−0.011**	−0.027***
				(0.017)	(0.005)	(0.002)
Age	−0.103***	−0.107***	−0.103***	−0.104***	−0.110***	−0.103***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Male	0.040***	0.042***	0.040***	0.041***	0.044***	0.040***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White	−0.019***	−0.023***	−0.019***	−0.019***	−0.023***	−0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
const	0.451***	0.512***	0.451***	0.454***	0.517***	0.456***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Month Ctrl	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County Ctrl	*N*	*Y*	*N*	*Y*	*N*	*N*
Officer Ctrl	*Y*	*N*	*Y*	*N*	*Y*	*Y*
Observations	187483	187483	187483	187483	187483	187483
R^2	0.030	0.021	0.030	0.030	0.020	0.030

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at issuing-officer level

one would generally expect recidivism to decrease, consistent with the findings of Krumholz (2019). However, a suspended license can be a source of major personal and economic disruption for the driver in question. Increasing traffic enforcement with the aim of curbing recidivism may be less desirable if the impact is contingent upon increased suspensions. See Mello (2018) and Graham and Makowsky (2021) for discussions of the negative spillovers associated with stringent civil penalties.

While court ordered suspensions are not always recorded in the data, one can draw inferences based on when payment was submitted to clerk and whether additional fines were added. Tables 2.12, 2.13, 2.14, and 2.15 apply the same specifications as tables 2.9, 2.10, 2.11, and 2.8, excluding those citations that were either never

Table 2.11: Stop Outcome, Probability of FHP Speeding Citations Next Year

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	0.023**	0.009*	−0.010***			
	(0.011)	(0.005)	(0.002)			
Lenience				0.024**	0.027***	−0.010***
				(0.010)	(0.006)	(0.002)
Age	−0.046***	−0.046***	−0.042***	−0.046***	−0.049***	−0.042***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male	0.021***	0.021***	0.019***	0.021***	0.022***	0.019***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
White	−0.008***	−0.008***	−0.007***	−0.008***	−0.009***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
const	0.184***	0.222***	0.184***	0.179***	0.220***	0.186***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Month Ctrl	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County Ctrl	*N*	*Y*	*N*	*Y*	*N*	*N*
Officer Ctrl	*Y*	*N*	*Y*	*N*	*Y*	*Y*
Observations	187483	187483	187483	187483	187483	187483
R^2	0.015	0.006	0.017	0.015	0.004	0.017

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at issuing-officer level

resolved or took more than 120 days for payment to be submitted.

Broadly speaking, drivers with suspended licenses do not appear to be the primary force behind the results. Point estimates for the treatment variables in IV specifications generally increase for regressions on this restricted sample. The policy of suspending licenses due to failure to pay may still influence safety indirectly, insofar as the threat of suspension may add weight to the monetary penalties issued. However, the analysis of those that resolve their citations promptly suggests that enforcement's impact on recidivism applies to a relatively broad collection of drivers.

Discerning the impact of license suspension on drivers and communities is beyond the scope of this analysis. However, Goncalves and Mello (2021) finds substantial

Table 2.12: Stop Outcome, Probability of an FHP Stop Next Year, No Suspension

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	0.028**	0.024***	−0.022***			
	(0.013)	(0.008)	(0.003)			
Lenience				0.038**	0.027***	−0.021***
				(0.014)	(0.006)	(0.003)
Age	−0.128***	−0.129***	−0.120***	−0.130***	−0.129***	−0.120***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Male	0.056***	0.058***	0.053***	0.057***	0.058***	0.053***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
White	−0.029***	−0.032***	−0.029***	−0.029***	−0.033***	−0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
const	0.544***	0.620***	0.560***	0.536***	0.617***	0.562***
	(0.014)	(0.012)	(0.013)	(0.015)	(0.012)	(0.013)
Month Ctrl	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County Ctrl	*N*	*Y*	*N*	*Y*	*N*	*N*
Officer Ctrl	*Y*	*N*	*Y*	*N*	*Y*	*Y*
Observations	117244	117244	117244	117244	117244	117244
R^2	0.027	0.021	0.032	0.026	0.021	0.032

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at officer/pollen level

negative socioeconomic consequences associated with traffic sanctions in general and suspended licenses in particular.

2.6 Differentiated Impact

The main analysis treated pollen's impact on officer disposition as uniform across all of an officer's interactions with speeders. However, one might expect an officer's mood to have a more differentiated impact on their work. For example, affected officers may exhibit exaggerated prejudice rather than uniformly shifting their standard for lenience.

These heterogeneous effects would have to be particularly extreme in order to

Table 2.13: Stop Outcome, Probability of Speeding Next Year, No Suspension

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	-0.022	-0.028^{***}	-0.031^{***}			
	(0.018)	(0.006)	(0.002)			
Lenience				-0.012	-0.003	-0.027^{***}
				(0.017)	(0.006)	(0.002)
Age	-0.104^{***}	-0.107^{***}	-0.103^{***}	-0.105^{***}	-0.111^{***}	-0.103^{***}
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Male	0.040^{***}	0.043^{***}	0.040^{***}	0.041^{***}	0.045^{***}	0.040^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White	-0.019^{***}	-0.022^{***}	-0.018^{***}	-0.018^{***}	-0.022^{***}	-0.018^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
const	0.444^{***}	0.512^{***}	0.446^{***}	0.444^{***}	0.514^{***}	0.449^{***}
	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)
Month Ctrl	Y	Y	Y	Y	Y	Y
County Ctrl	N	Y	N	Y	N	N
Officer Ctrl	Y	N	Y	N	Y	Y
Obs	161519	161519	161519	161519	161519	161519
R^2	0.030	0.021	0.030	0.030	0.020	0.030

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at officer/pollen level

bias IV estimation. In particular, if some officers that seemingly become less lenient with pollen actually become more lenient towards some subset of stopped drivers, that would present a clear violation of the monotonicity assumption.

To assess those concerns, I re-estimate the structural model while allowing for more flexibility in the impact of pollen across officers. In the first, I estimate separate pollen-shift parameters for white and minority drivers, replacing a_j with a_{rj}. This entails a further sample restriction, as all officers must have sufficient stops of both white and minority drivers on both high and low pollen days. This restriction cuts the set of officers available for inclusion to just under 350.

In an additional specification I allow pollen levels to influence officer responses to

Table 2.14: Stop Outcome, Probability of FHP Citation Next Year, No Suspension

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	0.028**	0.013**	−0.011***			
	(0.012)	(0.005)	(0.002)			
Lenience				0.029***	0.032***	−0.010***
				(0.011)	(0.007)	(0.002)
Age	−0.046***	−0.047***	−0.042***	−0.046***	−0.049***	−0.042***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male	0.021***	0.021***	0.019***	0.021***	0.022***	0.019***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
White	−0.008***	−0.008***	−0.008***	−0.008***	−0.009***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
const	0.178***	0.221***	0.185***	0.174***	0.218***	0.186***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Month Ctrl	Y	Y	Y	Y	Y	Y
County Ctrl	N	Y	N	Y	N	N
Officer Ctrl	Y	N	Y	N	Y	Y
Observations	161519	161519	161519	161519	161519	161519
R^2	0.015	0.006	0.018	0.015	0.004	0.018

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at officer/pollen level

the demographic and driver history variables in $Z^{(2)}$. These shifts,ι_c , are estimated at the county, rather than officer, level. However, these shifts are multiplied by an officer-specific pollen sensitivity variable. Essentially, the 'shape' of the pollen effect is specific to each county while the 'scale' is officer specific. So, an officer's disposition towards lenience in a stop under this specification is

$$t_{rj} + \alpha Z_{ik}^{(2)} + a_j \times p_k \times (1 + \iota_c Z_{ik}^{(2)}) + \epsilon_{ij}$$

For the first specification, with racially differentiated pollen parameters, 53 officers have at least one significant pollen shift parameter. Of these, both parameters are significant and of the same sign for 40 officers. For the remaining 13, only one parameter is significant and the other is not. So, analysis here finds no officers for

Table 2.15: Stop Outcome, Probability of a Crash Next Year, No Suspension

	(Warn) Pol IV	(Warn) Off IV	(Warn) OLS	(Leni.) Pol IV	(Leni.) Off IV	(Leni.) OLS
Warning	0.034*	0.037***	−0.014***			
	(0.018)	(0.006)	(0.003)			
Lenience				0.030*	0.024***	−0.013***
				(0.017)	(0.006)	(0.003)
Age	−0.082***	−0.086***	−0.077***	−0.082***	−0.084***	−0.077***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Male	0.017***	0.020***	0.014***	0.017***	0.019***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
White	−0.029***	−0.037***	−0.028***	−0.029***	−0.038***	−0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
const	0.379***	0.446***	0.388***	0.376***	0.441***	0.389***
	(0.011)	(0.009)	(0.012)	(0.012)	(0.009)	(0.012)
Month Ctrl	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
County Ctrl	*N*	*Y*	*N*	*Y*	*N*	*N*
Officer Ctrl	*Y*	*N*	*Y*	*N*	*Y*	*Y*
Observations	161519	161519	161519	161519	161519	161519
R^2	0.019	0.010	0.021	0.019	0.012	0.021

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Standard errors are clustered at officer/pollen level

whom pollen levels shift lenience in opposing directions for different racial groups.

In the second specification, analysis finds evidence to suggest that pollen-driven shifts in lenience vary notably with driver demographic factors. None of the ι_c parameters for driver age, sex, or weather conditions are significant. However, 7 counties have significant and negative ι_c values for driver citations in the previous year, indicating that, among officers that vary behavior with pollen, driver history is an exacerbating factor.

2.7 Interpretation

Treatment effects estimated here represent the average impact on recidivism among those drivers for whom the instrument was pivotal. So, while the coefficients are generally noteworthy, understanding broader significance requires characterizing the set of "compliers."

In the case of the pollen instrument, this process is relatively straight forward. The relevant counterfactual comprises of encountering the same officer under conditions that are identical but for the pollen level. A complier in that framework is a driver that would have received a more (less) lenient outcome had the detaining FHP officer been more (less) predisposed towards lenience under counterfactual pollen levels.

In the case of the officer-level instrument, the relevant counterfactual is less clear. Dobbie et al. (2018) and Dahl et al. (2014) set a relatively broad definition of compliers, encompassing all individuals that would have received different treatment from the most and least lenient decision makers.

In the case of the pollen instrument, the first stage results suggest that just under 2% of stopped drivers are compliers with respect to receiving a warning. That is, about 3500 of the 187 thousand drivers in the data would have (not) received a citation had their interaction taken place under more (or less) favorable conditions.

The officer instrument, unsurprisingly, suggests a notably broader set of compliers. There is substantially greater variation in lenience across officers than the within officer variation induced by pollen, so differing values for the instrument imply different treatments notably more frequently. The difference between the 95^{th} and 5^{th} percentile of tendency towards issuing a warning is over 50 percentage points, implying over 60 percent of stopped drivers were compliers.

3

Municipal Finance and Traffic Safety

3.1 Introduction

Public policy surrounding traffic enforcement is subject to competing concerns. Traffic accidents are a major cause of death in the US, causing over 15 deaths per 100,000 inhabitants in recent years.[1] Existing research supports the notion that drivers respond to increased traffic enforcement with greater adherence to traffic law (Bertoli and Grembi (2021), Makowsky and Stratmann (2011), Feng et al. (2020)).

Other work has found evidence that interests other than public safety influence enforcement activity. Several authors have found that police departments increase enforcement in response to local budget pressure (Makowsky and Stratmann (2009), Su (2020)) and political factors (Bertoli and Grembi (2021)). Racial bias in enforcement at both the officer and department level have also been the subject of much recent work (Pacewicz and N.Robinson (2020), Goncalves and Mello (2021)).

To examine the impact of enforcement on road safety the analysis that follows relies on a detailed data of traffic citations and accidents across Florida's more than

[1] https://www.cdc.gov/nchs/products/databriefs/db385.htm

400 municipalities. Data include all recorded citations and accidents between 2010 and 2020. During this period, the state government enacted laws that strongly discouraged perceived over-reliance on citation revenue by sub-state governments.

Using pre-reform reliance on infraction revenue as an instrument for how severely the change impacted various Floridian subdivisions, I find evidence that the reforms both reduced intensity of traffic enforcement and that this reduction led to a corresponding increase in traffic accidents and injuries. Moreover, I also find evidence that pre-reform aggressive enforcement fell disproportionately on minority drivers.

3.2 Municipalities

3.2.1 Disposition of Revenue

Revenue from citations is divided between the state and the county and municipality where the citation was issued, with the municipal government claiming the majority of the revenue. In general, few counties are particularly reliant on citation revenue. Few counties have generated more than 2 percent of their revenue from civil citations in the past decade, and none more than 5 percent.

At the municipal level, reliance on infractions for revenue is often notably more pronounced. Between 2010 and 2014, 30 of Florida's roughly 400 municipalities received 5 percent or more of their revenue in at least one fiscal year. 12 relied on infraction fees for 10 percent or more of revenue at least once, and such fees made up between 30 and 50 percent of revenue in some cases. Concern over the practices in one such case led to public concern and legislative action.

3.2.2 Waldo Bill

Waldo Florida, in Alachua county, had a longstanding reputation for aggressive speed enforcement. The town of roughly 1000 people had been consistently designated a "speed trap" by the American Automotive Association since 1995 [2], along with a handful of other low density locales.

An 2014 investigation into Waldo's policing practices uncovered an aggressive quota system imposed on municipal officers, as well as other improprieties. The incident prompted state lawmakers to impose stricter limits on similar behavior statewide. The 2015 session's SB 264 (generally dubbed the 'Waldo Bill') was filed in early 2015 and entered into force in June of that year. The bill banned all traffic enforcement agencies from using civil citation issuance as a requirement or performance metric, explicitly or otherwise.Moreover, agencies that recouped a notable fraction of their operating cost from citation revenue were to be subject to additional scrutiny.

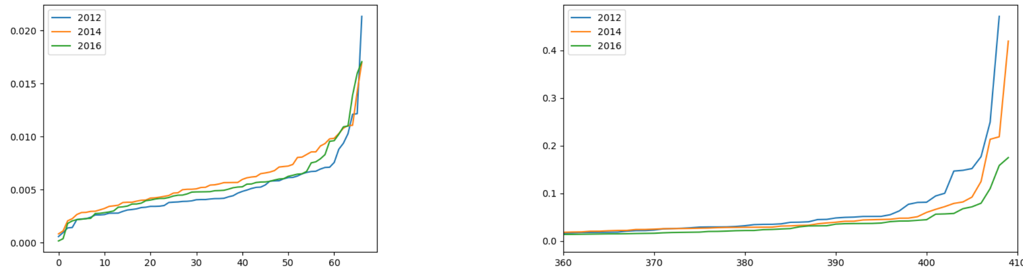
While municipal police practices were the driving force behind SB264, concerns about overzealous policing extended to other agencies. In 2017, two state highway patrol administrators resigned following revelations they had suggested two citations per hour was a desirable target, while expressly stating they were not establishing a quota.

3.2.3 Waldo and Policy

The passage of SB264 was associated with a notable decline in municipal reliance on infraction revenue. Figure 3.1 gives a general picture. While the shift is most pronounced at the upper most extreme of the distribution, the shift in reliance is also apparent in the fraction of municipalities earning more than 5 or 10 percent of their revenue from infraction revenue.

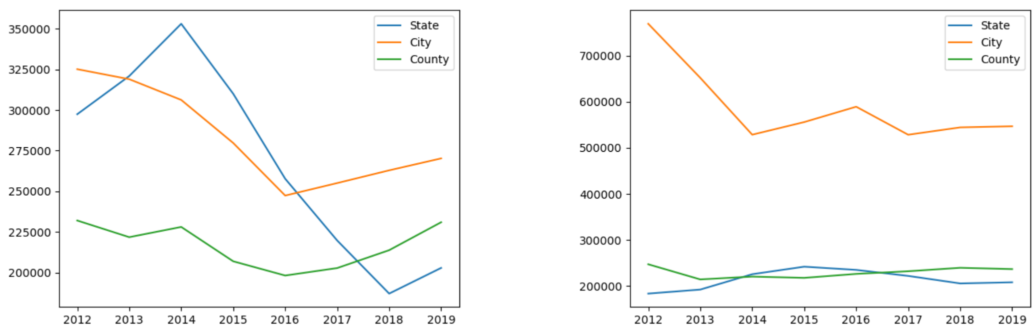
With respect to police activity, speeding citations issued (particularly by state and municipal police) became notably less frequent during the sample period. Overall values are presented in figure 3.2. Analysis below will show that local pre-reform fine reliance on fees is strongly associated with with decreased speeding citations by

[2] https://apnews.com/article/4c4f2902e66e907b37ba856a578b0e4c



(a) County (b) Municipal

FIGURE 3.1: Reliance on infraction revenue



(a) Speeding Citations (b) Other Citations

FIGURE 3.2: Citations Issued, Agency Type

municipal police, but not those of state or county police.

During that same period, traffic accidents and fatalities increased notably. Floridians died in traffic accidents at a rates ranging from 13.9 and 12.5 per hundred thousand residents between 2009 and 2014, compared with 14.8 and 15.9 in the years following 2015. Crashes in general grew by an even greater margin, from roughly 700 per day from 2010 to 2013, and over 1 thousand per day from 2015 to 2019.

3.3 Data

3.3.1 Citations

The analysis is largely based on Florida's Traffic Accounting Transmission System (TCATS) data, provided by the Florida Clerks and Comptrollers. Data cover all citations reported to Florida Highway Safety and Motor Vehicles (FLHSMV) between 2005 and 2021, including information about the offense, officer/agency that issued the citation, and driver information available to the FLHSMV.

Citation-level information include substantial detail about the alleged event, including reported and observed speed in the case of speeding. The data also specify whether or not the citation was connected to another offense (e.g. a speeding citation issued to a drunk driver), or led to a crash, property damage, or injury.

Lastly, TCATS data include the judicial resolution of the offense. Such outcomes include failing to pay the citation (generally leading to a suspended license), paying the listed fee or electing to attend traffic school, or contesting the citation in court. Outcomes of judicial proceedings and/or amount and timing of fines paid are also included.

3.3.2 Additional Data

Florida's Office of Economic and Demographic Research (EDR) supplies information on the revenues and outlays of Florida's state and local governments. Revenue figures include the corresponding source.

Geocoding services provided by the Census Bureau and the Federal Financial Institutions Examination Council (FFIEC) were used to identify neighborhood characteristics for cited drivers. Between the two services, just over 90% of citations were successfully coded and linked to a census tract. For said citations, income and demographic data were included.

Information on municipal road mileage and county average vehicle-miles travelled was gathered from Florida's Department of Transportation. To get a sense of municipal level traffic, county averages will generally be included as a control along side the municipality's share of population and public road mileage.

3.4 Estimation

3.4.1 Municipalities

As mentioned, simultaneity of local driver behavior and law enforcement priorities poses a clear problem for straightforward estimation of the relationship between the two. Both public safety and revenue conscious law enforcement agents ought respond accordingly to changes in driver safety, to fulfill some combination of incentivizing safety and exploiting opportunities for revenue generation.

To sidestep this concern, the results below exploit the varying extents to which SB264's limits impacted Florida's municipalities. The estimation that follows largely focuses on the percentage point change in non-criminal citations in municipality i by agency j in month t for speeding or other matters s between 2013 and 2016. Reliance on citation revenue is measured as the 2012 share of the municipal budget that came from said sources. Other controls include state-wide monthly fixed effects and changes in quarterly property valuation assessments and unemployment claims. The first stage, then, is:

$$\begin{aligned}\Delta\text{Citations}_{i,j,t,s} = \beta_0 + \beta_1\text{fineReliance}_{i,2012} + \beta_2\Delta\text{unempClaims}_{i,t} \\ + \beta_3\Delta\text{propValues} + \text{Month}_t + \mu_{i,j,t,s}\end{aligned} \tag{3.1}$$

Table 3.1 presents the results for 6 different outcome variables, namely the cross product of two citation types (speeding, other) and municipal/state/total agency types.

Table 3.1: Percent Change in Monthly Citations, 2013 to 2016

	Speeding Citations			Other Citations		
	muni	state	total	muni	state	total
Revenue	−1.48**	−0.07	−1.04**	−0.36**	−0.03	−0.11**
Prop Val	0.04	−0.02	0.00	0.03	−0.00	0.00
Unemp	0.05**	0.01	0.03	0.01	0.03	0.02

One and two stars represent significance at 5% and 1%, respectively
Property values, unemployment claims and property values are expressed in percent change at the county level.

Pre-reform reliance on citations is strongly associated with a shift in municipal enforcement. For each percentage point of revenue arising from citations in 2012, municipal police were expected to reduce speeding citations by nearly 1.5% between 2013 and 2016, with no corresponding shift in state police activity. Shifts in other non-criminal citations were present, though less pronounced.

The next results present OLS and IV estimates for determinants of municipal-level accidents and injuries, using (3) as the first stage. Values are presented in Table 3.2. Straightforward OLS finds a positive association between issued speeding tickets and accidents and no discernible association with injuries. Under the instrumental approach, however, speeding citations are negatively associated with both accidents and injuries.

While the set of citation-heavy municipalities included some medium sized locations, low population jurisdictions were definitely over-represented. To assure that the analysis is not confounding some trend among smaller municipalities with an SB264 effect, tables 3.3 and 3.4 repeat the analysis on the 190 municipalities with a 2012 population of less than 10 thousand.

Table 3.2: Speeding Tickets, Accidents, and Injuries

	Accidents		Injuries	
	OLS	IV	OLS	IV
Citations	0.09**	−0.21**	0.01	−0.07**
Prop Value, per capita	0.02	−0.01	0.03	0.01
Unemp Claims, per capita	0.05	0.01	0.03	0.01

One and two stars represent significance at 5% and 1%, respectively
Also includes monthly fixed effect.

Table 3.3: Change in Monthly Citations, ⩽10k population

	Speed Citations			Oth Citations		
	muni	state	total	muni	state	total
Revenue	−1.80**	−0.11*	−1.09**	−0.46**	−0.00	−0.22*
Prop Value	0.02	−0.02	0.07	0.01	−0.03	0.00
Unemp	0.06	0.04	0.04	0.02	0.01	0.02

One and two stars represent significance at 5% and 1%, respectively
Property values, unemployment claims and property values are expressed in percent change at the county level.

Table 3.4: Speeding Tickets, Accidents, and Injuries, ⩽10k population

	Accidents		Injuries	
	OLS	IV	OLS	IV
Citations	0.04	−0.32**	0.01	−0.07**
Prop Value	−0.02	0.01	0.05	0.05
Unemp	0.21	0.11	−0.09	0.06

One and two stars represent significance at 5% and 1%, respectively
Also includes monthly fixed effect.

Table 3.5: Cited Drivers, Overview

Year	2011	2013
One Citation	335,213	328,080
Black	22.3%	22.1%
Hispanic	18.9%	18.4%
Male	60%	59%
Age	39.9	39.6
Speed (mph)	19.3	18.9

3.4.2 Driver-level

Modelling driver safety based on law enforcement records poses a problem, particularly when the strictness of enforcement is thought to shift over time. Variable vigilance of enforcement, particularly for minor offenses, alters the selection criteria for observation and limits the usefulness of estimating outcomes conditional on inclusion without further information.

Analysis here will consider FL drivers that were cited for speeding between 2010 and 2015, the circumstances under which the citation was issued, and their subsequent activity. This population accounts for roughly 1.88 million Florida residents. Tables 3.5 and 3.6 describe the individuals that received a speeding citation in 2011 and 2013 and their subsequent activity.

About 12 percent of cited drivers were involved in a traffic accident over the next three years, generally in the same municipality they were cited. Involvement in multiple crashes during this period was comparatively rare, as were crashes in the same county but outside the original municipality. By contrast, just over 20 percent of cited drivers received an additional speeding ticket in subsequent years, generally outside of the county of their initial citation.

The analysis here examines the probability of crash involvement in the 12 months

Table 3.6: Cited Drivers, Outcomes

	2011		2013	
	Same Muni	Other	Same Muni	Other
Crash, y+1	3.1%	1.7%	3.1%	1.8%
Crash, y+2	2.4%	1.2%	2.8%	1.1%
Crash, y+3	2.1%	0.9%	3.3%	1.9%
Crash, Multi	0.0%	0.0%	0.1%	0.0%
Speed, y+1	3.6%	6.1%	3.5%	5.8%
Speed, y+2	2.5%	5.2%	2.4%	4.7%
Speed, y+3	2.2%	4.8%	1.6%	3.8%

following the original citation. Relevant driver-level controls include the usual driver demographics and indicators for driver's residence in the given municipality, the same county, or a neighboring one, as well as log of census tract income. Other indicators include accidents in the preceding 12 months, whether the driver attended traffic school in connection with the citation, or had their license suspended.

On the enforcement side, first stage analysis will again focus on speeding citations issued in the jurisdiction in question. In particular, citations per hundred thousand vehicle miles travelled (mean of between 2.12 and 3.40 across years). Determinants include population, average cited speed, unemployment claims, and property values. Values are computed at the monthly level, and aggregated across the 12 months following a given driver's citation. The instrument is again the municipal-level reliance on infraction revenue, scaled by the portion of each driver's 12 month period that fell after SB264's implementation.

Table 3.7 gives estimates under OLS and instrumental variable approach for determinants of crash involvement, both in the original municipality and elsewhere. OLS estimates find no relationship between local speeding citations and the probability of crash involvement. On the other hand, the IV estimates imply that an

Table 3.7: Crash Involvement, Driver Level

	Same Muni		Other	
	OLS	IV	OLS	IV
Citations/(100k VMT)	0.013	−0.022**	0.012	−0.009
Cited Speed	0.011**	0.014**	0.008*	0.010*
School Elect	−0.035**	−0.040**	−0.022**	−0.014**
Recent Crash	0.117**	0.139**	0.065*	0.058*
Sus. DL	−0.013**	−0.017**	−0.011**	−0.012**
Home muni	0.055**	0.044**	−0.018	0.011
Home county	0.012	0.024	−0.011	0.012
Neighbor county	0.002	0.001	−0.003	0.025

One and two stars represent significance at 5% and 1%, respectively
Includes controls for driver demographics, issuing agency, and time of citation.
Standard errors clustered at issuing-agency level

increasing local speeding citations by 1 per 100 thousand vehicle miles travelled is associated with a 2.2 percentage point decline in crash likelihood, a relative decline of over 30 percent.

3.4.3 Interpretation

Taking the mean decline in citations per 100k VMT, decreased enforcement between 2014 and 2016 was associated with more than 5000 additional accidents among the 300 thousand drivers cited in the 12 months preceding SB264's implementation. This implied shift is large relative to that implied by the municipal level regression, in which the mean decline in citations issued (24%) was associated with an overall increase in accidents of roughly 1 percentage point. This may be driven by differences between the broader driving population and those with recent citations in general, or due to a particular heightened sensitivity to local law enforcement among recently cited drivers. That is, the extent to which a given driver responds to an observed or expected decline in law enforcement intensity may vary across the population. In particular, those drivers with recent citations may be particularly likely prone to alter their behavior in response to the perceived reduction in likelihood of encountering a traffic officer.

As in other analysis presented here, it must be stressed that the impact of changing enforcement on traffic safety does not completely characterize the welfare implications of stricter traffic enforcement. The direct effects of fines and possible criminal penalties for non-compliance generate substantial welfare losses for impacted drivers that are not represented in this analysis.

But with that in mind, the results here are consistent with earlier findings that show a clear potential benefit of relatively strict traffic enforcement. While the case of Florida's municipalities in the lead-up to 2014 suggest substantial interest in revenue generation from traffic enforcement, the apparent increase in traffic fatalities in the following years indicate a genuine public policy interest. So while the public has a genuine basis for suspecting that local governments look to traffic enforcement as a revenue source, public safety motivations ought not be dismissed out of hand.

4

Public Finance and Judicial Incentives

4.1 Introduction

US state and local governments engage in traffic enforcement to serve a variety of state interests. Previous theoretical work reasons that state actors will set and enforce rules to maximize public welfare, increasing penalties with the degree of infringement on public safety (Becker (1974), Ehrlich (1996)). Beyond public safety, however, law enforcement and judicial officials may take an interest in other objectives. Police interactions with the public may, for example, reflect institutional or officer-level racial prejudice or perceived criminality (Anwar and Fang (2006), Horrace and Rohlin (2016)). Police employed by a given locality may also respond to local budgetary pressure or political concerns, issuing citations in an effort to raise revenue or assuage voters rather than to promote public safety (Makowsky and Stratmann (2009)).

This analysis will assess the how institutions in US states, particularly with the State of Maryland, weigh these incentives. While previous work has examined the link between law enforcement incentives and fiscal needs, few have examined how this incentive may influence other state objectives. Using inter-jurisdictional variation in fiscal conditions and driver responses to judicial action, I examine how governments weigh their fiscal needs against public safety.

In the analysis below, I find broad support for the notion that Maryland District Courts place greater value on providing revenue to relatively credit constrained counties than they do in other settings. Judges are generally more likely to grant probation to those stopped in districts with relatively poor credit, conditional on other observables. Moreover, judges may also be more inclined to consider the fiscal health of their 'home' county governments than that of others they serve in, though this result is not consistently demonstrated. I further consider the impact of selection effects, and find little reason to attribute this tendency to self selection by drivers. I also present evidence that police and judges show considerable preferences to local defendants, and that judges take a greater interest in the fiscal needs of their locality.

Judicial concern for local public finance is particularly noteworthy in this setting, as these judges are not particularly dependent on their local government for funding. As will be discussed in more detail, Maryland's district courts rely almost exclusively on funding from the state government. Thus, their apparent interest in bolstering county public finance ought not be attributed to financial self interest.

4.2 US Traffic Enforcement

Most American drivers likely have some experience with the role of traffic enforcement in shaping incentives. Police officers observe driving behavior and may, at their discretion, issue a citation if they observe a violation. For minor offenses with only monetary and administrative consequences, drivers are generally free to submit a guilty plea and pay the assessed fine without visiting the courtroom. Drivers that are not required to appear before a judge may opt to do so regardless, with or without the aid of an attorney. Those appearing before the court often contest the facts underlying the citation, or accept the allegations but seek leniency on the basis of circumstance.

The penalties faced by drivers depend on the outcome of their interactions with the police and judiciary. Drivers that are convicted of an offense, whether or not they opted to contest their citation, will face a monetary penalty and may have administrative points marked against their driving record. These points, assessed based on the severity of the infraction, may result in the suspension of revocation of the driver's license if too many are accrued in a given period. Moreover, points are public information generally known to automobile insurance firms, which tend to associate points with higher expected costs.

Drivers that successfully argue their case in court may receive relief via several mechanisms. Most obviously, the charges may be dismissed- sparing the driver from all penalties, with the possible exception of court fees. In many states, the driver may agree to be convicted of some lesser offense. In the case of traffic offenses, this usually involves pleading guilty to a violation that carries no or few administrative points. For example, those convicted of speeding may agree to a charge of driving with faulty equipment. Under these arrangements, the driver will still be liable for the penalties associated with the lesser charge (typically a fine), but avoid the increase in insurance premiums associated with their original offense. Alternatively, drivers may be found guilty of the original offense but with a lesser fine.

In some jurisdictions, the courts may also allow drivers access to some probationary mechanism. In these cases, the driver is essentially able to avoid some or all the penalties of their original charge even though the judge found sufficient evidence to convict. The driver will then be able to avoid the results of the initial charges only if they avoid future offenses for some probationary period- typically several months or a year. This arrangement is relatively common in Maryland, which is the focus of this analysis.

Interest in the consequences of local law enforcement concerning itself with raising revenue has grown in recent years, particularly since revelations about incentives faced by officials in Ferguson Missouri.[1] Studies on the subject include Goldstein et al. (2020), which found that a shift towards revenue generating activities carried substantial costs in terms of fulfilling other obligations. On the positive side, Makowsky and Stratmann (2011) find that revenue constrained localities tend to engage in harsher traffic enforcement, and experience fewer traffic accidents as a result.

4.3 Enforcement in Maryland

Traffic enforcement in Maryland is undertaken by several agencies, often with overlapping jurisdictions. Many municipalities operate their own police force, headed by a Chief of Police that serves at the pleasure of the municipal governing authority. Similarly, five counties (as well as Baltimore City) employ a county police department with a Chief of Police appointed by the county executive. Moreover, all counties as well as the city of Baltimore employ a directly elected sheriff that serves a four year term. Sheriffs' offices in Maryland employ between a few dozen and several hundred deputies, and are the primary law enforcement agency in counties without a county police department.

The Maryland State Police (MSP) also engage in traffic enforcement, particularly (but not exclusively) on the state or interstate highway system.[2] The Department of State Police is overseen by a superintendent, whom is appointed by the governor

[1] Outside scrutiny, particularly from the US Department of Justice, revealed that Ferguson's found substantial racial bias and distortion of public services as courts and police focused increasingly on revenue. https://www.justice.gov/sites/default/files/opa/press-releases/attachments/2015/03/04/ferguson_police_department_report.pdf

[2] Counties and municipalities with relevant highways in their borders generally cede "routine enforcement" duties to the MSP on some subset of said roads. In Anne Arundel County, for example, the MSP is responsible for enforcement on interstates and and one of several Maryland State Highways https://www.powerdms.com/public/aac/documents/29

and must be confirmed by the Maryland State Senate. Maryland State Troopers operate from 23 barracks throughout the state, though officers assigned to a given barracks seem to engage in enforcement beyond the area immediately surrounding their barracks.

Proceeds from citations issued by law enforcement agencies in Maryland is remitted (in part) to their parent government, which in turn funds the agency. While Maryland law forbids the use of quotas as a formal or informal measure of job performance[3], officers employed by governments under fiscal pressure may be subject to additional pressure to aid budget shortfalls with further citations. So incentivized, officers would then be inclined to issue more citations. However, it seems unlikely that the impact of this incentive would be uniform across all types of citations. While officers may have broad discretion in issuing citations for relatively minor matters, many citations for offenses that represent more imminent threats to public safety.

Moreover, as shown in other work (Goncalves and Mello (2017)), officers may exercise discretion in reporting the speed associated with a stop. In the case of Maryland, penalties for speeding are constant within given brackets (1 to 9 MPH, 10 to 19 MPH, etc). Insofar as officers have a desire to be lenient, one would expect reported speeds to bunch around these important thresholds to spare drivers greater penalties. For departments looking to raise revenue, one would expect a shift away from leniency. However, the existence of bunching in reported speeds could also result from drivers' awareness of the schedule of penalties.

While one cannot rule out the potential for geographic variation in the number of minor offenses relative to severe ones or extent of actual speed bunching below thresholds, overlaps in jurisdiction allow for the separation of departmental effects from geographic ones. State, county, and city police regularly issue citations in the same areas and it seems reasonable to assume that they observe the same activity

[3] Maryland Code, Public Safety § 3-504

when in the same area at comparable times.

4.4 Maryland Courts

Traffic cases in Maryland are heard in District Courts by judges appointed by the Governor and confirmed by the State Senate. Maryland's district courts are funded almost entirely by the Maryland General Assembly, rather than by county or municipal governing authorities. These courts have jurisdiction over routine cases, including traffic violations- most felonies and all jury trails take place in Maryland's Circuit Courts.

The disposition of revenues from fines and fees imposed by the District Court is not perfectly transparent, though some aspects are clear. First, resulting revenue is not supplied directly to law enforcement agencies, but rather to the general fund of the relevant state or locality. Second, the disposition of revenues depend on both the location of the offense and the agency that originated the case. That is, while localities do receive a share of revenue resulting from citations issued by their sheriff's offices and/or police department, the state government receives revenues from citations issued by state police. Many Maryland jurisdictions lean quite heavily on fines as a revenue source- in 2012, Maryland cities accounted for 6 of the 100 municipalities most reliant, including three for which fines and fees accounted for over 10 percent of gross revenue.[4]

Maryland's criminal procedures[5] provides judges with broad authority to (provisionally) waive the sanctions from a conviction by placing the defendant on probation (specifically, "Probation Before Judgement", or PBJ). In these cases, the judge is effectively ruling that the evidence is sufficient for conviction, but the legal system will not impose any of the associated administrated penalties and some subset of the

[4] https://www.usccr.gov/pubs/2017/Statutory_Enforcement_Report2017.pdf

[5] Maryland Code, Criminal Procedure, title 6

financial penalties, if the probationary period is completed without incident. District courts may impose probationary periods of up to 3 years, but 1 year or shorter is all but uniform for traffic cases.

The existence of PBJ in Maryland can influence driver incentives in several ways. Firstly, drivers that anticipate they may receive PBJ may be less averse to receiving a citation and therefore drive less safely, though these data provide little hope of identifying that effect. Conversely, drivers that have received PBJ face a clearly heightened incentive to avoid receiving further citations. Committing a traffic offense during the probationary period and being convicted will lead to the driver facing the remaining penalty of both the original and further offense, including suspended financial and administrative penalties (particularly "points" assessed on the driving record, which influences insurance rates).

As noted, judges enjoy substantial discretion in when to grant PBJ and how much of the fine to waive. While there is little statutory guidance, one might reasonably speculate on what factors influence judicial disposition. In terms of serving the broader public, judges may be motivated to offer PBJ for its potential to disincentivize unsafe behavior, and opt to waive a notable portion of the associated fine for the same reason. Pushing towards the opposing outcome, judges may be hesitant to deny the concerned jurisdiction access to revenue from the fines in question. Furthermore, judges might also be influenced by personal biases or political factors, leading to differential treatment based on the demographic characteristics of the defendant.

4.5 Data

Data for this analysis were collected from the Maryland Judiciary Case Search website, and cover all public records between 2011 and early 2020. Serious offenses and unresolved cases remain on the public record indefinitely, but decisions on more routine matters are removed from the public record after 3 years. Thus, relevant data

Table 4.1: Summary statistics

	Att	AA	nine	act	age	lim	dif	oos	PBJ
mean	0.00	0.31	0.33	65.68	36.13	46.73	18.95	0.16	0.27
std	0.06	0.46	0.47	16.02	14.06	12.99	8.20	0.36	0.44
min	0.00	0.00	0.00	24.00	15.95	5.00	2.00	0.00	0.00
25%	0.00	0.00	0.00	52.00	24.39	35.00	14.00	0.00	0.00
50%	0.00	0.00	0.00	66.00	32.72	50.00	19.00	0.00	0.00
75%	0.00	1.00	1.00	79.00	46.14	55.00	23.00	0.00	1.00

are only comprehensive starting in mid 2016. Moreover, since a driver's record may influence both their own driving behavior and their treatment by the legal system, analysis on cases that occurred towards the start of this period would be of limited use. Fortunately, routine traffic cases fade from a driver's MD record in only two years, meaning that for cases that entered the record after mid 2018, the data give a complete picture of both the incident and the relevant history.

While a given defendant in the data does not have a unique identifier assigned by the state, there is enough information to identify an individual with a high degree of confidence. For all cases on Case Search, the defendant's name, full address, date of birth, race, and (for vehicular cases) license plate number are available. For the purposes of this analysis, I've assumed two cases have the same defendant when they list the same name, race, and date of birth and at least one of address and license plate number match. Under this classification scheme, the data contains about 260 thousand drivers that have opted to contest a citation for speeding in Maryland since July 2016, 50 thousand of which received their citation during or after July 2018. Descriptive statistics are presented in table 4.1.

Supplementary data were collected from other sources. S&P credit ratings on recent locality bond issuances were collected as a measure of local fiscal health. To assess the potential for differential treatment based on economic status, I also collected information on the census tract of the defendant's address. The Census

Bureau maintains an API for mapping address to administrative geographies, which I connected with the 2015 estimate of tract-level median family income.

4.6 Analysis

To assess the potential for a trade off between public safety and revenue, it's important to establish whether or not PBJ has a detectable impact of deterrence. As PBJ is assigned at the discretion of the judge, it is necessary to consider a few confounding factors when seeking to identify an effect. First and foremost, defendants found not guilty, having their case dismissed, or that have chosen not to appear in court are not eligible for PBJ and so are excluded from this portion of the analysis. Secondly, a poor prior driving record may make a judge less likely to grant PBJ and also indicate a tendency towards unsafe driving. While in principle this can be accounted for by (for example) controlling for the number of points on a given defendant's license, for now I focus on offenders with no other offenses on their record. And since the relevant question is the impact on incentives, the analysis needs to include driver behavior for some time after conviction.

Thus, the basis for this analysis are the drivers (roughly 85 thousand) that committed their first observable offense in 2018 (and chose to appear in court, and were either found guilty or received PBJ) and their likelihood of committing a further offense during the following year.[6] Of these, some 23 thousand received probation. Of those, some 10 percent committed another traffic offense within a year of judgement. By contrast, the over 15 percent of those that *did not* receive probation committed an additional offense in the next year. The probit model includes controls for the logs of the speed limit and driver age (lLim and lAge, respectively) and the number of points associated with the citation (assocPt). Other controls include whether or

[6] The analysis also excludes first offenses that contributed to accident or injury, as the severity of these incidents are more difficult to determine from court records.

Table 4.2: Determinants of Future Citations, First Time Offenders

	coeff	std err	pvals
lLim	0.01	0.04	0.81
assocPt	0.01	0.02	0.50
lAge	−0.43	0.04	0.00
oos	−0.37	0.07	0.00
MSP	−0.07	0.06	0.22
AA	0.15	0.03	0.00
lowRate	−0.16	0.19	0.41
att	−0.23	0.15	0.11
PBJ	−0.16	0.04	0.00
lTractInc	−0.07	0.02	0.00
homeCounty	0.03	0.03	0.36

Standard errors are clustered at the issuing-agency level.

not the officer that issued the citation was a member of the state police (MSP), if the driver is identified as African American (AA), whether or not the driver appeared with an attorney (Att), and the log of 2015 census tract median income (lTractInc) for the driver's address. The results, shown in table 4.2 suggest that those that receive PBJ were notably less likely to be found guilty of a further offense in the first half of 2019. The coefficient corresponded to a marginal effect of over 5 percentage points, which is quite substantial given the relatively low rate of reoffending.

While this is encouraging, the construction of the data means we cannot perfectly identify first time offenders, even with the above restriction. Defendants may have judicial history prior to 2011, and judges may take traffic convictions older than three years into account even though they do not appear on the administrative driving record. If this (unobserved) past behavior is correlated with driving habits and the disposition of the judge, the analysis presented above would run a clear risk of bias. To account for this, the following regression is identical to the previous one, but only includes defendants age 20 or younger. Such defendants ought be notably less likely to have criminal convictions older than 10 years, or traffic citations older

Table 4.3: Determinants of Future Citations, Young First Time Offenders

	coeff	std err	pvals
lLim	−0.10	0.12	0.41
assocPt	−0.03	0.03	0.38
lAge	−0.61	0.20	0.00
oos	−0.53	0.15	0.00
MSP	0.08	0.11	0.48
AA	0.41	0.10	0.00
att	0.11	0.40	0.79
PBJ	−0.13	0.04	0.00
lTractInc	0.01	0.04	0.72
homeCounty	−0.01	0.09	0.95

Standard errors are clustered at the issuing-agency level.

than 3 years. As shown in table 4.3, the negative relationship between probation and reoffending remains prominent among this subset of drivers.

Beyond the decision to grant or refuse probation, judges have substantial discretion in discerning how much (if any) of the associated fine to suspend upon granting probation. In principle, judges can opt to disregard the statutory fine entirely and impose any fine less than $500 for a given citation, but this is rarely invoked. By contrast, judges don't have any such flexibility with suspending the administrative points associated with a citation- probation suspends all associated points, a guilty verdict imposes all. The next tables examine determinants of reoffending for all first time offenders (table 4.4) and young first time offenders (table 4.5, using the same subset as in table 4.3). Both sets are motivated by the suspended fine, but apparently not by the number of points associated with the initial offense. This is a perplexing result- sample information from the Maryland Insurance Administration suggests that a 2 point assessment typically results in premium increases of several hundred dollars per year, almost certainly outweighing the waived fine for most drivers. It's likely that this result is driven by the relatively limited variation in points associated

Table 4.4: Future Citations among PBJ recipients, First Time Offenders

	coeff	std err	pvals
lLim	−0.01	0.07	0.85
assocPt	0.08	0.04	0.06
lAge	−0.44	0.07	0.00
oos	−0.20	0.16	0.20
MSP	−0.08	0.09	0.36
AA	0.04	0.07	0.56
lowRate	−0.19	0.22	0.40
att	−0.26	0.21	0.22
lSuspVal	−0.08	0.01	0.00
lTractInc	−0.06	0.03	0.02
homeCounty	0.03	0.07	0.66

Standard errors are clustered at the issuing-agency level.

Table 4.5: Future Citations among PBJ recipients, Young First Time Offenders

	coeff	std err	pvals
lLim	0.04	0.21	0.86
assocPt	0.07	0.06	0.26
lAge	−1.05	0.37	0.00
oos	−5.72	0.13	0.00
MSP	0.08	0.16	0.60
AA	0.35	0.13	0.01
att	−0.02	0.49	0.98
lSuspVal	−0.14	0.06	0.01
lTractInc	0.11	0.08	0.18
homeCounty	−0.05	0.13	0.70

Standard errors are clustered at the issuing-agency level.

with Maryland's speeding offenses.[7]

I further examine the determinants of receiving PBJ, with the aim of identifying whether or not District Court judges take an interest in the fiscal conditions of the relevant locality. Using the credit ratings assigned to recent bond issuances by S&P, I separate localities with low credit ratings (lower than AA+) from the others. We

[7] For offenses that do not result in injury or accident, the vast majority carry two points. Only the most minor offenses carry 1, and only those that involve speeding by more than 30+ MPH carry more.

Table 4.6: Determinants of Granting Probation

	coeff	std err	pvals
lLim	−0.17	0.09	0.05
assocPt	0.06	0.04	0.10
lAge	0.23	0.04	0.00
oos	−0.92	0.05	0.00
MSP	−0.18	0.03	0.00
lowRate	−0.19	0.04	0.00
MSPxlowRate	0.20	0.07	0.01
AA	−0.08	0.05	0.10
att	0.70	0.10	0.00
occ	−0.11	0.05	0.02
lTractInc	−0.04	0.03	0.16
homeCounty	−0.04	0.05	0.39

Standard errors are clustered at the issuing-agency level.

see that defendants in localities with poor credit ratings are notably less likely to receive PBJ than others in table 4.6. Judges also seem more willing to show leniency to those pulled over by the state police, and less likely for those from out of state. The regressions also includes an interaction term for citations issued by the MSP in localities with poor credit ratings. This coefficient is essentially equal and opposite that associated with a citation being issued in a locality with poor credit. Thus, the apparent reticence of judges to award PBJ to defendants in less well rated districts does not extend to those that were cited by the MSP- consistent with the notion that judges are taking an interest in local finances.

Differences in the sort of traffic enforcement undertaken by local and state police may confound identification of the MSP coefficient, if the effect is not a simple function of speed. To assess this, table 4.7 shows the same model as table 4.3, but restricted to those stopped on roads with speed limits of 55 or higher. Values of coefficients change, but the overall picture remains more or less unchanged.

Table 4.8 restricts the analysis to cases in Maryland's second and third districts, both of which contain multiple counties (for a total of 9), which vary in their degree

Table 4.7: Determinants of Granting Probation, high speed road

	coeff	std err	pvals
lLim	−0.13	0.17	0.44
assocPt	0.00	0.03	0.94
lAge	0.21	0.05	0.00
oos	−1.00	0.06	0.00
MSP	−0.26	0.05	0.00
lowRate	−0.22	0.04	0.00
MSPxlowRate	0.18	0.07	0.01
AA	−0.06	0.05	0.20
att	0.72	0.15	0.00
occ	−0.10	0.05	0.06
lTractInc	−0.03	0.05	0.50
homeCounty	−0.07	0.05	0.16

Standard errors are clustered at the issuing-agency level.

of fiscal health. I'm also able to identify the judges involved in each case, which I use differentiate cases heard by judges in their "home" counties from others.[8] The results for this subset differ in a few notable ways. The apparent impact of MSP citations is no longer significant, and those from higher income census tracts and those cited in their home county tend to preform better. Moreover, the importance of district credit worthiness is notably more pronounced- partially ameliorated when cases in said counties are heard by an "out of town" judge. This is consistent with the notion that working relationships with local government officials inform the disposition of judges in these cases.

While the previous several tables focus on the binary decision faced by the court, the proportion of the fine to collect (rather than suspend) is also left to the discretion of the judge. This factors impacting this decision are explored in 4.9, focusing on drivers that received probation. Drivers that received probation generally received

[8] In principle, estimation might be compromised if assignment to a particular judge is nonrandom. This seems somewhat unlikely- court dates are assigned by the District Court Traffic Processing Center in Annapolis by an automated system, whereas judicial assignments are handled by the administrative judge in each district. Conversations with court administrative clerks suggested that the two processes work independently.

Table 4.8: Determinants of Granting Probation, “mixed” districts

	coeff	std err	pvals
lLim	−0.04	0.07	0.62
assocPt	−0.37	0.03	0.00
lAge	0.36	0.07	0.00
oos	−0.52	0.09	0.00
MSP	−0.01	0.15	0.97
lowRate	−0.42	0.15	0.01
MSPxlowRate	0.27	0.20	0.19
AA	−0.26	0.07	0.00
judgeAway	−0.03	0.13	0.79
away/lowRate	0.29	0.09	0.00
away/defHome	0.04	0.08	0.64
att	−0.34	0.25	0.18
occ	−0.66	0.06	0.00
lTractInc	0.07	0.02	0.00
homeCounty	0.13	0.06	0.03

Standard errors are clustered at the judge-level.

suspended fine some $35 less than if they were cited by local police in a district with a poor credit rating, while those in similar locations cited by MSP were not notably differently from the general population.

While the findings presented above are consistent with a fiscally-conscious judiciary, selection effects might be confounding estimation of judicial preferences. If drivers have private information about the likely outcome of seeking leniency for their citation, inter-district variation in the distribution of likely marginal costs could induce a difference in outcomes conditional on other observables. With this concern in mind, table 4.10 assess the determinants of opting to prepay for the roughly 300 thousand citations that were able to do so during the sample period. I find no reason to conclude that drivers cited in districts with poor credit differ in their decision to prepay, nor do those with higher local incomes. As one might expect, those from out of state are notably more likely to prepay and those cited in their home county are less likely.

Table 4.9: Determinants of Suspended Fine Conditional on Probation, OLS

	coeff	std err	pvals
lLim	1.00	13.02	0.939
assocPt	16.53	6.14	0.007
lAge	13.01	4.76	0.006
oos	−35.54	6.94	0.000
MSP	−13.72	18.57	0.460
lowRate	−35.44	12.23	0.004
MSPxlowRate	34.76	15.45	0.024
AA	−1.66	4.24	0.696
att	8.67	13.56	0.522
occ	−9.18	4.33	0.034
lTractInc	−1.10	3.03	0.716

Standard errors are clustered at the issuing-agency level.

Lastly, to assess the impact of budget conditions on police incentives, I examine the determinants of a given citation having a "bunched" speed- that is, a listed speed one short of a threshold value. To illustrate this clustering, figure 4.1 shows the distribution of recorded excess speeds. There is a clear spike at 9 mph over, and a less pronounced point at 19. The results shown in table 4.11 are consistent with the notion that local police officers are sensitive to local fiscal conditions, whereas

Table 4.10: Self Selection into Prepayment

	coeff	std err	pvals
lLim	0.27	0.09	0.00
assocPt	-0.19	0.03	0.00
lAge	0.10	0.05	0.02
oos	0.54	0.06	0.00
MSP	0.18	0.18	0.34
lowRate	-0.30	0.33	0.36
AA	-0.27	0.07	0.00
occ	-0.03	0.02	0.22
lTractInc	0.01	0.02	0.54
homeCounty	-0.10	0.03	0.01

Standard errors are clustered at the issuing-agency level.

MSP officers generally are not.

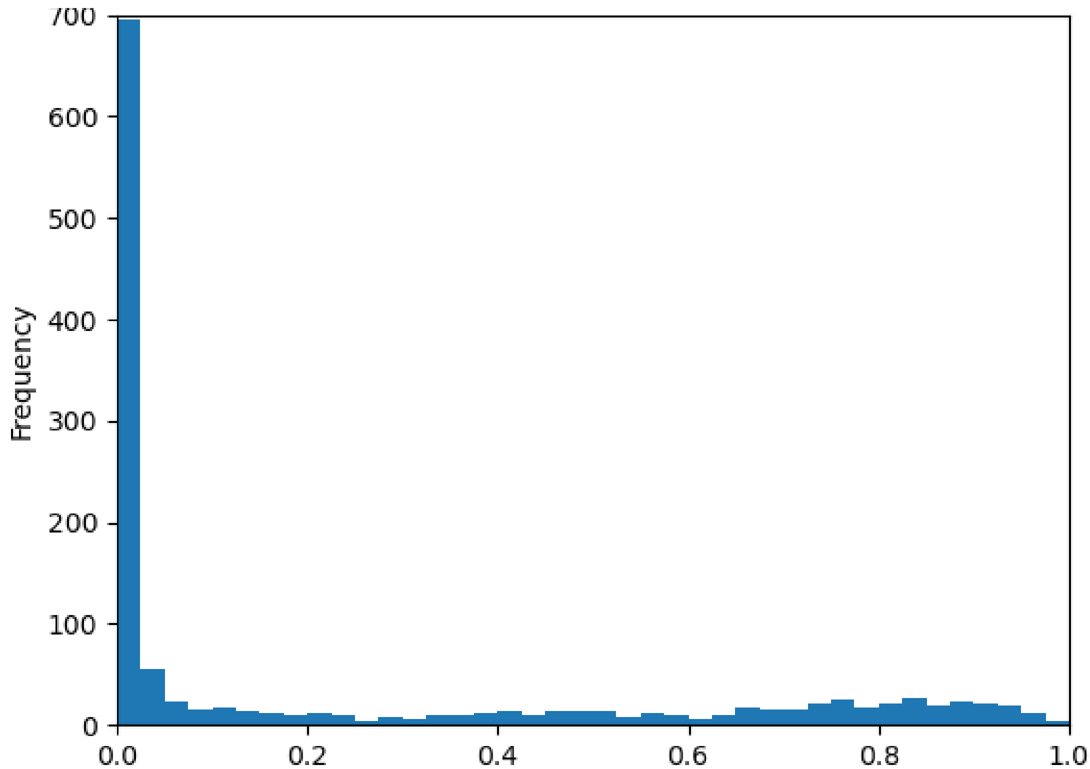


FIGURE 4.1: Officer-level Bunching

4.7 Visiting Judges

While the preceding analysis made a preliminary attempt at disentangling county and judge effects, it did so by focusing on a select few districts. However, Maryland's system does allow for a somewhat more general approach. While District Court judges are appointed to serve in specific court, they are permitted to serve elsewhere in the state under certain circumstances.

While the division of judges among Maryland's district court is generally sufficient to meet the districts' needs, occasional difficulties arise. Unexpected upticks in law enforcement activity or judicial vacations or medical leave can, for example, create

Table 4.11: Determinants of Threshold Speed Offense

	coeff	std err	pvals
lLim	−0.1764	0.073	0.015
lAge	0.0165	0.053	0.757
MSP	0.4221	0.251	0.093
lowRate	−0.5447	0.193	0.005
MSPxlowRate	0.6072	0.215	0.002
AA	−0.1668	0.060	0.005
occ	−0.0902	0.060	0.132

Standard errors are clustered at the issuing-agency level.

notable short term backlogs. More persistently, a vacant judicial position during the appointment process can generate a longer term problem.

While cases cannot be freely shifted between districts, district administrative judges can temporarily increase the throughput of their districts via the use of a visiting judge. A visiting judge must be otherwise qualified to preside in the court in question, and so the pool of potential visiting judges largely consists of former Maryland judges or current judges in other Maryland jurisdictions.

The existence of this practice, for a subset of cases, breaks the link between judge and judicial district. For those judges that hear a non-negligible number of cases in multiple jurisdictions, one can assess the extent to which the judge's conduct varies with the characteristics of the location.

The major limitation of this approach, of course, is that relatively few judges are prolific as visiting judges. Just under 4 percent of the available cases in the data were heard by designed visiting judge, or roughly 10 thousand in total. Of these, many were heard by judges that rarely acted as a visiting judge. Restricting the sample to judges that had heard at least 100 cases in at least two districts during the sample period leaves about 7000 cases heard by 14 judges.

With this subset, I augment the regression from earlier with judge fixed effects. To account for possible changes in judicial behavior when acting as a visiting judge

Table 4.12: Determinants of Granting Probation, Visiting Judges

	coeff	std err	pvals
lLim	−0.17	0.19	0.37
assocPt	0.12	0.04	0.00
lAge	0.13	0.14	0.34
oos	−0.84	0.15	0.00
MSP	−0.22	0.19	0.27
lowRate	−0.32	0.09	0.01
MSPxlowRate	0.34	0.12	0.01
AA	−0.03	0.15	0.87
att	0.55	0.20	0.01
occ	−0.12	0.17	0.44
lTractInc	−0.06	0.39	0.88
homeCounty	−0.14	0.21	0.50
visitJudge	−0.04	0.19	0.83

Standard errors are clustered at the issuing-agency level.
Includes fixed effects for judges

that are not dependent on the characteristics of the host jurisdiction, I also include an indicator for the presence of a visiting judge in a particular case.

The results of this, shown in table 4.12, exercise provide further support for the notion that judges take an interest in local fiscal conditions. Visiting judges are notably less likely to award probation when hearing cases in credit-constrained counties, but not when those cases pertain to citations issued by the state police. Moreover, the fact that a judge is hearing a case outside of their usual jurisdiction does not appear to have any clear impact on their conduct. Though it ought be stressed that, given the notably reduced sample size used in the analysis, null results ought not be weighted particularly greatly.

4.8 Drivers and Police

To examine the impact of fiscal constraints on officer and driver conduct, analysis here will turn to a model similar to that of chapter 2. Officer use of discretion in reporting drivers' speeds is not directly observable. Citations list only the speed reported by the officer, which could in principle be a faithful or altered representation. Moreover, one might expect speeding drivers in Maryland to be somewhat strategic in their choice of excess speed. While much of the driving population may not be aware of the exact schedule of penalties, those that are might conclude that the marginal benefit from adding one more MPH while traveling at a threshold speed falls below the cost. If strategic behavior differs notably across various subsets of drivers, apparent differences in officer-level or aggregate discounting may actually be a function of exposure to different groups of drivers.

Examination of officer-level data suggests that this is not the case. Across jurisdictions and departments, a sizable portion of officers issue few or none of their citations for speeds exactly 9MPH in excess of the speed limit. In aggregate, roughly 40% of officers included in the data issued zero such tickets. Across agencies, the proportion varies from 20% to nearly 70%. As 9MPH over the speed limit is the single most common cited speed, it might be seen as odd that many officers with over 50 citations issued none at this threshold. However, if discounting is relatively common among officers, we need not be surprised. There are comparatively few citations issued for speeds just above and below 9MPH in excess. If it is genuinely rare to cite drivers for these comparatively slow speeds, but relatively common for a subset of officers to discount, we'd expect officers that don't engage in discounting to have few or none of their citations for this threshold. Figure 4.2 shows the distribution of officers by their fraction of speeds reported at relevant thresholds.

To the extent that bunched cited speeds result from officer discretion, the following analysis examines the factors that influence officer decision making. Figures 4.3 and 4.4 plot the frequencies of cited speeds (relative to the limit) for white/Hispanic drivers and black drivers, respectively. The overall discount probabilities show (subjectively) significant differences. The former group is cited for exceeding the speed

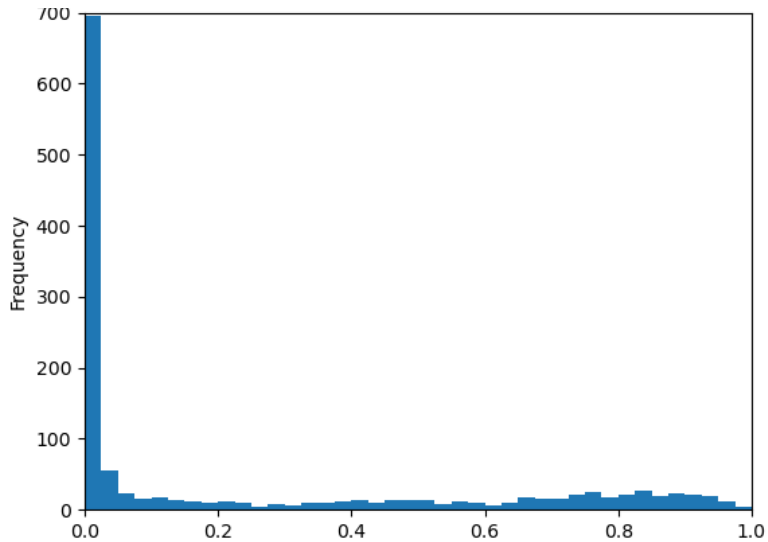


FIGURE 4.2: Officer-level Bunching

limit by 9 mph and 19 mph in 16 and 11 percent of stops (respectively). Black drivers, by contrast, are cited for those speeds in 11 and 4 percent citations.

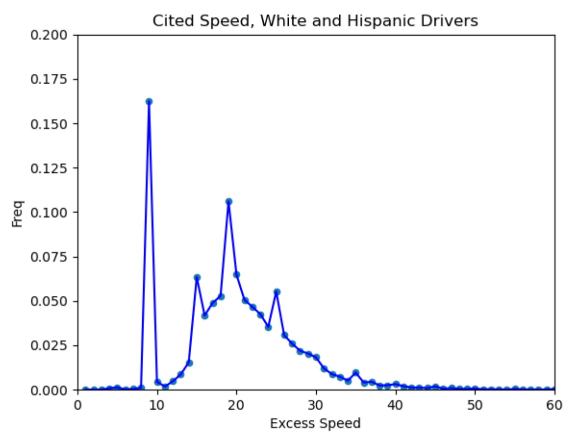


FIGURE 4.3: Cited Speeds, White and Hispanic Drivers

Table 4.13 presents results from a linear estimation of the probability of being cited for driving at a threshold speed. The leftmost columns assess drivers cited for exceeding the speed limit by between 9 and 18 MPH on roads with speed limits of less than 65 MPH. For these drivers, the difference between the two fines is only $10.

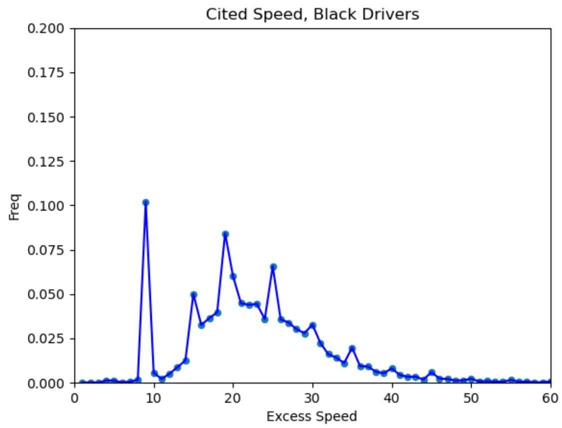


FIGURE 4.4: Cited Speeds, Black Drivers

The rightmost columns examine citations issued either on high speed roads or by drivers exceeding the limit by greater degrees. In these cases, the jump in fine for exceeding the threshold is notably larger.

Variables include drivers' sex (sex), an indicator for African Americans (AA), log of home census tract income (lTractInc), and whether or not the driver was cited in their home county (homeCounty). On the institutional side, analysis identifies

Table 4.13: Discounted speeds, 2016-2020

	Discount, small jump mean = .49		Discount, large jump mean = .18	
	coeff	pvals	coeff	pvals
sex	−0.0177	0.000	0.0035	0.000
AA	−0.0490	0.000	−0.0413	0.000
MSP	0.1484	0.000	0.0416	0.000
lowRate	−0.3815	0.000	−0.0807	0.000
lowRate x MSP	0.4756	0.000	0.0747	0.000
lTractInc	0.0399	0.000	0.0233	0.000
homeCounty	0.0087	0.001	−0.0005	0.818
revFall	−0.0021	0.827	−0.1466	0.000
fall x MSP	0.0023	0.866	0.1765	0.000

Standard errors clustered at county/agency level.
Includes fixed effects for day of week, time of day, year

citations issued by state police (MSP), those issued in counties with low credit ratings (lowRate), and in those county/quarters that had experienced a decline in quarterly income revenue relative to both the previous quarter and the same quarter in the previous year (revFall).

Consistent with what others have found, African Americans seem to be less likely to benefit from officer discretion. Moreover, we see that local police (but not state police) are notably less likely to issue citations for threshold speeds for both small and large increments in fines. Somewhat similarly, while quarterly revenue declines don't seem to influence officer behavior for small jumps in fine revenue, the discounting among local officers in such quarters declines substantially. Again, this shift is entirely mitigated for stops made by state police. The next section will model officer-level behavior and possible racial/county-level differences in driver behavior.

4.9 Discounting and Speed

As mentioned, previous analysis assumed that driver behavior (conditional on speeding) did not vary across racial groups. If the assumption is false, some component of the apparent bias in discounting decisions may be driven by non-discriminatory factors. The analysis below follows a pattern similar to that used in (Goncalves and Mello (2021)).

A given speeder encountered by an officer exceeds the speed limit by $s_t \sim P_{\lambda_{r,c}}(s)$, drawn from a Poisson distribution with a race/county specific mean. The officer either issues the citation for the observed speed s_t or the nearest lower threshold s_d. Essentially, the estimation procedure assumes that all citations that present non-threshold speeds are truthful while those that present threshold speeds are either truthful or discounted from some speed below the next threshold.

Officers in the model consider a driver's affluence (log of census tract income), race, and the change in penalty associated with discounting. All officers j have a fixed preference for issuing a discounted ticket to driver i of race j ($d_{j,r}$), a race-specific preference for revenue ($m_{r,j}$), and an agency-level sensitivity (w_A) to driver affluence (l_i). Lastly, each stop has an associated error term $\epsilon_{i,j} \sim \mathcal{N}(0,1)$ and an change in revenue that would be associated with issuing a discounted ticket r_i.

So upon observing driver i exceeding the speed limit by s_t, an officer will issue a discount if:

$$d_{j,r} + r_i m_{r,j} + w_A l_i - e_{i,j} > 0$$

A given driver's probability of receiving a discount, given their own characteristics, those of the officer, and speed s_t is then:

$$P(D|s_t) = \Phi(d_{j,r} + r_i m_{r,j} + w_A l_i)$$

Taken together, the likelihood function for cited speeds becomes:

$$P(S = s) = \begin{cases} P_{\lambda_{r,c}}(s) & \text{if } s < 9 \\ P_{\lambda_{r,c}}(9) + \sum_{x=1}^{9} P_{\lambda_{r,c}}(9+x)(\Phi(d_{j,r} + r_i m_{r,j} + w_A l_i)) & \text{if } s = s_d \\ P_{\lambda_{r,c}}(s)(1 - \Phi(d_{j,r} + r_i m_{r,j} + w_A l_i)) & \text{ow} \end{cases}$$

Estimation finds that black drivers stopped for speeding do tend to be travelling somewhat faster than the general population. This gap (mean 1.4 mph, varying between 0 and 2.1 mph) is fairly consistent across counties. The figures 4.5 and 4.6 the average excess speed on citations for all counties for black and non-black drivers by county.

However, even when this is taken into consideration, among those officers than engage in discounting, roughly a quarter had a bias against black drivers significantly greater than zero. The CDF of officer-level bias values given in figure 4.6.

Black drivers in almost all of Maryland's counties are less likely to benefit from officer discretion, though the extent of discretion and bias vary substantially. Discount probabilities for white drivers vary from over 80 percent in Garrett and Allegheny

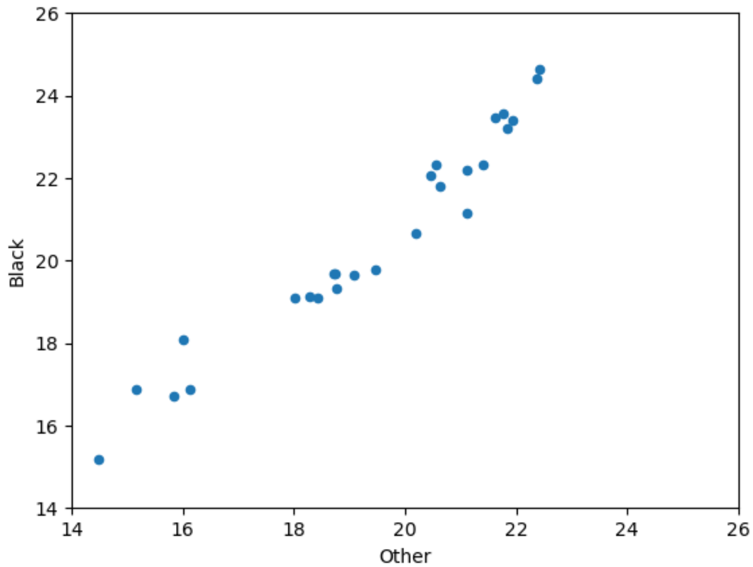


FIGURE 4.5: Excess Speed Among Cited Drivers, by County and Race

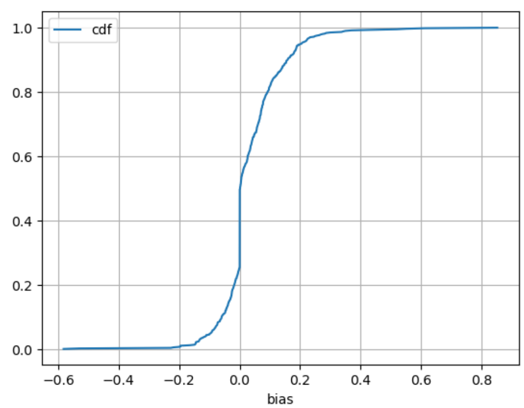


FIGURE 4.6: Distribution of Bias in Favor of White Drivers

county to under 10 percent in several others. Black drivers face such probabilities ranging from roughly equal to as much as 10 percentage points lower.

In terms of composition of bias, difference in preference for revenue is the dominant factor. Nearly 80 percent of biased officers (about 20% of the total) have a significant bias against black drivers with respect to revenue preference. By contrast, less than half of such officers exhibit the corresponding bias with respect to administrative points.

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