Political Economy at Any Speed: What Determines Traffic Citations?

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In this paper we study the political economy determinants of traffic fines. Speeding tickets are not only determined by the speed of the offender, but by incentives faced by police officers and their vote maximizing principals. Our model predicts that police officers issue higher fines when drivers have a higher opportunity cost of contesting a ticket, and when drivers do not reside in the community where they are stopped. The model also predicts that local officers are more likely to issue a ticket when legal limits prevent the local government from increasing revenues though other instruments such as property taxes. We find support for the hypotheses. The farther the residence of a driver from the municipality where the ticket could be contested, the higher is the likelihood of a speeding fine, and the larger the amount of the fine. The probability of a fine issued by a local officer is higher in towns when constraints on increasing property taxes are binding, the property tax base is lower, and the town is less dependent on revenues from tourism. For state troopers, who are not employed by the local, but the state government, we do not find evidence that the likelihood traffic fines varies with town characteristics. Finally, personal characteristics, such as gender and race are among the determinants of traffic fines.

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I. Introduction

Can speeding tickets be solely explained with the driver's speed, or do they serve as a supplement for local revenue and reflect officer preferences? It is not uncommon for drivers, especially those from out of town, to question the motivations of local police officers and what they deem to be the optimal enforcement of traffic laws. Theory suggests that the levels of enforcement and punishment for traffic violations are based on the degree of infringement by the offending party and the marginal returns to local safety (Becker 1968; Polinsky and Shavell 1992; Ehrlich 1996). This view, however, may not be an accurate description of actual enforcement, as it neglects that police officers carry out enforcement in a manner that maximizes their own utility. Further, this view does not account for police officers being a part of the local or state government, and that their vote-maximizing principals may have incentives to encourage officers to increase government revenues through issuing speeding tickets to non-voters. It also neglects personal preferences, with regards to characteristics such as race or gender, which may motivate the officer to issue traffic tickets.

The imposition of traffic fines to increase revenues is reminiscent of Niskanen's (1971) long-standing hypothesis that bureaucrats maximize their agency's budget. Evidence has been scarce, however, and the hypothesis has been called into question because bureaucrats may not receive any direct benefit when their agency's budget size is enlarged (Johnson and Libecap 1994) . The budget maximizing hypothesis, however, has not been applied to the behavior of police officers engaged in the enforcement of traffic laws. We hypothesize that police officers, and their monitoring superiors, have incentives divergent from optimal enforcement. Those incentives include the increasing of government revenues. More frequent and larger fines may lead to favorable employee evaluations, and contribute to a larger budget for the police department, higher officer salaries, and improved amenities.

Anecdotes suggest that local governments use traffic fines as substitutes for collecting tax revenues and that these fines often provide a substantial source of revenue (Costello 2002; Diamond 2005). And there is anecdotal evidence that police officers are having the number of tickets they issue enter their job performance review and that state troopers are rewarded for writing traffic tickets by receiving overtime work, which is compensated with one and half times base pay (Diamond 2005). Although these anecdotes are consistent with the hypothesis of budget maximizing municipalities, there is no statistical evidence supporting the hypothesis traffic fines are issued with the objective to increase government revenues.[1]

Further, while there is evidence of racial-profiling in the searching of vehicles by officers (Knowles, Persico et al. 2001), there is little evidence that an officer's personal preferences are an important determinant of whether a driver receives a fine. A recent comparison of traffic ticket recipients found a difference in the probability of receiving a warning across race and gender (Dedman and Latour 2003). This study, however, did not hold constant the degree of the offense and other characteristics of the incident.

Our paper presents a theoretical and empirical framework to analyze the determinants of speeding tickets and tests the resulting theoretical predictions. Our framework emphasizes that police officers maximize their own utility by minimizing effort and seeking favorable work evaluations. Superiors' incentives are reflected by

[1] However evidence of budget maximizing police departments has been presented with regards to property seizures associated with drug offenses (Benson, Rasmussen et al. 1995).

local fiscal conditions and superiors monitor police officers. This framework generates hypotheses which we test using a data set containing all speeding traffic stops in Massachusetts for a two month period in 2001.

Table 1 reports means and standard deviations for the data which come from traffic stops in Massachusetts during a 2 month period in 2001. Forty-six percent of individuals stopped by police officers due to speeding receive a citation (column 1). The mean fine for individuals who received a citation is $122 (column 2). Not surprisingly the speed of drivers is higher in the sample of individuals that had to pay a fine than in the sample of individuals that includes both fines and warnings. More conspicuously, while out of state drivers account for sixteen percent of traffic stops, they receive twenty-two percent of the fines issued. Similarly the means for the out of town driver indicator is higher in the sub-sample of stops resulting in fines than in the sample that includes all stops. Computing differences in the likelihood of fines and the amount of fines reveals that when stopped by a police officer, an out of town drivers has a 51 percent likelihood of receiving a fine as opposed to a warning while a local driver has a 30 percent chance of receiving a fine. With respect to the amount of the fine, the average fine for out of town drivers is $123, while it is $118 for local drivers. A t-test reveals that differences are statistically significant. These findings provide us with a starting point for a model that sheds light on the determinants of the differential treatment of drivers and provides testable hypotheses.

Using a variety of model specifications, we present evidence that fines for speeding are not solely determined by an objective standard of law enforcement. We show that officers use drivers' differences in opportunity costs of contesting a fine as a criterion for both whether they issue a speeding ticket or a non-consequential warning, and, in the event of a ticket, the dollar amount the driver must pay. The likelihood and dollar amount of a fine are decreasing functions of local property tax revenue. Further, the likelihood of receiving a speeding fine is higher in towns that are in a fiscal crunch caused by a rejected increase in the property tax limit.

II. Background on Institutions

Our empirical analysis uses data from traffic stops and citations in Massachusetts. All citations, tickets and warnings, are issued using the same form, the Massachusetts Uniform Citation. A checked box on the form results in a driver having to pay a fine and points are applied to his official state driving record. Further, his car insurance premium may increase under insurance rates that are regulated by the state of Massachusetts to correspond to driving records (Blackmon and Zeckhauser 1991). A warning has no consequences. By Massachusetts State law, whether the officer issues ticket or a warning is up to the discretion of the officer.[2]

Once the officer has decided whether to impose a warning or a fine, he has to decide on the fine amount. State law sets an explicit formula for the fine amount, and fines are allowed to be imposed if a vehicle operates in excess of 10 miles per hour over the speed limit.[3] If all fines are set according to the formula, the fine amounts are $50 +

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[2] The ability of the officer to issue a warning under Massachuessetts General Law Part I Chapter 90C Section 3 was recently challenged by the Newton (Ma) Police Association. Their appeal was ruled against by the Massachusetts State Court of Appeals, protecting the capacity of officers to issue warnings. *NEWTON POLICE ASSOCIATION vs. POLICE CHIEF OF NEWTON* (Massachusetts State Court of Appeals, 6/9/2005).

[3] The law regulating speeding fines states, "Any person convicted of a violation of the provisions of section seventeen, or of a violation of a special regulation lawfully made under the authority of section eighteen shall be punished by a fine of not less than fifty dollars. Where said conviction is for operating a vehicle at a rate of speed exceeding ten miles per hour over the speed limit for the way upon which the person was

10 * (speed – (speed limit + 10)). Officers compute the fine on their own during the traffic stop. The form on which every traffic ticket is written (*Massachusetts Uniform Citation*) does not contain any reference to the formula for calculating the minimum fine.

To examine whether officers use discretion we ran a simple regression of the fine imposed on the vehicle's speed over the posted speed limit. This regression is based on 29,752 observations, using observations where a fine is imposed and the driver's speed is at least 10 miles per hour over the speed limit. The intercept of this estimate is 2.44, the slope estimate is 7.01 (fines are expressed in dollars and speeding in miles per hour), and both point estimates are highly statistically significant. These results indicate a ticket of $108 for driving 15 mph over the speed limit. The recommended fine according the statue would have been $100. Figure 1 shows that for speeds below about 17 mph over the speed limit officers fine more than the amount suggested in the statue, and above 17 mph that they fine less. These simple regression results indicate that officers, on average, exercise discretion in their decisions regarding the amount of the fine issued. We already noted that officers are allowed discretion when deciding whether to impose a fine or a warning.

Massachusetts police officers who are employed by a municipality operate within a hierarchy that is headed by a Chief of Police. The Chief of Police is a position appointed to for a period not exceeding three years by the elected officials on the governing board. In a town the governing board is the Board of Selectmen, in a city the Board of Aldermen. Officials on the governing board are elected by voters of the municipality, and by Massachusetts law given the power to form a police department,

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operating, an additional fine of ten dollars for each mile per hour in excess of the ten miles per hour shall be assessed." (Massachusetts State Law. Paragraph 2. Section 90. Part 20.)

appoint its chief, and remove that chief at any time. The major responsibilities of Board officials are the assessment of taxes and the appointment of town officials.[4] More generally, Board members are the acting executives of the town.

A traffic citation, which carries a fine, can be paid by the offender or appealed in court. An appeal will be brought forth through the assigned District Court, which is indicated on the ticket. When appearing in court the case will be a heard by a magistrate, who may or may not be a justice.[5] Not every town and city in Massachusetts has a District court, and in-state drivers who want to contest a ticket may have to travel out of town. Massachusetts has 62 district courts. District court justices are appointed by the governor.

Regressions using 2005 data from the Massachusetts Department of Revenue demonstrate a positive relationship between per capita police budgets and traffic fines, controlling for town revenues. For example, per capita police budgets increase with revenues from fines and forfeitures. Additionally, minimum and maximum salaries for officers and sergeants increase with the size of the per capita police budget across municipalities. Also relevant to officer salaries and benefits, the size of the per capita police personnel budget increases with fine and forfeiture revenues.[6] These results are

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[4] Massachusetts Code Of Laws, Part I,Title VII, Chapter 41, Section 97: Police departments; establishment. Massachusetts Code Of Laws, Part I,Title VII, Chapter 41, Sections 20 and 21: Power of Selectmen to assess taxes and appoint officers. See the *Citizen's Guide to Town Meetings*, http://www.sec.state.ma.us/cis/cistwn/twnidx.htm).

[5] Any decision reached by a magistrate who is not a justice may appeal to be heard by a District Court justice, though a fee of $20 must be paid prior to the commencement of the appeal hearing (Massachusetts Code Of Laws, Part I, Title XIV Chapter 90C Section 3).

[6] In these exploratory regressions of the form, $y=\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$, y measures police officer salaries or police budgets, x_1 is a measure of traffic fine revenue, and x_2 is a control variable for either total municipal revenue of the entire police budget. The unit of analysis is a municipality in Massachusetts in 2005.

consistent with the hypothesis that police officers have incentives to increase fine revenues.

Legal limits in Massachusetts impede municipalities' ability to increase property taxes and excise fees. In 1980 Massachusetts voters passed referendum Proposition 2 ½, placing explicit limits on both the maximum amount of revenue generated through property taxation by Massachusetts municipalities and the amount by which any municipality may increase this revenue from one year to the next.

Limits on personal property taxation have made Massachusetts local governments more dependent on other local sources of revenues.[7] Local receipts include revenues from the motor vehicle excise, charges for services, departmental revenue (e.g. libraries) licenses and permits, and fines. Traffic citations fall under the category of fines.[8]

There are limitations, however, placed on revenue generated from fees, licenses, and permits. Municipalities are allowed only to recover one hundred percent of the cost of providing fee based services.[9] While there is little flexibility in how much municipalities can raise through fees, licenses and permits, no statute or regulation places limits on fines. Municipalities retain 50 percent of the revenues collected from traffic fines.[10] The remainder is allocated to the state treasury and the Highway Fund.

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[7] "Since the passage of Proposition 2 ½ in 1980, municipal budgeting has been revenue driven…Therefore, at the start of the annual budget process, a community should review its four major sources of revenue – tax levy, state aid, local estimated receipts, and available funds…However, because of the constraints of Proposition 2 ½, recent fluctuations in state aid, and the depletion of local reserves, communities have become more aware of local receipts as a source of needed funds." – Services, D. o. L. Best Practices, User Fees. Technical Assistance Section, Massachusetts Department of Revenue.

[8] (*Massachusetts Department of Revenue, Division of Local Services official Budget Control Worksheet for Local Receipts* http://www.dls.state.ma.us/publ/misc/umas.pdf, accessed January 23, 2006)

[9] Some municipalities choose to recover only direct costs, while others include "indirect" costs as well, such as administrative and debt management costs.

[10] "Fines imposed under the provisions of chapters eighty-nine and ninety, including fines, penalties and assessments imposed under the provisions of chapter ninety C for the violation of the provisions of chapters eighty-nine and ninety, fines assessed by a hearing officer of a city or town as defined in sections twenty A and twenty A 1/2 of chapter ninety and forfeitures imposed under the provisions of section one hundred and

In most of the 350 of the 351 municipalities in Massachusetts analyzed here, property taxes are the single largest source of revenue. In 2001, property taxes comprise 57 percent of total revenues, state aid 20 percent, local receipts 15 percent and the remaining 8 percent falls in the "all other category" (State of Massachusetts, Department of Revenue). The mean property tax levy is $1,270 while local receipts and "the all other" category account for $448 and $180 per capita respectively (State of Massachusetts, Department of Revenue).[11]

In the event that the town government wishes to raise funds from property taxes beyond the levy limit prescribed by Proposition 2 ½ the town has the option to pass an "override" referendum. An override question can be proposed and placed on an electoral ballot by a majority vote of the town board of selectmen (aldermen). The override question must be presented in dollar terms and specify the purpose of the additional funds. Passage of the override requires a majority vote of approval by the electorate (Massachusetts Department of Revenue 2001).

III. Theoretical Framework

The cost of speeding is a financial penalty which increases with the speed of the vehicle, consistent with economic models of optimal deterrence of unlawful behavior. However, in the execution of their occupational obligation to deter speeding, officers are operating within their own set of incentives. These incentives include the disutility of

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forty-one of chapter one hundred and forty, shall be paid over to the treasury of the city or town wherein the offense was committed; provided, however, that only fifty per cent of the amount of fines, penalties and assessments collected for violations of section seventeen of chapter ninety or of a special speed regulation lawfully made under the authority of section eighteen of said chapter ninety shall be paid over to the treasury of the city or town wherein the offense was committed and the remaining fifty per cent shall be paid over to the state treasurer and credited to the Highway Fund. "(Massachusetts State Law. Part IV, Title II, Chapter 280, Section 2.)

[11] This calculations are based on Massachusetts' 350 municipalities and exclude Boston.

labor, the requirements of their superiors, and their personal sense of obligation to foster safety within their community. The objectives of their superiors and the manner in which officers are monitored, on the other hand, reflect a hierarchy that is headed within the department by the Chief of Police, who is himself appointed and monitored by the town Board of Selectmen (or city Aldermen), whose responsibilities include the assessing of taxes. Officers report to the Chief of Police, and the Chief reports to the elected Board.

Suppose an officer has discretion as to whether to issue a traffic fine or a warning. The officer's decision to cite and thus issue a fine, as opposed to give the driver a warning, is based on utility maximization. A police officer is generally disinclined to issue a ticket because it requires work without immediate personal benefit. The Chief, however, is monitoring her work, evaluating her with regards to the number of traffic stops and issued fines, and how many drivers eventually pay their fines (as opposed to having the fine successfully overturned in court). Road safety in the officer's area of operation enters the officer's utility function as well as the superior's performance evaluation.

$$(1) \qquad Utility_{officer} = f(\overset{(-)}{work\ effort}, \overset{(+)}{performance\ evaluation}, \overset{(+)}{road\ safety})$$

The amount of work effort associated with a citation issuance depends on the probability that a driver will appeal the ticket to a judge.[12] If the driver appeals the ticket, work effort for the police officer increases, as she is required to attend the proceedings.

$$(2) \qquad work\ effort = f(\overset{(+)}{\text{Prob(appeal)}})$$

[12] Initial appeals are heard before a clerk magistrate; the citing officer is not required to attend. If the ticket is upheld, the defendant may request an appeal hearing before a district court judge. This request is may not be denied, by Massachusetts law, and at this hearing the officer will be subpoenaed and must attend.

Whether a driver appeal a ticket depends on the expected cost and benefit. The expected cost includes the time and effort of going to court, which is a function of the distance from the driver's home to the assigned District courthouse. The expected benefit increases with the size of the fine and the probability that the citation will be overruled (or at least the fine reduced in size). The probability of a citation being overturned increases with the amount the assigned fine exceeds the minimum fine as determined by Massachusetts law (overcharge).

$$(3) \qquad P(\text{challenge}) = f(\overset{(-)}{\text{distance to court}},\ \overset{(+)}{\text{fine amount}},\ \overset{(+)}{\text{overcharge}})$$

This model predicts that the officer has an incentive to issue fines to drivers whose residence is farther from the municipality where the ticket can be appealed in court. An officer has information about a driver's residence that allows the police officer to discriminate among drivers in this dimension. A police officer knows from the car's license plate the driver's state and sometimes the driver's town of residence.[13] Once a driver is pulled over, the officer can observe the home address on the driver's license.

Selectmen and Aldermen are elected and by law serve as the assessors of taxes and executives of town employees. Selectmen and Aldermen appoint and monitor the Chief of Police. Since Board members are elected by local citizens using majority rule we assume that these politicians maximize votes. Votes for politicians increase with higher services and lower levies. Further, local residents have incentives to vote with their feet and leave the municipality when taxes and fines increase, holding services constant (Tiebout 1956). This in turn leads to an erosion of the property tax base and

[13] Many towns without municipal trash pickup require the purchase of a sticker, displayed on the car, to depose of refuse. This sticker is a potential signal of being a town citizen.

thereby reduces voter satisfaction. As such, the Board has an incentive to monitor their appointed police chiefs to ensure that tickets are issued to out-of-towners, as opposed to local voters, and that more revenue is raised from out of town drivers though traffic fines when the municipality's fiscal situation is worsening. This is the case, for example, when the property tax base falls or when voters fail to approve override referendums. If the police do not act to the satisfaction of the Board, it can remove the Police Chief, fail to reappoint, deny appropriations, and deny salary increases.

The Chief can in turn respond to this monitoring through his evaluation of police officers with regards to the number of citations being issued and who receives the citations. An officer's evaluation by her Chief will impact her propensity to be retained, promoted, and receive raises in pay. The Chief can monitor his agents by counting the number of citations and warnings, the results of those citations, and the perceived road safety in her area of responsibility.

(4) $$\textit{Officer evaluation} = f(\textit{number of tickets}, \textit{fine amount}, \textit{road safety})$$

The previous discussion suggests that police officers issue more tickets when desired by politicians because the Chief serves at the pleasure of politicians and officers' professional lives depend on the Chief's performance evaluations. Furthermore, police officers will find their incentives in alignment with revenue maximizing politicians if more traffic fines lead to a larger police budget.

As suggested previously, police officers benefit from a larger budget though higher salaries and amenities. A police department's budget is increasing with the size of the greater municipal government budget, the amount of the revenue the department generates through fines, and the amount of "slack" within the municipal budget. More slack implies the availability of funds which are not earmarked for a specific use. These funds hold the potential to be allocated to the law enforcement budget. Thus, slack, and in turn the police budget, increases with revenue generated through fines.

(5) $$PoliceBudget = f(\overset{(+)}{Government\ Revenue}, \overset{(+)}{Fines}, \overset{(+)}{Slack})$$

Because pay is related to the size of the budget, police officers also have an incentive to raise the budget through fines, but this effect is mitigated by free-riding by police officers and the common pool problem. However, since police chiefs prefer a larger budget they instruct officers to issue tickets to increase revenue and can monitor officers though performance evaluations and provide extra incentives for police officers to issue tickets when government revenue is low.

Suppose raising property tax revenues is limited through legislation or propositions such as Proposition 13 in California, or Proposition 2 ½ in Massachusetts. Under these conditions slack in the budget will be increasingly determined by the degree to which revenues can be raised through instruments besides property taxes. When there is little slack, the marginal return from raising non-tax revenues increases.[14]

While this model predicts that out of town residents are receiving higher fines because they have a higher opportunity cost of contesting the ticket, an alternative model suggests that non-residents are targeted because they do not vote, and that traffic fines are one form of revenue collection that potentially allows for discriminatory treatment of voters and non-voters. This practice is often referred to as “tax exporting” in the local

[14] However, police officers also face a free rider problem, lowering the number of tickets issued. This is because the revenue from tickets goes into a common pool and a police officer will receive only a small benefit from issuing an extra ticket. To prevent free-riding, police Chiefs monitor police officers.

public finance literature (McLure 1967; Arnott and Grieson 1981, Helland and Tabarrok 2002).

Each model has different implications. The voting model predicts that fines are determined by whether a person resides in the officer's jurisdiction. Thus, state troopers are predicted to treat in-town drivers the same as all other drivers in the state while they charge a higher fine to drivers from out of state. Further, the voting model predicts that local officers have only preferential treatment for those in town, and treat everyone else, in state or out of state, equally. In contrast, the opportunity cost of ticket contestation model predicts that state troopers and local officers are more likely to ticket the further the driver resides from the court of jurisdiction.[15]

IV. Empirical Specification and Data

The data on traffic citations are from the Boston Globe (Dedman and Latour 2003), which the newspaper obtained through the Massachusetts Registry of Motor Vehicles. The Boston Globe created a data set consisting of all traffic tickets written and warnings issued in the state from April 1, 2001 through May 31, 2001.[16]

The data set includes all individual traffic stops by Massachusetts State, Boston, and local police officers. Speeding comprises the majority of citations (56 percent)

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[15] Another alternative hypothesis is that out of state drivers do not know what constitutes a typical fine and are thus less likely to contest the ticket. However, lacking knowledge may also make them more likely to contest the ticket. Further this knowledge hypothesis predicts that in-state drivers are treated equally by the police as they all have similar levels of knowledge. Both the opportunity cost of contestation and voting model predict that in-state drivers are treated differently, depending on their location of residence or distance to the traffic court.

[16] These records were collected by police officers throughout the state in compliance with a requirement of the Massachusetts Legislature, Chapter 228 of the Acts of 2000. The act required the Registry to collect race and sex information from tickets and warnings for a one-year period beginning April 1, 2001. The Massachusetts Registry, however, entered information on warnings into a database for only the two months, citing a lack of funds from the Legislature.

followed by failure to stop (16 percent) and by not displaying an inspection sticker (4 percent). We will focus on traffic citations due to speeding. Speeding citations are more comparable to each other than to other types of offenses, and allow for a quantitative comparison of the relative magnitudes of the violations. We exclude Boston from our analysis. This allows us to focus on citations issued by officers connected to specific municipalities, where a share of the fine revenue generated accrues to the local government.[17] In our data set all traffic stops due to speeding resulted either in the issuance of a speeding citation which carries a fine, or in an official warning.

After having stopped a driver for speeding police officers first decide whether to issue a warning or a fine. If they decided to fine, they subsequently determine the amount of the fine. We model the decision process as to whether to issue a fine with

(9) $\text{Cite}_{ijk} = \beta_0 + \beta_2 \mathbf{Fiscal}_k + \beta_3 \mathbf{DriverX}_{ijk} + \text{Officer}_j + \varepsilon_{ijk}$

The Cite_{ijk} indicator variable measures whether a driver *i* received a fine or a warning from officer *j* in municipality *k*. The indicator is defined as one if the driver is fined and zero if the driver receives a warning. A warning is an officially documented issuance, as opposed to a citation with a fine of zero dollars.[18] To account for the various propensities and preferences idiosyncratic to the individual officers we include officer effects in some specifications.[19] We estimate equation (9) as a probit model when we do not include officer effects, and as a random effects probit model when we include these effects. The random effects model is appropriate when the effects are uncorrelated with

[17] Boston is composed of several neighborhoods, each with its own police department, but with greater overlap of enforcement. The connection of a neighborhood to revenue from its police department, however, is unclear, as it would appear that Boston revenues flow into one pool. Fiscal information can not be reliably connected to departments and jurisdictions.
[18] Observations indicating a fine was issued, but with a corresponding amount of zero, were dropped from the analysis as reflective of data error.
[19] An officer code allows for identification of individual officers. However, no other information about the officer is included in the data set.

the other covariates in the regression. The assumption that driver characteristics are uncorrelated with officer effects seems reasonable. A fixed effects model allows for a correlation between the effect and other covariates, but since local officers tend to patrol only in their own towns, fixed effects for local officers are perfectly co-linear with municipality characteristics.

The **Fiscal** vector contains variables indicating whether a municipality rejected a tax increase via an override referendum and the value of its property tax base. Failure to pass an override referendum is our measure of slack. Lower slack increases the marginal value of traffic fines.

Out of town drivers have incentives to avoid municipalities that impose high fines. Many tourists are out of state drivers and a reputation for frequent fines may reduce the attractiveness of the area. Tourists generate revenue for local businesses, and thus indirectly for the local government through higher tax revenues. Thus, higher revenues from tourists lessen the incentive to impose fines. For this reason we include a tourism variable, measured as the percent of the municipality's employment that falls within the hospitality industry.

The **DriverX** vector includes driver characteristics, such as a measure of whether the driver is from out of town and whether the driver is from out of state. In our specification we code the out-of-town variable to equal one when the driver is from out of town. It takes the value of one if the driver's license indicates that the driver is from a different municipality than the municipality in which he or she was stopped.[20] The out-of-state variable is a subset of the out-of-town variable and equals one if the driver is

[20] For less than half percent of all observations from the original set a vehicle bears an out of state license plate, but whose driver's license indicates they are town residents. Due to the ambiguity how to classify these drivers, we dropped these observations from the analysis.

from out of state. The point estimate on the out-of-state variable measures whether out of state drivers are more likely to receive a fine relative to drivers who reside outside of the town, but inside the state of Massachusetts. The left out category is drivers who reside in the town where the ticket is issued.

The inclusion of the out-of-town and out-of-state variables is motivated by our model which predicts that drivers who have a higher opportunity cost of appealing the ticket in court will face a higher likelihood of a fine. Assuming that the court of jurisdiction is in the town where the ticket was issued, this model predicts that being from out of town increases the likelihood of receiving a fine and, additionally, being from out of state increases this likelihood even more. As described below, we will also employ a "distance to court" measure to test the opportunity cost model. The alternative model, hypothesizing that politicians issue traffic tickets to non-voters, predicts that the probability of being fined is higher for out of town drivers, but does not predict that out of state drivers face a higher probability of being fined than out of town drivers who reside in Massachusetts.

As a substitute for the aforementioned out of state and out of town indicators we also develop an additional measure for the distance from the driver's residence to the court of jurisdiction. In Massachusetts there are 62 districts courts that hear cases on traffic fines. Since we have information on the residence of the driver, we can calculate the distance between the court of jurisdiction and the driver's residence.[21]

[21] Distance is calculated based on the distance between the court of jurisdiction (with depends on where the traffic stop occurred) and the zip code listed on the driver's license. For drivers who reside in the same zip code as the zip code address as the court, and for drivers with less than 5 miles of distance from their residence zip code to the court we imputed the distance as 5 miles. This is because even if drivers reside in the same zip code as the court, the distance that has to be traveled is greater than zero.

Our data set allows us to distinguish whether the traffic stop was made by a local officer or by a state trooper. For local officers both the vote maximizing politician hypothesis and the opportunity cost hypothesis predict that in-town drivers receive less frequent fines. The availability of traffic stops by state troopers allows us to distinguish between these two hypotheses.

The opportunity cost hypothesis applies to all police officers. In contrast, since the employer of state troopers is the state government, the political economy hypothesis implies that state troopers discriminate only between out-of-state drivers and in-state drivers, while local police discriminates between drivers who reside in the community where they are stopped and those who do not. Further, the vote maximizing hypothesis implies that only local officers issue fines based on local fiscal conditions. As discussed in more detail later, to test these hypotheses we will include interaction effects between state troopers and the out-of-town and out-of-state indicators as well as between state troopers and local fiscal conditions.

Other driver characteristics included in the **DriverX** vector is a variable measuring the miles per hour over the posted speed limit. Additionally, we include the age of the driver, and indicator variables for the race and the gender of the driver. This allows for testing whether officers are discriminate between population groups. To the officer, the cost of discrimination is close to zero, and thus evidence for discrimination may be more likely to be found here, than, for example in businesses that "pay" for racial or gender discrimination through lower profits. We will also include an interaction between age and female, to test whether young females are less likely to receive a fine than males and older females.

Our model implies that local police officer ticketing behavior is a function of the local fiscal situation, such as slack in the budget, the property tax base, and the degree to which the municipality's finances depend on out of town drivers, as measured by tourism. State troopers' incentives, however, are not dependent on the finances of the municipality but on those of the state. We estimate one set of specifications using only stops by local police officers, and a second set of specifications using stops by local and state officers Our model predicts that local slack in the budget, tourism, and the property tax base have an effect on local officer, but not state trooper, behavior. To test this prediction the specifications based on local and state officers include interaction effects between a state officer indicator and municipality variables.

To estimate the determinants of the speeding fine amount, we estimate a Heckman selection model (Heckman 1979).

(10) $\text{Cite}_{ij} = \beta_0 + \beta_2 \mathbf{Fiscal}_j + \beta_3 \mathbf{DriverX}_{ij} + \beta_4 \mathbf{CDL} + \varepsilon_{ij}$

(11) $\text{FineAmount}_{ij} = \beta_0 + \beta_2 \mathbf{Fiscal}_j + \beta_3 \mathbf{DriverX}_{ij} + \mu_{ij}$

The unit of observation is driver *i* stopped in municipality *j*. The Heckman model allows for a correlation of the error terms in the regression for whether a citation occurred and for the amount of the citation. We estimate this model via maximum likelihood. We include the same covariates in the $\mathbf{Fiscal}_j$ and $\mathbf{DriverX}_{ij}$ vectors as in equation.

To identify the Heckman selection model, we use an indicator variable for whether the driver has a commercial driver's license (**CDL**). A commercial driver's license is a signal that the driver's employment is dependent on his capacity as a vehicle operator. If drivers with a commercial drivers' license receive a ticket, it can cause the loss of their employment and impact their future income, either because employers believe that drivers with a moving violation are more likely to be involved in accidents costly to the firm, or because the accumulation of points leads to the suspension of the driver's license. Thus, the police officer may be more reluctant to issue a ticket to drivers with a commercial license. For identification, one needs to assume that the mere ownership of a commercial driver's license is unrelated to the amount of the speeding fine. This seems like a reasonable assumption. Once the police officer has made the decision to issue a ticket, it seems the officer has little incentive to lower or increase the fine relative to other drivers.

V. Results

Regression results from the probit model of whether a driver receives a fine are presented in Table 2. A fine is coded as one, a warning as zero, and the reported point estimates are marginal effects. The probit model does not include officer random effects. Standard errors are clustered by municipality in all regression specifications. Column 1 shows that a driver who resides outside of the municipality where he was stopped has a 10 percent higher probability of receiving a fine from a local officer as opposed to a driver who resides in the municipality. If the driver resides out-of-state this probability increases by an additional 10 percent, raising the probability of a fine to 20 percent. The out of town effects are consistent with both the opportunity cost and voting hypotheses. The positive and statistically significant coefficient on the out of state variable is only predicted by the opportunity cost hypothesis. [22]

[22] An alternative explanation to the voting explanation that in-town drivers are less likely to receive a citation is that local police officers know local drivers, have repeated interactions with them, and are more lenient to them, while local officers like to signal a though law enforcement rules to out of town drivers. However, this interpretation is not consistent with the finding that local police are more likely to give a citation to drivers from out of state than to drivers who reside in state but not in their town. To examine the

Column 5 substitutes a variable measuring the distance (in miles) to the court of jurisdiction for out-of-town and out-of-state variables.[23] Distance is statistically significant and quantitatively important. A one log point increase in distance increases the likelihood of a fine by 3 percent. These results further bolster the hypothesis that local police officers are more likely to issue a fine to drivers who have a higher opportunity cost of contesting the fine.[24]

Columns 2 and 4 include additional observations for drivers who were stopped by state troopers, as well as additional regressands for the interactions between state trooper and the out-of-state and out-of-town indicators. The point estimate on the state police indicator is negative and not statistically significant (Table 2, column 2). The estimate on the state police and out-of-town driver interaction variable is statistically insignificant. However, the point estimate on the interaction of state trooper and out of state driver indicates that an out of state driver has a 28 percent higher probability of receiving a fine than an in state driver. The reported estimates lend support to the prediction that state troopers are more likely to issue a speeding ticket to out of state drivers, but not to the prediction that state troopers fine all Massachusetts residents with equal probability.[25] In

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competing hypothesis that local officers are more lenient to locals because they know them, we also estimated specifications with local police only using only municipalities with more than 50,000 inhabitants where it is less likely that the police officer knows the local driver. Consistent with our reported specifications, we find that local police is more likely to fine out of town drivers, and even more likely to fine out of state drivers.

[23] We computed distance to court based on the zip code of the driver's residence. The number of observations in the specifications with court distance is slightly lower than in the other specifications because some observations had missed the zip code of the driver's residence.

[24] Given the hypothesis that the probability of appeal is lower the longer the distance to court, the expected revenue of a ticket increases with distance. Thus issuing more tickets to those living farther away from court could be consistent with the actions of a revenue maximizer. However, at any traffic stop a police officer's effort of issuing a ticket is likely higher than the expected gain through promotions. Thus the lower probability of appeal is important to officers as a criteria because this is an indicator of future work effort, rather than revenue maximizing by using the distance criteria.

[25] This is because the interaction between the state trooper and out of town variable is not statistically significant. If state troopers would treat all Massachusetts residents equally, this point estimate would have

these results the voting hypothesis finds partial support, while both the point estimates on the state trooper interactions are consistent with the opportunity cost hypothesis. This is further validated by the results in Column 6, which interacts distance to court with state troopers. The coefficient on the interaction effect is positive, suggesting that while a driver has a 3 percent higher probability of being fined for each distance log point when stopped by a local police officer, this probability increases to 6 percent when stopped by a state trooper.

The point estimate on the override loss variable shows that drivers have a 28 percent higher probability of being fined when they are stopped in municipalities where voters rejected an override referendum, i.e. they rejected an increase in taxes (Table 2, column 1). This finding is consistent with our model's prediction that less slack in the town budget leads to higher speeding fines.

An interaction between state troopers and an override vote failure is included in column 2. If state police do not respond to local conditions, perhaps because they are not employed by the town but by the state, a negative coefficient on the interaction variable is predicted. Column 2 shows a negative point estimate on the interaction variable, but the point estimate is not statistically significant applying a two-tailed test.

Columns 3 and 4 report specifications that include the interaction between the override loss variable with the out-of-state and out-of-town variables. The point estimates on the interaction effect between override loss and out-of-town drivers are large and statistically significant, while the magnitudes of the coefficients on out-of-state and out-of-town variables remain very similar to those in the previously discussed

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been negative and statistically significant, and of the same magnitude as the coefficient on the out-of-town variable.

specifications. In municipalities that had a failed override vote, out of town drivers face a 28 percent higher probability of being fined. This estimate is statistically significant at the five percent level. The finding on override loss and the interaction effect in columns 3 and 4 shows that the results on override loss in columns 1 and 2 are driven by the fact that drivers from out of town are more likely to receive a speeding fine when they drive in towns where an override referendum failed. The finding that drivers from out of town have a higher likelihood to receive a fine when they are stopped in a town with failed override referendums supports the voting model and the hypothesis that taxes are exported.

Column 4 (as well as columns 2 and 6) includes an interaction effect between state troopers and the override loss variable. The point estimate on this variable is negative and statistically significant at the 10 percent level. This shows that state troopers are much less likely than local officers to react to a failed override referendum by ticketing more, offering further evidence that these results are due to incentives generated by local political economy.

The importance of local public finance on the likelihood of being fined is also documented by the negative impact of per capita property values across all specifications in Table 2. Higher assessed property values which are associated with a larger tax base are associated with a lower probability of being fined. State troopers are less likely to react to a larger tax base by reducing the probability of a fine, but the point estimates on the interactions between property value and state troopers are not statistically significant.

All of the previously discussed results were derived controlling for the speed of the vehicle, and for driver characteristics. Those estimates show that greater speed in excess of the legal limit increases the likelihood of a fine. This reflects the legal framework within which police officers operate and is consistent with the theory of optimal deterrence.

The estimates on the race variables show that Hispanics are more likely to be fined, while the data do not show any discrimination against blacks. Part of the explanation for the latter finding may be that police officers could have been aware of the data collection effort by the state, and thus were especially careful not to discriminate against black drivers.[26]

Age and gender are further determinants of the likelihood of a speeding ticket. The likelihood of a fine decreases with age, and females are less likely to receive a fine. The interaction effect between the gender variable and age shows that females are more likely to receive a citation when they are older. Ceteris paribus, young females have the lowest probability of receiving a speeding ticket. The coefficients on female and the interaction between female and age show that the benefit of being female, in terms of reducing the likelihood of a fine, disappears around age seventy-five.

Table 3 reports random effects probit regressions using the same specification as in Table 2, but with officer random effects, while continuing to allow for clustering by officer. The point estimates measure how police officers react to driver and municipality characteristics, holding each officer's propensity to ticket constant.

In the regressions with local officers the point estimates on out of state and out of town drivers remain positive and statistically significant and the implied marginal effects are similar to those in Table 2. Being out of town but in-state increases the likelihood of

[26] We also examined the data using only observations when cars were stopped at night, because officers are less able to identify the race of a driver from a distance without the benefit of daylight. The night time selection produced no significant changes in the estimates on either of the race variables.

being fined by 10 percent, and being out of state increase the likelihood of a fine by another 10 percent (Table 3, column 2). Similar to the probit model reported in Table 2, these results lend support to the opportunity cost hypothesis.

Columns 5 and 6 present models that substitute the distance to court variable for the driver location indicator. The opportunity cost hypothesis still finds support, as the point estimate on log distance to court remains positive and statistically significant for both local police and state troopers. With each point of log distance, the likelihood of a fine is higher for a driver stopped by a state trooper than one stopped by a local officer.

Fiscal variables continue to have a statistically significant impact on the likelihood of a fine. Fines remain less likely in towns with a high property tax base. The point estimate on the override referendum failure variables remains positive and is statistically significant at the 1 percent level (Table 3, columns 1 and 2). The interaction of the override loss variable with residing outside of the municipality remains positive and statistically significant as in Table 2 (Table 3, columns 3 and 4). This is further evidence that police officers fine out of town drivers when an override vote fails and lends support to the hypothesis that local politics and public finance are determinants of traffic tickets.

Columns 7 and 8 include hospitality employment variables. Since data on hospitality employment is not available for many municipalities, the data set has only about fifteen percent of the observations from the previously discussed data. The results show a negative (Tables 2 and 3) and statistically significant (Table 3 only) point estimate on hospitality employment indicating that fines are less frequent as dependence on tourism related business increases. The results are statistically significant only when the model includes officer random effects.[27]

Column 8 of Table 3 adds an interaction variable between hospitality employment and being an out of state driver. The point estimate is negative and statistically significant, showing that fines are even less frequent for out of state drivers where tourism is more important to the local economy. The finding is consistent with the hypothesis that municipalities do not want to discourage tourists from visiting and potentially endanger future tourism revenues.

The remaining control variables in Table 3 have a similar effect on the likelihood of a fine as in Table 2. Hispanics, younger individuals and males have a significantly higher likelihood of receiving a fine. The point estimate on black drivers is still not statistically significant.

Table 4 presents Heckman selection model estimations using the dollar amount of the fine as the dependent variable. The outcome equation for the fine amount includes the same variables as the selection equation, except for a commercial driver's license (CDL) indicator. Results from the selection equation are reported in the appendix. As predicted, we find that drivers are less likely to be fined when they have a commercial drivers' license. The point estimate of -0.26 on the CDL variable in the first column of the appendix implies an approximately 10 percent reduction in the probability of receiving a citation.

The dependent variable for the outcome equation is the log fine. In most cases, the point estimates have the same signs as in the previously discussed regressions in Tables 2

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[27] However, the point estimate on hospitality employment is negative and statistically significant in the first step probit of the Heckman model.

and 3. Out of town drivers pay a 4 percent higher fine and out of state drivers pay a 13 percent higher fine when stopped by a local officer (Table 4, columns 1 and 3). A fine issued by a state trooper is 8 percent higher for out of town drivers than for in town drivers. The interaction effect between state police and out of state is not statistically significant. However, since state troopers charge all out of town drivers more than local police, an out of state driver pays a 16 percent higher fine when stopped by a state trooper (Table 4, columns 2 and 4).

These results are consistent with the hypothesis that police are writing larger fines for those drivers who live farther away from the court of jurisdiction. The point estimates on the distance-to-court variable has the hypothesized positive sign and are statistically significant. Each point of log distance is associated with a 3 percent higher fine when a local officer issues a ticket and with a 4 percent higher fine when a state trooper issues a ticket.

The point estimate on override failure is statistically significant in columns 1, 2, 4 and 5 of Table 4, suggesting an up to 10 percent larger fine when there is little slack in a town's budget. In contrast to the model explaining whether a driver was fined, the interaction variable between out of town driver and override loss is not statistically significant (Table 4, column 3 and 4). However, override loss and the aforementioned interaction variable are jointly statistically significant at the two percent level, indicating that out of town drivers receive a higher fine than local drivers.[28]

While property value was important in determining whether a driver was fined, the municipality property tax base does not seem to affect the amount of the fine. The

[28] Further, the point estimates of override loss, override loss *OT, and override loss *OS are also jointly significant at the five percent level.

point estimate is statistically significant with the predicted negative sign in only in one specification (Table 4, column 8). Here the point estimate on the interaction between state police and police and property value also has the predicted positive sign and is statistically significant, showing that local fiscal conditions are of less importance for state police in their decision how much to fine.

The hypothesis that smaller fines are issued in tourist towns finds no support. In fact, the results show that although the probability of a fine is smaller in tourist towns, as indicated by the negative coefficient on hospitality employment in the selection equation (see Appendix), conditional on being issued a fine, the amount fined is higher in tourist towns, although this is not statistically significant in column 9 and statistically significant at the ten percent level in column 8 of Table 4.

As predicted, drivers operating in greater excess of the speed limit receive a higher fine. Hispanics are charged up to 5 percent higher fine amount than whites. Blacks are charged less than whites, but for the most part, the point estimates in Table 4 are not statistically significant. The signs of the point estimates on sex and age mirror those in the regressions that explain whether a driver receives a warning. Fines for females are approximately nine percent lower, and in most specifications a one percent increase in age raises the fine by between 2 and 3 percent.

In Table 5 we employ specifications that run a horse race between the opportunity cost and voting hypotheses of traffic enforcement. These regressions include a separate measure for whether the driver lives in the municipality where the driver was stopped and the travel distance from his or her residence to the court where the ticket can be contested. Besides these variables, the regressions with only local officers include the same controls as in column 1 of Tables 2, 3, and 4. The estimates on these variables are not reported, since they are similar to those estimates already reported. When the specifications include traffic stops by both local and state officers, the controls are the same as in column 2 of Tables 2, 3, and 4 and the point estimates on these controls are also similarly not reported. In Table 5, the first 3 columns are specifications corresponding to the probit model in Table 2. The next three columns are based on a random effects model, similar as Table 3. And the final three columns are based on the Heckman specifications, similar as Table 4.

Column 1 of Table 5 includes an indicator for whether the driver is a local resident and the distance of the driver's residence to the court where the ticket could be contested. This specification uses traffic stops by local officers only. Both point estimates on driver location and distance are statistically significant. In-town drivers have a 10 percent lower probability to receive a fine than out of town residents, supporting the voting hypothesis. The opportunity cost hypothesis also finds support as each distance log point increases the probability of a fine by 2 percent.[29] These results are robust to the inclusion of officer random effects (Table 5, column 4).

Column 2 and 3 in Table 5 add traffic stops made by state troopers. The positive interaction term between in-town drivers and state troopers shows that state troopers favor in-town drivers less than local police, although the difference in favorable treatment is not statistically significant. They also react to each log point distance with a higher

[29] If local drivers have less income and police issues lower fines to drivers with less income, we may find that local drivers have a lower likelihood to be fined. Our data do not have an income measure, but for about sixty percent of our observations we have three categories of age (new, old and older), and the make of the vehicle. When adding indictors for vehicle make and age group, serving as a measure of income, we found that our reported results are robust to this alternative specification.

probability of a fine than local officers. Column 3 adds an interaction term between out of state-drivers and state troopers. The voting hypothesis that state troopers have the highest likelihood of issuing a fine when they stop out of state drivers finds support, and controlling for this effect, the estimates show that state troopers react to each log mile distance similar as local officers.

The opportunity cost hypothesis finds support within the ranks of both state troopers and local officers. The voting hypothesis also finds support because state troopers are more likely to fine drivers from out of state even controlling for distance to court (Table 5, columns 3 and 6). However, we also found that state troopers favor local drivers relative to other drivers from Massachusetts (the left-out category in Table 5 is Massachusetts out of town drivers). The magnitude of the latter effect, however, diminishes when we include officer random effects (Table 5, column 5) with local police now having a 6.6% lower probability of issuing a fine to locals and state troopers having a 2.5 percent lower probability.

The last three specifications examine the fine amount using the Heckman selection model. Those findings go in the same direction as the previously discussed findings. For local officers, both the opportunity cost and voting hypothesis find support. State officers issue higher fines to residents from out of state, and both local and state officers issue a 3 to 4 percent higher fine for each log point distance to court.

A final implication of the voting model that we examine is based on the population size in a municipality. This test addresses the concern that the finding that local police favors local residents can not only be explained by the voting hypothesis, but also by the hypothesis that in small towns police have developed personal relations with residents, and may be more lenient with those drivers they have befriended. To address this issue we control for town size using municipality fixed effects in a linear probability model that explains the likelihood of a fine as opposed to a warning. These fixed effects control for town population and thus the probability that the in some town, citing officers are more likely to have personal ties to the local drivers being stopped.

The voting hypothesis has the further implication that police are less likely to fine those locals whose vote matters more in the next election. In small towns voters have a higher likelihood of being decisive than in larger towns, and as such we predict that locals have a lower probability of being fined in smaller towns. To test this hypothesis, we will estimate the regression using the aforementioned municipality fixed effects, and estimate separate slopes for the intown variable based on four categories of town sizes. The first category is the first quartile of towns in terms of population (less than 12,000 inhabitants), the second category the second quartile (between 12,000 and 21,000 inhabitants), the third category the third quartile (21,000 to 40,000 inhabitants), and finally a fourth category for towns with more than 40,000 in population.

Regression results are shown in Table 6. Controlling for the heterogeneity of police officers knowing locals via municipality fixed effects, we find in column 1 that locals have a five percent lower likelihood of receiving a ticket, while the sign on distance to court remains positive and statistically significant. Column 2 estimates different slopes for the intown variable based on the four categories of town sizes. As predicted by the voting hypothesis, the smaller the town, the more likely is the officer to issue a warning to a local driver. The point estimates are monotonically decreasing, with local drivers in the smallest town having the highest probability of receiving a warning.

Columns 3 and 4 estimate the same set of regressions for state troopers. Here we add the variable for out of state drivers since we predicted and found that troopers issue more fines to out of state drivers, but results are not sensitive to its inclusion. Results in columns 3 and 4 strengthen support for the voting hypothesis. We do not find that state troopers favor local drivers over other Massachusetts drivers as predicted by the voting hypothesis. Moreover, state troopers' likelihood of issuing a ticket is not affected by town size, as predicted by the voting hypothesis. As in previous tables, we also find support for the opportunity cost hypothesis.

We had predicted that state troopers treat intown drivers similar as other Massachusetts drives. Table 6 column 3 shows that with town fixed effects the point estimates on intown drivers for the state trooper regressions are statistically insignificant, showing support for the voting hypothesis. Without town fixed effects the point estimate on intown drivers would have been negative and statistically significant, consistent with some of the results in the previous tables. The comparison of these two specifications shows that controlling for town effects is important for disentangling the increasing likelihood that officers will personally know drivers as town size diminishes from the voting hypothesis. However, since these effects do not allow for the inclusion of town specific characteristics, such as the override referendum, we have not included them in previous regressions.

VI. Conclusions

Miles per hour in excess of the speed limit is neither the sole determinant of whether an individual is fined, nor the dollar amount one is fined. An important, and consistent, determinant of citations and the size of their accompanying fine is whether the driver is a resident of the municipality where the speeding occurred. If drivers reside out of state, they face a higher probability of a fine and a higher fine than if they were to reside in state. Drivers who face a higher cost to appeal a ticket are more likely to receive a citation and receive a higher fine. The coefficients on the distance between the location of the court where the ticket can be contested and the residence of the driver are statistically significant in all specifications. In many specifications, both state troopers and local officers ticketing behavior respond similar to this measure of distance. In some specifications we were able to distinguish empirically between the opportunity cost hypothesis and the hypothesis that fines are disproportionately levied on non-voters. Acceptance of one hypothesis does not necessarily rule out the other hypothesis. We find that police officers prefer to issue fines to those drivers who have a higher opportunity cost of contesting the fine while also working as agents of revenue-maximizing principals and effectively "exporting" taxes to drivers who are not local constituents.

The data supports the hypothesis that local economic characteristics are one of the determinants of traffic fines. Traffic fines are more frequently imposed in those municipalities where revenues from property taxes are lower. Fines are also more frequent when voters rejected an override referendum to temporarily increase the limit on property tax revenue. This is consistent with our model that officers will issue more frequent and larger fines when the net impact of revenue raised through speeding fines is greater and when other sources of revenue are restricted.

While local officers are more likely to issue a fine and issue a higher fine when voters failed to pass an override referendum, state officers' responses to these fiscal constraints were muted. This finding reflects that the incentives of state officers differ from those of local officers.

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Table 1. Variable Summary Statistics

Variable	Analysis of Citations (N=64036)		Analysis of Fine $Amount (N=29416)	
	Mean	Std. Dev.	Mean	Std. Dev.
Fine Amount / $			122.24	56.12
Citation Issued = 1, 0 otherwise	0.459	0.498		
Out of State Driver = 1, 0 otherwise	0.156	0.363	0.225	0.418
Out of Town Driver = 1, 0 otherwise	0.774	0.418	0.853	0.354
Override loss = 1, 0 otherwise	0.020	0.139	0.027	0.163
Distance to Court (miles)	52.09	232.91	75.66	284.16
Hospitality employment (percent of total employment)+	3.783	1.179	3.479	1.027
Mph over speed limit	15.143	5.039	17.082	5.748
Property value (per capita)	89,070	52,437	81,408	49,919
Black = 1, 0 otherwise	0.044	0.206	0.051	0.220
Hispanic = 1, 0 otherwise	0.035	0.183	0.047	0.211
Female = 1, 0 otherwise	0.391	0.487	0.331	0.471
Age	35.56	13.51	33.52	12.72
State Police = 1, 0 otherwise	0.273	0.446	0.456	0.498
Commercial Drivers License = 1, 0 otherwise	0.029	0.169	0.023	0.149

Notes:
+ Hospitality employment summaries relates to 10698 observations in the citation data and 5934 observations in the fine amount analysis.
Hospitality employment % is the percent of the municipality that is employed in the hospitality sector as defined (Source: 1997 Economic Census).
Override loss is a dummy variable for the failure of a budget override vote for the 2001 fiscal year.
Property value per capital is value as assessed by the local government. (Source: Massachusetts Department of Revenue).

Table 2. Probit – Marginal effects: Determinants of Citation Issued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Out of State (OS)	0.099** (0.017)	0.104** (0.018)	0.099** (0.017)	0.104** (0.018)			0.244* (0.096)	0.147 (0.039)
State Police * OS		0.060* (0.029)		0.060* (0.029)				
Out of Town (OT)	0.099** (0.013)	0.112** (0.014)	0.096** (0.013)	0.109** (0.014)			0.063* (0.029)	0.069* (0.028)
State Police * OT		0.017 (0.028)		0.019 (0.028)				
State Police		-0.383 (0.561)		-0.386 (0.560)		-0.400 (0.549)		-0.963** (0.132)
Log Distance to Court					0.033** (0.006)	0.036** (0.007)		
State Police * Log Distance						0.031* (0.013)		
Log mph over	0.521** (0.051)	0.652** (0.042)	0.522** (0.051)	0.652** (0.042)	0.520** (0.052)	0.649** (0.043)	0.595** (0.109)	0.626** (0.070)
Override loss	0.279** (0.088)	0.273** (0.079)	0.024 (0.074)	0.034 (0.076)	0.294** (0.090)	0.286** (0.080)		
Override loss * State Police		-0.156 (0.108)		-0.175 (0.108)		-0.165 (0.110)		
Override loss * OS			-0.005 (0.049)	0.0004 (0.053)				
Override loss * OT			0.281* (0.120)	0.267* (0.105)				

Log Hospitality Employment							-0.183 (0.133)	-0.194 (0.137)
Log Hospitality Employment *OS							-0.111 (0.076)	
Log Hosp. Emp. * State Police								-0.098 (0.321)
Log Prop. Value (per capita)	-0.146** (0.041)	-0.162** (0.045)	-0.146** (0.041)	-0.162** (0.045)	-0.144** (0.041)	-0.159** (0.046)	-0.265+ (0.145)	-0.267+ (0.147)
Log property value * State Police		0.076 (0.064)		0.076 (0.064)		0.072 (0.065)		0.221 (0.191)
Black	0.009 (0.026)	0.003 (0.025)	0.010 (0.025)	0.004 (0.025)	0.014 (0.024)	0.007 (0.023)	-0.012 (0.037)	-0.021 (0.038)
Hispanic	0.146** (0.026)	0.116** (0.023)	0.146** (0.026)	0.115** (0.023)	0.149** (0.026)	0.119** (0.023)	0.093+ (0.056)	0.055 (0.046)
Female	-0.354** (0.040)	-0.335** (0.041)	-0.355** (0.040)	-0.335** (0.041)	-0.335** (0.040)	-0.313** (0.041)	-0.245* (0.108)	-0.236* (0.095)
Log Age	-0.160** (0.011)	-0.166** (0.011)	-0.161** (0.011)	-0.167** (0.011)	-0.151** (0.011)	-0.158** (0.011)	-0.153** (0.029)	-0.156** (0.022)
Log Age * Female	0.087** (0.014)	0.078** (0.013)	0.087** (0.014)	0.078** (0.013)	0.080** (0.014)	0.071** (0.013)	0.061+ (0.033)	0.056* (0.028)
Officers included	Local	Local and State	Local	Local and State	Local	Local and State	Local	Local and State
Clustering by municipality?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46,526	64,036	46,526	64,036	46,498	63,989	7,265	10,698

Standard errors clustered at the municipality level. The dependent variable equals 1 for a citation and 0 for a warning
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 3. Random Effects Probit: Determinants of Citation issued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Out of State (OS)	0.235** (0.025)	0.257** (0.028)	0.235** (0.025)	0.257** (0.029)			0.500** (0.180)	0.168** (0.030)
State Police * OS		0.072+ (0.043)		0.073+ (0.044)				
Out of Town (OT)	0.238** (0.020)	0.248** (0.024)	0.231** (0.020)	0.241** (0.024)			0.083** (0.030)	0.084** (0.028)
State Police * OT		0.010 (0.054)		0.016 (0.054)				
State Police		0.265 (1.369)		0.255 (1.372)		0.191 (1.380)		2.225 (2.773)
Log Distance to Court					0.081** (0.008)	0.086** (0.009)		
State Police * Log Distance						0.053** (0.017)		
Log mph over	1.521** (0.098)	1.681** (0.088)	1.523** (0.098)	1.683** (0.088)	1.526** (0.102)	1.682** (0.089)	1.297** (0.183)	1.365** (0.128)
Override loss	0.542** (0.113)	0.644** (0.124)	-0.067 (0.180)	0.020 (0.167)	0.595** (0.116)	0.695** (0.130)		
Override loss * State Police		-0.403* (0.187)		-0.457* (0.190)		-0.431* (0.197)		
Override loss * OS			-0.007 (0.142)	-0.022 (0.133)				
Override loss * OT			0.680** (0.190)	0.697** (0.189)				

Log Hospitality Employment							-0.644+ (0.332)	-0.676* (0.330)
Log Hosp. Empl. *OS							-0.276* (0.137)	
Log Hosp. Emp. * State Police								0.813* (0.369)
Log property value per capita	-0.237** (0.075)	-0.247* (0.101)	-0.238* (0.076) *	-0.248* (0.101)	-0.238* (0.079) *	-0.254* (0.099)	-0.023 (0.249)	0.002 (0.252)
State Police * Log Prop. Value		0.081 (0.119)		0.081 (0.119)		0.077 (0.119)		-0.207 (0.285)
Black	-0.012 (0.033)	-0.016 (0.031)	-0.011 (0.033)	-0.016 (0.031)	0.002 (0.034)	-0.004 (0.031)	0.010 (0.054)	-0.015 (0.043)
Hispanic	0.180+ (0.106)	0.100 (0.142)	0.179+ (0.107)	0.099 (0.143)	0.178 (0.124)	0.103 (0.151)	0.162** (0.062)	0.121* (0.056)
Female	-1.059** (0.116)	-0.887** (0.105)	-1.062** (0.116)	-0.888** (0.105)	-1.004** (0.117)	-0.834* (0.106) *	-0.543* (0.259)	-0.486* (0.218)
Log Age	-0.462** (0.025)	-0.436** (0.025)	-0.464** (0.025)	-0.437** (0.025)	-0.440** (0.026)	-0.417** (0.025)	-0.345** (0.054)	-0.334** (0.047)
Log age * Female	0.245** (0.033)	0.201** (0.030)	0.245** (0.033)	0.201** (0.030)	0.228** (0.033)	0.186** (0.030)	0.131+ (0.074)	0.114+ (0.062)
Officers included	Local	Local and State	Local	Local and State	Local	Local and State	Local	Local and State
N	46,526	64,013	46,526	64,013	46,498	63,966	7,265	10,698

Standard errors clustered at the officer level. The dependent variable equals 1 for a citation and 0 for a warning
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4 Heckman outcome equation: Fine Amount if a Citation is Issued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Out of State (OS)	0.086** (0.012)	0.080** (0.012)	0.086** (0.013)	0.080* (0.013)			-0.110 (0.085)	0.077** (0.018)
State Police * OS		0.008 (0.014)		0.007 (0.014)				
Out of Town (OT)	0.044** (0.013)	0.038** (0.013)	0.043** (0.014)	0.036** (0.013)			-0.053+ (0.032)	0.022 (0.014)
State Police * OT		0.043* (0.020)		0.044* (0.020)				
State Police		-0.036 (0.391)		-0.036* (0.391)		0.064 (0.376)		-2.661** (0.914)
Log Distance to Court					0.032** (0.004)	0.030** (0.003)		
State Police * Log Distance						0.009** (0.004)		
Log mph over	0.975** (0.025)	0.967** (0.015)	0.975** (0.025)	0.967** (0.015)	0.977** (0.025)	0.966** (0.015)	0.405** (0.121)	0.900** (0.035)
Override loss	0.095** (0.036)	0.081* (0.034)	0.014 (0.074)	0.022 (0.067)	0.104** (0.036)	0.088* (0.034)		
Override loss * State Police		-0.060+ (0.032)		-0.064+ (0.033)		-0.062* (0.036)		
Override loss * OS			-0.003 (0.038)	-0.005 (0.031)				
Override loss * OT			0.088 (0.066)	0.066 (0.060)				

Log Hospitality Employment							0.206+ (0.110)	0.035 (0.059)
Log Hosp. Empl. *OS							0.087 (0.075)	
Log Hosp. Emp. * State Police								-0.155 (0.129)
Log property value per capita	-0.035 (0.031)	-0.026 (0.030)	-0.034 (0.031)	-0.026 (0.030)	-0.038 (0.031)	-0.028 (0.029)	0.118 (0.094)	-0.184* (0.076)
State Police * Log Prop. Value		0.011 (0.035		0.011 (0.035)		0.014 (0.034)		0.271** (0.092)
Black	-0.023 (0.018)	-0.019+ (0.010)	-0.023 (0.018)	-0.019+ (0.010)	-0.022 (0.017)	-0.020* (0.010)	0.008 (0.036)	-0.023 (0.015)
Hispanic	0.048** (0.016)	0.038** (0.011)	0.048** (0.016)	0.038** (0.011)	0.050** (0.016)	0.039** (0.011)	0.065 (0.040)	0.017 (0.018)
Female	-0.095+ (0.055)	-0.090* (0.039)	-0.095+ (0.055)	-0.090* (0.039)	-0.095+ (0.054)	-0.084* (0.039)	0.058 (0.122)	-0.111+ (0.054)
Log Age	-0.034* (0.013)	-0.023* (0.009)	-0.034* (0.013)	-0.023** (0.009)	-0.031* (0.013)	-0.021* (0.009)	0.122** (0.035)	-0.009 (0.018)
Log age * Female	0.014 (0.015)	0.015 (0.011)	0.014 (0.015)	0.015 (0.011)	0.013 (0.015)	0.014 (0.011)	-0.008 (0.034)	0.027+ (0.015)
Officers included	Local	Local and State	Local	Local and State	Local	Local and State	Local	Local and State
N (uncensored)	16,001	29,416	16,001	29,416	15,986	28,491	3,130	5,934

Standard errors clustered at the municipality level. The dependent variable in the outcome equation is log fines. + significant at 10%; * significant at 5%; ** significant at 1%. The Heckman selection model is estimated using the maximum likelihood estimator.

Table 5 Opportunity cost hypothesis vs. fining non-voter hypothesis

Dependent variable	Whether to fine			Whether to fine			Log fine amount		
	Probit – Marginal Effects			Random Effects Probit - Marginal Effects			Heckman		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
In town	-0.097** (0.013)	-0.111** (0.015)	-0.109** (0.014)	-0.079** (0.007)	-0.095** (0.010)	-0.238** (0.022)	-0.034** (0.014)	-0.022+ (0.013)	-0.028** (0.011)
State Police * In town		0.024 (0.026)			0.024** (0.002)			-0.027 (0.021)	
State Police * Out of State			0.100** (0.024)			0.209** (0.041)			0.048** (0.007)
Log Distance to Court	0.019** (0.007)	0.021** (0.008)	0.021** (0.008)	0.016** (0.003)	0.020** (0.004)	0.052** (0.009)	0.028** (0.004)	0.038** (0.004)	0.036** (0.004)
State Poli * Log Dist		0.041** (0.013)	0.019 (0.014)		0.027 (0.007)	0.022 (0.020)		-5.1E-4 (0.005)	-0.006 (0.005)
Other controls in columns 1 and 2 of previous tables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Officers included	Local	Local and State	Local and State	Local	Local and State	Local and State	Local	Local and State	Local and State
Clustering?	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes
N	46,498	63,989	63,989	46,498	63,989	63,989	15,986	28,491	28,491

Standard errors clustered at the municipality level, except for the random effects probit model, where standard errors are clustered at the officer level. The dependent variable equals 1 for a citation and 0 for a warning + significant at 10%; * significant at 5%; ** significant at 1%

Table 6. OLS – Probability of fines for local drivers and town size. Municipality fixed effects.

	(1)	(2)	(3)	(4)
	Local Police Officers		State Police Officers	
In town	-0.054** (0.008)		-0.024 (0.015)	
Intown*Town Size 1		-0.129** (0.014)		-0.002 (0.035)
Intown*Town Size 2		-0.060** (0.015)		0.001 (0.042)
Intown*Town Size 3		-0.032* (0.015)		-0.040 (0.025)
Intown*Town Size 4		-0.028* (0.012)		-0.036 (0.022)
Outstate			0.028** (0.008)	0.028** (0.008)
Log Distance to Court	0.011** (0.002)	0.011** (0.002)	0.014** (0.004)	0.014** (0.004)
Driver specific controls as in previous tables?	Yes	Yes	Yes	Yes
Municipality fixed effects?	Yes	Yes	Yes	Yes
Clustering by municipality?	Yes	Yes	Yes	Yes
N	46,498	46,498	17,491	17,491

Ordinary Least Square regressions. Standard errors clustered at the municipality level. The dependent variable equals 1 for a citation and 0 for a warning . + significant at 10%; * significant at 5%; ** significant at 1%

Appendix
Heckman selection equation: Citation Issued. Probit.

	(1)	(2)	(3)	(5)	(7)
Constant	1.598	1.007	1.606	1.465	3.510
	(1.363)	(1.343)	(1.365)	(1.369)	(3.186)
Commercial Drivers License	-0.258**	-0.285**	-0.259**	-0.258**	-0.179**
	(0.045)	(0.036)	(0.045)	(0.045)	(0.041)
Out of State	0.259**	0.258**	0.259**		0.346+
(OS)	(0.044)	(0.045)	(0.046)		(0.178)
State Police * OS		0.146*			
		(0.072)			
Out of Town	0.283**	0.286**	0.275**		0.130+
(OT)	(0.036)	(0.037)	(0.036)		(0.068)
State Police * OT		0.043			
		(0.071)			
State Police		-1.249*			
		(1.794)			
Log Distance to Court				0.090**	
				(0.017)	
Log mph over	1.483**	1.674**	1.484**	1.478**	1.436**
	(0.146)	(0.107)	(0.146)	(0.148)	(0.219)
Override loss	0.719**	0.728**	0.060	0.757**	
	(0.228)	(0.240)	(0.202)	(0.236)	
Override Loss * State Police		-0.387			
		(0.312)			
Override Loss * OS			-0.023		
			(0.131)		
Override Loss * OT			0.732*		
			(0.308)		
Log Hospitality Employment					-0.478+
					(0.271)
Log Hospital Employment * OS					-0.169
					(0.146)
Log Property Value (per capita)	-0.409**	-0.412**	-0.409**	-0.403**	-0.526+
	(0.113)	(0.115)	(0.114)	(0.114)	(0.294)
State Police * Log Prop. Value		0.208			
		(0.159)			
Black	0.028	0.010	0.028	0.041	-0.013
	(0.070)	(0.062)	(0.070)	(0.067)	(0.091)

Hispanic	0.383**	0.293**	0.382**	0.390**	0.175
	(0.064)	(0.059)	(0.064)	(0.064)	(0.118)
Female	-1.041**	-0.863**	-1.044**	-0.974**	-0.540+
	(0.131)	(0.114)	(0.131)	(0.129)	(0.287)
Log Age	-0.435**	-0.408**	-0.437**	-0.408**	-0.348**
	(0.031)	(0.026)	(0.031)	(0.031)	(0.072)
Log Age * Female	0.232**	0.189**	0.233**	0.212**	0.130
	(0.037)	(0.033)	(0.037)	(0.037)	(0.082)
Officer Observations included	Local	Local and State	Local	Local	Local
Clustering by municipality?	Yes	Yes	Yes	Yes	Yes
N	46,526	64,036	46,526	46,498	7,265

Standard errors clustered at the municipality level.; + significant at 10%; * significant at 5%; ** significant at 1%.

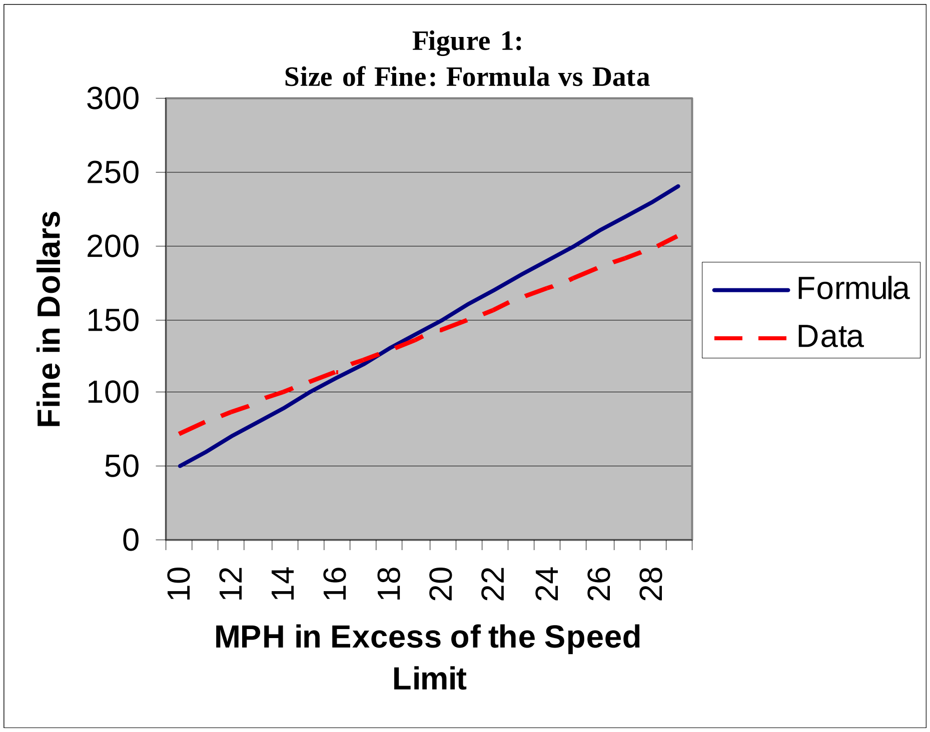
Figure 1:
Size of Fine: Formula vs Data
300
250
200
150
100
50
0
Fine in Dollars
10
12
14
16
18
20
22
24
26
28
MPH in Excess of the Speed Limit
Formula
Data