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Political Economy at Any Speed: What Determines Traffic Citations?

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Can speeding tickets be explained solely by a driver's excessive speed, or could they be seen as serving as supplemental local revenue, or reflecting officer preferences? 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 (Gary S. Becker 1968; Isaac Ehrlich 1996; A. Mitchell Polinsky and Steven Shavell 1992). This view neglects other potential objectives for the police. Police officers are agents of the local or state government; these principals may be concerned about total revenues raised and about voter satisfaction. Furthermore, officers may have personal preferences, with regards to characteristics such as race or gender, which may motivate differential issuance of traffic tickets.

The imposition of traffic fines to increase revenues is reminiscent of William A. 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 (Ronald N. Johnson and Gary D. Libecap 1994). The budget maximizing hypothesis, however, has not been applied to the behavior of police officers engaged in the enforcement of traffic laws, although anecdotal evidence abounds[1]. 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. As police officers' monitoring superiors are elected officials, those officials may also encourage police officers to disproportionately raise revenues from nonvoters as opposed to local, voting citizens.

Further, while there is evidence of racial profiling in the searching of vehicles by officers (John Knowles, Nicola Persico, and Petra Todd 2001), there is little evidence that an officer's personal preferences are an important determinant of whether a driver receives a fine. Recent work on who receives traffic tickets finds a difference in the probability of receiving a warning across race and gender (Bill Dedman and Francie Latour 2003). This study does not, however, hold constant the degree of the offense and other characteristics of the incident.

Our paper presents a framework to analyze the determinants of speeding tickets. We hypothesize that officers are agents of budget maximizing principals and, as such, when deciding whether to issue a fine, will consider their local government's fiscal condition and the driver's ability to vote in local elections. We also hypothesize that because police officers maximize their own utility in seeking favorable work evaluations, they base their decision whether to issue a fine and the fine amount on drivers' opportunity cost, and thus likelihood, of contesting the ticket

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[1] Martine Costello, "The Need for Speed—It Will Cost You!" *CNN Money*, May 24, 2002. http://money.cnn.com/2002/05/22/q_speed_cost/.

in court. We test these hypotheses by analyzing all speeding traffic stops in Massachusetts for a two-month period in 2001.

Using a variety of model specifications, we find support for our hypotheses. Fines for speeding are not solely determined by an objective standard of law enforcement. We find evidence that the likelihood and dollar amounts of fines 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. We show that officers use drivers' differences in opportunity costs of contesting a fine as a criterion for whether to issue a speeding ticket, and, in the event of a ticket, the dollar amount of the fine. We also present evidence that officers are not completely race and gender blind in issuing tickets.

I. Background on Institutions

Our data are 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 drivers' having to pay a fine and points are applied to their official state driving record. Further, drivers' car insurance premiums may increase under insurance rates that are regulated by the state of Massachusetts (B. Glenn Blackmon, Jr., and Richard Zeckhauser 1991). A warning has no consequences. By Massachusetts state law, whether the officer issues a ticket or a warning is at the discretion of the officer.[2]

While the decision of whether to issue a fine or a warning is within an officer's discretion, state law sets an explicit formula for the amount of a fine, which is $\$50 + 10 \times (\text{speed} - (\text{speed limit} + 10))$.[3] 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 fine.

To examine whether officers deviate from the explicit formula, we run a simple regression of the dollar amount of the fine imposed on the vehicle's speed over the posted speed limit. This regression is based on 31,486 observations, using observations where a fine is imposed and a driver's speed is at least 10 miles per hour (mph) over the speed limit. The intercept of this estimate is 3.36, the slope estimate is 6.94 (fines are expressed in dollars and speeding in miles per hour), and both point estimates are highly statistically significant. These results imply that officers, on average, issue a ticket of \$107 for driving 15 mph over the speed limit. The recommended fine according to the statute would have been \$100. For speeds below about 17 mph over the speed limit, officers fine more than the amount suggested in the statute, and above 17 mph they fine less. These simple regression results indicate that officers, on average, deviate from the formula in their decisions of how much to fine.[4]

A traffic citation that 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

[2] Officers' use of discretion under Massachusetts 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 v. 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 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).

[4] Of 31,486 observations for drivers operating at least 10 mph in excess of the limit, 3,453 recorded a fine amount congruent with the formula; 7,410 were below the expected fine; and 20,623 were above it.

the individual appears 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 their tickets may have to travel out of town to attend the court proceedings. Massachusetts has 62 district courts. District court justices are appointed by the governor.

Massachusetts police officers who are employed by a municipality answer to the chief of police, who is appointed for a period not exceeding three years by the elected officials on the governing board. In a Massachusetts town, the governing board is the board of selectmen; in a city it is the board of aldermen. Officials on the governing board are elected by voters of the municipality. By Massachusetts law, the board has the power to form a police department, 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.[6] More generally, board members are the acting executives of the town.

To examine how police budgets, officer salaries, and revenues from fines are related, we estimated regressions using 2005 data from the Massachusetts Department of Revenue. These regressions show a positive correlation between per capita police budgets and revenues from fines and forfeitures. Additionally, minimum and maximum salaries for officers and sergeants positively correlate with the size of per capita police budgets across municipalities. Finally, the size of the per capita police personnel budget is positively correlated with fine and forfeiture revenues.[7] Because revenues are positively correlated with budgets and police salaries, these findings are 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 a referendum called Proposition 2½, which places explicit limits on both the maximum amount of revenue generated through property taxation by municipalities, and the amount that revenue may be increased from one year to the next. Evidence suggests that while limits on personal property taxation have curtailed spending (Katharine L. Bradbury, Christopher J. Mayer, and Karl E. Case 2001; David M. Cutler, Douglas W. Elmendorf, and Zeckhauser 1999), they have also made Massachusetts local governments more dependent on other local sources of revenues.[8] Gary M. Galles and Robert L. Sexton (1998), for example, suggest that increases in nontax revenue may have returned spending to pre–Proposition 2½ levels. Non–property tax revenues include receipts from the motor vehicle excise tax, charges for services, departmental revenue (e.g., libraries), licenses and permits, and fines. Traffic citations fall under the category of fines.[9]

There are limitations, however, placed on revenue generated from fees, licenses, and permits. Municipalities are allowed to recover only 100 percent of the cost of providing fee-based

[5] Any decision reached by a magistrate who is not a justice may be appealed 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] 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.

[7] 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 or the entire police budget. The unit of analysis is a municipality in Massachusetts in 2005.

[8] "Since the passage of Proposition 2½ 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 2½, 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" (Massachusetts Department of Revenue, Division of Local Services, 2006, Best Practices, User Fees: Technical Assistance Section. http://massgov/Ador/docs/dls/mdmstuf/Technical_Assistance/Best_Practices/userfees.PDF, accessed January 23, 2006).

[9] *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.

services.[10] In contrast, no statute or regulation limits revenue accrued from fines. Municipalities retain 50 percent of the revenues collected from traffic fines issued in their jurisdictions, regardless of whether the issuer is a local officer or state trooper.[11] The remainder is allocated to the state treasury and the Highway Fund.

To focus on citations issued by officers connected to specific municipalities, where a share of the fine revenue generated accrues to the local government, we exclude the Boston municipality from our analysis of determinants of traffic fines.[12] In most of the 350 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 per capita, while local receipts and the "all other" category account for $448 and $180 per capita, respectively (State of Massachusetts Department of Revenue).[13]

While Department of Revenue data regarding fine revenue are sparse and incomplete, the two months of speeding ticket data in 2001, on which we base our analysis, allow for a rough measure of annually collected traffic fine revenues. The mean municipality assessed $12,723 in speeding fines during the two-month period reported, which implies $38,171 in annual revenue (and an additional $38,171 for the state, as well). The municipality with the largest total assessment of fines is Sturbridge, whose fines extrapolate to $438,525 annually. For 25 Massachusetts municipalities, these figures are the equivalent of more than 1 percent of their total tax revenue.

If a town government wishes to raise funds from property taxes beyond the levy limit prescribed by Proposition 2½, it has the option to pass an "override" referendum. An override referendum 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).

II. Modeling the Determinants of Speeding Tickets

Economic models of optimal deterrence of unlawful behavior predict that the fine for speeding will increase with the speed of the vehicle.[14] Officers who patrol the roads to deter speeding face a set of incentives that will also determine whether to fine, and the amount to fine, for speeding. These incentives include the disutility of labor, the requirements of their superiors, and their personal sense of obligation to foster safety within their community.

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

[11] "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 ½ of chapter ninety, and forfeitures imposed under the provisions of section one hundred and 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).

[12] 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 is unclear, however, as Boston revenues flow into one pool. Fiscal information cannot be reliably connected to departments or jurisdictions.

[13] These calculations are based on Massachusetts's 350 municipalities and exclude Boston.

[14] The optimal amount of ticketing also depends on the elasticity of speeding to ticketing. If residents have a higher elasticity than out-of-town drivers, then fewer tickets are predicted for out-of-town drivers.

The chief of police is the head of the police department and has the responsibility of monitoring officers. Chiefs of police are appointed and monitored by the town board of selectmen (or city aldermen), and can be fired at will. Local voters, in turn, elect members to the board of selectmen or aldermen. In this institutional framework, fiscal incentives of budget maximizing elected officials can influence the officer's decision making. Based on the incentives and institutional setting faced by police officers, we develop two hypotheses of officer behavior: the "political economy" hypothesis and the "opportunity-cost" hypothesis.

A political economy model predicts that officers respond to the fiscal condition of the government that employs them and to whether the driver is a potential voter in local elections. Local elections decide who is in the local government and thus who is the employer of police officers. If drivers are from out of town, they do not vote in the municipality employing the local officer, and officers have a stronger incentive to fine these drivers than they do the local drivers. This is because local drivers may respond by voting against the current government when they believe that they received a ticket because of a desire to increase the town's revenues. Out-of-town drivers have no such voice in the city's voting booths. The practice of raising revenues from nonvoters is sometimes referred to as "tax exporting" in the local public finance literature (Richard J. Arnott and Ronald E. Grieson 1981; Charles E. McLure 1967).

The political economy hypothesis includes not just the tax exporting hypothesis, but also the hypothesis that the likelihood of fines depends on the local fiscal conditions. Specifically, a Proposition 2½ override referendum indicates that a municipal government anticipates insufficient revenues to support desired spending levels. An override referendum that fails to pass increases the local government's incentive to pursue alternative sources of revenue. We predict that drivers in towns that failed to pass a proposed override referendum face a higher likelihood of a fine, and even more so if the driver is from out of town and does not vote in that town. A political economy model also predicts that lower property values are associated with a greater number of fines, as local governments face greater dependence on nontax revenue in low property value municipalities. Finally, tourists generate revenue for local businesses, indirectly generating additional revenues for the local government through higher receipts from taxes. A reputation for issuing many traffic tickets reduces the attractiveness of the area to prospective visitors and therefore higher revenues from tourists reduce the incentive to impose fines.

The opportunity-cost hypothesis predicts that officers have a higher likelihood of issuing a ticket and issuing a larger fine amount when the opportunity cost for contesting the ticket is higher for drivers. When an officer chooses to issue a fine, the driver has the option of appealing the citation, first to a magistrate and then to a district court judge. A citation is revenue raising if it is uncontested, but a citation that results in a court visit could be revenue lowering. If the ticket is appealed to a judge, the officer will be subpoenaed to appear in court. Quantifiable evidence of officers' performance available to their superiors includes driver contacts and citations. Frequent court attendance reduces the time available for such activities and may reflect poorly on the judgment and performance of the officer. For these reasons, officers have incentives to base their decisions whether or not to issue a fine on the probability of drivers challenging their tickets. Further, appearing in court is potentially unpleasant for the officer.[15] Officers can reduce the likelihood of having tickets challenged in court by issuing tickets only to drivers who are unlikely to contest them, specifically those who have a high opportunity cost of contesting the tickets. Drivers whose residences are farther from the district courthouse bear a great opportunity cost to challenge a fine, and are therefore less likely to challenge their ticket in court. These

[15] Officers receive no additional compensation for appearing in court during regular work hours.

are drivers we predict have a greater likelihood of receiving a citation, and a higher fine in dollar terms.

To test these hypotheses, we model the officer's decision to issue a fine as follows:

$$\text{Cite}_{ijk} = \beta_0 + \beta_2\mathbf{Fiscal}_j + \beta_3\mathbf{DriverX}_{ij} + \text{Officer}_k + \varepsilon_{ijk}. \tag{1}$$

The Cite_{ijk} indicator variable measures whether a driver i received a fine or a warning in municipality j from officer k. We define the indicator 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, which is associated with a fine.[16] To account for the heterogeneity of officers with respect to issuing warnings as opposed to fines, we include officer effects (Officer_k) in some of our specifications.[17] We estimate equation (1) as a probit model, a random effects probit model with officer effects, and a linear probability model with officer fixed effects.[18] The random effects model is appropriate when the effects are uncorrelated with the other covariates in the regression. The assumption that driver and municipality characteristics are uncorrelated with officer effects seems reasonable. The fixed effects model allows for correlation between the effect and other covariates.

If local officers patrol only their own towns, no point estimates on the town-specific fiscal variables can be estimated in the officer fixed effects model, because officer fixed effects are perfectly collinear with the fiscal variables. In our case the point estimates on the fiscal variables are identified by officers writing tickets to drivers in towns that are not in their home town jurisdiction. This may occur when officers pursue drivers from their own town and issue tickets in towns where they finally stop the driver, or when officers are "lent out" for special events to other jurisdictions. Because both events do not occur that often, the point estimates for the fiscal variables are identified by relatively few observations.[19]

The **Fiscal** vector contains variables indicating whether a municipality rejected a tax increase via an override referendum applicable to the operating budget of the 2001 fiscal year,[20] the value of its property tax base, and the percentage of town employment in the tourism and hospitality industry. The **DriverX** vector includes driver characteristics, such as dummies for whether the driver is from out of town or out of state. In our specification we code the out-of-town variable to equal 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.[21] The out-of-state variable is a subset of the out-of-town variable and equals one if the driver is 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

[16] Observations indicating a fine was issued, but with a corresponding amount of zero, were dropped from the analysis as reflective of data error. Analysis of recorded speeds and fine amounts revealed unimodal distributions of both recorded speeds and fine amounts across high- and low-income municipalities.

[17] An officer code allows for identification of individual officers. The data, however, do not include information regarding officer characteristics, such as gender or race.

[18] The fixed effects model is estimated with OLS in light of the inconsistency probit models with fixed effects (Gary Chamberlain 1980).

[19] In our dataset, about 20 percent of local officers have had at least one traffic stop outside their home town.

[20] We coded the override indicator to equal one when the failed override vote took place in the spring of 2000. This date implies that the municipal operating budgets were affected at the time of the citations (the 2001 fiscal year, which runs from July 1, 2000, to June 31, 2001).

[21] In less than half of 1 percent of all observations from the original set, a vehicle bears an out-of-state license plate, but the drivers' licenses indicate they are town residents. Due to the ambiguity of how to classify these drivers, we dropped these observations from the analysis.

drivers who reside outside of the town, but inside the state of Massachusetts. In most specifications the category left out is drivers who reside in the town where the ticket is issued.[22]

To test the opportunity cost hypothesis, we develop an additional measure for the distance from the driver's residence to the court of jurisdiction. In Massachusetts there are 62 district 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.[23] The opportunity cost hypothesis predicts a positive sign on this variable. Other driver characteristics in the **DriverX** vector include the log of miles per hour over the posted speed limit, a dummy for whether the driver operates with a commercial driver's license, the age of the driver, indicator variables for the race and gender of the driver, and an interaction effect between age and gender.

Both the political economy and opportunity cost hypotheses predict that drivers from out of town and out of state will face a higher probability of receiving a fine instead of a warning. We use a number of specifications to test both hypotheses. Several specifications include the distance from the driver's residence to the district courthouse, as well as indicators for out-of-town drivers and out-of-state drivers.

Because the employer of local officers is the local government, we predicted that fines issued by local officers will respond to local fiscal conditions. The employer of state troopers, however, is the state government. State troopers' incentives are to discriminate between out-of-state drivers and in-state drivers, and not between local town residents and out-of-town residents. To test for differences in behavior between local and state police officers, we include interaction effects between several of our control variables and state troopers.

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

$$\text{Cite}_{ij} = \beta_0 + \beta_2\mathbf{Fiscal}_j + \beta_3\mathbf{DriverX}_{ij} + \beta_5\mathbf{CDL}_i + \varepsilon_{ij}, \tag{2}$$

$$\text{FineAmount}_{ij} = \beta_0 + \beta_2\mathbf{Fiscal}_j + \beta_3\mathbf{DriverX}_{ij} + \mu_{ij}. \tag{3}$$

The unit of observation is driver i stopped in municipality j. The Heckman model allows for a correlation of the error terms in equations (2) and (3). We estimate this model via maximum likelihood, including the same covariates in the $\mathbf{Fiscal}_j$ and $\mathbf{DriverX}_{ij}$ vectors as in equation (1).

To identify the Heckman selection model, we use an indicator variable for whether the driver has a commercial driver's license (**CDL**). This variable was included in the $\mathbf{DriverX}_{ij}$ vector in equation (1). A commercial driver's license is a signal that the drivers' employment is dependent on his or her capacity as a vehicle operator. If drivers with a commercial driver's license receive a ticket, it can cause the loss of their employment and affect their future income, either because

[22] Rates of increase in premiums from speeding citations and accidents differ across insurance companies. Since we do not have information on drivers' individual car insurance plans, we cannot control for varying disincentives to unsafe driving created by these differing insurance plans. In the case of Massachusetts, its "Safe Driver Insurance Program" mandates a specific point and premium system through the state's regulated auto insurance program. Thus in-state drivers may face a steeper penalty in raised insurance premiums than out-of-state drivers. Out-of-state drivers may drive faster or slower than Massachusetts drivers, depending on their auto insurance, although their insurance plans also penalize unsafe driving. We control for differences in speed by including a variable measuring miles per hour over the speed limit. If police officers know that Massachusetts drivers face more severe penalties than out-of-state drivers, it may motivate them to issue more warnings instead of fines to Massachusetts drivers.

[23] Distance is calculated based on the distance between the court of jurisdiction (which 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 of the court, and for drivers with fewer than five miles of distance from their residence zip code to the court, we imputed the distance as five 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.

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. Once the police officer has made the decision to issue a ticket, the officer's incentive to impose a lower fine on these drivers relative to drivers without a commercial driver's license is not obvious. For identification, we assume that ownership of a commercial driver's license is unrelated to the amount of the speeding fine.

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 dataset consisting of all traffic tickets written and warnings issued in the state from April 1, 2001, through May 31, 2001,[24] by Massachusetts State, Boston, and local police officers. Speeding comprises the majority of citations (56 percent), followed by failure to stop (16 percent) and not displaying an inspection sticker (4 percent). We focus on traffic citations due to speeding. Speeding citations are more comparable to each other than other types of offenses, and allow for a quantitative comparison of the relative magnitudes of the violations.

III. Results

Our data include all speeding-related traffic stops that resulted in either a ticket or an official warning. Summary statistics are presented in Table 1. In addition to the citation and driver data from the *Boston Globe* dataset, the table shows a number of variables on municipal economic and fiscal conditions: drivers were traveling an average 15 mph above the speed limit, for which about 46 percent were issued a fine; of drivers stopped, 77 percent were not from the municipality they were stopped in, and 16 percent were not from Massachusetts; and the average driver's residence was 52 miles from the district courthouse where a citation appeal would be heard. A comparison of means shows that a local driver has a 30 percent chance of getting a ticket while an out-of-state driver has a 66 percent chance; the average fine for cited out-of-state drivers is \$126 while it is \$118 for cited local drivers. At the same time, stopped out-of-state drivers, out-of-town drivers (but within state), and local drivers all drive 15 miles per hour over the speed limit, on average.

Regression results from the probit model of whether a driver receives a fine are presented in Table 2A. A fine is coded as one, a warning as zero, and the reported point estimates are marginal effects. The first four columns' specifications are estimated by probit; the next four columns are estimated by probit with random effects for police officers. Standard errors are clustered by municipality in all regression specifications.

Column 1 shows that drivers who reside outside of the municipality where they are stopped have an 11 percentage point higher probability of receiving a fine from a local officer, as opposed to a driver who resides in the municipality. If drivers reside out of state, this probability increases by an additional 10 percent, raising the probability of a fine to 21 percent.[25] These findings are consistent with both the opportunity cost hypothesis and the tax exporting hypothesis. The tax exporting hypothesis finds support because fines are more likely for out-of-town drivers. The opportunity cost hypothesis finds support because out-of-state drivers have a higher probability

[24] 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 Massachusetts Registry to collect race and sex information from tickets and warnings for a one-year period beginning April 1, 2001. The Registry, however, entered information on warnings into a database for only the two months, citing a lack of funds from the Legislature.

[25] These results suggest that drivers do not adjust their behavior to the extent that the probabilities of receiving a fine equalize across different types of drivers.

Table 1—Variable Summary Statistics

	Analysis of citations ($N = 68{,}357$)		Analysis of fine \$ amount ($N = 31{,}674$)	
Variable	Mean	Std. dev.	Mean	Std. dev.
Fine amount / $			122.03	56.25
Citation issued = 1, 0 otherwise	0.463	0.499		
Out of state driver = 1, 0 otherwise	0.156	0.362	0.221	0.415
Out of town driver = 1, 0 otherwise	0.773	0.419	0.847	0.360
Override loss = 1, 0 otherwise	0.020	0.139	0.026	0.160
Distance to court (miles)	52.93	257.94	73.61	280.09
Hospitality employment (percent of total employment)	3.661	1.201	3.378	1.040
Mph over speed limit	15.158	5.083	17.079	5.790
Property value (per capita)	88,194	52,847	80,644	50,416
Black = 1, 0 otherwise	0.045	0.206	0.051	0.219
Hispanic = 1, 0 otherwise	0.035	0.184	0.047	0.211
Female = 1, 0 otherwise	0.390	0.488	0.332	0.471
Age	35.46	13.48	33.44	12.73
State police = 1, 0 otherwise	0.269	0.444	0.445	0.497
Commercial driver's license = 1, 0 otherwise	0.030	0.169	0.023	0.149

Notes: Hospitality employment summaries relate to 11,955 observations in the citation data and 6,700 observations in the fine amount analysis. Hospitality employment percent is the percent of the municipality that is employed in the hospitality sector as defined by the 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 (Massachusetts Department of Revenue).

of being fined relative to other out-of-town drivers.[26] The inclusion of random officer effects generates similar results (column 5). The point estimates on the out-of-town and out-of-state indicator in columns 1 and 5 are consistent with both the tax exporting and opportunity cost hypotheses, and we will turn to disentangling both hypotheses in Table 4.

The point estimate on the override loss variable shows that drivers have a 26 percentage point 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 2A, column 1). This finding is consistent with the political economy model's prediction that fiscal distress leads to higher speeding fines.

The specification includes an interaction effect between state troopers and an override vote failure. We include this variable because state police may not respond to local conditions, since they are not employed by the town but by the state. If this is the case, the estimated coefficient on the interaction term is negative. Column 2 shows a negative point estimate on the interaction variable, but the point estimate is not statistically significant when applying a two-tailed test. Column 5, however, shows that the estimate is negative and statistically significant if random officer effects are included in the specification.

Columns 2 and 6 of Table 2A report specifications that include interaction terms between the override loss variable and out-of-state and out-of-town indicators. The point estimates on

[26] An alternative explanation to the political economy 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 toward them, while local officers like to signal strict law enforcement standards to out-of-town drivers. This generates a reputation for strictness to out-of-town drivers while this reputation is less important with local drivers with whom officers have repeated interactions. However, this interpretation is not consistent with the finding that local police are more likely to fine out-of-state drivers who reside in state but not in their town since both types of drivers are not local drivers. In Table 5, we report a test to control for the possibility that local officers are more lenient to locals because they know them.

Table 2A—Determinants of Citations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Out of town	0.109***	0.106***	0.104***	0.161	0.093***	0.090***	0.088***	−0.001
	(0.014)	(0.014)	(0.014)	(0.118)	(0.008)	(0.008)	(0.008)	(0.046)
Out of state	0.102***	0.102***		0.298***	0.093***	0.093***		0.097*
	(0.017)	(0.018)		(0.078)	(0.010)	(0.010)		(0.057)
Log distance to court			0.021***				0.019***	
			(0.007)				(0.003)	
Override loss	0.255***	0.006	−0.001		0.202***	−0.040	−0.046	
	(0.080)	(0.076)	(0.080)		(0.044)	(0.066)	(0.073)	
Override loss × out of town		0.271***	0.288***			0.263***	0.281***	
		(0.097)	(0.102)			(0.063)	(0.067)	
Override loss × out of state		0.004				0.001		
		(0.051)				(0.048)		
Override loss × log distance			−0.004				−0.005	
			(0.033)				(0.020)	
Log hospitality employment				−0.121				−0.274**
				(0.162)				(0.127)
Log hospitality out of town				−0.086				0.019
				(0.086)				(0.035)
Log hospitality × out of state				−0.184**				−0.043
				(0.087)				(0.045)
Log hospitality × state police				0.038				0.333**
				(0.258)				(0.142)
Log mph over	0.642***	0.643***	0.641***	0.624***	0.646***	0.647***	0.646***	0.549***
	(0.041)	(0.041)	(0.041)	(0.076)	(0.029)	(0.029)	(0.029)	(0.045)
Log property value	−0.173***	−0.173***	−0.176***	−0.274*	−0.100***	−0.100***	−0.103***	−0.027
	(0.045)	(0.045)	(0.045)	(0.141)	(0.035)	(0.035)	(0.035)	(0.094)
Black	−0.004	−0.004	−0.004	−0.044	−0.013	−0.013	−0.013	−0.022
	(0.023)	(0.023)	(0.023)	(0.036)	(0.011)	(0.011)	(0.011)	(0.017)
Hispanic	0.116***	0.115***	0.115***	0.051	0.047	0.047	0.046	0.049**
	(0.022)	(0.022)	(0.022)	(0.044)	(0.047)	(0.048)	(0.048)	(0.021)
Female	−0.329***	−0.330***	−0.329***	−0.229***	−0.324***	−0.324***	−0.324***	−0.171**
	(0.039)	(0.039)	(0.040)	(0.085)	(0.034)	(0.034)	(0.034)	(0.081)
Log age	−0.162***	−0.162***	−0.161***	−0.158***	−0.167***	−0.168***	−0.166***	−0.131***
	(0.010)	(0.010)	(0.010)	(0.020)	(0.009)	(0.009)	(0.009)	(0.017)
Log age × female	0.075***	0.075***	0.075***	0.053**	0.075***	0.075***	0.075***	0.038*
	(0.012)	(0.013)	(0.013)	(0.025)	(0.011)	(0.011)	(0.011)	(0.023)
Commercial driver's license	−0.122***	−0.123***	−0.127***	−0.157***	−0.109***	−0.110***	−0.113***	−0.117***
	(0.014)	(0.013)	(0.013)	(0.026)	(0.012)	(0.012)	(0.012)	(0.025)
State police	−0.521	−0.523	−0.547	−0.987***	−0.122	−0.125	−0.166	0.446
	(0.429)	(0.427)	(0.404)	(0.053)	(0.451)	(0.451)	(0.442)	(0.804)
State police × out of town	0.007	0.009	−0.034	0.038	−0.011	−0.008	−0.034*	0.006
	(0.028)	(0.028)	(0.025)	(0.050)	(0.019)	(0.019)	(0.019)	(0.028)
State police × out of state	0.059**	0.060**		0.090*	0.020	0.021		0.034
	(0.028)	(0.028)		(0.052)	(0.015)	(0.015)		(0.025)
State police × log distance			0.039***				0.021***	
			(0.013)				(0.006)	
State police × override loss	−0.133	−0.153	−0.150		−0.119**	−0.138**	−0.138**	
	(0.110)	(0.109)	(0.107)		(0.061)	(0.061)	(0.061)	
State police × log property value	0.093	0.094	0.091	0.243	0.053	0.053	0.053	−0.048
	(0.062)	(0.062)	(0.063)	(0.180)	(0.041)	(0.041)	(0.041)	(0.107)
N	68,357	68,357	68,306	11,955	68,357	68,357	68,306	11,955
Officer RE/FE?	No	No	No	No	RE	RE	RE	RE
Clustering by municipality?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable equals one for the issue of a citation and zero for a warning. Regressions are estimated with probit and the point estimates are marginal effects. Robust standard errors in parentheses. RE = random effects, FE = fixed effects.

*** Significant at 1 percent.
** Significant at 5 percent.
* Significant at 10 percent.

the interaction effect between override loss and out-of-town drivers are large and statistically significant at the 1 percent level, while the magnitudes of the coefficients on out-of-state and out-of-town variables remain very similar to those in the previously discussed specifications. In municipalities that had a failed override vote, out-of-town drivers face a 38 percentage point higher probability of being fined (Table 2A, column 2).[27] The estimates on the override loss variables and their interactions in columns 2 and 6 show that the results on the override loss variables in columns 1 and 5 are driven by the fact that drivers from out of town are more likely to receive a speeding fine when they are stopped in towns where an override referendum failed. This supports the political economy hypothesis that taxes are exported to nonvoters. The importance of local public finance on the likelihood of being fined is also documented by the negative and statistically significant impact of per capita property values in columns 1 through 7 in Table 2A. Higher assessed property values, which indicate a larger tax base, are associated with a lower probability of being fined.

Columns 3 and 7 in Table 2A substitute log distance (in miles) to the court of jurisdiction for the out-of-state driver variable.[28] The point estimate on the distance variable is statistically significant and quantitatively important. A one-log-point increase in distance increases the likelihood of a fine by 2 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.[29]

The estimates on the state police and out-of-town driver interaction variable are small in magnitude and not statistically significant. However, the point estimate on the interaction effect between the state troopers and the out-of-state drivers indicates that an out-of-state driver has an additional 6 percentage point probability of receiving a fine from a state trooper than from a local officer. 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.[30]

Columns 3 and 7 of Table 2A interact distance to court with state troopers. The coefficient on the interaction effect is positive, suggesting that while a driver has a 2 percent higher probability of being fined for each distance log point when stopped by a local police officer, it increases to 6 percent per log point when stopped by a state trooper.

The point estimate on the interaction effect between state troopers and the override loss variable is negative in columns 1 and 5, and is statistically significant at the 5 percent level when random officer effects are included. This is consistent with the prediction that state troopers are less likely than local officers to issue a citation when an override referendum fails. Compared to local officers, state troopers are also less likely to factor in the size of the local tax base when deciding whether to issue a citation, although the point estimates on the interactions between property value and state troopers are not statistically significant.

[27] When we add an indicator variable for when a town passed an override vote, the point estimate on this variable is small and statistically insignificant, while our other point estimates are not affected by the inclusion of this variable.

[28] 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 were missing the zip code of the driver's residence.

[29] 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 revenue maximizing. However, at any traffic stop a police officer's effort from issuing a ticket is likely higher than the expected gain through promotions that arise from issuing this particular ticket. Therefore, the lower probability of appeal is probably the more important determinant of issuing a citation.

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

Columns 4 and 8 of Table 2A include hospitality employment variables. Since data on hospitality employment is not available for many municipalities, the dataset has only about 15 percent of the observations from the previously discussed data. The results show a negative and statistically significant point estimate on hospitality employment (column 8). This shows that fines are less likely when a municipality's dependence on tourism-related business increases. In column 4, hospitality employment is no longer statistically significant, but the interaction effect between out-of-state drivers and hospitality employment is, indicating that fines are less frequent for out-of-state drivers where tourism is more important to the local economy. These findings are consistent with the hypothesis that municipalities do not want to discourage tourists from visiting and potentially endanger future tourism revenues.

All previously discussed regressions include controls for the speed of the vehicle and for driver characteristics. The estimates on speed show that the greater the speed, in excess of the legal limit, the higher is the likelihood of a fine.[31] 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.

The findings show that age and gender are determinants of the likelihood of a speeding ticket. The likelihood of a fine decreases with age. Females are less likely to receive a fine than males. The interaction effect between the gender and age variables 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 75.

Table 2B presents an OLS regression model with officer fixed effects, using the same dependent and independent variables as in Table 2A. The results in Table 2B are qualitatively and quantitatively similar to those found in the probit and random effects probit specifications (Table 2A), although the estimates in the fixed effects model are somewhat smaller in magnitude and have larger standard errors than the random effects specifications. The exception with respect to statistical significance is the override loss variable in column 1, which is no longer statistically significant in Table 2B. Columns 2 and 3 of Table 2B show, however, that the previous finding, namely that out-of-town drivers are more likely to receive a fine when they drive through a town that failed to reject an override referendum, holds when one estimates the model with officer effects. The latter estimates are statistically significant at the 5 percent level, and indicate that for out-of-town drivers the likelihood of receiving a fine increases in a town with a rejected override referendum by approximately 20 percent.

Table 3 presents Heckman selection model estimations using the log 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. The selection equations are the regressions in Tables 2A and 2B, which include a CDL indicator. The point estimates on this variable show that drivers with this license face a lower probability of fines.[32]

[31] We tested for the robustness of our results by introducing several measures of the speed variable, including a linear specification, a quadratic specification, interaction effects between driver speed and the speed limit, excess speed as a fraction of the limit, and indicator variables for each mile per hour over the speed limit. All specifications showed that faster speeds over the speed limit increase the likelihood of a fine, and the results for our other variables were robust to these specifications.

[32] We also ran a two-part OLS model, assuming errors in the outcome and selection equation are not correlated. While some of the point estimates lose statistical significance, notably the out-of-town indicator, most remain statistically significant, including court distance, the out-of-state dummy, and the ethnicity indicators.

TABLE 2B—DETERMINANTS OF CITATIONS

	(1)	(2)	(3)	(4)
Out of town	0.066***	0.064***	0.063***	0.001
	(0.008)	(0.007)	(0.008)	(0.052)
Out of state	0.060***	0.060***		0.079
	(0.008)	(0.008)		(0.051)
Log distance to court			0.011***	
			(0.003)	
Override loss	0.103	−0.083	−0.104	
	(0.068)	(0.093)	(0.093)	
Override loss × out of town		0.207	0.213	
		(0.089)**	(0.091)**	
Override loss × out of state		−0.003		
		(0.023)		
Override loss × log distance			0.006	
			(0.015)	
Log hospitality employment				−0.337***
				(0.073)
Log hospitality × out of town				0.015
				(0.037)
Log hospitality × out of state				−0.034
				(0.039)
Log hospitality × state police				0.368***
				(0.083)
Log mph over	0.457***	0.457***	0.457***	0.398***
	(0.022)	(0.022)	(0.023)	(0.042)
Log property value	−0.090***	−0.091***	−0.093***	0.173
	(0.034)	(0.034)	(0.034)	(0.154)
Black	−0.009	−0.009	−0.009	−0.019
	(0.008)	(0.008)	(0.008)	(0.018)
Hispanic	0.054***	0.054***	0.054***	0.038
	(0.012)	(0.012)	(0.012)	(0.028)
Female	−0.246***	−0.246***	−0.246***	−0.124**
	(0.030)	(0.030)	(0.030)	(0.052)
Log age	−0.120***	−0.120***	−0.119***	−0.097***
	(0.007)	(0.007)	(0.007)	(0.012)
Log age × female	0.054***	0.054***	0.054***	0.027*
	(0.008)	(0.008)	(0.008)	(0.014)
Commercial driver's license	−0.078***	−0.079***	−0.080***	−0.087***
	(0.009)	(0.009)	(0.009)	(0.015)
State police				
State police × out of town	−0.032**	−0.030**	−0.036***	−0.009
	(0.013)	(0.013)	(0.013)	(0.021)
State police × out of state	−0.020**	−0.020**		0.007
	(0.010)	(0.010)		(0.022)
State police × log distance			0.002	
			(0.004)	
State police × override loss	−0.127*	−0.144**	−0.151**	
	(0.067)	(0.068)	(0.069)	
State police × log property value	0.092***	0.092***	0.094***	−0.198
	(0.034)	(0.034)	(0.035)	(0.164)
N	68,357	68,357	68,306	11,955
Officer RE/FE?	FE	FE	FE	FE
Clustering by municipality?	Yes	Yes	Yes	Yes

Notes: The dependent variable equals one for the issue of a citation and zero for a warning. Regressions are estimated with probit, and the point estimates are marginal effects. Robust standard errors in parentheses. RE = random effects, FE = fixed effects.
*** Significant at 1 percent.
** Significant at 5 percent.
* Significant at 10 percent.

Table 3—Determinants of Fine Amounts if Citations Are Issued

	(1)	(2)	(3)	(4)
Out of town	0.037***	0.036***	0.027**	0.008
	(0.012)	(0.012)	(0.012)	(0.065)
Out of state	0.084***	0.084***		0.061
	(0.011)	(0.012)		(0.055)
Log distance to court			0.026***	
			(0.004)	
Override loss	0.077**	0.017	0.022	
	(0.035)	(0.067)	(0.074)	
Override loss × out of town		0.066	0.057	
		(0.060)	(0.065)	
Override loss × out of state		−0.002		
		(0.028)		
Override loss × log distance			0.001	
			(0.011)	
Log hospitality employment				0.020
				(0.081)
Log hospitality × out of town				0.007
				(0.049)
Log hospitality × out of state				0.033
				(0.040)
Log hospitality emp × state police				−0.160
				(0.117)
Log mph over	0.959***	0.959***	0.952***	0.908***
	(0.015)	(0.015)	(0.015)	(0.032)
Log property value	−0.035	−0.034	−0.037	−0.195**
	(0.028)	(0.028)	(0.027)	(0.076)
Black	−0.022**	−0.022**	−0.023**	−0.023
	(0.010)	(0.010)	(0.010)	(0.017)
Hispanic	0.035***	0.035***	0.036***	0.014
	(0.011)	(0.011)	(0.011)	(0.018)
Female	−0.094**	−0.095**	−0.094**	−0.091
	(0.039)	(0.039)	(0.039)	(0.056)
Log age	−0.023***	−0.023***	−0.021**	−0.011
	(0.009)	(0.009)	(0.009)	(0.018)
Log age × female	0.016	0.016	0.016	0.023
	(0.011)	(0.011)	(0.011)	(0.015)
State police	−0.119	−0.120	−0.153	−2.745***
	(0.359)	(0.359)	(0.340)	(0.924)
State police × out of town	0.034*	0.035*	0.014	0.016
	(0.019)	(0.019)	(0.020)	(0.033)
State police × out of state	0.004	0.004		−0.024
	(0.013)	(0.013)		(0.028)
State police × log distance			0.009**	
			(0.004)	
State police × override loss	−0.054*	−0.058*	−0.055*	
	(0.032)	(0.033)	(0.032)	
State police × log property value	0.019	0.019	0.020	0.279***
	(0.032)	(0.032)	(0.032)	(0.095)
Constant	2.328***	2.329***	2.333***	4.177***
	(0.309)	(0.310)	(0.305)	(0.761)
Clustering by municipality?	Yes	Yes	Yes	Yes
N	31,674	31,674	31,642	6,700

Notes: The regressions are estimated using the two-step Heckman procedure. Selection equations are the corresponding regressions in Tables 2A and 2B. Robust standard errors in parentheses.

*** Significant at 1 percent. ** Significant at 5 percent. * Significant at 10 percent.

In most cases, the point estimates in Table 3 have the same signs as in the previously discussed regressions in Tables 2a and 2b. Out-of-town drivers pay a 4 percent higher fine and out-of-state drivers pay a 12 percent higher fine when stopped by a local officer (column 1). A fine issued by a state trooper is 7 percent higher for out-of-town drivers than for in-town drivers. The interaction effect between state police and out-of-state drivers is not statistically significant.

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 have the hypothesized positive sign and are statistically significant. Each point of log distance leads to a 3 percent higher fine when a local officer issues a ticket and to a 4 percent higher fine when a state trooper issues a ticket.

The point estimate on override failure is statistically significant (column 1 of Table 3), suggesting an up to 8 percent larger fine when a town is in a fiscal crunch. In contrast to the model explaining whether a driver was fined, the interaction effect between out-of-town driver and override loss is not statistically significant (column 2). However, override loss and the aforementioned interaction effect are jointly statistically significant at the 2 percent level, indicating that out-of-town drivers receive higher fines than local drivers.[33] While property value was important in determining whether a driver was fined, a municipality's property tax base does not seem to affect the amount of the fine. The hypothesis that smaller fines are issued in tourist towns also finds no support.

The results show that drivers operating a vehicle in greater excess of the speed limit receive higher fines. The signs of the point estimates on sex and age mirror those in the regressions that explain whether a driver receives a warning. Hispanic drivers are issued fines that are 4 percent higher than those issued to whites. Blacks, conversely, are charged 2 percent less than whites. Fines for females are 9 percent lower, and a 1 percent increase in age lowers the fine by 2 percent (columns 1, 2, and 3). Unlike in the regressions of whether police officers issue a citation, however, the interaction of age and gender is not statistically significant.

In Table 4 we employ specifications that run a horse race between the opportunity cost and tax exporting hypotheses of traffic enforcement. They differ from the previous regressions in that they use observations only from Massachusetts drivers.[34] These regressions include an indicator for out-of-town drivers and the travel distance from their residence to the court where the ticket can be contested, as well as the same controls as in column 1 of Tables 2A, 2B, and 3. We do not report the point estimates on the latter variables, since they are similar to those estimates already reported. The first column reports estimates from a probit model of whether a warning or a citation was issued; the second column shows estimates from the outcome equation from the Heckman model of log fine amount.

Column 1 offers evidence supporting both the hypothesis that the likelihood of a fine is higher for nonvoters and the hypothesis that the likelihood is higher for voters living farther from the court. The out-of-town indicator and log distance are both statistically significant. Out-of-town drivers have a 10 percentage point higher probability of receiving a fine than local residents, and that likelihood increases by 2 percentage points for each log point of distance.

[33] Further, the point estimates of override loss, override loss *OT, and override loss *OS are also jointly significant at the 5 percent level.

[34] Focusing on this subsample removes the heterogeneity introduced by out-of-state drivers. The regression cannot disentangle whether out-of-state driver variables receive a larger fine because they do not vote in Massachusetts or because they live far from the court location. Focusing on in-state drivers provides a sample that allows us to test both the tax exporting and opportunity cost hypotheses. Further, focusing on this subsample removes a potential selection bias because typically officers cannot determine from the license plate if the driver resides in town or somewhere else in Massachusetts, while the officer can infer out-of-town status from an out-of-state license plate. Finally, focusing solely on Massachusetts makes the sample more homogeneous because all of these drivers face the same increase in insurance cost via the Massachusetts Safe Drive Insurance Plan.

Table 4—Effects of Distance to Court and Voter Status for In-State Drivers

	Citation (1)	Log amount (2)
Out of town	0.096***	0.025***
	(0.006)	(0.007)
Log distance to court	0.016***	0.031***
	(0.004)	(0.004)
State police	−0.575***	−0.183*
	(0.050)	(0.105)
State police × out of town	−0.064***	0.001
	(0.019)	(0.016)
State police × log distance	0.060***	0.015**
	(0.008)	(0.006)
N	57,712	24,631

Notes: Robust standard errors in parentheses. In the first column the dependent variable equals one if a citation is issued and zero for a warning. The regression is estimated by probit, and point estimates are marginal effects. Control variables from the regressions in Tables 2A, 2B, and 3 are included, but not reported. The specifications in the second column come from a Heckman selection model.
*** Significant at 1 percent.
** Significant at 5 percent.
* Significant at 10 percent.

Both hypotheses are further supported by the negative and significant interaction of state police and the out-of-town variable, which supports the hypothesis that state troopers are less likely to react to local conditions.

The second column in Table 4 reports the Heckman selection model of log fine amount using the same variable specification as column 1. The results here continue to support the opportunitycost and tax exporting hypotheses, as the coefficients on the out-of-town and log distance are positive and statistically significant. However, the point estimates on the interaction between state police officers and out-of-town drivers, and interaction between override loss and out-of-town drivers, are not.

Our final test examines whether ticketing differs by population size of municipalities. In small towns, voters have a higher likelihood of being decisive than in larger towns. The political economy hypothesis implies that local police are less likely to fine local drivers as the value of their votes increase, while state troopers do not consider the value of the local drivers' votes in local elections. Thus, we predict that locals have a lower probability of being fined by local officers in smaller towns, but that town size does not influence state troopers' ticketing behavior. To test this hypothesis, we estimate the regression using the municipality fixed effects. These fixed effects also control for the possibility that local officers are more likely to know drivers personally in smaller towns, and may thus be more likely to issue a warning as opposed to a citation. For ease of interpretation of the estimated coefficients, we create an in-town variable, which is defined as one minus the out-of-town variable, and estimate separate slopes for this variable based on four categories of town sizes in terms of population: fewer than 10,000 inhabitants; between 10,000 and 20,000; between 20,000 to 30,000; and greater than 30,000.

Regression results are shown in Table 5.[35] Because all regressions in Table 5 include municipality indicators, they control for the possibility that officers are more likely to know people in

[35] Included in these regressions are driver characteristics and speed over the speed limit. Since these regressions have municipality fixed effects, we cannot include the town-specific characteristics, such as the override referendum, included in previous regressions.

Table 5—OLS – Probability of Fines for Local Drivers and Town Size

	Municipality fixed effects			
	(1)	(2)	(3)	(4)
In town	−0.053***		−0.017	
	(0.008)		(0.014)	
Town size 1 × in town		−0.149***		−0.014
		(0.015)		(0.045)
Town size 2 × in town		−0.059***		0.025
		(0.014)		(0.044)
Town size 3 × in town		−0.043***		−0.058**
		(0.014)		(0.024)
Town size 4 × in town		−0.025**		−0.019
		(0.012)		(0.018)
Out of state			0.031***	0.031***
			(0.008)	(0.008)
Log distance to court	0.011***	0.011***	0.012***	0.012***
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	−0.363***	−0.358***	−0.337***	−0.335***
	(0.094)	(0.093)	(0.067)	(0.066)
N	49,906	49,906	18,400	18,400
R^2	0.35	0.36	0.36	0.36

Notes: All regressions include municipality fixed effects, and standard errors are clustered by municipality and are estimated by ordinary least squares. The first two columns include drivers stopped by local police. The last two columns include drivers stopped by state troopers. These regressions include the same control variables as in Tables 2A and 2B, although municipality characteristics are not included since they are perfectly collinear with municipality fixed effects.
*** Significant at 1 percent.
** Significant at 5 percent.
* Significant at 10 percent.

some towns than in others. The first two columns of this table include only drivers stopped by local police. The next two columns include only drivers stopped by state troopers. Controlling for differing town sizes via municipality fixed effects,[36] we find in column 1 that locals have a 5 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 in-town variable based on the four categories of town sizes, while still controlling for municipality fixed effects. As predicted by the political economy 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 of Table 5 estimate the same set of regressions as columns 1 and 2, but for drivers stopped by state troopers. Here we also include a variable for out-of-state drivers, since our model predicts that troopers are more likely to fine out-of-state drivers, although the reported results are not sensitive to the inclusion of this variable. The results show that in the state trooper regressions the point estimate on in-town drivers is not statistically significant and the point estimate on out-of-state drivers has the predicted positive and statistically significant sign (column 3). This finding strengthens the support for the hypothesis that state troopers discriminate against out-of-state drivers, and that they do not discriminate between local and other

[36] Using municipal fixed effects helps address the concern that the finding that local police favor local residents can be explained not only 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 drivers they have befriended.

in-state drivers.[37] Assuming that state troopers tend to live in or near the towns they patrol, the hypothesis that officers issue fewer fines when they are more likely to know the drivers predicts fewer fines for local drivers with decreasing town size, contrary to the political economy hypothesis, which predicts that state troopers do not give breaks to locals. We find that with one exception, the interactions between local drivers and town size are not statistically significant (Table 5, column 4), indicating that state troopers' behavior is not affected by town size, and that they do not give breaks to locals. As in previous tables, in all four specifications of Table 5 we also find a positive and statistically significant coefficient on distance to court, as predicted by the opportunity cost hypothesis.

IV. Conclusions

Miles per hour in excess of the speed limit is not the sole determinant of whether an individual is fined; nor does it determine the dollar amount of the fine. 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 town, they face a higher probability of a citation and a higher fine. This is consistent with the hypothesis that police officers are agents of revenue-maximizing principals, effectively "exporting" taxes to drivers who are not local constituents.[38] Additionally, we find that 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. This suggests that drivers who face a higher opportunity cost to appeal a ticket are more likely to receive a citation and receive a higher fine.

The data support the hypothesis that municipal economic characteristics are 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 where voters rejected an override referendum to increase temporarily the limit on property tax revenue. This is consistent with our hypothesis 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 are muted. This finding reflects that the incentives of state officers differ from those of local officers.

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[37] Without municipal fixed effects, the point estimate on in-town drivers would have been negative and statistically significant, consistent with some of the results in the previous tables.

[38] These findings are related to two legal issues. First, the equal protection clause of the 14th Amendment of the US Constitution requires that government prove that any discriminatory treatment is substantially related to a legitimate government interest. Second, the privileges and immunities clause in Article 4 of the Constitution provides that a state is not allowed to discriminate against individuals from out of state.

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