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# **Red Ink in the Rearview Mirror:** Local Fiscal Conditions and the Issuance of Traffic Tickets

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## Abstract

Municipalities have revenue motives for enforcing traffic laws in addition to public safety motives because many traffic offenses are punished via fines and the issuing municipality often retains the revenue. Anecdotal evidence supports this revenue motive. We empirically test this revenue motive using a panel of annual data for North Carolina counties from 1990 to 2003. We find that significantly more tickets are issued in the year following a decline in revenue, but the issuance of traffic tickets does not decline in years following revenue increases. Elasticity estimates reveal that a ten percent decrease in negative revenue growth results in a 6.4 percent increase in the growth rate of traffic tickets. Our results suggest that tickets are used as a revenue generation tool rather than solely a means to increase public safety.

*JEL* Codes: H72, D72

Keywords: traffic tickets, public safety, political interest, law enforcement

## **1. Introduction**

Each year traffic-related accidents in the U.S. injure nearly 3 million people and are responsible for approximately 40,000 deaths. The National Highway Traffic and Safety Administration (2002) estimates that the direct costs of vehicle-related accidents are in excess of \$230 billion a year. Traffic accidents are so prevalent in the U.S. that the National Highway Traffic and Safety Administration annually publishes a "Crime Crash Clock" showing that individuals are far more likely to be involved in a traffic accident than to be a victim of crime.<sup>1</sup>

Traffic laws are designed to improve public safety and a major traffic law enforcement tool is the issuance of tickets. Law enforcement agencies and officials expend considerable resources to monitor, and at times penalize, driving behavior. According to the National Center for State Courts (2006), states filed, reopened, or reactivated nearly 55 million traffic violation cases in trial courts in 2004. This is a rate of more than 18,000 cases for every 100,000 U.S. residents, and traffic violation cases accounted for more than half of all state court cases during the year.

Given that the punishment for many traffic offenses is a fine, as opposed to incarceration, the volume of cases suggests that traffic citations have the potential to produce considerable revenue. And since many municipalities are permitted to retain fines generated by traffic tickets for offenses occurring in their jurisdiction, municipalities may have an incentive, independent of any public safety motives, to enforce traffic laws as a means of increasing revenue. There is considerable anecdotal evidence that government officials consider traffic tickets to be an important source of revenue. For instance, after a decrease in the number of traffic tickets issued in Milwaukee, Wisconsin, one city official expressed concern stating that "traffic tickets provide much needed revenue" (*Milwaukee Journal Sentinel* 2001). In response to a reduction in traffic

fines, Houston city officials predicted an increase in the number of traffic tickets to offset the revenue loss (*The Houston Chronicle* 1999). More recently, *The Washington Times* (2005) reported that D.C. Mayor Anthony Williams requested continuation of the city's traffic camera program in a letter to the Council Chair referring to the city's "urgent need" to collect revenue from the program. And in May of 2006 Nashville Mayor Bill Purcell actually included a 33 percent increase in traffic ticket revenue in his proposed budget (*Tennessean* 2006).

In this paper we utilize county-level data from North Carolina over a 14 year period to test such a potential revenue motive by examining if changes in the issuance of traffic tickets are influenced by changes in local government fiscal health. Controlling for demographic, economic, and enforcement factors, we find that there is a statistically significant increase in number of traffic tickets issued in the year immediately following a decline in local government revenue. Moreover, given that we find no evidence that fewer tickets are issued in response to increases in local government revenue, our results support the view that traffic tickets are, at least to some extent, viewed as a revenue tool by local governments.

## 2. Public versus Political Interests in Law Enforcement

The notion that local governments may use traffic tickets as a revenue tool has received considerable attention in recent years largely because of the growing use of traffic cameras to enforce red-light violations. While most studies find that red-light cameras have reduced right-angle collisions and red-light violations, some studies have also noted a significant increase in rear-end collisions following the installation of the cameras, making their net effect on safety a point of contention.<sup>2</sup> Combined with the fact that local governments frequently share in the ticket fines with camera manufacturers, many observers have concluded that red-light cameras

are revenue generation devices rather than tools to improve public safety. In a more general sense, this view essentially holds that local traffic enforcement policies, much like other government policies, may be a function of two (often opposing) motives of public officials – political interests and public interests (Becker 1986; Saffer and Grossman 1987; Mixon 1995).

Given the limited revenue-raising options, erosion of property and sales tax bases, and a general distaste for tax increases by the public, local policy makers are under increased pressures to find alternative revenue sources (Tannenwald 2001; Crain 2003; Brunori 2006). Other factors constant, it seems reasonable to prefer new or additional revenue from indirect, less traditional sources and from non-residents and non-voters. State governments have accomplished this by expanding taxation to a variety of goods and services such as lottery sales, casino gaming, hotel occupancy, and prepared foods. Traffic tickets provide an attractive revenue source for local governments because the amount of revenue that can be generated is often unrestricted, they provide a mechanism to capture revenue from non-residents and non-voters, and most traffic offenses possess a low strict-liability threshold to achieve a conviction (as opposed to the higher criminal intent standard).

Although we are not aware of any previous studies that formally explore a revenue motive in traffic enforcement, several papers find that political interests are important factors in the design and enforcement of traffic and criminal-related public policies. For instance, while state-mandated vehicle inspections are presumably aimed at improving safety by regularly monitoring minimum vehicle safety standards, Crain (1980), Leigh (1994), Merrell, Poitras, and Sutter (1999), and Sutter and Poitras (2002) find that inspections fail to significantly reduce motor vehicle fatalities or injuries. Sutter and Poitras (2002) argue that inspections exist partially because of political transaction costs in the sense that the laws appease safety advocates

but are not costly enough to eliminate. Crain (1980) argues that state vehicle inspections exist as a means to transfer wealth to gas stations and repair shops, a claim that is empirically supported by Leigh (1994) and Sutter and Poitras (2002).

Research on drug-related asset seizures provides consistent evidence that law enforcement officials alter their policing behavior in response to incentives (Baicker and Jacobson 2007; Mast, Benson, and Rasmussen 2000). Using a panel of U.S. cities, Mast, Benson, and Rasmussen (2000) find that when law enforcement agencies are permitted to retain assets seized from drug arrests, the fraction of drug arrests to total arrests increases by roughly 20 percent. Baicker and Jacobson (2007) reach similar conclusions after examining policing behavior and local budget allocations with county-level data from five states. Despite asset seizures accounting for a small portion of police budgets, Baicker and Jacobson (2007) find that police make significantly more drug-related arrests when they are able to retain seized assets and direct their efforts toward possession rather than sales offenses. Such an enforcement shift is consistent with Blumenson and Nilson's (1998) assertion that drug-related policing behavior tends to focus more on money than on the actual drugs.

In addition, Baicker and Jacobson (2007) find that the parent governments of law enforcement agencies routinely capture a portion of the "gains" from seized assets by reducing police budgets in the following year. This behavior is more pronounced during periods of fiscal distress, when parent governments capture up to 90 cents of every dollar from seized assets, depending on the type of seizure. And while law enforcement agencies may not statutorily benefit directly from ticket fines as they do with drug-related seizures, Baicker and Jacobson (2007) find that police respond to the net incentives they face – seizures less parent government budget offsets – rather than the statutory incentives. This suggests that if local governments

include law enforcement agencies in any potential revenue gains from increased traffic enforcement, possibly in the form of increased budgets, pay increases, or smaller budget cuts during periods of distress, then it is plausible that police may alter their enforcement efforts and issue more tickets.

There is evidence that some jurisdictions have linked police performance and pay to the number of tickets that officers issue. In New York City for instance, an arbitrator recently ruled that the commanding officer of a Brooklyn area precinct imposed illegal ticket quotas on police officers and noted that at least one officer received poor performance evaluations simply because of issuing an insufficient number of traffic citations (*The New York Times* 2006). Moreover, according to *The Boston Herald* (2006), some state troopers in Massachusetts are now operating under a pilot program that rewards officers more for writing tickets than for giving verbal or written warnings, reflecting a change from the practice of treating these forms of enforcement equally when measuring performance. As Santiago (2003) notes, law enforcement agencies have a long history of using the raw number of arrests and tickets issued as performance measures, which he claims improperly focuses police efforts on rates of production rather than on quality policing.

#### 3. Data and Empirical Methodology

#### 3.1 Traffic Ticket Data and Empirical Specification

Our empirical model will focus on the annual percentage change in traffic tickets issued. If local governments view traffic tickets (or traffic enforcement more generally) as a source of revenue that may be used to mitigate the fiscal stress associated with downturns and, consequently, issue more tickets during difficult fiscal times, then modeling how the issuance of

traffic tickets change in response to annual changes in local fiscal conditions, holding constant other relevant factors, will allow us to capture any such effect.<sup>3</sup> The percentage change specification best captures the budgeting process and how this process, by construct, forces public officials to make budgeting decisions 'on the margin.' The budgeting process occurs annually in each county, and public officials in each county are concerned only with the condition of their county's budget, not that of other counties in the state. Thus, public officials in a county are going to make marginal changes in their budget year-to-year. In addition, incremental changes in the budget (such as increasing traffic ticket revenues) rather than large changes (increasing taxes or expanding tax bases) in response to an economic downturn is more likely in the budgeting process given the complicated nature of the process, as well as the highly political nature of the process (see Simon 1955, 1959; Lindblom 1959; Wildavsky 1964).

Nearly all of the county-level data we employ in this paper, including our data on traffic tickets, come from the online database LINC (Log into North Carolina).<sup>4</sup> Traffic tickets are defined as the number of traffic infraction cases filed in each county's District Court during the fiscal year. In accordance with Article VII, Section 7 of the North Carolina Constitution of 1971, ticket revenue in North Carolina is retained by the county in which the violation occurred and placed in a school fund to finance education. However, because there is no limitation on how much ticket revenue a county may collect nor any requirement that school fund monies be used *in addition* to existing education expenditures, like drug-related seizure gains, municipalities may simply substitute ticket revenue in place of other revenue that would have been used to finance education.<sup>5,6</sup>

All traffic tickets issued by law enforcement officials are filed in the District Court in which the offense is alleged to have occurred regardless of whether a ticket is appealed. Traffic

infractions include both offenses that require a court appearance (non-waivable offenses) and offenses that do not require a court appearance (waivable offenses). Common examples of non-waivable offenses include driving with a suspended or revoked license, driving while subject to an impairing substance, racing, driving in excess of 80 mph, and reckless driving, while examples of waivable offenses include speeding (below 80 mph), speeding in a school or work zone, failure to use seat belts, following too closely, parking violations, and improper turning/signaling.<sup>7</sup>

Our empirical model is applied to county-level data on 96 North Carolina counties over the period from 1990 to 2003, resulting in 1,344 observations.<sup>8</sup> The mean number of traffic infraction cases filed per fiscal year exceeded 700,000 over our sample period, with the smallest and largest number of cases, 644,478 and 767,889 respectively, occurring in fiscal years 2000 and 2002. The number of traffic tickets issued at the county level ranged from a low of 369 in Graham County in 1993 to a high of 57,404 in Wake County in 2002, with a county-wide average of approximately 7,000 cases filed each fiscal year. On a per capita basis, North Carolina counties issued an average of 0.108 tickets per capita over our sample period, or about 11 tickets per 100 residents. Tickets per capita ranged from a low of 0.057 in Caldwell County to a high of 0.287 in Dare County. Figure 1 shows the aggregate number of traffic tickets (in levels) issued in North Carolina from 1989 to 2003.

Denoting the annual percentage change in per capita traffic tickets issued in county *i* at time *t* as  $\%\Delta T_{it}$ , the empirical model may formally be expressed as:

$$\%\Delta T_{it} = \alpha + \delta \mathbf{X}_{it} + \theta_t + \lambda_i + \varepsilon_{it} : i = 1, ..., N; t = 1, ..., T,$$
<sup>[1]</sup>

where  $\mathbf{X}_{it}$  is a matrix of local fiscal, economic, enforcement, and demographic factors in county *i* at time *t* assumed to influence the change in traffic tickets,  $\theta_t$  and  $\lambda_i$  denote the fixed time and

county effects,  $\alpha$  is the constant term,  $\varepsilon_{it}$  is the error term, *i* is the index of the *N* counties, and *t* denotes the index of the *T* time periods. The inclusion of fixed county-effects will control for county-specific, time-invariant factors or preferences that may affect the issuance of tickets, while the fixed time-effects will control for unobserved aggregate factors such as national or statewide economic downturns and public safety campaigns (such as "Click It or Ticket").

# 3.2 Variables in the Empirical Models

The number of traffic tickets issued in a county is a function of county demographics and a given level of law enforcement (Lee 1985; Lave 1985; Graves, Lee, and Sexton 1993). We include several variables broadly classified as demographic and economic to control for changes in county characteristics that may be correlated with changes in the number of traffic tickets issued. Population density, the number of people per square mile, is included to capture potential differences in the number of traffic tickets issued in rural versus more urban areas. Given that data on vehicle miles driven, or any similar miles driven/traveled measures are not available at the county level, registered vehicles per mile of roadway is included as a proxy for roadway congestion, reflecting the notion that more increases in the number vehicles per mile of roadway may translate into a greater number of traffic tickets being issued.<sup>9</sup> The share of the population age 15 to 24 controls for the population segment that is traditionally considered the 'highest risk' by car insurance companies. According to the National Highway Transportation and Safety Administration, traffic accidents are the leading cause of death for individuals in this age group and they are also the most likely segment of the driving population to be involved in a traffic accident (U.S. Department of Transportation 2004). Other factors constant, we expect a positive increase in this segment of the population to be correlated with an increase in the

number of tickets issued. Similarly, racial profiling has received considerable attention in recent years (see, for example, Hernandez-Murillo and Knowles 2004) so the county's minority population age 15 and older (expressed as a share of the total population) is included as a regressor to account for changes in the pool of potential minority drivers. The final demographic variable, *registered voters as a share of the voting age population*, is included to capture the activity and political strength of the electorate. If there is any Tiebout-type competition between local governments, implying that government officials may react to citizen 'exit and voice', then it seems reasonable that local governments with more politically active residents may rely on traffic tickets as more of a pure enforcement tool rather than a revenue tool. Complete descriptions, summary statistics in both percentage change and level form, and sources for all the variables may be found below in Table 1.

In addition to demographic factors, several regressors are included to control for county economic conditions, such as the *unemployment rate*, *tourism spending per capita* and *median family income*. The percentage change in *median family income* will capture changes in the economic health of the typical household, while the percentage change in the *unemployment rate* will control for current changes in county-wide economic conditions. If the issuance of traffic tickets is related to tough fiscal times, independent of any potential effects that local government fiscal health may have, then positive changes in the unemployment rate may lead to more tickets being issued. The final economic control, *tourism spending per capita*, will account for the fact tourism is a large sector of many North Carolina counties, especially along the coast and in the Western region of the state. Increased tourism is expected to increase the issuance of traffic tickets for several reasons. First, greater tourism has the potential to produce increased traffic flows from out-of-county residents, which may result in an increase in traffic tickets. Second,

law enforcement officials may be more likely to issue tickets to tourists because, relative to county residents, tourists may be less likely to contest a ticket.<sup>10</sup>

Although traffic enforcement is relatively difficult to directly measure, it is an important component in the issuance of tickets and our model contains several variables that are aimed at controlling for county-level differences in enforcement.<sup>11</sup> The first variable, the percentage change in law enforcement officers per capita, is included to measure the change in police presence and, other factors constant, is expected to be positively related to the change in tickets issued.<sup>12</sup> Our model also includes the change in the *number of arrests per capita* in the county and the change in vehicle-related criminal cases filed in the county's District Court. We believe these variables may have an ambiguous influence on the change in traffic tickets because of potentially offsetting effects. For example, if changes in the number of arrests and vehiclerelated criminal cases reflect or follow changes in a county's preference for law enforcement in general, then positive changes in these variables may be correlated with a positive change in the number of tickets issued. On the other hand, because law enforcement officials have limited resources, positive changes in the number of arrests and vehicle-related criminal cases may capture increases in the demand for law enforcement officials' time, which could result in a reduction in the number of tickets being issued. The final enforcement-type variable that we include is the percentage change in the mean number injuries & deaths over the previous 3 years in the county from traffic accidents (in per capita terms).<sup>13</sup> This variable is averaged over the previous 3 year period because in our sample there are several instances, particularly in rural counties, in which the number of injuries and deaths per capita from traffic accidents was extremely small. Using an average of the very recent past controls for how changes in the shortterm trend number of injuries and deaths influences the current change in tickets. We expect that

increases in the number of injuries and deaths will result in increased demand for traffic law enforcement (either from citizens or law enforcement) and lead to an increase in the number of tickets issued.

The final independent variable, and our primary variable of interest, is the annual percentage change in local government revenue per capita.<sup>14</sup> This variable is the sum of the six major revenue sources for local governments in North Carolina: Federal aid, state aid, property taxes, license taxes, permits and fees, and local sales taxes. North Carolina is one of 31 states with a local sales tax option, and all counties in the state have a sales tax. Over the sample period, the average contribution of each revenue source toward total local government revenue was, in descending order: property taxes (50 percent), sales taxes (20 percent), state aid (17 percent), federal aid (10 percent), license taxes (2 percent), and permits and fees (1 percent). The nominal level of local revenue averaged \$607 per capita over the sample period, with Hyde County averaging the highest level of per capita revenue (\$1,232) and Onslow County averaging the lowest level (\$403). Local government revenue grew at an average rate of 6.1 percent during our sample period, with the average growth in local revenue ranging from a low of 2.7 percent in Cleveland County to a high of 10.5 percent in Hertford County.

In addition to exploring how local revenue changes influence the number of traffic tickets issued as evidence of a political motive for traffic law enforcement, it is straightforward to examine whether the timing of tickets issued responds symmetrically or asymmetrically to changes local revenue, if at all. This is accomplished by interacting the local revenue variable with positive and negative dummy variables that equal unity if revenue growth is, respectively, positive or negative, and equal to zero otherwise.<sup>15</sup> If changes in traffic tickets are countercyclical with regard to changes local government revenue, we expect a decrease in local

revenue to have a positive influence on the change in traffic tickets and an increase in revenue to be negatively related to the change in tickets. A symmetric response can then be tested under the null hypothesis that the sum of the two revenue variable coefficients equals zero.

Finally, government budgets are planned and enacted well in advance of the start of the fiscal year and officials have (at best) imperfect information regarding contemporaneous revenues (see, for example, Wong 1995 and Cirincione, Gurrieri, and van de Sande 1999). As a result, it is conceivable that any political motive for traffic enforcement may depend not only on current fiscal conditions (which are not known with absolute certainty), but also on fiscal conditions in the recent past (which are known with absolute certainty). To account for this possibility, we also include lagged values of the change in local revenue to cover changes in fiscal conditions over the previous three years.

## 4. Estimation Results

We consider five different specifications to both assess the robustness of our findings and allow for the possibility that changes in traffic tickets may also depend on changes in local revenue apart from changes in the current fiscal year.<sup>16</sup> Year and county fixed effects are included in each specification to control for unobserved factors that may have influenced changes in traffic tickets. Estimates excluding all local revenue variables are presented for comparison purposes in column (1) of Table 2. The remaining columns in Table 2 range from specifications that include only current changes in local government revenue as a regressor (column (2)) to models that include current changes in local government revenue plus changes in local revenue over the previous three fiscal years (column (5)).<sup>17</sup>

Focusing first on the economic, demographic, and law enforcement control variables, the results in Table 2 indicate that several factors are significantly correlated with the timing of traffic tickets and our findings are generally robust across specifications. Specifically, we find that a one percentage point increase in the county's unemployment rate results in an 0.0801 to 0.0849 percentage point increase in the number of tickets issued per person, which is significant at the five percent level in each regression. This suggests that, independent of the fiscal health of local governments, the timing of traffic tickets tends to mimic changes in county-wide economic conditions. In addition, we find counties that experience positive increases in tourism spending per capita also tend to issue more traffic tickets, other factors constant. In fact, a one percentage point increase in tourism spending is found to be correlated (at the one percent level in each regression) with a 0.122 to 0.132 percentage point increase in tickets. This finding may be capturing additional congestion associated with tourism or reflecting the possibility that law enforcement officials target out-of-county residents because it is more costly for outside residents to appeal an alleged infraction.

In terms of our enforcement variables, we find that the fraction of criminal cases filed in the county that are vehicle-related is both positive and statistically significant at the one percent level in each specification. A one percentage point increase in the share of criminal cases filed that are vehicle-related is correlated with a 0.77 percentage point increase in the number of traffic tickets issued. In addition, we find that *mean traffic injuries and deaths over the previous 3 years* to be significant in explaining changes in tickets issued at the five percent level in each specification, but the estimated coefficient is negative. This suggests that county's issue significantly fewer traffic tickets following an increase in the average number of injuries and deaths resulting from traffic accidents over the previous three years.<sup>18</sup> While this finding may

seem to contradict conventional wisdom, there are several possible explanations for why this estimated coefficient is negative. First, if a growing number of injuries and/or deaths from traffic accidents lead to greater traffic enforcement, then drivers may alter their behavior and drive more safely in response to the additional enforcement. Second, if a county experiences a growing increase in the number of traffic accident injuries and/or deaths, this may then induce citizens or government officials to demand more roadway safety. Such added safety could manifest itself in design improvements to unsafe roads and dangerous intersections, the addition of stop signs or traffic signals, or merely speed limit reductions, all of which have the potential to reduce the future number of traffic accidents and infractions.

While the *share of the population 15 to 24* and *minority population age 15 and older* are not found to be significant in explaining the change in tickets, *registered voters as a share of the voting age population* and the county's *population density* are both found to be negatively correlated with the issuance of tickets. Since *population density* essentially captures increases in county population (because county land area is fixed), the negative coefficient reveals that traffic tickets per capita have tended to increase at a slower rate than the population. With regard to registered voters, our results suggest that marginal increases in the political activity/strength of the county's population leads to a reduction in the growth rate of tickets issued.

Turning our attention to the change in local government revenue, we find that both positive and negative changes in current local revenue have no statistical effect on the timing of tickets. However, we find that negative changes in local revenue from the previous fiscal year are significantly correlated with the change in tickets issued. And because non-zero values of the negative revenue variables are negative, our estimates indicate that a one-percentage point reduction in last year's revenue growth leads to a 0.316 to 0.327 percentage point *increase* in the

current number of tickets issued. This finding is significant at the five percent level in most specifications and is robust to the inclusion of revenue variables lagged up to three fiscal years. Using the coefficient estimate of 0.32 and the means of the respective variables (see Table 1), we compute an elasticity of -0.64 – a ten percent decrease in negative revenue growth results in a 6.4 percent increase in the growth rate of traffic tickets. Although it may seem unusual for revenue changes from the previous fiscal year to be related to the current issuance of tickets (when current revenue changes are unrelated), recall that the change in last year's revenue provides the most current information about the county's fiscal health that is known with certainty. In other words, a negative change in last year's revenue is a very strong indicator of the county's fiscal position, as opposed to current revenue projections that are often revised as the fiscal year progresses.

In addition, F-tests conducted under the null hypothesis that the sum of the two revenue coefficients from the previous fiscal year equals zero are rejected at the five percent level for each of the empirical specifications in columns (3), (4), and (5). This indicates that the issuance of traffic tickets by local governments responds asymmetrically to changes in local revenue. In other words, there is a significant increase in the number of tickets issued in response to a decline in revenue, but no significant reduction in the issuance of tickets following increases in revenue. Thus, independent of a public safety motive, our results suggest that local governments behave, in part, as though traffic tickets are a revenue tool to help offset periods of fiscal distress.<sup>19</sup>

There are several potential implications of our findings. First, if local governments are maximizing the production of public safety through their enforcement efforts in traffic and non-traffic related offenses, then public safety in non-traffic related areas could potentially decrease during periods of fiscal distress if police face incentives to shift resources toward more revenue-

generating forms of enforcement.<sup>20</sup> And while Baicker and Jacobson (2007) find that parent governments capture more drug-related seizure gains during periods of fiscal strain, neither Baicker and Jacobson (2007) nor Mast, Benson, and Rasmussen (2000) explore whether police expand drug-related asset seizures during times of fiscal distress. Finally, since removing the financial link between local governments and ticket revenue should eliminate the revenue-motive for issuing tickets, states and local communities may wish to evaluate their own allocations of ticket revenue and its consequences on the provision of public safety.

### 5. Summary and Conclusions

There is ample anecdotal evidence that local government use traffic tickets as a means of generating revenue, implying that traffic law enforcement may be motivated by political interests as well as public safety interests. Our paper provides the first empirical evidence to support this view by examining how changes in the number of traffic tickets issued in North Carolina counties are effected by changes in local fiscal conditions. The results indicate that, while changes in local government revenue are significantly correlated with the number of tickets issued, the response is asymmetric to positive and negative changes in local revenue. Positive changes in local revenue have no statistical effect on the changes in the tickets issued, but we find evidence that law enforcement officials issue significantly more tickets in the year following a decline in local government revenue. Specifically, a one percentage point decrease in last year's local government revenue results in roughly a 0.32 percentage point increase in the number of traffic tickets in the following year. In terms of elasticity, we find that a ten percent decrease in negative revenue growth results in a 6.4 percent increase in the growth rate of traffic tickets.

Future research can focus on several issues. First, this study uses the change in the number of traffic tickets issued as our dependent variable rather than changes in traffic ticket revenue because ticket revenue data are not readily available for North Carolina counties. The availability of such data would permit a more precise analysis of the degree to which traffic ticket revenue offset local revenue losses during periods of fiscal distress. In addition, with ticket revenue data one could answer the question of whether local governments that derive a larger share of their budget from ticket revenue react more strongly to periods of fiscal stress. Second, given that states tend to allocate ticket revenue differently, it would be interesting to examine how sensitive the issuance of traffic tickets and ticket revenues are to such rules. If law enforcement officials face incentives to shift their enforcement efforts toward more revenuegenerating activities during difficult fiscal times, perhaps in ticket writing or drug-related asset seizures, then these incentives may have implications for the provision of public safety. Finally, since our results suggest the number of traffic tickets issued changes in a systematic manner in response to local fiscal conditions rather than systematic changes in driving behavior, decreases in government revenue may improve the efficiency of automobile insurance markets by reducing the asymmetric information between insurers and drivers. While numerous studies of asymmetric information in the automobile insurance exist (Chiappori 2001), we are not aware of any that examine local fiscal conditions as a potential means to reduce asymmetric information.

# Footnotes

<sup>\*</sup> The views expressed here are those of the authors and not those of the Federal Reserve Bank of St. Louis or the Federal Reserve System. The authors would like to thank Erick Elder, Mark Funk, and an anonymous referee for several valuable suggestions that have improved the paper. An earlier version of this paper was circulated as "Are Traffic Tickets Counter-cyclical?" Any errors are the responsibility of the authors.

<sup>1</sup> The National Highway Traffic and Safety Administration (2002) report and the "Crime Crash Clock" are both available at http://www.nhtsa.dot.gov.

<sup>2</sup> See the U.S. Department of Transportation, Federal Highway Administration (2005) for an overview of the literature on red-light cameras and safety. Depken and Sonora (2006) provide a theoretical perspective on red-light cameras.

<sup>3</sup> The use of a percentage change specification eliminates the assumption that a one dollar per capita change in revenue has the same effect in a high spending county as it does in a low spending county. Certainly a one dollar decrease in revenue for a low spending county would induce greater action by officials than a one dollar decrease in revenue in a high spending county since one dollar per capita makes up a greater portion of a low spending county's budget than a high spending county's budget.

<sup>4</sup> LINC contains over 1,300 data series on local governments in North Carolina and may be accessed at http://linc.state.nc.us/.

<sup>5</sup> There is considerable variation in the allocation of ticket revenue across states. For example, municipalities in Texas (Transportation Code, Chapter 542) may only retain ticket revenue equal to 30 percent of the previous year's revenue, while in Indiana (Code § 9-21-1-2 part (c)) ticket revenue becomes part of the general fund with no restrictions. In Utah (Code § 63-63a-2), ticket revenue is shared between the State and municipalities in accordance with codified formulas.

<sup>6</sup> There is very strong evidence to support the view that local school spending in North Carolina is fungible. North Carolina's school finance system differs from most states in that the state government is responsible for funding basic operating expenses, while local governments (counties) are required only to finance school construction and maintenance (Hansen et al. 2007). In practice, current operating expenses for public schools in North Carolina are

financed 65-70 percent from the state, 20-25 percent locally, and the remainder from the federal government (Hansen et al. 2007). The 20-25 percent of funding provided by local governments, which is derived primarily from property and local option sales tax revenue, is completely discretionary. In fact, Testerman and Brown (1999, 3) note that "[n]o local contribution is required for basic program support. Although none is required for current expenditures, all counties provide some assistance." Article IX of the state constitution, which is referenced by Hansen et al. (2007, 11), states that "[t]he governing boards of units of local government with financial responsibility for public education may use local revenues to add to or supplement any public school or post-secondary school program." Thus, given that local governments are not required to provide any funding for current operating expenses, it is plausible that local governments could rely on additional revenues from traffic tickets during periods of distress and utilize the funds that would have been allocated to schools in some other capacity. <sup>7</sup> A list of all waivable traffic offenses, published by the North Carolina Magistrates Association, may be found at http://www.aoc.state.nc.us/magistrate/waivable.htm. Non-waivable offenses are located at

http://www.aoc.state.nc.us/magistrate/non-waivable.htm.

<sup>8</sup> North Carolina has 100 counties. Mitchell, Tyrrell, Wayne, and Yancey counties were omitted from our sample due to incomplete data.

<sup>9</sup> Registrations are for automobiles and trucks in the county the vehicles were registered. Excluded are registrations for trailers, buses, motorcycles, dealers, transporters, drive away and public-owned passenger vehicles, mobile homes, tractor trucks, and wreckers.

<sup>10</sup> Tourism spending is the total domestic travel spending at the county level produced through the North Carolina Department of Commerce's County Travel Economic Impact Model, a computerized economic model that is an extension of the U.S. Travel Data Center's Travel Economic Impact Model. Estimates represent expenditures by U.S. residents traveling in North Carolina and include both state and out-of-state visitors traveling away from home overnight or on day trips to places 100 miles or more away from home during the calendar year. Excluded is travel commuting to and from work; travel by those operating an airplane, bus, truck, or other form of common carrier transportation; military travel on active duty; travel by students away at school; and travel by foreign visitors. See http://linc.state.nc.us/ for more information.

<sup>11</sup> We also explored the use of the county's per capita public safety spending as a regressor under the notion that it may reflect changes in the resources available to law enforcement officials. However, we have omitted it from the

model because we found no evidence that it was significant in explaining the issuance of tickets and the variable includes spending on numerous factors other than simply law enforcement (such as emergency management, fire, inspectors, rescue units, animal control, and jails and medical examiners).

<sup>12</sup> Klick and Tabarrok (2005) find evidence that police deter crime by examining how increased police presence due to exogenously determined terror alert levels influences daily crime rates in Washington, D.C.

<sup>13</sup> LINC defines injuries from traffic accidents as "the number of persons injured in reportable traffic accidents as determined from the investigating officer's reports," which are filed within 24 hours of the accident. Injuries include (1) bleeding wounds, distorted members, or any condition that required the victim to be carried from the scene, (2) other visible injuries such as bruises, abrasions, swelling, limping, or other painful movement, and (3) complaint of pain, without visible signs of injury; or momentary unconsciousness." A reportable accident is one that involves a motor vehicle resulting in injury, death, or total property damage of \$1,000 or more. The property damage amount was \$500 until January 1, 1996. See http://linc.state.nc.us/ for more information.

<sup>14</sup> While it is common to measure fiscal stress using budget deficits, this is not appropriate for our study for several reasons. First, local governments in North Carolina are constrained by a strict, annual balanced budget ordinance (General Statute § 159-8) and compliance is monitored annually by the Department of State Treasurer. In fact, in our data, local governments experienced three times more periods of negative revenue growth than budget deficits. This suggests that municipalities aggressively adjusted expenditures in response to revenue shocks. Second, while a negative percentage change in revenue is a strong indicator of fiscal strain, a negative percentage change in a county's budget surplus/deficit is not because this could easily be caused by a reduction in the budget surplus.

<sup>15</sup> Overall in our sample, 78 percent of the observations are periods of positive revenue growth and the remaining 22 percent are periods of negative growth. The typical county experienced roughly 11 years of positive revenue growth and three years of negative revenue growth, but these figures ranged from a high of seven years of both positive and negative growth in Cherokee County to zero years of negative revenue growth in Durham and Jackson Counties. <sup>16</sup> We initially estimated the models using each of the six components of total revenue (property taxes, sales taxes, license taxes, permits and fees, state aid, and federal aid) rather than the single total revenue variable in hopes of capturing differences in the effect of changes in each revenue source on traffic tickets. None of the variables were statistically significant. Diagnostic tests revealed relatively large standard deviations for each variable compared to the total revenue variable. Summing the six revenue variables thus produces a total revenue variable with relatively less variation than the individual revenue series.

<sup>17</sup> Our finding that significantly more tickets are issued in the year following a decline in revenue growth is robust if our specification is pooled OLS, includes only fixed year effects, or includes only fixed county effects. In addition, we also estimated our standard errors using the White, Newey-West, panel-corrected, and feasible generalized least squares estimators and the relationship between revenue and tickets issued remains statistically significant. These alternative regression results will be provided upon request.

<sup>18</sup> Out of concern that this finding may depend on the lag length we selected, we also re-estimated our models using injuries and deaths from the previous year and the average number of injuries and deaths from the previous two years. In each case the estimated coefficients were found to be negative and statistically significant.

<sup>19</sup> We also estimated specifications that included the level of tourism spending and primary highway mileage as regressors (in per capita level terms) and interacted these variables with our local revenue variable to explore whether law enforcement may be using traffic tickets as a form of a new tax on locals or passing it off to others. We found no evidence of statistical significance between the fiscal pressure measure and local attributes.

<sup>20</sup> While there is evidence that some types of crime are countercyclical (see, for example, Cook and Zarkin 1985; Raphael and Winter-Ebmer 2001), we are not aware of any study demonstrating that changes in policing behavior lead to increases in other types of crimes.

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Table 1					
Variable Descri	ptions, Summary	y Statistics, a	nd Data Sources		

	MEAN	MEAN		
VARIABLE	(Std.Dev) (Std.Dev) DESCRIPTION		SOURCE	
	%Δ	levels		
Traffic tickets per capita	.007	.108	Number of per capita traffic infraction cases filed in	LINC
	(.175)	(.044)	District Court during the fiscal year	
Unemployment rate	.056	5.462	Average annual unemployment rate by place of	LINC
· ·	(.199)	(2.442)	residence (rate * 100)	
Law enforcement officers per capita	.015	.002	Number of full-time sworn law enforcement officers	Crime in
1 I	(.059)	(.001)	per capita	North Carolina
	100	1000 200	North Carolina Department of Commerce's	
	.109	1088.299	estimated domestic travel spending (per capita)	LING
Tourism spending per capita	(.275)	(1597.798)	produced through the County Travel Economic	LINC
			Impact Model. See Footnote 19 for a more detailed	
Pagistarad votors as a share voting aga	012	750	Erection of the county's voting are population that	
population	.012	(105)	are registered to vote	LINC
population	(.037)	64 102	Number of outomobile and truck registrations per	
Registered vehicles per mile of roadway	.020	(57.044)	mile of primary and secondary roadway	LINC
	004	060	Number of persons (per capita) arrested cited or	
Number of arrests per capita	(417)	(020)	summonsed for committing an offense during the	LINC
Number of artesis per capita	(.417)	(.029)	calendar year	LINC
	- 010	140	Number of persons ages 15 to 24 as a share of the	
Share of population age 15 to 24	(018)	(035)	total population	LINC
	015	490	Fraction of all criminal cases filed in District Court	
Vehicle-related criminal cases	(087)	(.080)	during the fiscal year that are vehicle-related	LINC
	001	249	Number of minority persons age 15 and older as a	
Minority population age 15 and older	(014)	(.089)	share of the total population	LINC
	005	.017	Mean number of per capita injuries & deaths	
Traffic injuries & deaths over previous 3 vrs	(.054)	(.004)	resulting from traffic accidents over the previous 3	LINC
	(	()	year period	
	.015	155.857	Number of persons per square mile of land area	1.010
Population density	(.012)	(185.625)		LINC
	004	36242 743	U.S. Department of Housing and Urban	
Median family income	(141)	(9743 479)	Development's estimate of median family income	
	(.111)	()/13.17)	for the ending the of federal fiscal year	LINC
			County-level revenue for the current fiscal year.	
			which is the sum of the six major revenue sources	
			for local governments in North Carolina: Federal	
	.075	607.412	aid, state aid, property taxes, license taxes, permits	LDIC
Current revenue * (positive dummy)	(.091)	(222.465)	and fees, and local sales taxes. This variable is	LINC
			interacted with a dummy variable that equals 1 if	
			revenue growth at time <i>t</i> is non-negative and equals	
			zero otherwise.	
			County-level revenue for the current fiscal year	
Current revenue * (negative dummy)	014		interacted with a dummy variable that equals 1 if	
Current revenue · (negative dunniny)	(.038)		revenue growth at time t is negative and equals zero	LINC
			otherwise.	

Note: Sample includes 96 of North Carolina's 100 counties. Mitchell, Tyrrell, Wayne, and Yancey counties were omitted due to incomplete data. Descriptive statistics in annual percentage change form are computed from 1990 to 2003 (1344 observations), while descriptive statistics in level form are computed from 1989 to 2003 (1440 observations). Calendar year data at time *t* are the average of observations at time *t* and *t*-*1* to make them compatible with the traffic ticket data, which are measured in fiscal years. The variables measured in calendar years (and hence averaged) include the unemployment rate, law enforcement officers, tourism spending, registered voters, registered vehicles, number of arrests, population age 15 to 24, minority population age 15 and older, population density, and median family income. *Crime in North Carolina* is published by the state's Department of Justice and the online database LINC (Log Into North Carolina) may be accessed at http://linc.state.nc.us/.

Constant         -,154+         -,1425+         -,1524+         -,1362+         -,1289           Unemployment rate         (0.817)         (0.0805)         (0.0794)         (0.0801)           Law enforcement officers per capita         (1.0331)         (0.0332)         (0.03330)         (0.0330)           Law enforcement officers per capita         (1.107)         (1.133)         (1.103)         (1.132)         (1.143)           Tourism spending per capita         .3222*         .1304**         .1243**         .1220*         .3664           Registered voters as a hare voting age population        3704*        3920*        4016*        3762*        3614*           Number of arrests per capita         .0087         .0092         .0076         .0072         .0073           Share of population age 15 to 24        2016         .1674        2008         .2018         .1859           Vehicle-related criminal cases         .7793*         .7783*         .7742*         .7765*         .7789           Minority population age 15 and older         .6094         .5410         .63303         .63375         .6303           Minority population desity         .1.070*         .1.128         .1557         .2216*         .2325*         .2217* <t< th=""><th>Variable</th><th>(1)</th><th>(2)</th><th>(3)</th><th>(4)</th><th>(5)</th></t<>	Variable	(1)	(2)	(3)	(4)	(5)
(0817)         (0805)         (0794)         (0794)         (0801)           Unemployment rate         (0331)         (0322)         (0324)         (0330)         (0335)           Law enforcement officers per capita         1.785         1.820         1.713         1.745         1.718           Tourism spending per capita         1.322         1.304         1.243         1.220         1.248           Registered voters as a share voting age population        3704'        3202'        4016'         .3762'        3614'           Registered votiers as a share voting age population        3704'        3202'        4016'         .3762'         .3614'           Registered vohicles per mile of roadway        0565        0276        0560         .0072         .0073           Number of arrests per capita         .0087         .0092         .0076         .0072         .0073           Stare of population age 15 to 24        2016        1674        2068        2018         .1889           Vehicle-related criminal cases         .7793 '''''''''''''''''''''''''''''''''''	Constant	1544 +	1425 +	1524+	1362+	1289
Unemployment rate         (0849)*         (0821)*         (0826)*         (0810)*         (0830)           Law enforcement officers per capita         .1785         .1820         .1731         .1745         .1781           Tourism spending per capita         .1322*         .1304*         .1243*         .1220*         .1248*           Registered voters as a share voting age population        3704*        3920*        4016*        362*        3614*           Registered voters as a share voting age population        3704*        3920*        4016*        376*        3614*           Registered voters as a share voting age population        3704*        3920*        4016*        3614*           Number of arrests per capita         .0087         .0092        0076        0353        0138           Number of arrests per capita         .0087         .0092        0076        0072        0073           Share of population age 15 to 24        2016        1674*        2080*        2018*        1859           Minority population age 15 and older         .6094         .5810         .5993         .5726         .6333           Minority population age 15 and older         .6094         .5810         .5993		(.0817)	(.0805)	(.0794)	(.0794)	(.0801)
(D331)         (D332)         (D333)         (D333)<	Unemployment rate	.0849*	.0821 *	.0826*	.0810*	.0801 *
Law enforcement officers per capita (1785 1820 1731 1745 1781 (1107) (1133) (1103) (11132) (11140) Tourism spending per capita (1107) (1133) (1103) (11132) (11140) Tourism spending per capita (2117) (21140) Registered voters as a share voting age population -3702 -30614* (2237) (2246) (2210) (2175) (2146) Registered vehicles per mile of roadway -0565 -0276 0.5050 -0353 -0138 (4385) (4420) (4502) (4485) (4450) Number of arrests per capita 0087 0092 0076 0072 0073 (0196) (01098) (00202) (0206) (0200) Share of population age 15 to 24 -2016 -1674 -2068 -2018 -1859 (3368) (3413) (3316) (3360) (3331) Vehicle-related criminal cases 7793 * 7778* 7742 * 7765 * 7789* Vehicle-related criminal cases (5793 * 0778* 0778* 7742 * 7765 * 7789* Vehicle-related set over previous 3 years -2249* -2210* (2225* -2257* -2217* (5403) (5433) (5433) (5482) (5575) (5260) Mean traffic injuries & deaths over previous 3 years -2249* -2210* -2225* -2257* -2217* (5903) (0963) (0964) (0973) (0975) (0994) Population density -1.1070* -1.1124* -1.1011* -1.0719* -1.0867* (5701) (0753) (5598) (5588) (55915) Median family income -1950 -1789 -1774 -0733 (1598) (1581) (1551) Current local revenue * positive dummy -0.174 -0.731 (1598) (1583) (1581) (1551) Current local revenue * negative dummy -0.816 -1166 -1267 -1214 (1624) (1598) (1583) (1583) (1581) (1551) Local revenue lagged 1 period * negative dummy -0.7764 -0.731 (0659) (0566) (00567) Local revenue lagged 1 period * negative dummy -0.7764 -0.732 (1555) (1683) Local revenue lagged 2 periods * negative dummy -0.768 -0.789 0.0699 (0643) (06661) Local revenue lagged 2 periods * negative dummy -0.764 -0.329* (1422) (1555) (1683) Local revenue lagged 3 periods * negative dummy -0.764 -0.3206 (0643) (06661) Local revenue lagged 3 periods * negative dummy -0.764 -0.3206 (0643) (06661) Local revenue lagged 3 periods * negative dummy -0.972 (0643) -0.0729 (0643) (06661) Local revenue lagged 3 periods * negative dummy -0.974 (0673) -0.975 -0.200 200		(.0331)	(.0332)	(.0324)	(.0330)	(.0336)
Charlen and	Law enforcement officers per capita	.1785	.1820	.1731	.1745	.1781
Tourism spending per capita       1322**       1304**       1243**       1220**       1248**         (0415)       (0407)       (0379)       (0383)       (0377)         Registered voters as a share voting age population      3704*      3920*      4016*      3762*      3614*         Registered vehicles per mile of roadway      0565      0276      0560      0073       .0138         Number of arrests per capita       .0087       .0092       .0076       .0072       .0073         Share of population age 15 to 24      2016      1674      2068      2018      1859         Minority population age 15 and older       .6050)       (.0550)       (.0549)       (.0335)       (.0333)       (.0333)         Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years       .2249*       .2210*       .2225*       .2257*       .2217*         Median family income       .1950       .1789       .1784       .1633       .1662         Current local revenue * negative dummy       .0774       .0771       .0758*       .0583       .65833         Current local revenue * negative dummy       .0164		(.1107)	(.1133)	(.1103)	(.1132)	(.1140)
(0415)       (0407)       (0379)       (0383)       (0377)         Registered voters as a share voting age population      3704 *3920 *4016 *3762 *3614       (.2237)       (.2246)       (.2210)       (.2175)       (.2146)         Registered vehicles per mile of roadway      0556      0276      0560      0353      0138         Number of arrests per capita       .0087       .0092       .0076       .0072       .0073         Share of population age 15 to 24      2016      1674      2068      2018      1859         Vehicle-related criminal cases       .7793 **       .7778 **       .776 **       .7789 **       .7778 **       .776 **       .7778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 *       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .776 **       .778 **       .772 **       .6303       .0533       .0533       .0533       .0533       .0533       .0533       .0533       .0533       .0533       .0533	Tourism spending per capita	.1322 **	.1304 **	.1243 **	.1220 **	.1248 **
Registered voters as a share voting age population      3704 +      3920 +      4016 +      3762 +      3614 +         (.2237)       (.2246)       (.2210)       (.2175)       (.2146)         Registered vehicles per mile of roadway      0565      0276      0560      0353       .0138         Number of arrests per capita       .0087       .0092       .0076       .0070       .0073         Share of population age 15 to 24      2016      1674      2068      2018      1859         Vehicle-related criminal cases       .7793 **       .7774 **       .7765 **       .7789 **         Mority population age 15 and older       (.0550)       (.0543)       (.5435)       (.5432)       (.5375)       (.5200)         Mean traffic injuries & deaths over previous 3 years      2210 *      2210 *      225 *      225 *       .225 *       .225 *       .225 *       .225 *       .2217 *       .7263       .1662         Median family income      1070 *       1.1070 *       1.112 *       .1.011 *       .1.0719 *       .10867 *         Current local revenue * positive dummy       .0510       .1583)       (.1581)       (.1551)         Current local revenue * positive dummy       .0164 *       .1267 <td></td> <td>(.0415)</td> <td>(.0407)</td> <td>(.0379)</td> <td>(.0383)</td> <td>(.0377)</td>		(.0415)	(.0407)	(.0379)	(.0383)	(.0377)
(2237)       (2246)       (2210)       (2175)       (2146)         Registered vehicles per mile of roadway      0565      0276      0560      0353      0138         Number of arrests per capita       .0087       .0092       .0076       .0072       .0070         Share of population age 15 to 24      2016      1674      2068      2018      1859         (.3368)       (.3413)       (.3516)       (.3360)       (.3391)       (.0533)       (.0533)         Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years      2210*      2225*       .2257*       .2217*         (.0963)       (.0962)       (.0971)       (.0975)       (.0994)         Population density      11070*      1124*       -11011*       -1.0867*         Current local revenue * positive dummy       .0816       .1166       .1267       .1214         Current local revenue * negative dummy       .0519)       (.0543)       (.5483)       (.5183)       (.1581)       (.1551)         Current local revenue * positive dummy       .0519)       .1789       .1784       .1714*       .0735       .0623)	Registered voters as a share voting age population	3704 +	3920+	4016+	3762+	3614+
Registered vehicles per mile of roadway      0565      0276      0560      0333      0138         Number of arrests per capita       .0087       .0092       .0076       .0072       .0073         Share of population age 15 to 24      2016      1674      2068      2018      1859         (.3368)       (.3413)       (.3516)       (.3360)       (.3330)       (.3391)         Vehicle-related criminal cases       .7793*       .7778*       .7742*       .7765*       .7789*         Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years      2249*      2210*      2257*       .2217*         (.0963)       (.0962)       (.0971)       (.0975)       (.9994)         Population density       -1.1070*       -1.1124*       -1.101*       -1.079*       -1.163         Median family income      1950      1789       .1747      1633       .1662         Current local revenue * positive dummy       .0714       .0731       .0735       .0823         Current local revenue * negative dummy       .0786       .0789       .06691         Local revenue lagged 1 period * negative		(.2237)	(.2246)	(.2210)	(.2175)	(.2146)
(4385)       (.4420)       (.4502)       (.4485)       (.4546)         Number of arrests per capita       .0087       .0092       .0076       .0072       .00706         Share of population age 15 to 24      2016      1674      2068      2018      1859         (.3368)       (.3413)       (.3516)       (.3360)       (.3391)       (.0533)       (.0533)         Wehicle-related criminal cases       .7778*       .7778*       .7776*       .7776*       .7776*       .7776*       .7778*         Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years      2249*      2210*      2225*      2257*      2217*         Median family income       .1070*       -1.1170*       -1.111*       -1.011*       -1.0075       (.0994)         Current local revenue * positive dummy       .0774       .0731       .0735       .1682         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         Local revenue * negative dummy       .0786       .0789       .0699       .0643       .00643       .00661)         Local revenue lagged 1 period * negative dummy	Registered vehicles per mile of roadway	0565	0276	0560	0353	0138
Number of arrests per capita         .0087         .0092         .0076         .0072         .0073           Share of population age 15 to 24         .2016        1674         .2068        2018        1859           Vehicle-related criminal cases        7793"        7774"        7742"        765 *        7789 *           (.0550)         (.0550)         (.0533)         (.0533)         (.0533)         (.0533)         (.0533)           Minority population age 15 and older         .6094         .5810         .5993         .5726         .6303           Mean traffic injuries & deaths over previous 3 years         .2249"         .2210"         .2225"         .2217"         .2217"         .2217"         .2217"         .2217"         .2218"         .5755         (.0994)           Population density         -1.1070"         -1.1124"         -1.1011"         -1.0719"         -1.0867"           Median family income        1950        1789        1633        1662           Current local revenue * positive dummy        0774        0731        0733         .05915           Current local revenue * negative dummy        0816         .1166         .1267         .1214           (.1351)         (.1557)         (		(.4385)	(.4420)	(.4502)	(.4485)	(.4546)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Number of arrests per capita	.0087	.0092	.0076	.0072	.0073
Share of population age 15 to 24      2016      1674      2068      2018      1859         (.3368)       (.3413)       (.3516)       (.3360)       (.3371)         Vehicle-related criminal cases       .7793 **       .7778 **       .7742 **       .7765 **       .7789 **         Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years      2249'      2210*      2225 *      2257*       .2217*         (.0963)       (.0962)       (.0971)       (.0975)       (.0994)         Population density       -1.1070*       -1.1124*       -1.1011*       -1.0719*       -1.0867*         Median family income      1950      1789      1774      1633      1662         (.1624)       (.1598)       (.1583)       (.1581)       (.1551)         Current local revenue * negative dummy      0774      0731      0732      0823         Local revenue lagged 1 period * positive dummy       .0816       .1166       .1267       .1214         Local revenue lagged 2 periods * negative dummy       .0786       .0789       .0699         Local revenue lagged 2 periods * negative dummy       .		(.0196)	(.0198)	(.0202)	(.0206)	(.0200)
Vehicle-related criminal cases       (.3368)       (.3413)       (.3516)       (.3360)       (.3391)         Vehicle-related criminal cases       .7793"       .7778"       .7742"       .7765"       .7789"         Minority population age 15 and older       .6094       .5810       .5933       .5726       .6303         Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years       .22249"       .2210"       .2225"       .2257"       .2217"         (.0963)       .(.0962)       .(.0971)       .(.0975)       .(.0994)         Population density       -1.1070"       -1.1124"       -1.1011"       -1.0719"       -1.0867"         (.5701)       .(.5753)       .(.5883)       .(.5813)       .(.1581)       .(.1551)         Current local revenue * positive dummy       .0774       .0731       .0735       .0823         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * positive dummy       .03816       .11661       .1267       .1214         Local revenue lagged 2 periods * negative dummy       .0182       .00823       .00843       .00699 <t< td=""><td>Share of population age 15 to 24</td><td>2016</td><td>1674</td><td>2068</td><td>2018</td><td>1859</td></t<>	Share of population age 15 to 24	2016	1674	2068	2018	1859
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.3368)	(.3413)	(.3516)	(.3360)	(.3391)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Vehicle-related criminal cases	.7793 **	.7778 **	.7742 **	.7765 **	.7789**
Minority population age 15 and older       .6094       .5810       .5993       .5726       .6303         Mean traffic injuries & deaths over previous 3 years       .2249*       .2210*       .2225*       .2225*       .2217*         Mean traffic injuries & deaths over previous 3 years       .2249*       .2210*       .2225*       .2225*       .2227*       .2217*         Mean traffic injuries & deaths over previous 3 years       .1070*       .11124*       .10075)       (.0994)         Population density       -1.1070*       -1.1124*       -1.1011*       -1.0719*       -1.0867*         (.5701)       (.5753)       (.5958)       (.5883)       (.5915)         Median family income       .1950       .1774      1633      1662         (.1624)       (.1598)       (.1583)       (.1581)       (.1581)         Current local revenue * positive dummy       .0074      0731      0735      0823         Current local revenue * negative dummy       .0166       .1166       .1267       .1214         Local revenue lagged 1 period * negative dummy       .0786       .0789       .0699         Local revenue lagged 2 periods * negative dummy       .3276*       .3164*       .3259*         (.1442)       (.1555)       (.1683)<		(.0550)	(.0549)	(.0535)	(.0533)	(.0533)
Number $(.5493)$ $(.5435)$ $(.5482)$ $(.5375)$ $(.5260)$ Mean traffic injuries & deaths over previous 3 years $2249^{*}$ $2210^{*}$ $2225^{*}$ $2257^{*}$ $2217^{*}$ $(.0963)$ $(.0962)$ $(.0971)$ $(.0975)$ $(.0994)$ Population density $-1.1070^{*}$ $-1.1124^{*}$ $-1.1011^{*}$ $-1.0719^{*}$ $-1.0867^{*}$ Median family income $1950$ $1789$ $1774$ $1633$ $1662$ Current local revenue * positive dummy $0774$ $0731$ $0735$ $0823$ Current local revenue * negative dummy $.0816$ $.1166$ $.1267$ $.1214$ Local revenue a geged 1 period * positive dummy $.0816$ $.1166$ $.1267$ $.1214$ Local revenue lagged 1 period * negative dummy $.0786$ $.0789$ $.0699$ Local revenue lagged 2 periods * negative dummy $.2764$ $.2326^{*}$ $.2276^{*}$ $.2316^{*}$ Local revenue lagged 3 periods * negative dummy $.2764$ $.2306$ $(.0661)$ Local revenue lagged 3 periods * negative dummy $.2764$ $.2306$ $(.0617)$ Local revenue lagged 3 periods * negative dummy $.0977$ $.200$ $.200$ Local revenue lagged 3 periods * negative dummy $.1943$ $.1344$ $1344$ $1344$ Adjusted R-squared $.197$ $.197$ $.200$ $.200$ Derive hybric revenue $.2320$ $.2327$ $.2320$ $.2321$	Minority population age 15 and older	.6094	.5810	.5993	.5726	.6303
Mean traffic injuries & deaths over previous 3 years $2249^+$ $2210^+$ $2257^+$ $2217^+$ Mean traffic injuries & deaths over previous 3 years $2249^+$ $2210^+$ $2257^+$ $2217^+$ Median family income $-1.1070^+$ $-1.1124^+$ $-1.1011^+$ $-1.0719^+$ $-1.0867^+$ Median family income $1950^ 1789^ 1774^ 1633^ 1662^-$ Current local revenue * positive dummy $0774^ 0731^ 0735^ 0823^-$ Current local revenue * negative dummy $0774^ 0731^ 0735^ 0823^-$ Local revenue lagged 1 period * positive dummy $0.766^ 0.789^ 0.0569^-$ Local revenue lagged 1 period * negative dummy $3276^+$ $3164^+$ $3259^+$ Local revenue lagged 2 periods * positive dummy $3276^+$ $3164^+$ $3259^+$ Local revenue lagged 3 periods * negative dummy $0182^ 0239^ 0.0561^-$ Local revenue lagged 3 periods * negative dummy $.06617^ .06617^ .06617^-$ Local revenue lagged 3 periods * negative dummy $.0764^ .00561^-$		(.5493)	(.5435)	(.5482)	(.5375)	(.5260)
(.0963)       (.0962)       (.0971)       (.0975)       (.0994)         Population density       -1.1070*       -1.1124*       -1.1011*       -1.0719*       -1.0867*         (.5701)       (.5753)       (.5958)       (.5883)       (.5915)         Median family income      1950      1789      1774      1633      1662         (.1624)       (.1598)       (.1581)       (.1551)       (.1581)       (.1551)         Current local revenue * positive dummy      0774      0731      0735      0823         (.0519)       (.0522)       (.0523)       (.0543)         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         (.1351)       (.1557)       (.1600)       (.1669)       .00569       (.0567)         Local revenue lagged 1 period * positive dummy      3276*      3164*      3259*         Local revenue lagged 2 periods * negative dummy      0724       .2004       .2039         Local revenue lagged 2 periods * negative dummy       .2764       .2306       .00617         Local revenue lagged 3 periods * negative dummy       .2764       .2306       .00617         Local revenue lagged 3 periods * negative dummy       .2764	Mean traffic injuries & deaths over previous 3 years	2249*	2210*	2225 *	2257*	2217*
Population density $-1.1070^+$ $-1.1124^+$ $-1.011^+$ $-1.0719^+$ $-1.0867^+$ Median family income $1950$ $1789$ $1774$ $1633$ $1662$ Median family income $1950$ $1789$ $1774$ $1633$ $1662$ Current local revenue * positive dummy $0774$ $0731$ $0735$ $0823$ Current local revenue * negative dummy $0.0816$ $.1166$ $1.267$ $.1214$ Local revenue lagged 1 period * positive dummy $0.786$ $0.789$ $0.699$ Local revenue lagged 1 period * negative dummy $0.786$ $0.789$ $0.699$ Local revenue lagged 2 period * negative dummy $3276^*$ $3164^*$ $3229^+$ Local revenue lagged 2 periods * negative dummy $0182$ $0239$ $(.0643)$ $(.0661)$ Local revenue lagged 3 periods * negative dummy $0531$ $(.0617)$ $0531$ $(.2764$ $.2306$ Local revenue lagged 3 periods * negative dummy $.2764$ $.2306$ $(.249)$ $(.0617)$ Local revenue lagged 3 periods * negative dummy $.2764$ $.2306$ $(.2764$	5 1 5	(.0963)	(.0962)	(.0971)	(.0975)	(.0994)
(.5701)       (.5753)       (.5958)       (.5883)       (.5915)         Median family income      1950      1789      1774      1633      1662         (.1624)       (.1598)       (.1583)       (.1581)       (.1551)         Current local revenue * positive dummy      0774      0731      0735      0823         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         (.0519)       (.0522)       (.0523)       (.0543)         Local revenue lagged 1 period * positive dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * negative dummy       .0786       .0789       .0699         Local revenue lagged 2 periods * negative dummy      3276*      3164*      3259*         Local revenue lagged 2 periods * negative dummy       .0643)       (.0643)       (.0661)         Local revenue lagged 3 periods * negative dummy       .2764       .2306       .1772)       (.1831)         Local revenue lagged 3 periods * negative dummy       .0617)       .0617)       .0617)       .0617)         Local revenue lagged 3 periods * negative dummy       .0617)       .0617)       .0617)       .0249)         Sample Size       1344 <td>Population density</td> <td>-1.1070+</td> <td>-1.1124+</td> <td>-1.1011+</td> <td>-1.0719+</td> <td>-1.0867+</td>	Population density	-1.1070+	-1.1124+	-1.1011+	-1.0719+	-1.0867+
Median family income      1950      1789      1774      1633      1662         Current local revenue * positive dummy       .01624       (.1598)       (.1583)       (.1581)       (.1551)         Current local revenue * negative dummy       .0074      0731      0735      0823         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * positive dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * positive dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * positive dummy       .0816       .1166       .1267       .1214         Local revenue lagged 2 periods * positive dummy       .03786       .0789       .0699         Local revenue lagged 2 periods * positive dummy       .3276*      3164*      3259*         Local revenue lagged 2 periods * negative dummy       .0182      0239       .06643)       .00661)         Local revenue lagged 3 periods * positive dummy       .2764       .2306       .0531       .00511       .01617)         Local revenue lagged 3 periods * negative dummy       .1943       .2249)       .0193       .2249)       .2249)         Samp		(.5701)	(.5753)	(.5958)	(.5883)	(.5915)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Median family income	1950	1789	1774	1633	1662
Current local revenue * positive dummy      0774      0731      0735      0823         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * positive dummy       .0786       .0789       .0699         Local revenue lagged 1 period * negative dummy       .0376       .0789       .0699         Local revenue lagged 2 periods * negative dummy      3276*      3164*      3259*         Local revenue lagged 2 periods * positive dummy       .04142       (.1442)       (.1555)       (.1683)         Local revenue lagged 2 periods * negative dummy       .2764       .2039       (.0643)       (.0661)         Local revenue lagged 3 periods * negative dummy       .0751       .0531       (.0617)       .0531         Local revenue lagged 3 periods * negative dummy       .0531       .05617       .0531       .0249         Sample Size       1344       1344       1344       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200       .200		(.1624)	(.1598)	(.1583)	(.1581)	(.1551)
Current local revenue * negative dummy       (.0519)       (.0522)       (.0523)       (.0543)         Current local revenue * negative dummy       .0816       .1166       .1267       .1214         (.1351)       (.1557)       (.1600)       (.1669)         Local revenue lagged 1 period * positive dummy       .0786       .0789       .0699         Local revenue lagged 1 period * negative dummy      3276*      3164*      3259*         Local revenue lagged 2 periods * positive dummy      0182      0239       (.0643)       (.0661)         Local revenue lagged 3 periods * negative dummy       .2764       .2306       (.1772)       (.1831)         Local revenue lagged 3 periods * negative dummy       .00531       (.0617)       .00617)         Local revenue lagged 3 periods * negative dummy       .02764       .2306       (.2249)         Sample Size       1344       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200       .200         Paral Darkin Waterer       2.330       2.327       2.323       2.321       .2321	Current local revenue * positive dummy	(11021)	0774	0731	0735	0823
Current local revenue * negative dummy       .0816       .1166       .1267       .1214         Local revenue lagged 1 period * positive dummy       .0786       .0789       .0699         Local revenue lagged 1 period * negative dummy       .0786       .0789       .0699         Local revenue lagged 1 period * negative dummy       .03276*      3164*      3259*         Local revenue lagged 2 periods * positive dummy       .0412       (.1555)       (.1683)         Local revenue lagged 2 periods * negative dummy       .0182      0239         Local revenue lagged 3 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * negative dummy       .06177       .0531         Local revenue lagged 3 periods * negative dummy       .043       .06177         Local revenue lagged 3 periods * negative dummy       .2764       .2306         Migusted R-squared       .197       .197       .200       .200         Panel Dwribin Watsor       .2327       .2323       .2323       .2323       .2323			(.0519)	(.0522)	(.0523)	(.0543)
Local revenue lagged 1 period * positive dummy       (.1351)       (.1557)       (.1600)       (.1669)         Local revenue lagged 1 period * negative dummy       .0786       .0789       .0699         Local revenue lagged 1 period * negative dummy      3276*      3164*      3259*         Local revenue lagged 2 periods * positive dummy      0182      0239         Local revenue lagged 2 periods * negative dummy       .0764       .2039         Local revenue lagged 3 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * negative dummy       .2764       .2030         Local revenue lagged 3 periods * negative dummy       .0617)       (.1831)         Local revenue lagged 3 periods * negative dummy       .1943       .2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200       .200         Panel Durbin Wetson       .2327       .2323       .2323       .2321	Current local revenue * negative dummy		.0816	.1166	.1267	.1214
Local revenue lagged 1 period * positive dummy       (.1007)       (.0607)         Local revenue lagged 1 period * negative dummy      3276*      3164*      3259*       (.1067)       (.1067)       (.1067)         Local revenue lagged 2 periods * positive dummy      0182      0239       (.0661)       (.0661)         Local revenue lagged 3 periods * negative dummy       .2764       .2306       (.1772)       (.1831)         Local revenue lagged 3 periods * negative dummy       .1943       (.0617)       .0531       (.0617)         Local revenue lagged 3 periods * negative dummy       .1943       .1943       .2249)       .2249)       .2249)         Sample Size       1344       1344       1344       1344       1344       1344       .200       .200       .200       .200       .200       .201       .201       .201       .201       .201       .201       .201       .201<	Current local levenue - negative duning		(1351)	(1557)	(1600)	(1669)
Local revenue lagged 1 period * negative dummy       (.0549)       (.0566)       (.0567)         Local revenue lagged 2 periods * negative dummy      3276 *      3164 *      3259 *         Local revenue lagged 2 periods * positive dummy      0182      0239         Local revenue lagged 2 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * negative dummy       .0617)       .0617)         Local revenue lagged 3 periods * negative dummy       .1772)       (.1831)         Local revenue lagged 3 periods * negative dummy       .0617)       .00617)         Local revenue lagged 3 periods * negative dummy       .1943       .2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200       .200         Panel Duchin Wetson       .2320       .2327       .2323       .2323       .2321	Local revenue lagged 1 period * positive dummy		(.1551)	0786	0789	0699
Local revenue lagged 1 period * negative dummy      3276*      3164*      3259*         Local revenue lagged 2 periods * positive dummy      0182      0239         Local revenue lagged 2 periods * negative dummy       .0643)       (.0661)         Local revenue lagged 3 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * negative dummy       .0617)       .0531         Local revenue lagged 3 periods * negative dummy       .0617)       .0531         Local revenue lagged 3 periods * negative dummy       .0531       .0617)         Local revenue lagged 3 periods * negative dummy       .1943       .2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200       .200         Panal Durbin Watson       .2320       .2327       .2323       .2321       .2321	Zeen revenue hugged i period - positive duminy			(0549)	(0566)	(0567)
Local revenue lagged 2 periods * positive dummy       (.1442)       (.1555)       (.1683)         Local revenue lagged 2 periods * negative dummy      0182      0239         Local revenue lagged 2 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * positive dummy       .2764       .2306         Local revenue lagged 3 periods * positive dummy      0531       (.0617)         Local revenue lagged 3 periods * negative dummy       .1943       (.2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durkin Wetcorp       .2320       .2327       .2322       .2323       .2321	Local revenue lagged 1 period * negative dummy			- 3276*	- 3164*	- 3259+
Local revenue lagged 2 periods * positive dummy      0182      0239         Local revenue lagged 2 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * positive dummy       .2764       .2306         Local revenue lagged 3 periods * positive dummy      0531       (.0617)         Local revenue lagged 3 periods * negative dummy       .1943       (.2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durkin Watson       2.230       2.237       2.2323       2.2321	Local revenue hagged i period - negative duminy			(1442)	(1555)	(1683)
Local revenue lagged 2 periods * negative dummy       (.0643)       (.0661)         Local revenue lagged 3 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * positive dummy      0531       (.0617)         Local revenue lagged 3 periods * negative dummy       .1943       (.2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Wattorn       2.230       2.237       2.232       2.232       2.232	Local revenue lagged 2 periods * positive dummy			(.1112)	- 0182	- 0239
Local revenue lagged 2 periods * negative dummy       .2764       .2306         Local revenue lagged 3 periods * positive dummy       .1831)       .0531         Local revenue lagged 3 periods * negative dummy       .0617)       .0531         Local revenue lagged 3 periods * negative dummy       .1943       .2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Wetcop       .230       .2327       .2322       .2321	Local revenue hagged 2 periods positive duminy				(0643)	(0661)
Local revenue lagged 3 periods * positive dummy       (.1772)       (.1831)         Local revenue lagged 3 periods * negative dummy      0531       (.0617)         Local revenue lagged 3 periods * negative dummy       .1943       (.2249)         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Wetcop       2.230       2.237       2.232       2.232       2.232	Local revenue lagged 2 periods * negative dummy				2764	2306
Local revenue lagged 3 periods * positive dummy      0531         Local revenue lagged 3 periods * negative dummy       .1943         Local revenue lagged 3 periods * negative dummy       .1943         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Wetcop       2.230       2.237       2.232       2.232       2.232	Local revenue hagged 2 periods - hegalive duming				(1772)	(1831)
Local revenue lagged 3 periods * negative dummy       .0051         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Watton       2.230       2.237       2.232       2.232       2.232	Local revenue lagged 3 periods * positive dummy				(.1772)	- 0531
Local revenue lagged 3 periods * negative dummy       .1943         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Watton       2.230       2.237       2.232       2.232       2.232	Local revenue lagged 5 periods positive duminy					(0617)
Instance       Instance       Instance         Sample Size       1344       1344       1344       1344         Adjusted R-squared       .197       .197       .200       .200         Panal Durbin Watton       2.230       2.237       2.232       2.232	Local revenue lagged 3 periods * negative dummy					(.0017)
Sample Size         1344         1344         1344         1344         1344           Adjusted R-squared         .197         .197         .200         .200         .200           Panal Durbin Watton         2.230         2.237         2.232         2.232         2.231	Local revenue lagged 5 periods in regarive duminy					(2249)
Adjusted R-squared         .197         .197         .200         .200           Durbin Watton         2.230         2.237         2.232         2.231	Sample Size	1344	1344	1344	1344	1344
Augusted R-squared         .177         .1200         .200         .200           Daval Durkin Westoon         2.230         2.237         2.232         2.231	Adjusted R-squared	107	197	200	200	200
	Panel Durbin-Watson	2 230	2 227	200	2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2	2 200
Resch-Pagan I M test for heteroskedasticity       2.2.00       2.2.2.1       2.2.2.2       2.2.2.5       2.2.2.1	Rulesch-Pagan I M test for heteroskedasticity	2.230 431 020 **	441 656 **	438 376 **	438 057 **	۵.221 452 853 **
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	E-test for overall model significance		3 686 **	3 681 **	3 6/0**	3 607 **
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	E test for joint significance of year and county fixed affects	1 315*	1 207 *	1 202 *	1.78/1*	1 200*
F test for symmetric response to revenue larged 1 period $1.315$ $1.277$ $1.297$ $1.297$ $1.309$ $1.377$ $1.330$ $1.357$	F-test for symmetric response to revenue lagged 1 period	1.010	1.277	1.327*	1.339*	1.352*

Table 2Effect of Local Revenue Changes on the Change in Traffic Tickets Issued

Notes: Robust standard errors clustered by county in parentheses. Each model was estimated with year and county fixed effects that are not reported. The dependent variable is the annual percentage change in the number of traffic tickets issued per capita. Complete descriptions of all of the variables may be found in Table 1. Sample is 96 counties in North Carolina from 1990 to 2003. + P < .05; \*\* P < .05; \*\* P < .01.



Figure 1. Traffic Tickets Issued in North Carolina, 1989 to 2003.