Title

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Abstract

We estimate auto accident externalities (more specifically insurance externalities) using panel data on state-average insurance premiums and loss costs. Externalities appear to be substantial in traffic dense states: in California, for example, we find that the increase in traffic density from a typical additional driver increases total state-wide insurance costs of other drivers by \$1725 to \$3239 per year, depending upon the model. High traffic density states have large economically and statistically significant externalities in all specifications we check. In contrast, the accident externality per driver in low traffic states appears quite small. On balance, accident externalities are so large that a correcting Pigouvian tax could raise \$66 billion annually in California alone, more than all existing California state taxes during our study period, and over \$220 billion/yr. nationally.

Keywords: insurance, auto accidents, externalities.

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1 Introduction

Consider two vehicles that crash as one drives through a red light and the other a green light. The accident would not occur if either took the subway instead of driving: hence, strictly speaking, *both* cause the accident in full, even though only one is negligent. The average accident cost of the two people's driving is the damages to two vehicles ($2D$) divided by the driving of two vehicles (i.e., D per driven-vehicle). But the marginal cost exceeds this. In fact, the marginal cost of driving either vehicle is the damage to two vehicles ($2D$ per driven-vehicle)—fully twice the average cost. Surprisingly, this observation holds just as much for the non-negligent driver as for the negligent one.

Drivers pay the average cost of accidents (on average, anyway), not the marginal cost, so this example suggests that there is a substantial accident externality to driving, an externality that the tort system is not designed to address. The tort system is designed to allocate the damages from an accident among the involved drivers according to a judgment of their fault.

A damage allocation system can provide adequate incentives for careful driving, but it will not provide people with adequate incentives at the margin of deciding how much to drive or whether to become a driver (Vickrey [1968], Green [1976], Shavell [1980], and Cooter and Ulen [1988]). Indeed, contributory negligence, comparative negligence and no-fault systems all suffer this inadequacy because they are all simply different rules for *dividing* the cost of accidents among involved drivers and their insurers. Yet in many cases from the point of view of causation, as distinct from negligence, economic fault will sum to more than 100%. Whenever it does, then efficient driving incentives require that the drivers in a given accident should in aggregate be made to bear more than the total cost of the accident (with the balance going to a third party such as the government).

Does this theory of an accident externality from driving hold up in practice? Equivalently, as a new driver takes to the road, does she increase the accident risk to others as well as assuming risk herself? If so, then a one percent increase in aggregate driving increases aggregate accident costs by more than one percent. Such a relationship need not hold. The riskiness of driving could decrease as aggregate driving increases, because increased driving could worsen congestion and if people are forced to drive at lower speeds, accidents could become less severe or less frequent. Consequently, a one percent increase in driving could increase aggregate accident costs by less than one percent, and could even decrease those costs.

The stakes are large. During our sample period, auto accident insurance in the U.S. cost over \$100 billion each year, and total accident costs could have exceeded \$350 billion each year after including costs that were not insured (National Association of Insurance Commissioners [1997] and Urban Institute [1991]). Multi-vehicle accidents, which are the source of potential accident externalities, dominate these figures, accounting for over 70% of auto accidents. If we assume that exactly two vehicles are *necessary* for multi-vehicle accidents to occur, then one might expect the marginal cost of accidents to exceed the average cost by 70%. Put differently, one would expect aggregate accident costs to rise by 1.7% for every 1% increase in aggregate driving, corresponding to an elasticity of accident costs with respect to driving of 1.7.[1]

Compared to its economic significance, there is relatively little empirical work gauging the size (and sign) of the accident externality from driving. Vickrey [1968], who was the first to conceptualize clearly the accident externality from the quantity of driving (as opposed to the quality of driving), cites data on two groups of California highways and finds that the group with higher traffic density has substantially higher accident rates, suggesting an elasticity of the number of crashes with respect to aggregate driving of 1.5.

A strand of transportation literature takes a similar cross-sectional approach, and concentrates on the relationship between accident rates and traffic volume (average daily traffic). Although this literature does not conceptualize the problem as one of an externality, that interpretation is appropriate: Belmont [1953] and Lundy [1965], for example, compared freeways with different

[1]Suppose that the chance that a driver causes an accident is p,that with probability $.3p$ she has a one-vehicle accident causing damage of D, and that with probability $.7p$ she has a two-vehicle accident causing damage of D to each vehicle. Since by assumption she is the "but for" cause of each accident, the damages her driving causes is $.3pD + 2(.7pD) = 1.7pD$. This figure is also the marginal cost of driving per driver. The average cost of accidents per driver, however, is just pD. The elasticity of accident costs with respect to driving is the ratio of marginal to average cost.

average traffic volume and found that accident rates increased with traffic volume; Belmont found that the total number of accidents per vehicle-mile increased linearly with traffic until the traffic reached 650 vehicles/hr. after which it declined. More recently, Turner and Thomas [1986] examined various freeways in Britain, and reported similar findings. This literature matches up freeways that the authors considered similar (e.g., four lane highways) instead of doing panel analysis or using extensive controls.

Vickrey's study and these cross-sectional transportation crash studies share limitations. Without knowing the inherent safety of the roadways (roadway-specific effects), these studies could lead to biased estimates of how much traffic density increases accident rates on a given roadway. If drivers are attracted to safer roads, then high-density roads could end up with lower accident rates, because the roads themselves are inherently safer, not because traffic made them so. Likewise, if road expenditures are rational, then roads with more traffic will be better planned and better built in order to yield smoother traffic flow and fewer accidents: this again suggests that a cross-sectional study could considerably understate the rise in accident risk with density on a *given* roadway; in fact our regressions will suggest just these effects. Another difficulty is that these crash studies contain no measure of accident severity: if congestion caused severity to decrease, then the accident externality would be smaller than these studies imply; in contrast, if severity increased with density (perhaps more vehicles per accident), then Vickrey (and implicitly these other studies) could dramatically understate the externalities. The "micro" nature of these studies is another limitation for most plausible policies on the state or federal level, where aggregate measures are required. One cannot, for example, know the appropriate level of a second-best correcting gasoline tax from such studies, unless they are replicated across the full spectrum of roadway types, and they are combined with extensive microlevel data on driving and traffic patterns (including a matrix of how drivers will shift driving among roadway risks as density changes).

This study is an attempt to provide better estimates of the size (and sign) of the aggregate accident externality from driving. To begin, we choose a dependent variable, insurer costs, that is dollar-denominated and captures both accident frequency and severity; we also analyze insurance premiums as a dependent variable. We are concerned with aggregate effects across the full spectrum of driving in a given state. Our central question is whether one person's driving increases other people's accident costs.

Figure 1 shows that insurance premiums and insurer costs both tend to rise with a state's traffic density if we consider a cross-section of states. These correlations suggest that there is an accident externality from driving: an extra driver increases traffic density and according to Figure 1 that driver apparently increases the costs of every other driver in addition to incurring her own costs. If costs rise linearly or faster than linearly (as they appear to), this implies that the externality is higher in high density states.

Of course, the pattern in the scatter plot could result from differences in road conditions in the high density states. To address this we use panel data from 1987-1995 on insurer costs, insurance premiums, traffic density, aggregate driving, and various control variables. Our basic strategy is to estimate the extent to which an increase in traffic density in a given state increases (or decreases) average insurer costs and insurance premiums. Our regressions thereby provide a measure of the insurance externality of driving. Increases in traffic density can be caused by increases in the number of people who drive or by increases in the amount of driving each person does. To the extent that the external costs differ at these two margins, our results provide a weighted average of these two costs.

We find that traffic density increases accident costs substantially whether measured by insurer costs or insurance rates. This is robust to all our specifications; it is robust to linear and quadratic models, to IV and OLS and to cross-section or panel. If congestion eventually reverses this effect, it is only at traffic densities beyond those in our sample. Indeed, our estimates suggest that a typical extra driver raises others' insurance rates (by increasing traffic density) by the most in high traffic density states. In California, a very high-traffic state, we estimate that a typical additional driver increases the total statewide insurance costs by \$1725$\pm$744 to \$3239$\pm$1068 each year, depending upon the specification. In contrast, in North Dakota, a very low-traffic state, we estimate that others' insurance costs are increased only slightly (and statistically insignificantly): \$10±\$41 each year, as shown in Table 5, specification 10. These estimates of accident externalities are only for insured accident costs and do not include the cost of injuries that are uncompensated or undercompensated by insurance, nor other accident costs such as traffic delays after accidents.

The remainder of this paper is organized as follows. Section 2 provides a framework for determining the extent of accident externalities. Section 3 discusses our data. Section 4 reports our estimation results. Section 5 presents a state-by-state analysis of accident externalities. Finally, Section 6 discusses the policy implications of our results and directions for future research.

2 The Framework

Let r equal the expected accident cost of a driver-vehicle pair. A simple statistical-mechanics model of accidents would have the rate r determined as follows:

$$r = c_1 + c_2 \frac{M}{L} = c_1 + c_2 D \tag{1}$$

where

M= aggregate vehicle-miles driven per year by all vehicles combined;

L = total lane-miles in the region; and

D = traffic density = $\frac{M}{L}$.

The intercept, c_1, represents the expected rate at which a driver incurs cost from one-vehicle accidents, while the second term, $c_2 D$, represents the cost of two-vehicle accidents. The modelled prevalence of two-vehicle accidents increases with traffic density because such accidents can only occur when two vehicles are in proximity. This particular functional form can be derived under the assumptions that (1) a two-vehicle accident occurs with some probability q (independent of traffic density) whenever two vehicles are in the same location; (2) drivers make independent decisions about where to drive; and (3) drivers do not vary their driving quantity with traffic density. We will also estimate a model that abandons assumption (3) by normalizing accident costs per vehicle mile driven instead of per vehicle.

Levitt and Porter (2001), in a similar model, estimate the relative crash risk of drunk drivers using data on two-car crashes. Their model predicts that the number of accidents involving two drunk drivers increases quadratically in the number of drunk drivers, while the accidents involving a drunk driver and a sober driver has a linear relationship with both the number of drunk drivers and the number of sober drivers. In fact, it is this non-linearity which allows them to identify the relative crash risk separately from relative risk exposure. The Levitt-Porter non-linearity corresponds with $c_2 > 0$ and with a negative accident externality.[2]

If we extend the model of equation (1) to consider accidents where the proximity of three vehicles is required, we have:

$$r = c_1 + c_2 D + c_3 D^2, \tag{2}$$

where the quadratic term accounts for the likelihood that two other vehicles are in the same location at the same time. Equations (1) and (2) are the two basic equations that we estimate.

The coefficients do not need to be interpreted as corresponding to one- and two vehicle accidents. Equations (1) and (2) can alternatively be viewed as a reduced form model of accidents that accounts for the possibility that risk depends on traffic density. (Whatever be the exact mechanism, the connection is quite intuitive to anyone who finds herself concentrating more on a crowded highway and arriving home tired and stressed.) In principle, the coefficients c_1, c_2, c_3 need not be positive. For example, it is possible that the probability/severity of a multi-vehicle accident could begin to fall at high traffic densities because traffic will slow down.

An average person pays the average accident cost r either in the form of an insurance premium or by bearing accident risk. The accident externality from driving results (assuming that c_2 is positive) because a driver increases traffic density and thereby increases accident risks and costs

[2] If one multiplies equation (1) by the number of drivers, $N = M/\bar{m}$, where $\bar{m}$ is the miles driven per driver, one gets an equation for the total societal cost of accidents that is quadratic in M or N much as in Levitt and Porter.

for other drivers. Although the increase in D from a single driver will only affect r minutely, when multiplied by all the drivers who must pay r, the effect could be substantial. The driver does not pay under any of the existing tort systems for exerting this externality.

If there are N vehicle/driver pairs in the region under consideration (a state in our data), then the external cost is:

$$\textit{external marginal cost per mile of driving} = (N-1)\left(\frac{dr}{dM}\right) = (N-1)\left[\frac{c_2}{L} + 2c_3\frac{M}{L^2}\right]. \tag{3}$$

An average driver/vehicle pair drives $\bar{m} = \frac{M}{N}$ miles per year, and hence we have:

$$\textit{external marginal cost per vehicle} \approx \bar{m}(N-1)\frac{dr}{dM} \approx (c_2 D + 2c_3 D^2). \tag{4}$$

(The first approximation holds since any single driver contributes very little to overall traffic density so that the marginal cost given by equation (3) is a good approximation of the cost of each of the $\bar{m}$ miles she drives; the second approximation holds when N is large because then $N/(N-1) \approx 1$ so that $\bar{m}(N-1) \approx M$.)

The interpretation of these externalities is simple. If someone stops driving or reduces her driving, then not only does she suffer lower accident losses, but other drivers who would otherwise have gotten into accidents with her, suffer lower accident losses as well.

In this model of accident externalities, all drivers are equally proficient. In reality, some people are no doubt more dangerous drivers than others, and so the size of the externality will vary across drivers. Our regression estimates are for the marginal external cost of a typical or average driver. The main implication of driver heterogeneity is that the potential benefit from a Pigouvian tax that accounts for this heterogeneity exceeds what one would derive from this paper's estimates.

3 Data

We have constructed a panel data set with aggregate observations by state (s) and by year (t) for 1987-1995. Table 1 provides summary statistics. One of our measures for accident cost is the average state insurance rates per vehicle, r_{st}, for the sum of collision and liability coverages (we exclude comprehensive coverage for fire and theft). The National Association of Insurance Commissioners provides separately total statewide dollar premiums and car-years for liability and collision coverages for private passenger vehicles. We adjust these figures to account for commercial premiums by multiplying by 1.14,[3] and construct average liability and collision premiums. Our measure, r_{st}, is the sum of the average liability premium and the average collision premium in a state in a given year, after adjusting for inflation. Our second accident cost measure is an insurer cost series that we construct from loss cost data collected by the Insurance Research Council. The loss cost data LC_{st} represents the average amount of payouts per year per insured car for Bodily Injury (BI), Property Damage (PD) and Personal Injury Protection (PIP) from claims paid by insurers to accident victims. LC_{st} is substantially smaller than average premium r_{st} for three reasons. First, non-payout expenses such as salary expense and returns to capital are excluded. Second, several types of coverage categories such as collision, uninsured motorist, underinsured motorist and medical payments are excluded. Third, only the payouts of selected companies that represent 60% of the industry are reported. Despite its lack of comprehensiveness, this loss cost data has one feature that is valuable for our study. It is a direct measure of accident costs, and should therefore respond to changes in driving and traffic density without the lags that insurance premiums might be subject to, to the extent that such changes in traffic density were unpredictable to the insurance companies. We therefore "gross up" loss costs in order to make them comparable in magnitude to premiums, by constructing an insurer cost series as follows:

$$\widetilde{r}_{st} = LC_{st}\frac{\sum_t r_{st}}{\sum_t LC_{st}}.$$

This series represents what premiums would have been had companies known their loss costs in advance.

Both premium and insurer cost data have the advantage over crash data that they are dollar-denominated and therefore reflect both crash frequency and crash severity. This feature is impor-

[3] Insurance Information Institute 1998 Fact Book (p. 22).

tant, because the number of cars per accident (and hence crash severity) could increase as people drive more and traffic density increases. The average cost for both collision and liability insurance across all states in 1996 was $619 per vehicle, a substantial figure that represented roughly 2% of gross product per capita. Average insurance rates vary substantially among states: in New Jersey, for example, the average 1996 cost is $1091 per insured car-year, whereas in North Dakota the cost is $363 per insured car-year.

Our main explanatory variable is Traffic Density ($D_{st} = \frac{M_{st}}{L_{st}}$), where M_{st} is the total vehicle-miles traveled and L_{st} is the total lane-miles. Data on vehicle-miles traveled and lane-miles come from the U.S. Department of Transportation, Federal Highway Administration, *Highway Statistics*. The units for traffic density are vehicles/lane-year and can be understood as the number of vehicles crossing a given point on a typical lane of road over a one year period. The vehicle-miles traveled data is collected using methods that involve both statistical sampling with road counters and driving models.

We are concerned that the mileage data may have measurement error and that the year-to-year changes in M on which we base our estimates could therefore have substantial measurement errors. To correct for possible measurement errors, we instrument density in several specifications with the number of registered vehicles and with the number of licensed drivers.[4] Although these variables may also have measurement error, vehicle mile data are based primarily on road count data and gasoline consumption (not on registered vehicles and licensed drivers) so it seems safe to assume that these errors are orthogonal.

Traffic density, like premiums, varies substantially both among states and over time. In addition to traffic density, we introduce several control variables that seem likely to affect insurance costs: state- and time-fixed effects; state-liability fixed effects (tort, add-on, and no-fault);[5] malt-alcohol

[4] Both variables come from U.S. Dept. of Transportation, *Highway Statistics*, various years.

[5] Data comes from Insurance Research Council, *Trends in Auto Injury Claims* (1995). In states with traditional tort systems, accident victims can sue a negligent driver and recover damages. Injured parties in no-fault jurisdictions depend primarily on first-party insurance coverage because these jurisdictions limit the right to sue, usually requiring either that a monetary threshold or a "verbal" threshold be surpassed before suit is permitted. Add-on states require auto insurers to offer first-party personal injury protection (PIP) coverage, as in no-fault states, without restricting the right to sue.

beverage consumption per capita (*malt-alcohol beverage per cap.)*;[6] average cost of community hospitals per patient per day (*hosp. cost*);[7] percentage of male population that is between 15 and 24 years old (*% young male pop.*);[8] real gross state product per capita (*real gross prd. per cap.*);[9] yearly rainfall (*precipitation*); and yearly snowfall (*snowfall*).[10] All dollar figures are converted to 1996 real dollars.

We introduce real gross state product per capita as a control variable, because it is likely to both be correlated with density and directly affect insurance premiums. More affluent people tend to drive more which will create a density correlation. And, more affluent people can afford safer cars (e.g. cars with air bags), which could reduce insurance premiums; on the other hand, they may tend to buy more expensive cars and have higher lost wages when injured, which would increase premiums. If we do not control for this, then we could get a relationship between traffic density and premiums that did not reflect a true driving externality. We introduce *malt-alcohol beverage per cap.* because accident risk might be sensitive to alcohol consumption: 57.3 % of accident fatalities in 1982 and 40.9 % in 1996 were alcohol-related.[11] We include *% young male pop.* because the accident involvement rate for male licensed drivers under 25 was 15% per year, while only 7% for older male drivers.[12] We use *hosp. cost* as another control variable since higher hospital costs in certain states would increase insurance cost and hence insurance premiums there. Finally, we incorporate *precipitation* and *snowfall* since weather conditions in a given state could affect accident risk and could correlate with the driving decision.

[6] U.S. Brewers's Association, *The Brewer's Almanac*, various years.

[7] U.S. Department of Commerce, *Statistical Abstract of the United States*, various years.

[8] U.S. Bureau of the Census, *Census of Population*, various years.

[9] U.S. Department of Commerce, Bureau of Economic Analaysis. *Regional Statistics*, various years.

[10] Wood, Richard A. ed;, Weather Almanac, Ninth Edition, 1999. We use data from the largest city/metropolitan area available in each state.

[11] U.S. Dept of Transportation [1996], *Traffic Safety Facts*, Table 13.

[12] U.S. Dept of Transportation [1996], *Traffic Safety Facts*, Table 59.

4 Estimation

Here, we estimate 11 specifications of Equations (1) and (2) and report these in Tables 2 and 3. As a preliminary attempt to estimate the impact of traffic density on insurance rates, motivated by Figure 1, we run the following cross-sectional regression with 1995 data:

$$\widetilde{r_s} = c_1 + c_2 D_s + \mathbf{b} \cdot \mathbf{x}_s + \varepsilon_s, \tag{5}$$

where $\mathbf{x}_s$ represents our control variables. This regression yields an estimate $\hat{c}_2 = 4.2 * 10^{-04} \pm 0.9 * 10^{-04}$, as reported in Column (1) of Table 2. (Throughout, we report point estimates followed by "$\pm$" one standard deviation, where the standard errors are corrected for heteroskedasticity and autocorrelation using the method of Newey and West [1987] .)

These cross-sectional results do not account for the potential correlation of state-specific factors (such as road conditions) with traffic density. In particular, states with high accident costs would rationally spend money to make roads safer. Since this effect will work to offset the impact of traffic density, we would expect a cross-sectional regression to understate the effect of density holding other factors constant. Moreover, downward biases result if states switch to liability systems that insure a smaller percentage of losses in reaction to high insurance costs.

To address this possibility we identify density effects from within-state changes in density, using panel data to estimate the following model:

$$\widetilde{r_{st}} = \alpha_s + \gamma_t + c_1 + c_2 D_{st} + \mathbf{b} \cdot \mathbf{x}_s + \varepsilon_{st}. \tag{6}$$

This specification includes state fixed effects α_s and time fixed effects γ_t, so that our identification of the estimated effect of increases in traffic density comes from comparing changes in traffic density to changes in aggregate insurer cost in a given state, controlling for overall time trends. Including time fixed effects control for technological change such as the introduction of air bags or other shocks that hit states relatively equally. As expected and as reported in Column (2) of Table (2), this specification yields larger estimates than the pure cross-sectional regressions in specification (1). Specification (2) has a density coefficient of $5.8 * 10^{-04} \pm 2.9 * 10^{-04}$ compared with $4.2 * 10^{-04} \pm 0.9 * 10^{-04}$ in specification (1).

Measurement errors in the vehicle-miles traveled variable M could bias the traffic density coefficient toward 0 in both specifications (1) and (2). Therefore, we also perform instrumental variables estimation using licensed drivers per lane-mile and registered vehicles per lane-mile as instruments for traffic density. As justified above in the Data section, we assume that any measurement error in these variables is uncorrelated with errors in measuring traffic density. These variables do not enter our accident model directly, because licensed drivers and vehicles by themselves get into (almost) no accidents. A licensed driver *only* can increase the accident rate of others to the extent that she drives, and vehicles, only to the extent that they are driven: hence only through M. On the other hand, these variables seem likely to be highly correlated with traffic density; and in fact they are both positively correlated and jointly and individually highly significant as seen in Column (1) of Table 4 which gives our 1st stage regressions. Column (1) in Table (4) reports the first-stage regression for our linear model represented in equation (1). (We reject the null hypothesis that the instruments are jointly statistically insignificant with a p-value of 0.00.)

The instruments substantially increase our estimate of c_2, as one would expect if errors in variables were a problem for OLS. The IV estimate in Specification (3) of Table (2) is $19 * 10^{-04} \pm 9 * 10^{-04}$, roughly three times larger than in Specification (2). As reported in Table 2, the Durbin-Wu-Hausman test rejects the hypothesis that both OLS and IV are consistent.[13] Hansen's J-test does not reject the over-identifying restriction.[14] Specifications (4) and (5) in Table 2 use insurance premiums per vehicle as the dependent variable. Both the OLS and IV estimates yield similar coefficients to specifications with insurer costs per vehicle as the dependent variable. The consistency of results provides added confidence in our findings.

Columns (6) and (7) in Table 3 give OLS and IV estimates of our quadratic density model

[13] $\chi^2(1) = 13.42$, p-value=0.000.
[14] $\chi^2(1) = 1.17$, p-value=0.28.

(equation (2)) using insurer costs per vehicle as the dependent variable. Specifications (8) and (9) use insurance premiums per vehicle as the dependent variable.

Both the OLS and IV specifications in Table 3 reveal the same pattern. In particular, the density coefficient becomes negative (mostly insignificant) and the density-squared coefficient positive and significant. These two effects balance to make the effect of increases in density on insurance rates small and of indeterminate sign in low traffic states. The effect is positive, substantial, and statistically significant in high traffic states, as the quadratic term dominates.

Taken together, our regressions provide strong evidence that traffic density increases the risk of driving. All our specifications indicate that high traffic density states have *very* high accident costs and commensurately large external marginal costs not borne by the driver or his insurance carrier. The quadratic specifications imply that the effects of density increase at higher density. Congestion may eventually lower the external marginal accident costs, but any such effect appears to be at higher density levels than observed in our sample. Belmont [1953] indicates that crash rates fall only when roads have more than 650 vehicles per lane per hour, which corresponds to nearly 6 million vehicles per lane per year, a figure well above the highest average traffic density in our sample; hence it is not surprising that we have a positive coefficient on density squared.

The framework thus far, whether using insurer cost or premiums, could still suffer, however, from potential biases. These biases flow from normalizing insurance costs on a per-vehicle basis. Although that is the way prices are quoted in the market place, accident cost per vehicle will depend upon the amount the average vehicle is driven; the more it is driven, the higher will be costs. If miles per vehicle in a state rise, this could drive up both traffic density and insurance premiums per vehicle without any externality effect. Hence, if we seek to interpret the density term as reflecting an externality, our externality estimates might be biased up. On the other hand, if traffic density rises because more people become drivers, then each person will find driving less attractive and drive less, reducing her risk exposure. This would bias our externality estimate down, and could lead to a low density coefficient estimate even though the externality is large. Instead of simply assuming that these two biases perfectly offset each other, we can remove both biases with a new specification.

To remove the above biases, we normalize aggregate statewide premiums by vehicle-miles traveled in the state (M) instead of by the number of insured vehicles. Accordingly, columns (10) and (11) report estimates of a variant of equation (2) in which we have insurer costs per vehicle-mile traveled and premiums per vehicle-mile traveled as our dependent variable. This is our preferred specification because it removes the potential biases from variations in miles traveled per vehicle. Like our other estimates, we have a positive and significant coefficient on density squared; the estimates are naturally much smaller in absolute value because once normalized by miles traveled, the left-hand-side variable is roughly 10^{-4} smaller than in the other regressions. As we see in the next section, this specification leads to the largest estimates of the externality effect. This suggests that the largest bias in specification (7) is the downward bias from more drivers leading to less driving per driver.

5 The External Costs of Accidents

Here, we compute the extent to which the typical marginal driver increases others' insurance premiums or insurer's costs in a state. For specifications (3) and (7), equation (4) gives the externality on a per-vehicle basis. We convert this figure to a per-licensed-driver basis by multiplying by the ratio of registered vehicles to licensed drivers in a given state. The resulting figure implicitly assumes a self-insurance cost borne by uninsured drivers equal to the insurance cost of insured drivers.

We report results for select states in Table 5. Extra driving impose large accident costs on others in states with high traffic density like New Jersey, Hawaii, and California, according to our estimates. In California, for example, our estimates range from $\$1725 \pm 817$ per driver per year in the linear model using insurer costs per vehicle as the dependent variable to $\$3239 \pm 1068$ per driver in the quadratic model using insurer costs per mile as the dependent variable. This external marginal cost is in addition to the already substantial internalized cost of \$744 in premiums that an average driver paid in 1996 for liability and collision coverage in California.

We find that high traffic density states like California have large economically and statistically significant externalities across all specifications whether OLS or IV, whether controlling for serial correlation or not controlling, whether using insurer costs or premiums as a measure, whether normalizing by vehicle-miles traveled or by number of vehicles, whether panel or cross-sectional, and whether linear or quadratic. In contrast, low traffic density states have small economically insignificant and generally statistically insignificant externalities in our estimation: in South Dakota, for example, a state with roughly 1/15th the traffic density of California, our externality estimates range from $\$-50 \pm 57$ to $\$127 \pm 60$.

As a comparative matter, external marginal costs in high traffic density states are much larger than either insurance costs or gasoline expenditures. The point estimates of the external costs are quite large even in moderate density states like Kentucky, especially in the linear model, where the estimate in Kentucky, for example, is $\$561 \pm 266$.

Although our external cost estimates are large in high density states such as New Jersey, California and Hawaii, they are not unreasonably so. Consider that nationally, there are nearly three drivers involved per crash on average. According to the accident model in Section 2, this would suggest that the marginal accident cost of driving would typically be three times the average, and that the external marginal cost would be twice the average. Hence, we might expect that a 1% increase in driving could raise costs by 3%.[15] In California, a 1% increase in driving raises insurer costs by roughly 3.3%, according to Specification (3), our linear model, and by 5.4%, according to Specification (10). The linear model suggests that in almost all states a 1% increase in driving raises accident costs by substantially more than 1%.

Although we chose insurance loss costs and premiums because they implicitly include both crash frequency and crash severity effects, it is interesting to decompose these two effects. When we

[15] If accidents require the coincidence of three cars in the same place at the same time, then $r = c_3 D^2$ and external marginal costs equal $2c_3 D^2$. Internalized marginal costs are $c_3 D^2$, so that total marginal cost is $3c_3 D^2$. If there were no external marginal costs, then a 1 percent increase in driving would increase costs by 1 percent (the internalized figure).

do so, our point estimates suggest that increases in traffic density appear to consistently increase accident frequency, but not severity. The severity of accidents may fall somewhat with increases in density in low density states, and rise in high density states. However, both the severity externality and the frequency externality are statistically insignificant, and it is only when the two externalities are combined (as they should be) that we uncover statistically significant externalities.[16]

6 Implications

We find substantial negative insurance externalities in almost all specifications, even in states with only moderate traffic density such as Kentucky or South Carolina, and in all specifications, the externalities are at least somewhat negative for states of moderate or higher traffic density. By way of comparison, our point estimates exceeded existing taxes on gasoline in such states; externalities appear to dwarf existing taxes in states with high traffic density such as California in all specifications. The failure to charge for accident externalities provides the incentive for too much driving and too many accidents, at least from the standpoint of economic efficiency.

The true extent of accident externalities probably substantially exceeds our estimates because we neglected two important categories of losses. In particular, we did not include the costs of traffic delays following accidents, nor did we include damages in accidents when these losses are not covered by insurance. Both omissions could be quite substantial. According to one fairly comprehensive study by the Urban Institute [1991], the total cost of accidents (excluding congestion) exceeded $350 billion/yr., substantially more than the roughly $100 billion/yr. of insured accident cost during our sample period. If these uninsured accident costs behave like the insured costs we have studied, then accident externalities could be 3.5 times as large as we have estimated here. Externalities for California might be $11,000 per driver per year.

One potential solution would be to engage in a massive roadbuilding campaign to lower traffic density. Roadbuilding is unlikely to be the answer, however. California, for example, would need

[16] For details on this decomposition, see Edlin and Karaca-Mandic [2003]. There, we also studied the fatalities externality, which is largely uninsured. As with the measures of insured cost studied here, our point estimates suggest that in high density states increases in density raise fatality rates; however, this effect is not statistically significant.

to more than double its road infrastructure to get its density down to Kentucky levels, and it would still have substantial externalities. Moreover, if the new roads lead to more driving, even less would be gained.

The straightforward way to address large external marginal costs is to levy a substantial Pigouvian charge, either per mile, per driver, or per gallon, so that people pay something closer to the true social costs that they impose when they drive.[17] An alternative tax base is insurance premiums (coupled with getting very serious about requirements to be fully insured).

Pigouvian taxes could rectify the externality problem and raise significant funds. If each state charged our estimated external marginal cost as a Pigouvian tax for each mile driven or each new driver, the total national revenue would be $220 billion/year at the end of our sample, 1996, according to the estimates in specification (10), and neglecting the resulting reductions in driving. This figure exceeds the $163 billion collected in 1996 by all states combined for corporate and individual income taxes. In California alone, revenues would be $66 billion, more than the $57 billion for all California state tax collections. New Jersey, another high traffic state could likewise gather more revenue from an appropriate accident externality tax than it does from all its state taxes: $18 billion compared to $14 billion in 1996.[18] If uninsured externality costs are in fact 3.5 times insurance costs, as suggested by the Urban Institute study, then an appropriate Pigouvian tax might raise $770 billion per year before accounting for what would in fact be enormous driving reductions. That quantity is a shockingly large figure, but one that would reflect the magnitude of the problem. Of course, the number of drivers and the amount of driving would decline significantly with such a tax, and that would be the point of the tax, because less driving would result in fewer accidents.

The most administratively expedient Pigouvian tax would be a gasoline tax since states already have such taxes. And, importantly, gas taxes would bring the uninsured into the payment system.

[17] In principle, accident charges should vary by roadway and time of day to account for changes in traffic density.

[18] Tax figures are available from Census Bureau, 1996 State Government Tax Collections, http://www.census.gov/govs/www/statetax96.html.

On the negative side, such taxes take inadequate account of heterogeneity. Good and bad drivers are charged the same amount, even though the accident frequency and hence the accident externality of bad drivers could be considerably higher. In addition, fuel efficient vehicles would pay lower accident externality fees, even if they impose comparable accident costs.

The most efficient way to address the accident externality would probably be to levy a large tax on insurance premiums. A tax on insurance premiums, unlike a gas tax, would take into account heterogeneity because insurance premiums already do so. In California, a Pigouvian tax might be roughly 200-400%, as revealed in Table 5.

To an economist, raising significant funds with Pigouvian taxes on externalities is a dream come true. But Americans will strongly resist anything that raises the cost of driving (probably even if another tax comes down). Hence, these taxes are likely political non-starters in the U.S. Although high gasoline taxes are acceptable in Europe, the last serious U.S. presidential candidate to propose a large gasoline tax was Gary Hart, almost two decades ago.

Surprisingly, there is a potential second-best compromise, which is to shift a fixed cost to the margin, so as to leave overall driving costs comparable, but increase the marginal cost and thereby decrease the quantity of driving. The body politic has accepted mandatory insurance, so why not also require insurance companies to quote premiums by the mile instead of per car per year? Insurance premiums are surprisingly invariant to the amount a given individual drives,[19] and as a result, once one buys a car and insurance the price of gasoline alone becomes the limiting factor on quantity of driving.

Why not instead have "per-mile premiums," much as William Vickrey [1968] once suggested, in which insurance charges rise linearly with an individual's driving. This simple change in pricing

[19] For example, State Farm, the largest U.S. insurer, distinguishes in most states based upon whether a driver predicts driving under or over 7,500 miles annually and grants 15 percent discounts to drivers who drive under 7,500 miles. This discount is modest given that those who drive under 7,500 miles per year average 3,600 miles compared to 13,000 for those who drive over 7,500 according to our calculations from the 1994 Residential Transportation Energy Survey of the Department of Energy Information Administration. The implied elasticity of accident costs with respect to miles is 0.05, an order of magnitude below what the evidence suggests is the private elasticity of accident costs with respect to driving. The link between driving quantity and premiums may be attenuated in part because there is significant noise in self-reported estimates of future mileage, estimates whose accuracy does not affect insurance pay-outs.

structure could reduce driving substantially by moving a fixed cost to the margin without raising the overall cost of driving. Litman [1997] and Edlin [2003] provide more extensive discussions of this possibility.[20] People could then choose to save substantial amounts on insurance by reducing their driving. As driving distributions are skewed, most people drive less than the average (and so would save money under per-mile premiums). This fact makes the political prospects of such a change seem more promising than a tax which would raise overall driving costs. The National Organization for Women, Butler [1990], and Butler et al. [1988] have argued forcefully that such a policy would be more fair as well, pointing out that women drive roughly half what men do, have half the accidents, but still pay comparable premiums. (See also Ayres and Nalebuff, 2003).

An extremely valuable aspect of a per-mile premiums requirement is that it takes advantage of the fact that current insurance premiums account for heterogeneity in risk. As a result, those in highly dense areas and those with poor driving records, would face the highest per-mile rates and would reduce driving the most, creating a doubly large reduction in accidents – exactly as a social planner would wish.

Edlin [2003] estimated that the accident savings net of lost driving benefits from per-mile premiums would be $12.7 billion/year nationwide. Those estimates were, however, based upon a simulation model of accident externalities that assumed a much lower accident externality than the one estimated here, suggesting that the actual gains would be considerably larger.

One reason that insurers do not adopt per-mile premiums policies on their own is that so much of the gains are external and the monitoring costs are internal. Currently a firm that quotes such premium schedules bears all the costs of monitoring mileage, but gleans only a fraction of the benefits: as its insureds cut back their driving, others avoid accidents (with them) and these others and their insurance companies benefit considerably. This externality, which is exactly what we have estimated is what suggests that regulatory intervention could be warranted. Some have

[20] Several firms, such as Norwich-Union, a British insurer, have begun experimenting with various types of "pay as you drive insurance." See http://news.bbc.co.uk/hi/english business/newsid-1831000/1831181.stm, http://www.norwich-union.co.uk for information on Norwich-Union.

suggested that insurers might band together to adopt per-mile premiums without regulation, but there is little incentive to do that (even if it were not illegal price-fixing) as they would compete away any gains.

To conclude, substantially more research on accident externalities from driving seems appropriate, particularly given the apparent size of the external costs. There is substantial heterogeneity within states in traffic density, so more refined data (such as county-level data or time-of-day data) would yield more accurate estimates of the effect of traffic density and correspondingly of external marginal costs. In principle, it would also be instructive to disaggregate traffic density into its components by the age of driver and by vehicle type. Likewise, it would be instructive to study microlevel data correlating the number of vehicles involved in the average accident with accident costs and frequency.

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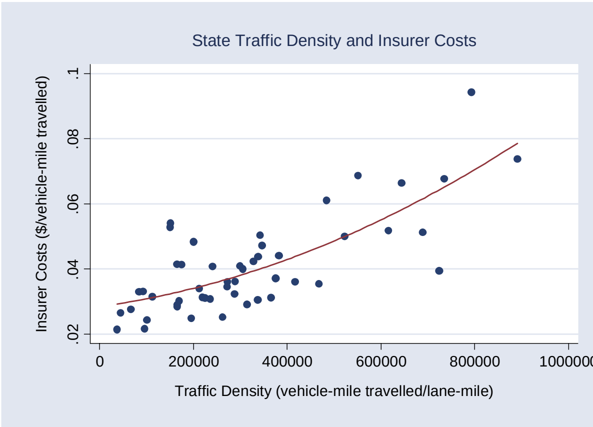
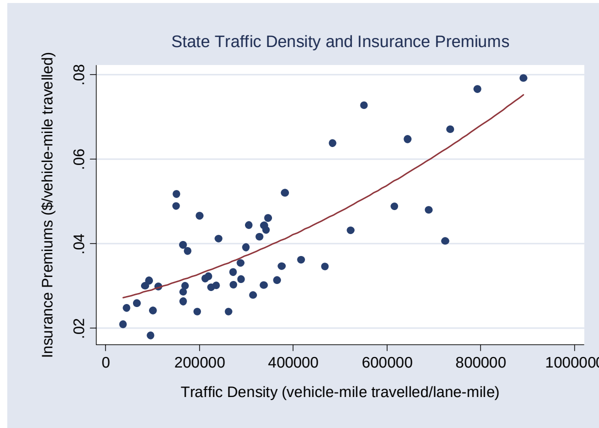
Figure 1

(A)



(B)



Note: Figures are for 1995 and are in 1996 dollars.

TABLE 1 - Summary Statistics

	1987		1995	
Variable	Mean	Standard deviation	Mean	Standard deviation
Insurance Premiums, r ($/insured car-year)	522	139	619	161
Traffic density, D=M/L (vehicle-mile/lane mile-year)	264,734	193,298	319,339	207,067
Estimated Insurer costs, $\tilde{r}$ ($/car-year)	488	148	618	151
Malt-Alcohol Beverage per cap. (gallons/person-year)	23.95	4.17	22.60	3.64
Real Gross Prd. per cap. ($/person-year)	23,590	5,322	26,898	4,471
% young male pop. (percentage)	8.1	n/a	7.2	n/a
Hospital Cost ($/patient-day)	620	138	936	220
precipitation (inches/year)	33.17	14.37	34.4	14.9
snowfall (inches/year)	25.33	24.46	36.69	35.92
% no-fault	28	n/a	26	n/a
% add-on	18	n/a	18	n/a

Notes:
1. All dollar values are real 1996 dollars deflated with the fixed-weighted GDP deflator.

TABLE 2 - Linear Insurance Rate Model

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable				
Regressors	Insurer Costs per Vehicle, $\tilde{r}$	Insurer Costs per Vehicle, $\tilde{r}$	Insurer Costs per Vehicle, $\tilde{r}$	Insurance Premiums per Vehicle, r	Insurance Premiums per Vehicle, r
	1995	1987-1995			
	(OLS)	(OLS)	(IV)	(OLS)	(IV)
traffic density, D	0.00042** (0.00009)	0.00058** (0.00029)	0.0019** (0.0009)	0.00036** (0.00018)	0.0014** (0.00067)
state dummy variables	no	yes	yes	yes	yes
time dummy variables	no	yes	yes	yes	yes
Malt-Alcohol Beverage per cap.	8.80* (4.54)	-2.04 (5.63)	0.43 (5.87)	0.79 (2.44)	2.80 (2.99)
Real Gross Prd. per cap.	6535.20* (3779.90)	5373.50 (3985.50)	2224.50 (4866.50)	2463.41 (2388.40)	-113.00 (3245.50)
Hospital Cost	0.16** (0.08)	-0.30** (0.12)	-0.40** (0.15)	0.02 (0.05)	-0.05 (0.07)
% young male pop.	30.99 (27.83)	-4.98 (14.52)	-0.75 (14.92)	8.18 (8.13)	11.64 (9.45)
precipitation	1.90** (0.92)	0.10 (0.36)	0.06 (0.37)	-0.49* (0.29)	-0.53* (0.33)
snowfall	0.32 (0.41)	0.01 (0.22)	-0.07 (0.23)	-0.12 (0.12)	-0.19 (0.14)
nofault	95.02** (32.08)	150.11** (17.04)	175.07** (28.06)	95.87** (8.80)	116.29** (18.40)
addon	-1.35 (37.59)	210.06** (51.66)	251.52** (58.46)	139.60** (39.48)	173.52** (43.74)
R-squared	0.73	0.92	0.91	0.97	0.96
Durbin-Wu-Hausman Test Ho: Traffic density is exogenous		Chi-sq (1) = 13.42 p-value = 0.00		Chi-sq (1) = 24.96 p-value = 0.00	
Hansen's J-statistic for over-identifying restrictions		Chi-sq (1) = 1.17 p-value = 0.28		Chi-sq (1) = 0.16 p-value= 0.69	

Notes:
1. Newey-West standard errors that account for heteroskedasticity and autocorrelation are reported below coefficients
2. IV uses as instruments registered vehicles per lane-mile, licensed drivers per lane-mile, time and state dummy variables, and all the control variables.
3. *: 10% significant, **: 5% significant
4. Number of observations for the panel: 450

TABLE 3 - Quadratic Insurance Rate Model

	(6)	(7)	(8)	(9)	(10)	(11)
	Dependent Variable					
Regressors	Insurer Costs per Vehicle, $\tilde{r}$	Insurer Costs per Vehicle, $\tilde{r}$	Insurance Premiums per Vehicle, r	Insurance Premiums per Vehicle, r	Insurer Costs per mile driven	Insurance Premiums per mile driven
	1987-1995					
	(OLS)	(IV)	(OLS)	(IV)	(IV)	(IV)
traffic density, D	-0.00040 (0.0006)	-0.00098 (0.0009)	-0.00057 (0.0004)	-0.0011** (0.0005)	-1.09e-07 (7.39e-08)	-3.81e-08 (5.65e-08)
D^2	1.05E-09* (6.49E-10)	2.51E-09** (7.38E-10)	9.94E-10** (4.24E-10)	2.19E-09** (6.13E-10)	2.22e-13** (8.39e-14)	1.79e-13** (6.18e-14)
state dummy variables	yes	yes	yes	yes	yes	yes
time dummy variables	yes	yes	yes	yes	yes	yes
Malt-Alcohol Beverage per cap.	-1.84 (5.88)	-0.06 (6.43)	0.97 (2.60)	2.40 (3.30)	0.00016 (0.0004)	0.00057* (0.0003)
Real Gross Prd. per cap.	5907* (3504)	4713 (3588)	2968 (2064)	2037 (2101)	-0.19 (0.31)	-0.43* (0.26)
Hospital Cost	-0.30* (0.12)	-0.35** (0.15)	0.03 (0.05)	-0.009 (0.07)	-1e-05 (0.00001)	-3E-6 (6.78E-6)
% young male pop.	10.62 (17.42)	34.84* (19.96)	22.93** (9.25)	42.68** (12.7)	0.0025 (0.0016)	0.0026** (0.0012)
precipitation	0.12 (0.3)	0.11 (0.33)	-0.48* (0.28)	-0.48* (0.29)	-4e-05 (3e-05)	-5e-05* (3e-05)
snowfall	-0.02 (0.22)	-0.11 (0.23)	-0.15 (0.12)	-0.23* (0.14)	-7e-06 (2e-05)	-3e-05** (1e-05)
nofault	140.85** (19.38)	143.35** (22.37)	87.11** (7.30)	88.79** (9.96)	0.008** (0.002)	0.007** (0.001)
addon	198.23** (48.66)	207.29** (55.32)	128.40** (38.70)	135.22** (38.70)	0.018** (0.004)	0.011 (0.003)
R-squared	0.92	0.92	0.97	0.97	0.91	0.95
Durbin-Wu-Hausman Test Ho: Traffic density is exogenous	23.59 p = 0.00		44.78 p = 0.00		53.30 p=0.00	119.70 p = 0.00
Hansen's J-statistic for over-identifying restrictions	2 p = 0.37		0.11 p = 0.95		0.10 0.95	1.10 p = 0.58

Notes:
1. Newey-West standard errors that account for heteroskedasticity and autocorrelation are reported below coefficients
2. IV uses as instruments registered vehicles per lane-mile, licensed drivers per lane-mile, square of registered vehicles per lane-mile, square of licensed drivers per lane-mile, time and state dummy variables, and all the control variables.
3. *: 10% significant, **: 5% significant
4. Number of observations for the panel: 450

TABLE 4 - First Stage Regressions

	Linear Model	Quadratic Model	
	Dependent Variable		
Regressors	traffic density, D	D	D^2
	1987-1995	1987-1995	
state dummy variables	yes	yes	yes
time dummy variables	yes	yes	yes
Malt-Alcohol Beverage per cap.	-1338	-1058	-2.03e+09*
	(940)	(958)	(1.10e+09)
Real Gross Prd. per cap. ($million)	2.80**	3.07**	1.39e+06*
	(0.92)	(0.96)	(8.03e+05)
Hospital Cost	50.94**	48.49**	4.13e+07**
	(16.74)	(17.39)	(1.91e+07)
% young male pop.	-3882	-5992*	-1.23e+10**
	(3264)	(3464)	(3.77e+09)
precipitation	57.81	39.96	8.73e+07
	(85.35)	(83.10)	(7.44e+07)
snowfall	83.04**	85.49**	9.96e+07**
	(39.42)	(40.19)	(4.45e+07)
nofault	-17701**	-16415**	-1.13e+10**
	(7030)	(7011)	(4.13e+09)
addon	-25716**	-24505**	-1.43e+10**
	(8275)	(8326)	(5.41e+09)
registered vehicles per lane-mile	1778**	2509**	-1.95e+09
	(671)	(1274)	(1.46e+09)
licensed drivers per lane-mile	3354**	5068**	1.92e+09
	(679)	(1563)	(1.67e+09)
(registered vehicles per lane-mile)^2		-8.52	4.79e+07**
		(14.33)	(2.00e+07)
(licensed drivers per lane-mile)^2		-15.22	1.07e+07
		(15.57)	(2.04e+07)
R-squared	0.9975	0.9975	0.9962
Ho: IV jointly have zero coefficient	F(2,382)=17.23 p-value=0.00	F(4,380)=10.87 p-value=0.00	F(4,380)=9.99 p-value=0.00

Notes:
1. Newey-West standard errors that account for heteroskedasticity and autocorrelation are reported below coefficients
2. *: 10% significant, **: 5% significant
3. Number of observations for the panel: 450

TABLE 5 - Yearly External Accident Cost of Marginal Driver for select states - 1996

State	Traffic Density (1996)	Insurance Prem., r ($/insured car-year)	Linear Insurer Costs per Vehicle Model (based on specification 3)		Quadratic Insurer Costs per Vehicle Model (based on specification 7)		Quadratic Insurer Cost per Vehicle Mile Model (based on specification 10)		Quadratic Insurance Premiums per Vehicle Mile Model (based on specification 11)	
			dollars/driver	standard error	dollars/driver	standard error	dollars/driver	standard error	dollars/driver	standard error
Low Density States										
North Dakota	38355	363	110	52	-46	50	10	41	-14	31
South Dakota	46276	413	127	60	-50	57	14	49	-15	37
Montana	66304	451	214	101	-73	94	32	75	-16	56
Moderate Density States										
Maine	277816	463	579	274	126	215	502	263	250	161
Kentucky	280899	604	561	266	127	208	581	302	291	184
South Carolina	295083	595	608	288	160	224	598	298	598	179
High Density States										
California	728974	744	1725	817	2432	764	3239	1068	2231	628
New Jersey	802828	1091	1619	767	2599	775	3250	1065	2273	639
Hawaii	899518	990	1831	867	3408	973	3933	1287	2796	791

Notes
1. External Marginal Cost of Additional Driver is calculated from per-mile cost assuming that a driver drives average number of miles in state.