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Publication Date
2003-06-01

The Accident Externality from Driving*

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DRAFT: June 2003

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 a typical additional driver increases the total of other people's insurance costs by $2231 per year. In such states, an increase in traffic density dramatically increases aggregate insurance premiums and loss costs. 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 $45 billion annually in California alone, and over $140 billion nationally. The extent to which this externality results from increases in accident rates, accident severity or both remains unclear. It is also not clear whether the same externality pertains to underinsured accident costs like fatality risk.

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Composed using speech recognition software. Misrecognized words are common.

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Keywords: insurance, auto accidents, externalities.

*We thank George Akerlof, Davin Cermak (National Association of Insurance Commissioners), Andrew Dick (U. Rochester), Rayola Dougher (American Petroleum Institute), Edward Glaeser (Harvard), Natalai Hughes (National Association of Insurance Commissioners), Theodore Keeler (U.C. Berkeley), Daniel Kessler (Stanford), Daniel McFadden (U.C. Berkeley), Stephen Morris (Yale), Jeffrey Miron (Boston University), Eric Nordman (National Association of Insurance Commissioners), Paul Ruud (U.C. Berkeley), Sam Sorich (National Association of Independent Inurers), Beth Sprinkel (Insurance Research Council), Paul Svercyl (U.S. Department of Transportation), and participants in seminars at the National Bureau of Economic Research, UC Berkeley, Columbia, Duke, USC and Stanford. We are grateful for financial support from the Committee on Research at UC Berkeley, from the Olin Program for Law and Economics at UC Berkeley, for a Sloan Faculty Research Grant, and for a Visiting Olin Fellowship at Columbia Law School.

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1 Introduction

Does driving entail substantial accident externalities that tort law does not internalize? Vickrey [1968] answers yes. He argues that as a new driver takes to the road, she increases the accident risk to others as well as assuming risk herself, and that tort law does not adequately account for this. If so, this implies that a one percent increase in aggregate driving increases aggregate accident costs by more than one percent. The reverse, however, could hold. The riskiness of driving could decrease as aggregate driving increases, because such increases could worsen congestion and if people are forced to drive at lower speeds, accidents could become less severe or less frequent. As a consequence, a one percent increase in driving could increase aggregate accident costs by less than one percent, and could even decrease those costs. [1]

The stakes are large. Auto accident insurance in the U.S. costs over $100 billion each year, and total accident costs could exceed $350 billion each year, after including costs that are not insured.[2] Moreover, 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%.[3] Put differently, one would expect aggregate accident costs to rise by 1.7% for every 1% increase in aggregate driving.[4] Edlin's [2003] estimates from calibrating

[1] A little introspection will probably convince most readers that crowded roadways are more dangerous than open ones. In heavy traffic, most us feel compelled to a constant vigilance to avoid the numerous moving hazards. This vigilance no doubt works to offset the dangers we perceive but seems unlikely to completely counter balance them. Note also that the cost of stress and tension that we experience in traffic are partly accident avoidance costs and should properly be included in a full measure of accident externality costs. So too, delay costs when traffic lower speeds should be included in a full measure.

[2] The $100 billion figure comes from the National Association of Insurance Commissioners [1997], and the $350 billion comes from Urban Institute [1991]. Even this $350 billion figure does not include the cost of traffic delays caused by accidents.

[3] Suppose that the chance that a driver causes an accident is p and that with probability $.3p$ she has a one vehicle accident causing damage of D and 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. The average cost of accidents per driver, however, is just pD. (Note: X was a "but for" cause of Y, if "but for" X, Y would not haveoccurred.)

[4] The elasticity of accident costs with respect to driving is the ratio of marginal to average cost. Marginal cost exceeds average cost if multiple drivers are the logical, or "but for," cause of the accident. This calculation neglects the possibility that extra driving increases congestion and thereby lowers accident costs, but it also neglects the possibility that more than two cars are necessary causes of many multi-car accidents, and that the per-vehicle damages in multicar accidents may be higher than the damages in single car accidents.

a simple theoretical model of two-vehicle accidents suggested that the size of accident externalities in a high traffic density state such as New Jersey is so large that a correcting Pigouvian tax could more than double the price of gasoline. Our research is motivated because calibration results like Edlin's [2003] could be over or underestimates depending upon how accidents actually scale with density. Externalities could be substantially larger, for example, if accidents typically involve more than two vehicles: consider the pileup in the picture below.[5]

If the elasticity of *aggregate* accident costs with respect to *aggregate* driving exceeds unity, then the tort system will not provide adequate incentives. The reason is that 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, at least not if the elasticity of accident costs exceeds unity (see Green [1976], Shavell [1980], and Cooter and Ulen [1988]).[6] 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%. Consider the provocative case of two vehicles that crash in an intersection, where one drove through a red light and the other drove through a green light. Assume that the accident would not have occured had either not been driving. From the vantage of causation, *both* caused the accident in full, even though only one is negligent. The average cost of accidents is the damages to two vehicles divided by the driving of two vehicles. But the marginal cost exeeds this. In fact, the marginal cost of either vehicle driving is the damage to two vehicles – twice the average cost. The marginal cost divided by the average, is of course the accident elasticity with respect

[5] Externalities might also be higher than one would guess from the 70% figure for multi-vehicle accidents because vehicles can be a "but-for" cause of an accident without being involved in the resulting crash and without appearing in government statistics.

[6] These authors do not put the matter in terms of the elasticity of aggregate accidents with respect to driving, but instead in terms of two parties being necessary causes of an accident. The two ideas are equivalent, however, as Edlin (1999) explains more fully.

A tangle of vehicles filled Interstate 74

Source: New York Times, A1, March 15, 2002.

to driving and in this case it equals two. Whenever the accident elasticity exceeds unity, then in order to provide efficient incentives both to drive safely and to regulate efficiently the quantity of driving, 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). In this case, each could bear her own cost and write the government a check equal to the accident cost of the other involved vehicle.[7]

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. We do not know, however, whether these groups of highways were otherwise comparable apart from traffic density, or whether they are representative of roadways more generally and can provide a helpful prediction of what would happen if overall traffic density increased. We would expect, in fact, that the roads would not be comparable. Drivers will tend to be attracted to safer roads, with wider lanes and easier driving conditions: such roads could end up with lower accident rates, but we could not conclude that this was from the high density as it could be from the inherent differences in the roadways. Without knowing the inherent safety of the roadways, crash comparison studies will understate how much traffic density increases accident rates. The flip side of this coin is that 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: as a result a cross-sectional study could likewise considerably understate the rise in accident risk with density on a *given* roadway. Another difficulty is that since Vickrey's data contains no measure of accident severity, his comparison leaves open the possibility that accidents become more frequent with higher density but that congestion causes accidents to be less severe, so

[7] Although such a system would be efficient in theory, it would be politically unacceptable for fairness reasons. It would also lead to few accidents being reported (which would make it inefficient in practice).

that on balance the accident externality is smaller than suggested or even negative. Alternatively, his data could considerably understate the externality if there are more vehicles involved in each accident when traffic density is higher, and this leads to higher costs per accident. These limitations are common to all the transportation literature on the effect of traffic density on accident rates that we have surveyed (e.g., Turner and Thomas [1986], Gwynn [1967], Lundy [1965], and Belmont [1953]).[8] Additionally, even if the transportation literature provided accurate estimates of the dollar value of accident externalities, since these estimates are only available for particular types of roadways, they do not provide a good guide for policy, until we begin to price driving by road. The coarse macro policies that are the most likely require macro studies such as the one we undertake here.

This study is an attempt to provide better estimates of the size (and sign) of the accident externality from driving. To begin, we choose a dependent variable, insurance rates, that is dollar-denominated and captures both accident frequency and severity; we also analyze insurer costs as a dependent variable. Our central question is whether one person's driving increases other people's insurance rates. We use panel data from 1987-1995 on insurance premiums, traffic density, aggregate driving, and various control variables including malt alcohol consumption and precipitation. Using the theoretical model of Edlin [2003], our basic strategy is to estimate the extent to which an increase in traffic density in a given state increases (or decreases) average insurance premiums. 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 at these two margins differ, our results provide a weighted average of these two costs. These regressions provide a measure of the insurance externality of driving.

We find that traffic density increases accident costs substantially whether measured by insur-

[8] Most of the papers we have surveyed in the transportation literature estimate the rate of increase of accidents with driving, a framework that does not admit accident externalities. A few papers such as the one cited above include quadratic or higher powers on the quantity of driving, or compare accidents/vehicle mile on roads with different traffic density. Although these papers do not state their results in terms of externalities, they all provide support for positive accident externalities.

ance rates or insurer costs. 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 insurance premiums that others pay by roughly \$2231 $\pm$\$549 each year.[9] In contrast, we estimate that others' insurance premiums are actually lowered slightly in Montana, a very low-traffic state, but the result is statistically and economically insignificant: -\$16$\pm$48 each year. These estimates of accident externalities are only for insurance 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.

Although we chose premiums and loss costs because they implicity include both crash frequency and crash severity effects, it would be interesting to decompose these two effects. Our efforts to do so unfortunately do not yield statistically significant results. 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. (Severity here includes only insured costs per crash.) As we said, though, 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.

The principle example of underinsured accident costs is fatalities. We also therefore study the fatalities externality. In particular, do fatalities per mile decline or increase with traffic density? Our regressions do not give a definitive answer to this question, as our fatality externality estimates are not statistically significant. Our point estimates suggest that in low density states increases in trafic density may lower fatality rates, whereas in high density states increases in density raise fatality rates.

[9] Here we report estimates derived from specification 12, as described subsequently.

None of our externality estimates distinguish the size of externality by the type of vehicle or the type of driver. We find average externalities, and specific externalities are apt to vary substantially. White [2002], for example, finds that SUV's damage other vehicles much more than lighter vehicles.[10]

The remainder of this paper is organized as follows. Section 2 provides a framework for determining the extent of accident externalities based upon Edlin's [1999] theoretical model of vehicle accidents. Section 3 discusses our data. Section 4 reports our estimation results. Section 5 presents a state-by-state analysis of accident externalities. Section 6 decomposes the externality into accident frequency and accident severity effects. Section 7 explores the effects of traffic density on fatality rates. Finally, Section 8 discusses the policy implications of our results and directions for future research.

2 The Framework

Let r equal the expected accident costs per vehicle. (For the sake of simplicity of discussion, consider a world where vehicles and drivers come in matched pairs.) 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 first term 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. Two-vehicle accidents increase with traffic density because they can only occur when two vehicles are in prox-

[10]White is not studying the effects of extra driving, but rather the effects of switching vehicle types.

imity. This particular functional form can be derived under the assumptions that (1) a two-vehicle accident occurs with some constant probability q (independent of traffic density) whenever two vehicles are in the same location; (2) driving locations are drawn independently from the L lane-miles of possible locations; and (3) that drivers do not vary the amount of their driving with traffic density. (See Edlin [2003]).[11] It can also be viewed as a reasonable reduced form. At the end of section 4, we will also estimate a model that abandons "assumption" (3) by normalizing accident costs per mile driven instead of per vehicle as the variable r does.

If we extend this model 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.

These are the two basic equations that we estimate. As we pointed out in the introduction, however, it is far from obvious that in practice the coefficients c_1, c_2, c_3 are all positive. In particular, it seems quite likely that such an accident model can go wrong because the probability or severity of an accident when two or several vehicles meet could ultimately 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 because a driver increases traffic density and thereby increases accident costs per driver. 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. For exerting this externality, the driver does not pay under any of the existing tort systems.

If there are N vehicles/driver pairs in the region under consideration (a state in our data), then

[11] To the extent that traffic locations are not drawn uniformly the "relevant" traffic density figure will differ (and be higher) than $\frac{M}{L}$. This actually only changes the coefficient c_2.

the external cost is:

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

An average driver/vehicle pair drives $\bar{m} = \frac{M}{N}$ miles per year, so that the external cost of a typical driver/vehicle is given by

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

(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. We will return to the subject of driver heterogeneity when we discuss the implications of our analysis. 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 and by year. The Data Appendix gives exact sources and specific notes. Table 1 provides summary statistics.

Our primary accident cost variable is average state insurance rates per vehicle, r_{st}, for private passenger vehicles for both collision and liability coverages. These rates are collected by year, t, and by state, s, by the National Association of Insurance Commissioners. Our second accident cost variable is an Insurer Cost Series that we construct from loss cost data collected by the Insurance Research Council. The loss cost data LC 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 premiums r for two reasons: first, non-payout expenses such as salary expense and returns to capital are excluded; and second, several types of coverage are excluded. 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:

$$\widetilde{r}_{st} = LC_{st} \frac{\sum_i r_{si}}{\sum_i LC_{si}}, \tag{5}$$

where s indexes states and i indexes years. This series represents what premiums would have been had companies known their loss costs in advance.

Both premiums 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 important if one is concerned about the effect of traffic density on accident costs, 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 1995 was \$619 per vehicle, a substantial figure that represents roughly 2% of gross product per capita. Average insurance rates vary substantially among states: in New Jersey, for example, the average cost is \$1032 per insured car year, whereas in North Dakota the cost is \$350 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 travelled and L_{st} is the total lane miles in state s and year t. 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. Data on vehicle-miles comes from the U.S. Department of Transportation, which collects it from states. Methods vary and 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 with the number of registered vehicles and with the number of licensed drivers. 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; (we include two separate state-liability fixed effects in each of the three states that switch their liability system (tort, add-on, and no-fault) over our time period;[12] malt-alcohol beverage consumption per capita (*malt-alcohol beverage per cap.)*; average cost to community hospitals per patient per day (*hosp. cost*); percentage of male population between 15 and 24 years old (*% young male pop.*); real gross state product per capita (*real gross prd. per cap.*); yearly rainfall (*precipitation*); and yearly snowfall (*snowfall*).

[12] 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.

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.[13] 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.[14] We use *hosp. cost* as another control variable since higher hospital costs in certain states would increase insurance cost and hence insurance premiums there. Likewise, *real gross prd. per cap.* could have a significant effect on insurance premiums in a given state. On the one hand, 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. Finally, we incorporate *precipitation* and *snowfall* since weather conditions in a given state could affect accident risk and are apt to correlate with the driving decision.

Our panel data only extends back until 1987, because the National Association of Insurance Commissioners does not provide earlier premiums data.

4 Estimation

Here, we estimate 11 specifications of Equations (1) and (2) and report these in Tables 2 and 3, together with three first-stage regressions.

As a preliminary attempt to estimate the impact of traffic density on insurance rates, we run the following cross-sectional regression with 1995 data:

$$r_s = c_1 + c_2 D_s + \mathbf{b} \cdot \mathbf{x}_s + \varepsilon_s, \tag{6}$$

where $\mathbf{x}_s$ represents our control variables. This regression yields an estimate of $\hat{c}_2 = 1.1 * 10^{-04} \pm 3.8 * 10^{-05}$, as reported in Column 1 of Table 2. (Throughout this discussion, we report point estimates followed by "±" one standard deviation, where the standard deviation is calculated robust to heteroskedasticity.)

[13] Traffic Safety Facts Table 13

[14] Traffic Safety Facts Table 59 (pg. 94)

These cross-sectional results do not account for the potential correlation of state-specific factors with traffic density.[15] This possibilitysuggests identifying density effects from within-state changes in density. For this reason, we use panel data to estimate the following model:

$$r_{st} = \alpha_s + \gamma_t + c_1 + c_2 D_{st} + \mathbf{b} \cdot \mathbf{x}_s + \varepsilon_{st} \tag{7}$$

where the indexes s and t denote state and time respectively. 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 insurance premiums in a given state, controlling for overall time trends. Including time fixed effects helps us to control for technological change such as the introduction of air bags or any other shocks that hit states relatively equally. States that switch from a tort system to a no-fault system or vice versa are given two different fixed effects, one while under each system.

Specification 2 (i.e., Column 2) reveals that above average increases in traffic density in states are associated with above average increases in insurance rates. This specification yields substantially larger estimates than the pure cross-sectional regressions in specification (1) – a coefficient of .00036 ± .00016 compared with .00011 ± .000038. There are several potential reasons why we would expect the cross section to be biased down. 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. Extra safety expenditures can, of course, be made in a given state in reaction to increased traffic density from year to year, but one might expect such reactions to be significantly delayed, so that the regression coefficient would be closer to the ceterus parabus

[15] For example, cross-sectional estimates could be biased downward if low-traffic states tend to have dangerous montainous roads, or contrarywise could be biased upward if low-traffic states more typically look like the safe flat roads of western Kansas. As the introduction observed in discussions of Vickrey, safer roads will encourage more driving and higher traffic density, tending to lead to underestimates of the effects of increases in traffic density on safety on a given roadway. Cross-sectional estimates could also be biased downward by safety expenditures (on roads or otherwise) in high-traffic states – this "bias" in the measure of externality might be addressed of course if accident prevention costs could be added to accident costs. (This latter bias probably exists to some extent in panel regressions as well, but if policy responses are slow, it should not be as big a problem)

figure we seek. Likewise, downward biases result if states switch to liability systems that insure a smaller percentage of losses in reaction to high insurance costs.

Measurement errors in the vehicle miles travelled variable M could bias the traffic density coefficient toward 0 in both specifications (1) and (2); relatively small errors in M_{st} could lead to substantial errors in year-to-year changes in miles, which form the basis of our estimates. The rest of our regressions we therefore report in pairs —an OLS together with an IV that uses 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.[16] 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. On the other hand, these variables seem likely to be highly correlated with traffic density. Column 6 of Table 2 reports the results of the first-stage regression. It reveals that the density of licensed drivers and registered cars are in fact highly positively correlated and predictive of traffic density as expected.

The instruments substantially increase our estimate of $\hat{c}_2$, as one would expect if errors in variables were a problem for OLS. The estimates do not change so much, though, that with a Hausman exogeneity test we could reject the hypothesis that both OLS and IV are consistent.[17] The test suggests that both might be consistent. The Hausman test is unfortunately not designed, however, to test our actual null hypothesis which is that IV is consistent and OLS is biased toward 0;[18] this hypothesis finds some (limited) support from the coefficient estimates. At the expense of the possibility of some inefficiency in our estimates, we therefore stick to our priors and focus on IV estimates, though we report both OLS and IV in Tables 2 and 3. If in fact there are errors

[16] This technique does not "cure" the bias toward 0 that would result if L is measured with error.

[17] The Hausman exogeneity test statistic is 17.3 for the linear model, comparing specifications (2) and (3), and is distributed as chi-squared with 61 degrees of freedom under the null hypothesis that both IV and OLS are consistent, but OLS is more efficient. The test statistic comparing specifications (7) and (8) is 30.

[18] The Hausman test tests the null hypothesis that both IV and OLS are consistent against the alternative hypothesis that only IV is consistent; in contrast our null is that only IV is consistent.

in the miles variable (a possibility that the Hausman test is not designed to reject), then we are probably better off for focusing on the IV estimates. The estimate in Specification (3) of Table 2 of the density effect is .0014, roughly three times larger than Specification (2).

Our approach and results should be compared to the studies in the transportation literature. The transportation studies we have found are cross-sectional, comparing crash rates on roads with high and low traffic density. Many studies seem to study variants of equation (1) without the density term on which we have focussed,[19] but we found four that estimate a form of equation (1) that includes the density term (Thomas and Turner [1986], Lundy [1965], McKerral [1962], and Belmont [1953]). The coefficients in these studies (once converted to the units in Table 2) range from .0001 to .0003, assuming that the $/crash is constant and equal to the average level in our sample. One reason that these cross-sectional crash studies may have lower estimates than our estimate of .0014 is that the severity per crash could increase with traffic density because the average number of involved vehicles per crash should grow. As we discuss later, we attempt to decompose our externality estimates into the effect of traffic density on crash frequency and on crash severity. We find that in high traffic density states increases in density substantially increase severity as measured by insurance expenses per crash.

The cross-sectional studies cited above may also be biased downward for reasons similar to Specification (1) (a cross-sectional regression with a roughly comparable estimate). Roads may be built better and safer in areas with high traffic density, either to reduce accidents or to improve the driving experience. People may also avoid driving on dangerous roads, causing those roads to have low traffic density. Put differently people may be attracted to live near safer roads where traffic flows smoothly and driving is easy, or arrange their driving to be on such roads. Measurement error may also lower coefficients in these regressions, much as they do in our Specification 2, and none of these studies used an instrumental variables approach. (For example, road counters may only have measured density on certain days, rather than for the whole period where accidents were

[19] For example, some regress accidents per mile of road on traffic flow.

measured.) Finally, these studies are all of high speed highways where accident costs per crash are probably substantially larger than our average.[20] Our estimates would also be higher if the costs of increased density were more severe for the non-highway driving which we include. To summarize, our results suggest that the cost of increased density are much higher than one would have inferred from transportation studies, but not unreasonably so given the many reasons one might expect the methodologies to yield different results.

Table 3 gives regression results from our quadratic density model, which can be viewed as a structural model of one-, two-, and three-vehicle accidents. An alternative view of these specifications is that they test whether the marginal effect of increased traffic density is greater in high-density states as would be suggested by the multi-vehicle accident model, or lower as might be the case if congestion ultimately lowered accident rates.

Both the instrumented and OLS specifications in Table 3 reveal the same pattern. In particular, the density coefficient becomes negative and the density-squared coefficient positive and significant. (The density coefficient is not significant in Specification (7).) These two effects balance to make the effect of increases in density on insurance rates small and of indeterminant sign in low traffic states and positive, substantial, and statistically significant in high traffic states.

These regressions provide strong evidence that traffic density increases the risk of driving, and that it does so at an increasing rate. Hence, high traffic density states have *very* high accident costs and commensurately large external marginal costs not borne by the driver or his insurance carrier. Congestion may eventually lower the external marginal accident costs, but such an effect is probably 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.

The extra costs from increases in traffic density may, of course, not be fully reflected in premi-

[20] Recall that to convert their crash coefficients to \$, we multiplied by \$/crash. We used the average figure for dollars per crash since we did not have a figure specific to highways.

ums; these costs may, at least in the short term, lower profits or increase losses in the insurance industry. This possibility could bias our estimates of the externality from traffic density downward. Instead of trying to handle this by introducing lagged density as an explanatory variable, we use our Insurer Cost Series, $\tilde{r}$, in place of premiums, r. This series, described above in the data section, is formed from data on selected companies' loss costs (payouts) on selected coverages.

Columns (9) and (10) revealed the same pattern as the premiums regressions, and similar magnitudes. The similarity of magnitudes suggests that insurers can accurately forecast the risk that comes from traffic density. (Otherwise, one might expect the Insurer Cost Series to yield much larger estimates). The consistency of results using our Insurer Cost Series lends us added confidence in our findings.

Our framework, whether using insurer cost or premiums, still suffers, however, from potential biases. These biases flow from normalizing insurance costs on a per-vehicle basis. 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, our 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 with a large externality. These potential biases offset each other, so one might hope that our estimates are roughly correct.

Both biases are removed if we try a different specification and normalize aggregate statewide premiums by M instead of by the number of insured vehicles. Accordingly, columns (11) and (12) report estimates of a variant of equation (2) in which we have premiums per vehicle mile driven, p, instead of premiums per vehicle per year, r, on the left-hand siide. The estimates in specification (12), like our other estimates, have a positive and significant coefficient on density squared; the estimates are naturally much smaller in absolute value because once normalized by miles driven, the left-hand-side variable is roughly 10^{-4} smaller than in the other regressions. Estimates from the premiums per-mile specification are our preferred estimates because they avoid the potential biases from variations in miles driven per vehicle. 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 regression (8) 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 in a state. For specifications (3), (8) and (10), 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.[21] The resulting figure implicitly assumes a self-insurance cost borne by uninsured drivers equal to the insurance cost of insured drivers.[22]

Extra driving and extra drivers impose large accident costs on others in states with high traffic density like New Jersey, Massachusetts, and California, according to our estimates. In California, for example, our estimates range from a level of $\$1271 \pm 490$ per driver per year in the linear model to \$2432 in the quadratic model using Insurer Costs. An additional driver doing the average amount of driving could increase others' insurance costs by .015 cents/vehicle or in statewide aggregate by $\$2432 \pm \$670$ per driver per year. 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. In contrast, in South Dakota, a state with roughly 1/15th the traffic density of California, our estimates of the external cost are quite low, ranging from $\$-60 \pm 28$ to $\$94 \pm 36$. The marginal accident externality is positive in most states according to our estimates. In the linear model, the externality is positive in all states. As a comparative matter, external marginal costs in high traffic density states are much larger than either insurance costs or

[21] In deriving equation (4) we did not distinguish between vehicles and drivers, assuming that they were matched. Because our data on r is in per-vehicle units, applying equation (4) with our estimates of coefficients c_2 and c_3 yields external costs per vehicle.

[22] This figure is an overestimate to the extent that insured drivers buy uninsured motorist coverage, and thereby bear a disproportionate fraction of overall costs.

gasoline expenditures.

Our external cost estimates are large in high density states such as Massachusetts, New Jersey, California and Hawaii, but not unexpectedly 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%.[23] In California, a 1% increase in driving raises insurance costs by roughly 2.5%, according to Specification (3), our linear model, and by 4%, according to Specification (12). The linear model suggests that in almost all states a 1% increase in driving raises accident costs by substantially more than 1%. (The lowest figure for the linear model is North Dakota where the estimate is a $1 + 81/363 = 1.2\%$ increase in costs.)[24] In the quadratic models, low density states have small, negative, and statistically insignificant externality costs.

6 Decomposing the externality into frequency and severity effects

Traffic density could increase insurance premiums by increasing the frequency of crashes or by increasing the severity as measured by premiums per crash (or, of course by both). Here, we explore the relative importance of these two avenues.

To do so, let

$$C = \text{the number of crashes in state} \tag{8}$$

$$\textit{and} \tag{9}$$

$$A = \text{total state insurance premiums} \tag{10}$$

[23] A few words of explanation are called for here. If accidents require the coincidence of three cars in the same place at the same time, then $r = c_3D^2$ and external marginal costs equal $2c_3D^2$. Internalized marginal costs are c_3D^2, so that total marginal cost is $3c_3D^2$. If there were no external marginal costs, then a 1 percent increase in driving would increase costs by 1 percent (the internalized figure). External costs are twice as large as internalized costs in this example.

[24] The figure is calculated as follows. The marginal external cost is 83. The marginal internal cost (which is just the average cost) is given by premiums and is \$363. Hence, the elasticity of accidents with respect to driving is $\frac{363+81}{363} = 1.2\%$

We can decompose premiums per vehicle mile driven $p = \frac{A}{M}$ as follows

$$\frac{A}{M} = \frac{C}{M}\frac{A}{C} \tag{11}$$

We estimate equations

$$\tfrac{C_{st}}{M_{st}} = \beta_s + \delta_t + c_4 + c_5 D_{st} + c_6 D_{st}^2 + \mathbf{b} \cdot \mathbf{x}_s + \varepsilon_{st} \quad (*)$$

$$\tfrac{A_{st}}{C_{st}} = \varrho_s + \sigma_t + c_7 + c_8 D_{st} + c_9 D_{st}^2 + \boldsymbol{\eta} \cdot \mathbf{x}_s + u_{st}. \ (**)$$

From expression (*), we can compute the impact of an extra person driving the average number of miles on the number of crashes: Column 3 of Table 5 reports what the impact of this increase in crash frequency would be on total premiums if premiums per crash remained constant. These figures can be interpreted as an estimate of the external marginal cost from increasing crash frequency. Thus a typical driver in Pennsylvania increases crash frequency enough to raise others' premiums by $288/year according to our point estimate even if crash severity remained fixed. Our point estimates suggest that crash frequency appears to increase with density at all density levels, though these estimates are not statistically significant.

The impact of a typical driver on insurance premiums though increases or decreases in severity $(\frac{A_{st}}{C_{st}})$ can be found from (**) as follows

$$\frac{M_{st}}{\#\text{Drivers in states } s \text{ at time } t} C_{st} \frac{d\frac{A_{st}}{C_{st}}}{dM_{st}} = \left[\frac{c_8}{l_{st}} + 2c_9 \ \frac{M_{st}}{l_{st}^2}\right] \ C_{st} \frac{M_{st}}{\# \text{ Drivers in state } s \text{ at time } t} \tag{12}$$

Column 5 of Table 5 gives external marginal cost from increase in crash severity. At low traffic density, these figures are somewhat negative. In high density states the figures become positive and economically substantial. In Massachusetts, the estimated frequency externality is $841 ± 987 per driver per year and the estimated severity externality is $702 ± 659 per driver per year. Unfortunately, our externality estimates for both frequency and severity are not statistically significant. Only when the two are combined together (as they should be to form a true externality estimate) as we did previously do we get statistically significant effects.

7 Fatalities

The Urban Institute has estimated that total accident costs are substantially in excess of insured costs. If these costs behave as insured costs do, the true externalities would far exceed our estimates. One of the biggest underinsured costs is fatalities. Viscusi [1993] estimates the cost of a life as $6 million, and yet few auto insurance policies cover more than $500,000. The bulk of fatality costs are therefore not in our insurance data. However, fatality data is separately available. We therefore estimate $\frac{F_{st}}{M_{st}} = \delta_s + \alpha_t + c_{10} + c_{11}D_{st} + c_{12}D_{st}^2 + \mathbf{c}_{13} \cdot \mathbf{x}_s + \mu_{st}$, where F_{st} are auto fatalities in state s in year t. We estimate this with instrumental variables, and from these estimates we can calculate the external marginal fatality cost. Column 3 of Table 6 gives these figures. Unfortunately none of the figures is statistically significant so nothing definite is learned from this exercise. The pattern of point estimates is similar to that for premiums - negative and small in low density states, positive and large in high density states.

8 Implications

For specifications (3), (10), and (12), even in states with only moderate traffic density such as Arizona or Georgia, the insurance externalities that we estimate are substantial. They exceed existing taxes on gasoline is such states and dwarf existing taxes in states with high traffic density such as California in all specifications.[25] The result of not charging for accident externalities is too much driving and too many accidents, at least from the standpoint of economic efficiency.

The true extent of accident externalities is probably substantially in excess of 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 and injuries to those in accidents

[25] This fact is not surprising since those taxes are designed to cover road repairs and construction, and not to remedy asked a externalities.

when these losses are not covered by insurance. This latter omission could be quite substantial.[26] According to one fairly comprehensive Urban Institute [1991] study, the total cost of accidents (excluding congestion) is over $350 billion, substantially over the roughly $100 billion of insured accident cost. If these uninsured accident costs behave like the insured costs we have studied, then accident externality costs could be 3.5 times as large as we have estimated here. Externality Costs for California might be $7000 per driver per year.

In principle, accident charges should vary by roadway and time of day to account for changes in traffic density. Technology may soon make such pricing cheap. GPS technology has already been used in a few instances.[27] Most of the social gains can probably be achieved, however, with less refined policies.

The straightforward way to address the large external marginal costs in certain states is to levy a substantially increased 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. If each state charged our estimated external marginal cost for each mile driven or each new driver, the total national revenue would be $140 billion/year, neglecting the resulting reductions in driving.[28] This figure exceeds all state income tax revenues combined. In California alone, revenues would be $45 billion, well in excess of California's income tax revenue. New Jersey, another high traffic state could likewise gather much more revenue from an appropriate accident externality tax than it does from its income tax: $12 billion compared to $5 billion. Of course, the number of drivers and the amount of driving would decline significantly with such tax, and that would be the point of the tax, because less driving would result in fewer accidents.

Although taxing driving is a conceptually straightforward response to the externality, proposing

[26] Some types of losses and some drivers are uninsured. For example, the pain and suffering of an at-fault driver is generally not insured, and in no-fault states, pain and suffering may go uncompensated for nonnegligent drivers as well. Moreover, there is substantial evidence that insurance settlements are often less than even pecuniary losses (Dewees et al., 1996).

[27] Progressive Corporation and Norwich have each run trial programs. See, Carnahan [2000] and http://www.norwich-union.co.uk. Oregon's Road User Fee Task Force would like to start a pilot program using GPS technology as the basis for mileage-based fee scenarios. EPA (2003).

[28] Here, we use the estimates from Specification 12.

to do so could be political death for elected officials. Few things are more sacrosact than an American's car. However, a simple second-best alternative might be palatable. 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? This simple change could reduce driving substantially by moving a fixed cost to the margin without raising the overall cost of driving.[29] (See Litman [1997] and Edlin [2003] for more extensive discussions of this possibility).[30] 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, so 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. Even per-mile premiums, though, have not been an easy sell politically. Entrenched insurance, highway and oil interests need to be conquered to mandate them. For this reason, pay-at-the-pump proposals have thus far failed (See Sugarman [1993]), and so too have mandatory per-mile premiums policies. Statutes allowing per-mile insurance but not requiring it have seen little take-up by insurance carriers.[31]

Edlin's [2003] estimates of the social gains from per-mile premiums are based on a simulation

[29] Edlin [2003] describes the limited extent to which current insurance premia vary with miles driven.

[30] A British firm, Norwich-Unions, is also now experimenting with "pay as you drive" insurance in the UK. See http://news.bbc.co.uk/hi/english business/newsid-1831000/1831181.stm, http://www.norwich-union.co.uk for information.

[31] Effective January 2002, Texas passed a law allowing insurance companies to charge premiums at per-mile rates, converting the standard unit of coverage from the vehicle-year to the vehicle-mile. One insurance carrier – Progressive – responded with an experimental program, but there appears to be little other interest thus far. See Wall Street Journal [1999], or Carnahan [2000] for information on the Texas pilot program run by Progressive Corporation

model of accident externalities that assumes a much lower accident externality than the one estimated here. Still he estimates that the accident savings net of lost driving benefits from per-mile premiums would be substantial at \$12.7 billion/year nationwide. The empirical estimates here suggest that the gains would be considerably larger. One reason that insurers do not adopt such policies on their own is that so much of the gains are external and the monitoring costs are internal.

Of the several taxes that could be imposed to correct for accident externalities, gasoline taxes stand out as administratively expedient since states already have such taxes. Importantly, gas taxes would bring the uninsured into the payment system. 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 though they may not impose substantially lower accident costs (in the extreme, an electric vehicle would pay no accident externality charge).[32] Environmental concerns may be a sound reason to levy a tax on gasoline, but once such taxes are sufficient to address environmental externalities, further gasoline taxes may not be the most efficient way to address accident externalities.

The most efficient way to get rid of the accident externality altogether (or for the most part anyway) would probably be to levy a large tax on insurance premiums. Just as the per-mile premium policy, a tax on insurance premiums would have the advantage over gasoline taxes of taking into account heterogeneity because insurance premiums already do so. In California, the tax might be roughly 300%. (If we consider, for example, the estimate of \$2234 for the external marginal cost from specification 12, and compare this figure to \$744, the internal cost, we would conclude that the tax should be $\frac{2234}{744} = 300\%$.) If uninsured externality costs are in fact 3.5 times insurance costs, as suggested by the Urban Institute study, then the tax should be closer to 1000%.

A substantial potential drawback with taxing insurance premiums is that the primary incentive such a tax would yield (at least initially) would be at the decision margin of whether to become

[32] This effect is not entirely unwarranted, since fuel efficiency is related to vehicle weight, and the external damages from accidents may be as well. Consider, e.g., a sport utility vehicle.

a driver, and not of how much to drive. Since existing insurance premiums are not very sensitive to actual driving (see Edlin [2003]), people who decide to drive despite the tax, once they have paid the fee, will feel free to drive a lot. Other people, who might be willing to pay high per-mile rates but who only want to drive a very few miles, may be inefficiently discouraged from driving at all. On the other hand, large taxes on insurance premiums would give insurance companies much larger incentives to adopt per-mile premium policies, or other premium schedules that are more sensitive to actual driving done.[33] 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 others benefit considerably. An appropriate premium tax internalizes these tax effects. Regardless of the form that premium schedules take, if taxes are imposed through insurance premiums, states will need to become much more serious about requiring insurance and enforcing these requirements.

Our research could also be used for decisions regarding the benefits of building an extra mile of road in terms of accident reduction. *If driving could be held constant*, we estimate that an extra lane mile would reduce insurance costs by $120,000 per year in California by lowering traffic density; Idaho, in contrast, saves nothing with the extra road. Of course, extra lanes will induce extra driving and the accident and other costs of this extra driving should be subtracted from these figures – and driving benefits should be added – to arrive at net social benefits. Such adjustments would not be necessary if appropriate Pigouvian taxes were already levied on driving.

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 dissagregate traffic density into its components

[33] The transaction cost of monitoring actual mileage has apparently fallen sufficiently that Progressive Insurance is now toward experimenting with distance-based insurance premiums for private passenger vehicles. Such policies have been used for some time for commercial vehicles where the stakes are larger.

by the age of driver and by vehicle type. In particular, it would be useful to divide traffic density by truck and non-truck; we did not do so because such data is only available on a comprehensive basis since 1993.

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10 Data Appendix

Data Variables, Sources and Notes

Our panel data comes primarily from the *Highway Statistics* of Federal Highway Administration, National Association of Insurance Commissioners (NAIC), Insurance Research Council (IRC), Department of Commerce Bureau of Economic Analysis, U.S. Census Bureau, the *Statistical Abstract of the United States*, the *Green Book* of National Association of Independent Insurers (NAII), the *Brewers' Almanac* of the Beer Institute and the *Weather Almanac* of the Gale Group.

All dollar figures are converted to 1996 real dollars.

1. $r_{liability}$: ($/liability car-year). *Source:* National Association of Insurance Commissioners, *State Average Expenditures & Premiums for Personal Automobile Insurance*, (various years), Table 7. The NAIC groups auto insurance coverages into three groups: liability, collision and comprehensive.

2. $r_{collision}$: ($/collision car-year). *Source:* National Association of Insurance Commissioners, *State Average Expenditures & Premiums for Personal Automobile Insurance*, (various years), Table 7. The NAIC groups auto insurance coverages into three groups: liability, collision and comprehensive.

3. r: Average premiums ($/ insured car-year). *Source:* National Association of Insurance Commissioners, *State Average Expenditures & Premiums for Personal Automobile Insurance*, (various years), Table 7. *Notes:* This variable is the sum of $r_{liability}$ and $r_{collision}$.

4. LC : *Average amount of loss per year per insured car for BI, PD, PIP claims. ($/vehicle-year). Source:* Insurance Research Council, *Trends in Auto Injury Claims*, 1995, Appendix A.

5. $\tilde{r}$: *Insurer Cost Series constructed from loss costs as described in the Data Section. ($/car years).* .

6. M : *Total Vehicle Miles Travelled (vehicle miles). Source*: U.S. Department of Transportation, Federal Highway Adminstration, *Highway Statistics,* (various years), data for: 1984-89,Table FI-1, data for: 1990-96,Table VM-2.

7. A: Total Insurance Premiums ($). *Source*: National Association of Insurance Commissioners [various years]

8. p: premiums per mile driven. Aggregate premiums are given by state and by year in National Association of Insurance Commissioners [various years]. $p_{st} = A_{st}/M_{st}$.

9. L : *Estimated Lane Mileage (miles). Source*: U.S. Department of Transportation, Federal Highway Adminstration, *Highway Statistics,* (various years), data for: 1984-89, Table HM-20 & Table HM-60, data for: 1990-96, Table HM-60.

10. *D : Traffic Density (vehicle miles / lane miles).* This variable is the ratio of M to L.

11. *Licensed drivers. Source:* U.S. Department of Transportation, Federal Highway Adminstration, *Highway Statistics,* (various years), data for: 1984-94, Table DL-1A , data for: 1994-96, Table DL-1C.

12. *Registered vehicles (all motor vehicles = private + commercial + publicly owned). Source*: U.S. Department of Transportation, Federal Highway Adminstration, *Highway Statistics,* (various years), Table MV-1.

13. *Pindex*: Fixed-Weighted Price Index for Gross Domestic Product. *Source:*U.S. Department of Commerce, Bureau of Economic Analysis web page, *Regional Statistics*, www.bea.doc.gov. *Notes:* The base year is 1996 (i.e. $Pindex = 1$, if year = 1996).

14. *pop*: *Population. Source:*U.S. Bureau of the Census, *Census of Population,* (various years), www.census.gov/population/www/estimates/statepop.html.

15. *malt-alcohol beverage per cap.*: This figure is the number of gallons of beer and other malted alcoholic beverages consumed per capita each year. *Source:* U.S. Brewers' Association, *The Brewers' Almanac,* (various years), Table 43 and Table 45.

16. *real gross prd. per cap.*: *Real gross state product per capita (millions/person). Source:* U.S. Department of Commerce, Bureau of Economic Analysis web page, *Regional Statistics*, www.bea.doc.gov/bea/ *Notes:* The values reported by Bureau of Economic Analysis are chained weighted 1992 dollars. We convert to 1996 dollars.

17. *% young male pop.*: *% of male population between 15-24. Source:* U.S. Bureau of the Census, *Census of Population,* (various years), www.census.gov/population/www/estimates/statepop.html.

18. *hosp. cost: Average cost to community hospitals per patient per day ($). Source*: U.S. Department of Commerce, *Statistical Abstract of the United States* (various years), Section on "Health and Nutrition".

19. *repair cost per veh.*: *Auto repair costs per registered vehicle ($/registered vehicle). Source: National Association of Independent Insurers (NAII) Greenbook : A Compilation of Property-Casualty Insurance Statistics, (* various years).

20. *% young male lic. drivers: % of male licensed drivers under 25. Source:* U.S. Department of Transportation, Federal Highway Adminstration, *Highway Statistics,* (various years), Table DL-22.

21. *precipitation*: *total annual precipitation (inches). Source:* Wood, Richard A., ed., *Weather Almanac, Ninth Edition,* 1999. *Notes:* We do not have aggregate weather data for the states. Data was available for specific locations in each state instead of a state overall. Therefore we use the data from the largest city/metropolitan area (in terms of its population) in every state.[34]

22. *snowfall*: *total annual snowfall (inches). Source:* Wood, Richard A., ed., *Weather Almanac, Ninth Edition,* 1999. *Notes:* Note on precipitation applies.

23. *State Liability Systems:* Dummy variables for no fault and add-on states. *Source:* Insurance Research Council, *Trends in Auto Injury Claims*, 1995, Appendix A. *Notes:* No fault states have laws that restrict the right to sue for minor auto injuries. Instead they substitute PIP

[34] The only exceptions are Colorado, New Hampshire and Ohio.

regardless of who was at fault. These states are: Colorado ,Connecticut (until 1/1/94), D.C, Florida, Georgia (until 10/1/91), Hawaii, Kansas,Kentucky, Massachusetts, Michigan, Minnesota, New Jersey, N.Y. , N.Dakota, Penssylvania (until 10/1/84, then beginning 7/1/90), Utah. Kentucky, NJ, PA are choice no-fault which means that vehicle owners can choose to operate under no-fault or tort. Add-on states require auto insurers to offer PIP benefits, but they do not restrict the right to pursue liability claim or lawsuit.These states are: Arkansas, Connecticut (as of 1/1/94), Delaware, D.C (after 6/1/86), Maryland, PA (from 10/1/84 to 6/30/90), S. Dakota, Texas, Virginia, Wisconsin, Washington.

TABLE 1 - SUMMARY STATISTICS

Variable	1987 Mean	1987 Standard deviation	1995 Mean	1995 Standard deviation
Premiums, r (dollars/insured car-year)	522	139	619	161
Traffic density, D=M/L (vehicle miles/lane miles-year)	264734	193298	319339	207067
Estimated Insurer costs, r~ (dollars/car per year)	488	148	618	151
Malt-Alcohol Beverage per cap. (gallons/person-year)	24	4	23	4
Real Gross Prd. per cap. ($/person-year)	23590	5322	26898	4471
% young male pop. (percentage)	8	0	7	1
Hospital Cost ($/patient per day)	620	138	936	220
precipitation (inches/year)	33	14	34	15
snowfall (inches/year)	25	24	37	36

Notes:

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

TABLE 2 - LINEAR INSURANCE MODEL

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6) First Stage Regression
Regressors	r	r	r	Insurer Costs, r~	Insurer Costs, r~	traffic density, D
	1995	1987-1995				1987-1995
	(OLS)	(OLS)	(IV)	(OLS)	(IV)	
traffic density, D	0.00011** (0.000038)	0.00036** (0.00016)	0.0014** (0.00054)	0.00058** (0.00028)	0.0019** (0.00078)	N/A
state dummies	no	yes	yes	yes	yes	yes
time dummies	no	yes	yes	yes	yes	yes
Malt-Alcohol Beverage per cap.	0.448 (1.52)	0.79 (2.12)	2.8 (2.59)	-2.04 (5.09)	0.43 (5.34)	-1337.54* (775.76)
Real Gross Prd. per cap.	2217.5 (1947.2)	2463.41 (1834.28)	-113 (2538.5)	5373.5 (3331.5)	2224.5 (4094.35)	2798127** (572450.6)
Hospital Cost	0.026 (0.035)	0.024 (0.04)	-0.051 (0.056)	-0.3 (0.11)	-0.4 (0.13)	50.94** (13.75)
% young male pop.	7.85 (10.73)	8.18 (7)	11.64 (8.24)	-4.98 (12.09)	-0.75 (12.71)	-3881.96 (2726.3)
precipitation	0.26 (0.38)	-0.49 (0.26)	-0.53* (0.28)	0.1 (0.36)	0.06 (0.37)	57.81 (87.57)
snowfall	0.13 (0.16)	-0.12 (0.13)	-0.19 (0.14)	0.014 (0.22)	-0.07 (0.23)	83.04** (42.27)
registered vehicles per lane-mile						1777.67** (400.36)
licensed drivers per lane-mile						3353.72** (447.54)

Notes:

1. White's robust standard errors 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

TABLE 3 - QUADRATIC INSURANCE RATE MODEL

	Dependent Variable							First Stage Regressions	
	(7)	(8)	(9)	(10)	(11)	(12)		(13)	(14)
Regressors	r	r	Insurer Costs, r~	Insurer Costs, r~	Premiums per mile driven	Premiums per mile driven		D	D^2
	1987-1995							1987-1995	
	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)			
traffic density, D	-0.00056*	-0.0011**	-0.0004	-0.00098	-1.14e-07**	-3.81e-08		N/A	N/A
	(0.0003)	(0.00046)	(0.00054)	(0.00075)	(3.19e-08)	(4.87e-08)			
D^2	9.94E-10**	2.19E-09**	1.05E-09**	2.51E-09**	9.15e-14**	1.79e-13**		N/A	N/A
	(3.57E-10)	(5.23E-10)	(5.81E-10)	(6.02E-10)	(3.56e-14)	(5.26e-14)			
state dummies	yes	yes	yes	yes	yes	yes		yes	yes
time dummies	yes	yes	yes	yes	yes	yes		yes	yes
Malt-Alcohol Beverage per cap.	0.97	2.4	-1.84	-0.059	0.00024	.00057**		-1057.66	-2.03E+09
	(2.2)	(2.75)	(5.18)	(5.5)	(0.00018)	(.00027)		(778.56)	(8.2E+08)
Real Gross Prd. per cap.	2968*	2036.5	5907.16*	4712.6	-0.082	-.43**		3072066**	1.39E+12
	(1667)	(1752.2)	(3077.66)	(3232.4)	(0.16)	(.2)		(580328.4)	(6.11E+11)
Hospital Cost	0.029	-0.0085	-0.3**	-0.35**	7.85e-06**	-2.9e-6		48.49**	4.13E+07**
	(0.04)	(0.053)	(0.11)	(0.13)	(3.91e-06)	(5.52e-6)		(13.71)	(1.44E+07)
% young male pop.	22.93**	42.68**	10.62	34.84**	0.00083	0.0026**		-5991.6**	-1.23E+10
	(7.74)	(10.54)	(14.96)	(16.41)	(0.0007)	(0.001)		(2864.3)	(3.02E+09)
precipitation	-0.48*	-0.48*	0.12	0.11	-0.000043**	-.000048*		39.96	8.73E+07
	(0.25)	(0.27)	(0.35)	(0.36)	(0.00002)	(.000025)		(87.29)	(9.19E+07)
snowfall	-0.15	-0.23	-0.017	-0.11	-0.000021*	-.00003**		85.49**	9.96E+07**
	(0.13)	(0.15)	(0.22)	(0.23)	(0.000011)	(.000013)		(42.03)	(4.43E+07)
							registered vehicles per lane-mile	2509.38**	-1.95E+09
								(872.14)	(9.18E+08)
							licensed drivers per lane-mile	5067.47**	1.92E+09
								(1010)	(1.06E+09)
							(registered vehicles per lane-mile)^2	-8.523	4.79E+07
								(9.3)	(9.8E+06)
							(licensed drivers per lane-mile)^2	-15.23*	1.07E+07
								(9.18)	(9.7E+06)

Notes:
1. White's robust standard errors 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

TABLE 4 - YEARLY EXTERNAL ACCIDENT COST OF MARGINAL DRIVER - for 1996

			Quadratic Premiums per Vehicle Model (based on specification 8)		Linear Premiums per Vehicle Model (based on specification 3)		Quadratic Insuror Costs Model (based on specification 10)		Quadratic Premiums per Mile Model (based on specification 12)	
State	Traffic Density (1996)	r (insurance rates per vehicle)	dollars/driver	standard error	dollars/driver	standard error	dollars/driver	standard error	dollars/driver	standard error
North Dakota	38355	363	-54	25	81	31	-46	42	-14	26
South Dakota	46276	413	-60	28	94	36	-50	48	-15	32
Montana	66304	451	-91	46	157	61	-73	79	-16	48
Nebraska	86412	423	-79	44	154	59	-60	76	-9	52
Kansas	95586	446	-77	44	158	61	-56	78	-5	58
Wyoming	104623	419	-110	66	240	93	-78	117	-1	94
Idoha	106675	457	-87	53	193	75	-61	94	0	70
Iowa	116447	410	-101	65	239	92	-68	115	6	66
Nevada	151224	793	-65	53	208	80	-33	98	31	75
Alaska	153453	774	-79	66	259	100	-39	122	24	56
Minnesota	166007	593	-84	79	317	122	-33	147	56	100
Oklahoma	169828	518	-78	76	306	118	-28	142	63	107
New Mexico	173811	655	-77	79	319	123	-24	147	76	121
Arkansas	176172	553	-54	57	230	89	-16	106	70	106
Oregon	178394	569	-62	67	273	105	-16	126	53	78
Mississippi	202024	578	-56	86	363	140	9	165	124	135
Colorado	206060	680	-51	85	359	139	14	163	96	99
Vermont	218398	503	-34	76	328	127	27	147	119	108
Utah	224380	570	-29	80	344	133	36	154	140	120
Wisconsin	230553	483	-22	79	344	133	44	154	145	118
Missouri	243347	566	-10	90	395	152	68	175	195	142
West Virginia	244869	668	-7	86	378	146	67	168	169	121
Alabama	266154	560	19	88	395	152	100	173	249	153
Maine	277816	463	36	94	427	165	126	187	250	142
Kentucky	280899	604	38	91	413	159	127	180	291	163
South Carolina	295083	595	62	98	448	173	160	195	308	159
Texas	295525	682	62	97	444	171	160	193	294	151
Louisiana	299164	786	80	116	530	204	197	230	300	151
Washington	301015	633	77	109	496	191	188	215	265	132
Tennessee	325458	545	134	126	578	223	270	249	392	173
Illinois	336716	589	146	119	546	211	277	235	353	148
Indiana	345358	543	201	149	681	263	367	293	528	214
New Hampshire	353359	603	192	131	601	232	341	258	375	148
Arizona	356960	723	181	120	547	211	317	235	494	192
Michigan	364955	695	217	134	609	235	371	262	454	171
Georgia	380431	631	273	149	674	260	447	289	670	240
North Carolina	386686	520	255	134	601	232	413	258	590	207
Pennsylvania	389975	663	249	128	574	221	401	247	465	162
Ohio	425902	530	406	170	742	286	614	320	639	202
Virginia	475461	530	555	193	791	305	795	347	955	275
New York	498337	920	547	178	708	273	769	313	794	221
Florida	527303	716	609	186	705	272	840	317	906	244
Rhode Island	559748	896	787	227	815	314	1066	374	967	253
Delaware	619775	787	1121	299	972	375	1480	466	1651	417
Connecticut	642792	865	1227	321	1002	386	1608	489	1480	371
Massachusetts	681249	801	1386	352	1030	397	1795	520	1610	399
Maryland	708803	708	1529	382	1068	412	1967	553	2091	516
California	728974	744	1900	470	1271	490	2432	670	2231	549
New Jersey	802828	1091	2059	496	1193	460	2599	676	2273	556
Hawaii	899518	990	2737	646	1349	520	3408	842	2796	686

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.

TABLE 5 - YEARLY EXTERNAL ACCIDENT COST DECOMPOSITION - for 1996

State	Traffic Density (1996)	External Accident Cost from Crash Frequency	standard error	External Accident Cost from Crash Severity	standard error
		(dollars/driver)		(dollars/driver)	
North Dakota	38355	10	26	-16	24
South Dakota	46276	13	31	-22	34
Montana	66304	22	47	-32	51
Nebraska	86412	19	36	-50	86
Kansas	95586	34	62	-36	64
Wyoming	104623	44	77	-40	74
Idaho	106675	38	66	-35	66
Iowa	116447	39	65	-35	69
Nevada	151224	64	89	-42	105
Alaska	153453	57	78	-27	69
Minnesota	166007	106	137	-32	94
Oklohoma	169828	66	84	-37	112
New Mexico	173811	75	95	-44	138
Arkansas	176172	140	174	-19	61
Oregon	178394	79	97	-23	78
Mississippi	202024	106	119	-21	107
Colorado	206060	147	163	-15	84
Vermont	218398	217	230	-5	46
Utah	224380	53	55	-22	252
Wisconsin	230553	100	102	-6	115
Missouri	243347	114	112	2	153
West Virginia	244869	121	118	3	144
Alabama	266154	154	144	16	113
Maine	277816	122	111	31	152
Kentucky	280899	171	155	36	162
South Carolina	295083	181	161	48	158
Texas	295525	117	103	59	194
Louisiana	299164	279	246	40	124
Washington	301015	129	114	58	175
Tennessee	325458	166	144	82	179
Illinois	336716	190	164	89	172
Indiana	345358	245	211	118	211
New Hampshire	353359	272	234	75	128
Arizona	356960	252	217	148	243
Michigan	364955	223	192	145	226
Georgia	380431	248	215	210	301
North Carolina	386686	197	172	221	307
Pennsylvania	389975	288	251	142	194
Ohio	425902	189	170	300	359
Virginia	475461	415	392	293	315
New York	498337	306	296	513	534
Florida	527303	322	323	443	446
Rhode Island	559748	514	534	494	486
Delaware	619775	837	927	614	586
Connecticut	642792	680	770	807	765
Massachusetts	681249	841	987	702	659
Maryland	708803	1220	1468	654	611
California	728974	1003	1227	763	711
New Jersey	802828	1035	1339	1507	1395
Hawaii	899518	1633	2247	1339	1236

TABLE 6 - YEARLY EXTERNAL ACCIDENT COST OF FATALITIES - for 1996

State	Traffic Density (1996)	External Accident Cost from Fatalities	standard error
		(dollars/driver)	
North Dakota	38355	7.52	3.65
South Dakota	46276	11.01	5.34
Montana	66304	24.68	11.98
Nebraska	86412	35.54	17.25
Kansas	95586	45.1	21.89
Wyoming	104623	80.02	38.84
Idaho	106675	61.5	29.85
Iowa	116447	63.57	30.85
Nevada	151224	99.1	48.1
Alaska	153453	75.17	36.48
Minnesota	166007	147.67	71.67
Oklohoma	169828	161.64	78.45
New Mexico	173811	187.71	91.11
Arkansas	176172	167.81	81.45
Oregon	178394	125.78	61.05
Mississippi	202024	250.35	121.51
Colorado	206060	189.49	91.97
Vermont	218398	221.19	107.36
Utah	224380	253.61	123.09
Wisconsin	230553	256.86	124.67
Missouri	243347	329.42	159.88
West Virginia	244869	283.8	137.74
Alabama	266154	395.41	191.91
Maine	277816	385.35	187.03
Kentucky	280899	446.33	216.63
South Carolina	295083	458.74	222.65
Texas	295525	438.11	212.64
Louisiana	299164	442.85	214.94
Washington	301015	390.32	189.44
Tennessee	325458	553.96	268.87
Illinois	336716	491.01	238.31
Indiana	345358	726.45	352.59
New Hampshire	353359	511.32	248.17
Arizona	356960	670.33	325.35
Michigan	364955	609.57	295.86
Georgia	380431	884.9	429.49
North Carolina	386686	775.09	376.19
Pennsylvania	389975	609	295.58
Ohio	425902	810.86	393.55
Virginia	475461	1170.72	568.22
New York	498337	960.68	466.27
Florida	527303	1080.62	524.48
Rhode Island	559748	1136.52	551.61
Delaware	619775	1897.01	920.72
Connecticut	642792	1688.22	819.39
Massachusetts	681249	1815.9	881.35
Maryland	708803	2342.08	1136.74
California	728974	2486.34	1206.75
New Jersey	802828	2494.47	1210.7
Hawaii	899518	3018.86	1465.22

Notes:
1. Estimates are computed assuming fatality cost of $6,000,000
2. Estimates are computed using IV estimates