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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 statewide insurance costs of other drivers by $1,725–$3,239 per year, depending on 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 per year nationally.

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I. Introduction

Consider two vehicles that crash as one drives through a red light and the other a green light. Assume that the accident would not occur if either driver 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 nonnegligent 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; 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 vantage of causation, as distinct from negligence, economic fault will sum to more than 100 percent. Whenever it does, 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 1 percent increase in aggregate driving increases aggregate accident costs by more than 1 percent. Such a positive connection between traffic density and accident risk will seem intuitive to anyone who finds herself concentrating more on a crowded highway and arriving home tired and stressed. Yet, such a relationship need not hold in principle. 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 1 percent increase in driving could increase aggregate accident costs by less than 1 percent and could even decrease those costs.

The stakes are large. During our sample period, auto accident insurance in the United States cost over \$100 billion each year, and total accident costs could have exceeded \$350 billion each year after costs that were not insured are included (National Association of Insurance Commissioners, various years; Miller, Rossman, and Viner 1991). Multivehicle accidents, which are the source of potential accident externalities, dominate these figures, accounting for over 70 percent of auto accidents. If we assume that exactly two vehicles are *necessary* for multivehicle accidents to occur, then one might expect the marginal cost of accidents to exceed the average cost by 70 percent. Put differently, one would expect aggregate accident costs to rise by 1.7 percent for every 1 percent 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 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 per hour, 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

[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 are $.3pD + 2(.7pD) = 1.7pD$. 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.

share limitations. Without knowledge of 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 corrective gasoline tax from such studies unless they are replicated across the full spectrum of roadway types and they are combined with extensive micro-level 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.

Figures 1 and 2 show 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 the figures, 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 1987–95 on insurer costs, insurance premiums, traffic density, aggregate driving, and various control variables. Our basic strat-

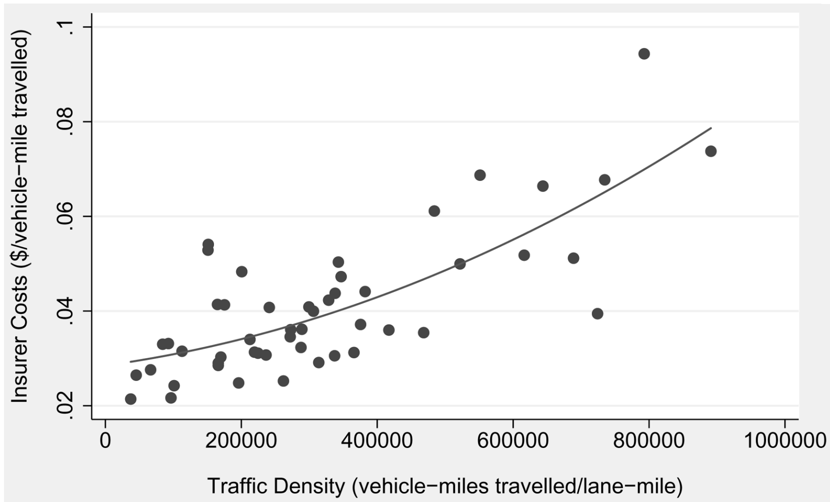

Fig. 1.—Traffic density and insurance costs (1996 dollars)

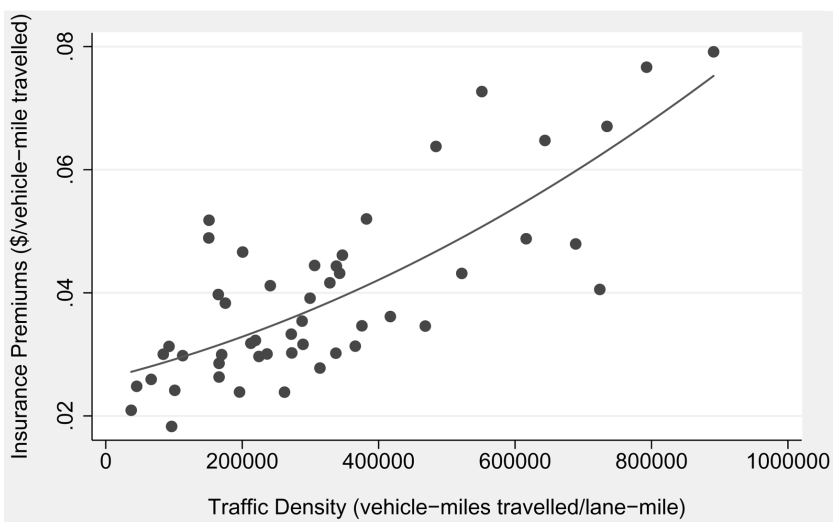

Fig. 2.—Traffic density and insurance premiums (1996 dollars)

egy 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 instrumental variables (IV) and ordinary least squares (OLS) estimation, and to cross-section or panel data. If congestion eventually reverses this effect, it occurs 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 \$1,725 ± \$817 to \$3,239 ± \$1,068 each year, depending on 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 specification 10 of table 5 below. These estimates of accident externalities pertain only to 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 II provides a framework for determining the extent of accident externalities. Section III discusses our data. Section IV reports our estimation results. Section V presents a state-by-state analysis of accident externalities. Finally, Section VI discusses the policy implications of our results and directions for future research.

II. The Framework

Two vehicles can have an accident only if they are in proximity, and the probability of proximity will increase with traffic density. In particular, let L equal the total number of lane miles, N be the number of drivers, and M equal the aggregate number of miles driven by all N drivers in some area. Consider the risk that a given driver i faces. With speed held constant and under the assumption that drivers make independent decisions about where to drive, the chance that another driver is in the same location as i will be proportionate to the amount of driving that these other drivers do (i.e., $M[(N-1)/N] \approx M$) and inversely proportional to the amount of roadway L over which this driving is distributed. Hence, for large N the probability of colocation will be proportionate to M/L, which we will call the traffic density $D \equiv M/L$. Intuitively, the more other cars are on the road, the greater the chance that they will be near me when I drive. If we assume that the probability or severity of accidents *conditional on colocation* does not depend on the traffic density, then the expected rate r at which a representative driver-vehicle pair such as i bears accident costs would be affine in traffic density:

$$r = c_1 + c_2\frac{M}{L} = c_1 + c_2D. \tag{1}$$

The intercept, c_1, represents the expected rate at which a driver incurs a cost from one-vehicle accidents, and the second term, c_2D, represents the expected cost of two-vehicle accidents.[2] Under the assumption that a vehicle's annual driving is not a function of traffic density, one can interpret r as the annual insurance cost associated with a representative vehicle. Some of our specifications do so. We will also estimate a model that abandons the assumption that driving quantity is independent of traffic density. To do so, we will normalize accident costs by vehicle miles driven instead of by the number of vehicles.

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

$$r = c_1 + c_2D + c_3D^2, \tag{2}$$

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. In principle, the coefficients c_1, c_2, and c_3 need not be positive: as pointed out earlier, it is possible that the probability/severity of a multivehicle accident could begin to fall at high traffic densities because traffic will slow down.

An average person pays the average accident cost r either by paying

[2] 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, whereas the number 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 nonlinearity that allows them to identify the relative crash risk separately from relative risk exposure. The Levitt-Porter nonlinearity corresponds with $c_2 > 0$ and with a negative accident externality. If one multiplies eq. (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's study.

an insurance premium or by bearing accident risk. The accident externality from driving results (if c_2 is assumed to be positive) because a driver increases traffic density and thereby increases accident risks and costs for other drivers. Although the increase in D from a single driver will affect r only 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

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

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

$$\begin{aligned}\text{external marginal cost per vehicle} &\approx \bar{m}(N-1)\frac{dr}{dM}\\ &\approx c_2D + 2c_3D^2.\end{aligned}\tag{4}$$

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 pertain to 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.

III. Data

We have constructed a panel data set with aggregate observations by state (s) and by year (t) for 1987–95. Table 1 provides summary statistics.

TABLE 1
Summary Statistics

Variable	1987 Mean	1987 Standard Deviation	1995 Mean	1995 Standard Deviation
Insurance premiums, r ($/insured car-year)	522	139	619	161
Traffic density, $D = M/L$ (vehicle-miles/lane-mile-year)	264,734	193,298	319,339	207,067
Estimated insurer costs, $\tilde{r}$ ($/car-year)	488	148	618	151
Malt alcohol beverages per capita (gallons/person-year)	23.95	4.17	22.60	3.64
Real gross state product per capita ($/person-year)	23,590	5,322	26,898	4,471
% young male population	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

Note.—All dollar values are real 1996 dollars deflated with the fixed-weighted gross domestic product deflator.

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 (Insurance Information Institute 1998, 22) 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 series, LC_{st}, represents the average amount of payouts per year per insured car for bodily injury, property damage, and personal injury protection from claims paid by insurers to accident victims. Loss costs LC_{st} are substantially smaller than average premium r_{st} for three reasons. First, nonpayout 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 percent of the industry are reported. Despite its lack of comprehensiveness, this loss cost data series has one feature that is valuable for our study. It is a direct measure of accident costs, and therefore we would expect it to 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:

$$\tilde{r}_{st} = LC_{st}\frac{\sum_i r_{si}}{\sum_i LC_{si}}.$$

This series roughly 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 important 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 percent of gross product per capita. Average insurance rates vary substantially among states: in New Jersey, for example, the average 1996 cost is \$1,091 per insured car-year, whereas in North Dakota the cost is \$363 per insured car-year.

Our main explanatory variable is traffic density ($D_{st} = M_{st}/L_{st}$), 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 various years of *Highway Statistics*, published by the U.S. Department of Transportation, Federal Highway Administration. The units for traffic density are vehicles per 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 are 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 (both from *Highway Statistics*). 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);[3] malt alcohol beverage consumption per capita; average cost of community hospitals per patient per day; percentage of male population that is between 15 and 24 years old; real gross state product per capita; yearly rainfall; and yearly snowfall.[4] 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 consumption per capita because accident risk might be sensitive to alcohol consumption: 57.3 percent of accident fatalities in 1982 and 40.9 percent in 1996 were alcohol-related. We include the percentage of 15–24-year-old males because the accident involvement rate for male licensed drivers under 25 was 15 percent per year, whereas it was only 7 percent for older male drivers (U.S. Department of Transportation 1996, tables 13, 59). We use hospital costs as another control variable since higher hospital costs in certain states would increase insurance costs 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.

IV. Estimation

Here, we estimate 11 specifications of equations (1) and (2) and report them in tables 2 and 3. As a preliminary attempt to estimate the impact

[3] Data come from Insurance Research Council (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 that either a monetary threshold or a "verbal" threshold be surpassed before a suit is permitted. Add-on states require auto insurers to offer first-party personal injury protection coverage, as in no-fault states, without restricting the right to sue.

[4] Data for these variables come from various years of the *Brewer's Almanac*, published by the U.S. Brewers' Association; *Statistical Abstract of the United States*; *Census of Population*; *Regional Statistics* from the Bureau of Economic Analysis; and Wood (1999). For measures of precipitation and snowfall, we use data from the largest city/metropolitan area available in each state.

TABLE 2
Linear Insurance Rate Model, 1987–95

Regressor	Dependent Variable: Insurer Costs per Vehicle, $\tilde{r}$ OLS (1995 Only) (1)	OLS (2)	IV (3)	Dependent Variable: Insurance Premiums per Vehicle, r OLS (4)	IV (5)
Traffic density, D	.00042**	.00058**	.0019**	.00036**	.0014**
	(.00009)	(.00029)	(.0009)	(.00018)	(.00067)
State dummy variables	No	Yes	Yes	Yes	Yes
Time dummy variables	No	Yes	Yes	Yes	Yes
Malt alcohol beverages per capita	8.80*	−2.04	.43	.79	2.80
	(4.54)	(5.63)	(5.87)	(2.44)	(2.99)
Real gross product per capita	6,535.20*	5,373.50	2,224.50	2,463.41	−113.00
	(3,779.90)	(3,985.50)	(4,866.50)	(2,388.40)	(3,245.50)
Hospital cost	.16**	−.30**	−.40**	.02	−.05
	(.08)	(.12)	(.15)	(.05)	(.07)
% young male population	30.99	−4.98	−.75	8.18	11.64
	(27.83)	(14.52)	(14.92)	(8.13)	(9.45)
Precipitation	1.90**	.10	.06	−.49*	−.53*
	(.92)	(.36)	(.37)	(.29)	(.33)
Snowfall	.32	.01	−.07	−.12	−.19
	(.41)	(.22)	(.23)	(.12)	(.14)
No-fault	95.02**	150.11**	175.07**	95.87**	116.29**
	(32.08)	(17.04)	(28.06)	(8.80)	(18.40)
Add-on	−1.35	210.06**	251.52**	139.60**	173.52**
	(37.59)	(51.66)	(58.46)	(39.48)	(43.74)
R^2	.73	.92	.91	.97	.96
Durbin-Wu-Hausman test H_0: Traffic density is exogenous		$\chi^2(1) = 13.42$ p-value $= .00$		$\chi^2(1) = 24.96$ p-value $= .00$	
Hansen's J-statistic for overidentifying restrictions		$\chi^2(1) = 1.17$ p-value $= .28$		$\chi^2(1) = .16$ p-value $= .69$	

Note.—Newey-West standard errors that account for heteroskedasticity and autocorrelation are reported in parentheses below coefficients. IV uses as instruments registered vehicles per lane mile, licensed drivers per lane mile, time and state dummy variables, and all the control variables. The number of observations for the panel is 450.
* Significant at the 10 percent level.
** Significant at the 5 percent level.

of traffic density on insurance rates, motivated by figure 1, we run the following cross-sectional regression with 1995 data:

$$\tilde{r}_s = c_1 + c_2 D_s + \boldsymbol{b} \cdot \boldsymbol{x}_s + \epsilon_s, \tag{5}$$

where $\boldsymbol{x}_s$ represents our control variables. This regression yields an estimate of $\hat{c}_2 = 4.2 \times 10^{-04} \pm 0.9 \times 10^{-04}$, as reported in column 1 of table 2. (Throughout, we report point estimates followed by "±" 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:

$$\tilde{r}_{st} = \alpha_s + \gamma_t + c_1 + c_2 D_{st} + \boldsymbol{b} \cdot \boldsymbol{x}_s + \epsilon_{st}. \tag{6}$$

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 controls 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 $5.8 \times 10^{-04} \pm 2.9 \times 10^{-04}$ compared with $4.2 \times 10^{-04} \pm 0.9 \times 10^{-04}$ in specification 1.

Measurement errors in the vehicle miles traveled variable M could bias the traffic density coefficient toward zero in both specifications 1 and 2. Therefore, we also perform IV estimation using licensed drivers per lane mile and registered vehicles per lane mile as instruments for traffic density. As justified above in Section III, 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 can increase the accident rate of others *only* 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; in fact they are both positively correlated and jointly and individually highly significant as seen in column 1 of table 4, which gives our first-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.

TABLE 3

QUADRATIC INSURANCE RATE MODEL, 1987–95

	Dependent Variable: Insurer Costs per Vehicle, $\tilde{r}$		Dependent Variable: Insurance Premiums per Vehicle, r		Dependent Variable: Insurer Costs per Mile Driven	Dependent Variable: Insurance Premiums per Mile Driven
Regressor	OLS (6)	IV (7)	OLS (8)	IV (9)	IV (10)	IV (11)
Traffic density, D	−.00040	−.00098	−.00057	−.0011**	−1.09E−07	−3.81E−08
	(.0006)	(.0009)	(.0004)	(.0005)	(7.39E−08)	(5.65E−08)
D^2	1.05E−09*	2.51E−09**	9.94E−10**	2.19E−09**	2.22E−13**	1.79E−13**
	(6.49E−10)	(7.38E−10)	(4.24E−10)	(6.13E−10)	(8.39E−14)	(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 capita	−1.84	−.06	.97	2.40	.00016	.00057*
	(5.88)	(6.43)	(2.60)	(3.30)	(.0004)	(.0003)

Real gross product per capita	5,907*	4,713	2,968	2,037	−.19	−.43*
	(3,504)	(3,588)	(2,064)	(2,101)	(.31)	(.26)
Hospital cost	−.30*	−.35**	.03	−.009	−1E−05	−3E−6
	(.12)	(.15)	(.05)	(.07)	(.00001)	(6.78E−6)
% young male population	10.62	34.84*	22.93**	42.68**	.0025	.0026**
	(17.42)	(19.96)	(9.25)	(12.7)	(.0016)	(.0012)
Precipitation	.12	.11	−.48*	−.48*	−4E−05	−5E−05*
	(.3)	(.33)	(.28)	(.29)	(3E−05)	(3E−05)
Snowfall	−.02	−.11	−.15	−.23*	−7E−06	−3E−05**
	(.22)	(.23)	(.12)	(.14)	(2E−05)	(1E−05)
No-fault	140.85**	143.35**	87.11**	88.79**	.008**	.007**
	(19.38)	(22.37)	(7.30)	(9.96)	(.002)	(.001)
Add-on	198.23**	207.29**	128.40**	135.22**	.018**	.011
	(48.66)	(55.32)	(38.70)	(38.70)	(.004)	(.003)
R^2	.92	.92	.97	.97	.91	.95
Durbin-Wu-Hausman test	23.59		44.78		53.30	119.70
H_0: Traffic density is exogenous	$p = .00$		$p = .00$		$p = .00$	$p = .00$
Hansen's J-statistic for overidentifying	2		.11		.10	1.10
restrictions	$p = .37$		$p = .95$		$p = .95$	$p = .58$

NOTE.—Newey-West standard errors that account for heteroskedasticity and autocorrelation are reported in parentheses below coefficients. IV uses as instruments registered vehicles per lane mile, licensed drivers per lane mile, time and state dummy variables, and all the control variables. The number of observations for the panel is 450.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

TABLE 4
First-Stage Regressions, 1987–95

	Dependent Variable		
	Linear Model	Quadratic Model	
Regressor	Traffic Density, D (1)	D (2)	D^2 (3)
State dummy variables	Yes	Yes	Yes
Time dummy variables	Yes	Yes	Yes
Malt alcohol beverage per capita	−1,338	−1,058	−2.03E+09*
	(940)	(958)	(1.10E+09)
Real gross product per capita ($millions)	2.80**	3.07**	1.39E+06*
	(.92)	(.96)	(8.03E+05)
Hospital cost	50.94**	48.49**	4.13E+07**
	(16.74)	(17.39)	(1.91E+07)
% young male population	−3,882	−5,992*	−1.23E+10**
	(3,264)	(3,464)	(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)
No-fault	−17,701**	−16,415**	−1.13E+10**
	(7,030)	(7,011)	(4.13E+09)
Add-on	−25,716**	−24,505**	−1.43E+10**
	(8,275)	(8,326)	(5.41E+09)
Registered vehicles per lane mile	1,778**	2,509**	−1.95E+09
	(671)	(1,274)	(1.46E+09)
Licensed drivers per lane mile	3,354**	5,068**	1.92E+09
	(679)	(1,563)	(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^2	.9975	.9975	.9962
H_0: IV jointly have zero coefficient	$F(2, 382) = 17.23$ p-value = .00	$F(4, 380) = 10.87$ p-value = .00	$F(4, 380) = 9.99$ p-value = .00

Note.—Newey-West standard errors that account for heteroskedasticity and autocorrelation are reported in parentheses below coefficients. The number of observations for the panel is 450.
* Significant at the 10 percent level.
** Significant at the 5 percent level.

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 $19 \times 10^{-04} \pm 9 \times 10^{-04}$, 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 ($\chi^2(1) = 13.42$, p-value = 0.000). Hansen's J-test does not reject the overidentifying restriction ($\chi^2(1) = 1.17$, p-value = 0.28). Specifications 4 and 5 in table 2 use insurance premiums per vehicle as the dependent variable. Both these OLS and IV estimates yield coefficients similar to specifications with insurer costs per vehicle as the dependent variable; and, again, the Durbin-Wu-Hausman test rejects the hypothesis that both OLS and IV are consistent, and Hansen's *J*-test does not reject the overidentifying restriction. The consistency of results across these two models provides added confidence in our findings.

Specifications 6 and 7 in table 3 give OLS and IV estimates of our quadratic density model (eq. [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, since 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 on the amount the average vehicle is driven: the more it is driven, the higher the costs will be. 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 variables. This is our preferred specification because it removes the potential biases from variations in miles traveled per vehicle. As with 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.

V. The External Costs of Accidents

Here we compute the extent to which the typical marginal driver increases others' insurance premiums or insurers' 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 three high-traffic states, three moderate-traffic states, and three low-traffic states in table 5. Extra driving imposes large accident costs on others in states with high traffic density such as New Jersey, Hawaii, and California, according to our estimates. In California, for example, our estimates range from \$1,725 ± \$817 per driver per year in the linear model using insurer costs per vehicle as the dependent variable to \$3,239 ± \$1,068 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 such as California have large economically and statistically significant externalities across all specifications whether using 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 using panel or cross-sectional data, and whether using linear or quadratic costs. In contrast, low–traffic density states have small economically insignificant and generally statistically insignificant externalities in our estimation: in South Dakota, for example,

TABLE 5

YEARLY EXTERNAL ACCIDENT COST OF MARGINAL DRIVER FOR SELECT STATES, 1996

State	Traffic Density (1996) (1)	Insurance Premium, r (\$/Insured Car-Year) (2)	Linear Insurer Costs per Vehicle Model (Based on Specification 3) (3)	Quadratic Insurer Costs per Vehicle Model (Based on Specification 7) (4)	Quadratic Insurer Costs per Vehicle Mile Model (Based on Specification 10) (5)	Quadratic Insurance Premiums per Vehicle Mile Model (Based on Specification 11) (6)
			Low-Density States			
North Dakota	38,355	363	110 (52)	−46 (50)	10 (41)	−14 (31)
South Dakota	46,276	413	127 (60)	−50 (57)	14 (49)	−15 (37)
Montana	66,304	451	214 (101)	−73 (94)	32 (75)	−16 (56)
			Moderate-Density States			
Maine	277,816	463	579 (274)	126 (215)	502 (263)	250 (161)
Kentucky	280,899	604	561 (266)	127 (208)	581 (302)	291 (184)
South Carolina	295,083	595	608 (288)	160 (224)	598 (298)	598 (179)
			High-Density States			
California	728,974	744	1,725 (817)	2,432 (764)	3,239 (1,068)	2,231 (628)
New Jersey	802,828	1,091	1,619 (767)	2,599 (775)	3,250 (1,065)	2,273 (639)
Hawaii	899,518	990	1,831 (867)	3,408 (973)	3,933 (1,287)	2,796 (791)

NOTE.—Entries for external accident cost in cols. 3–6 are in dollars per driver. Standard errors are in parentheses. External marginal cost of additional driver is calculated from the cost per mile assuming that a driver drives the average number of miles in the state.

a state with roughly one-fifteenth 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 such as 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 II, 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 percent increase in driving could raise costs by 3 percent.[5] In California, a 1 percent increase in driving raises insurer costs by roughly 3.3 percent according to specification 3, our linear model, and by 5.4 percent according to specification 10. The linear model suggests that in almost all states a 1 percent increase in driving raises accident costs by substantially more than 1 percent.

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 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.[6]

VI. Implications

We find substantial negative accident 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 den-

[5] 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).

[6] 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 costs studied here, our point estimates suggest that in high-density states increases in density raise fatality rates; however, this effect is not statistically significant.

sity. 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 (Miller et al. 1991), the total cost of accidents (excluding congestion) exceeded $350 billion per year, substantially more than the roughly $100 billion per year of insured accident costs 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 exceed $10,000 per driver per year.

One potential solution would be to engage in a massive road-building campaign to lower traffic density. Road building is unlikely to be the answer, however. California, for example, would need 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.[7] 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 per 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 rev-

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

enue from an appropriate accident externality tax than it does from all its state taxes: $18 billion compared to $14 billion in 1996.[8] 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 reflects 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. 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.

In principle, 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 percent, as revealed in table 5. A practical difficulty with taxing insurance is that it would drive people to become uninsured unless states simultaneously cracked down seriously on uninsured driving.

To an economist, raising significant funds with Pigouvian taxes on externalities is a dream come true. Many political watchers will doubt, though, that Americans will accept any policy that substantially raises the cost of driving. Gasoline taxes, for example, remain quite low in the United States compared with Europe.

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

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

invariant to the amount a given individual drives,[9] 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 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.[10] 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 that would raise overall driving costs. The National Organization for Women, Butler, Butler, and Williams (1988), and Butler (1990) 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 requirement of per mile premiums 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 per year nationwide. Those estimates were, however, based on 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.

[9] For example, State Farm, the largest U.S. insurer, distinguishes in most states on the basis of 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 payouts.

[10] 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 and http://www.norwich-union.co.uk for information on Norwich-Union.

One reason that insurers do not adopt per mile premium 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 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) since 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 the driver and by vehicle type. Likewise, it would be instructive to study micro-level data correlating the number of vehicles involved in the average accident with accident costs and frequency.

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