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Per-Mile Premiums for Auto Insurance

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* * * *

Composed using speech recognition software. Misrecognized words are common. Imagination is sometimes helpful…

...the manner in which [auto insurance] premiums are computed and paid fails miserably to bring home to the automobile user the costs he imposes in a manner that will appropriately influence his decisions.

– William Vickrey

Americans drive 2,360,000,000,000 miles each year, and the cost of auto accidents is commensurately large:[1] roughly $100 billion in accident insurance,[2] and according to the Urban Institute [1991] an additional $250 billion in uninsured accident costs per year.

Every time a driver takes to the road, and with each mile she drives, she exposes herself and others to the risk of accident. (The degree of risk depends, of course, upon a wide variety of factors such as a driver's skill or age, and the territory she drives in.) Yet, most auto insurance premiums have largely lump-sum characteristics and are only weakly linked to mileage. Mileage classifications are coarse, and low-mileage discounts are extremely modest and based on self-reported estimates of future mileage that have no implicit or explicit commitment.[3] (Two noteworthy exceptions are premiums on some commercial policies[4] and a few recent pilot programs.)[5] Few drivers therefore pay or perceive a significant

[1] See table No. 1030, Statistical Abstract of the United States, 1997, U.S. Department of Commerce. Figure for 1994.

[2] After subtracting comprehensive insurance coverage, which covers fire, theft, vandalism and other incidents unrelated to the amount of driving, the remaining premiums for private passenger vehicles totaled $84 billion in 1995. State Average Expenditures and Premiums for Personal Automobile Insurance in 1995, National Association of Insurance Commissioners, Jan. 1997. In additon, commercial premiums are approximately 15 percent of premiums for private passenger vehicles. The Insurance Information Institute 1998 Fact Book, p. 22.

[3] For example, State Farm distinguishes drivers based upon whether they report an estimated annual mileage of under or over 7500 miles. Drivers who estimate annual mileages of under 7500 miles receive 15% discounts (5% in Massachusetts). The 15% discount is modest given that those who drive less than 7500 miles per year drive an average of 3600 miles compared to 13,000 miles for those who drive over 7500 per year, according to the 1994 Residential Transportation Energy Consumption Survey of the Department of Energy. The implied elasticity of accident costs with respect to miles is .05, an order of magnitude below what the evidence suggests is the private or social elasticity of accident costs. The link between driving and premiums may be attenuated in part because there is significant noise in self-reported estimates of future mileage, estimates whose accuracy does not affect insurance pay-outs.

Insurance companies also classify based upon the distance of a commute to work. These categories are also coarse, however. State Farm, for example, classifies cars based upon whether they are used for commuting less than 20 miles per week, in between 20 and 100 miles per week, or over 100 miles per week.

[4] For private and public livery, taxicabs, and buses, because "rates are high and because there is no risk when the car is not in operation, a system of rating has been devised on an earnings basis per $100 of gross receipts or on a mileage basis." Bickelhaupt [1983, p. 613]. For details on per-mile commercial insurance, see "Commercial Automobile Supplementary Rating Procedures," Insurance Services Office, on file with author.

[5] One experiment is in Texas and another in the UK. See "Insurance by the Mile, " Wall Street Jour-

insurance cost from driving an extra mile, despite the substantial accident costs involved. An ideal tort and insurance system would charge each driver the full social cost of her particular risk exposure on the marginal mile of driving. Otherwise, people will drive too much and cause too many accidents (from the vantage of economic efficiency).

In principle, insurance companies could levy a substantial charge for driving an extra mile, as new car leases do; however, this would require them to incur the cost of verifying mileage (through periodic odometer checks or by installing a monitoring and broadcasting device in vehicles).[6] A central point of this paper is that externalities make their incentives to do so considerably less than the social incentives. If insurance company C is able to reduce the driving of its insureds, although it will save on accident payouts, substantial "external" savings will be realized by other insurance carriers and their insureds who will get into fewer accidents with C's insureds. These externalities follow from Vickrey's observation that if two drivers get into an accident, even the safer driver is typically a "but for" cause of the accident in the sense that had she opted for the metro, the accident would not have occurred.[7] Externalities help explain why we are only just now seeing pilot per-mile premiums programs.

Accident externalities suggest a valuable role for policy, and this paper investigates the

nal (1999), http://news.bbc.co.uk/hi/english business/newsid-1831000/1831181.stm, http://www.norwich-union.co.uk. Progressive Corporation has a pilot program in Texas in which miles (and locations) are monitored by a device using cellular-phone and satellite technology. Since January 2002 it is now legal for auto insurance policies in Texas to have the unit of exposure be the vehicle-mile rather than the more traditional vehicle-year.

[6]In practice there may be a regulatory constraint that has discouraged firms from per-mile pricing. The traditional unit of risk insurance that insurance companies price is the vehicle-year. Just recently after a lobbying campaign by the National Organization for Women, Texas adopted legislation allowing firms to adopt the vehicle-mile as the unit of exposure. (http://www.centspermilenow.org). Long before this, however, firms charged slight surcharges based upon unaudited reports of high usage. Obviously, there is a fuzzy line here because as such charges become more refined and audits of usage are performed, the vehicle-year exposure unit slips into a vehicle-mile unit. Firms have not generally pushed that direction, however, so it is unclear whether there has been a meaningful regulatory constraint.

[7]Sometimes, of course, only one driver is the cause of an accident, even when the accident involves multiple cars such as when a driver plows into a long line of cars. If one car wasn't there to absorb the impact, another would have, so the cars that are hit do not cause the accident in any respect. Such accident substitution is not accounted for by the theoretical model we present, and reduces the externalities from driving. This substitution effect is, however, accounted for by our regression results.

potential benefits of two proposals that would increase the marginal charge for driving, and consequently reduce driving and accidents. The first proposal is per-mile premiums, advocated by Litman [1997], Butler [1990], and the National Organization for Women [1998]. Under a per-mile premium system, the basic unit of exposure would shift from the car-year to the car-mile, either by requirement or by subtler policy tools, so that the total premiums of driver i would be $m_i p_i$, where m_i is the miles i travels and p_i is the per-mile rate. An individual's per-mile rate, p_i, would vary among drivers to reflect the per-mile risk of a given driver and could depend upon territory, driver age, safety records or other relevant characteristics used today for per-year rates. (In fact, the technology now used experimentally by Progressive in Texas also allows prices to vary by time of the day and by location.)[8] The second proposal is to couple per-mile premiums with a Pigouvian tax in order to account for the "Vickrey" accident externality. Both these proposals differ fundamentally from the uniform per-gallon gas tax proposals of Vickrey [1968],[9] Sugarman [1993], and Tobias [1993], because under gas tax proposals, unlike per-mile premiums, the additional cost of driving would be independent of driver age, driver safety records, or in some cases of territory (all highly important indicia of risk), yet would depend upon fuel efficiency (a relatively poor risk measure).

This paper makes several contributions. We begin by developing a simple model from primitives that relates miles driven to accidents, formalizing Vickrey's insights about the externalities of driving – this contribution is mainly pedagogical. Our second contribution is to provide evidence that these externalities are substantial. Our third is to provide the first estimates of the potential benefits of per-mile premiums that take into account Vickrey's externalities as well as the resulting fact that as driving falls, so too will accident rates and

[8] See Wall Street Journal [1999].

[9] Actually, Vickrey's first suggestion was that auto insurance be bundled with tires hoping that the wear on a tire would be roughly proportional to the amount it is driven. He worried about moral hazard (using a tire until it was threadbare), but concluded that this problem would be limited if refunds were issued in proportion to the amount of tread remaining.

per-mile premiums. [10] Our fourth contribution is to estimate the benefits of a per-mile premium policy coupled with a Pigouvian tax. (It's natural to consider taxing per-mile premiums to account for accident externalities once one incorporates externalities.) Finally our estimates incorporate lower bound estimates of congestion cost reductions. These estimates are a rough first cut and should be viewed as lower bounds for reasons we will elaborate.

Our evidence that accident externalities are significant in practice is that states with more traffic density have considerably higher insurance costs per mile driven. This suggests that the more people drive on the same roads, the more dangerous driving becomes. (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.)[11] Nationally, the insured cost of accidents is roughly 4 cents per-mile driven, but we estimate that the marginal cost – the cost if an extra mile is driven – is much higher, roughly 7 and a half cents, because of these accident externalities. In high traffic-density states like New Jersey, Hawaii, or Rhode Island, we estimate that the marginal cost is roughly 15 cents. For comparison, gasoline costs roughly 6 cents per mile, so an efficient Pigouvian charge for accidents at the margin would dramatically increase the marginal cost of driving, and would presumably reduce driving substantially.

Even without a Pigouvian charge to account for accident externalities, a system of per-mile premiums that shifted a fixed insurance charge to the margin would be roughly equivalent to a 70% hike in the gasoline price and could be expected to reduce driving

[10] Externalities turn out to increase the benefit estimates by 85-140%, over what one would calculate in a linear model of accidents (i.e. a model without externalities) as studied by Litman [1987)] and Rea [1992]. Note that a linear model is appropriate to estimate the gains to a given insurance carrier with small market share and its customers from switching to per-mile premiums as Rea does.

[11] 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.

nationally by 9.2% - 9.5%, and insured accident costs by $14 - $17 billion. After subtracting the lost driving benefits of $4.3 - $4.4 billion, the net accident reductions would be $9.8 - $12.7 billion or $58 - $75 per insured vehicle. The net savings would be $10.7 - $15.3 billion if per-mile premiums were taxed to account for the external effect of one person's driving on raising others' insurance premiums .[12]

These estimates are probably a lower bound on what savings would actually be under a per-mile system. The reason is that these estimates use state level data and assume that drivers and territories are homogeneous within a state. Currently intrastate heterogeneity in accident risks and costs is reflected in yearly insurance premiums. In a per-mile system, this heterogeneity would likewise be reflected in per-mile rates that vary substantially by territory, driver age, and driver accident record. Since the most dangerous drivers in the most dangerous territories would face the steepest rise in marginal driving cost and therefore reduce driving the most, actual benefits could be considerably larger than our estimates. If state heterogeneity is a useful guide, territory heterogeneity alone would raise the benefits of per-mile premiums by 10%. Other types of heterogeneity (such as age) could raise benefits substantially more.

The main reason insurance companies have not switched to per-mile premiums is probably that monitoring actual mileage with yearly odometer checks seems too costly given their potential gains, as suggested by Rea [1992] and Williamson *et al.* [1967, p. 247].[13] However, our analysis suggests that the gains a given insurance company could realize by switching to per-mile premiums are considerably less than the social gains. A single company and its customers might stand to gain only $31 per vehicle per year from the switch, far less than the potential social gains of $58 per insured vehicle that we estimate when we

[12] These ranges represent point estimates obtained with the regression and calibration methods described in section 4.

[13] Monitoring costs are cited as the principal reason by actuaries I have interviewed (see also Nelson [1990] and Cardoso [1993]).

include the Vickrey externality (i.e., the reduction in others' insurance costs.) Moreover, the $31 in private gains would be temporary from an insurer's vantage, and would all go to consumers once other firms match its new policies. [14] This discrepancy implies that the social gains from per-mile premiums might justify the monitoring costs (and the fixed costs of transition), even if no single insurance company could profit from the change itself.

Other external benefits could make the discrepancy between the private gains from per-mile premiums and the social gains even larger. A great deal of accident costs are uninsured or underinsured (more than half according to the Urban Institute) and the driving reductions caused by per-mile premiums should reduce these costs just as they reduce insured accident costs.[15] Policy intervention looks more attractive still when nonaccident benefits such as congestion are taken into account. Congestion reductions raise our estimates of the benefits from per-mile premiums by $5.5-$5.7 billion. This brings our estimates of total national benefits from per-mile premiums to $15.5-$18.2 billion ($18.7-24.7 billion with a Pigouvian tax), or $91.5-107.5 per insured vehicle ($110.8-146.2 with a Pigouvian tax). Benefits would be higher still, if pollution costs, road maintenance costs, and other externality costs are higher than we assume here.[16] The fact that accident and congestion externalities could make up more than two thirds of the benefits from per-mile premiums suggests that even if monitoring costs are so large that it is rational for insurance companies to maintain the current premium structure, it is likely that per-mile premiums could still enhance efficiency in many states. Likewise, it suggests that as mileage monitoring technology becomes cheaper (e.g., cellular phone and global positioning system technology), insurance companies may be slower at adopting these technologies than is socially efficient.

[14] In a competitive industry, insurance companies cannot profit from a coordinated change, because the efficiency gains would be competed away in lower prices.

[15] See e.g. Dewees, Duff and Trebilcock [1996] for evidence of substantial undercompensation. See also the estimates of the Urban Institute [1991].

[16] We assume in this article that existing gasoline taxes of 20-40 cents per gallon account for these costs. Many estimates, however, suggest that these costs may be much higher. Delucci [1997] estimates that the pollution costs of motor vehicles in terms of extra mortality and morbidity are $26.5-$461.9 billion per year in the U.S.

Some caution is required, of course, in relying upon this paper's estimates. This paper offers only a first-cut estimate of the accident externality effect, and the benefit estimates rely upon highly uncertain estimates of the price sensitivity of driving. Nonetheless, the estimates are large enough to strongly recommend further research, and provide some support for policy reform.

Section 1 presents a simple model of accidents that formalizes Vickrey's insights about accident externalities and incorporates congestion. Section 2 describes the data. Section 3 estimates the marginal accident cost of driving. Section 4 simulates driving and accident reductions under per-mile premiums. Section 5 concludes and explores the policy implications of this research.

1 A Simple Model of Accidents and Congestion.

We now develop a model relating driving to accidents and use it to simulate the consequences of various pricing scenarios. For simplicity, we construct an entirely symmetric model in which drivers, territory, and roads are undifferentiated and identical. The central insights continue to hold in a world where some drivers, roads, and territories are more dangerous than others, with some provisos. The relationship between aggregate accidents and aggregate miles will only hold exactly if the demand elasticity is the same across types of driving and drivers. Otherwise, accidents will be either more or less responsive to driving according to whether extra miles are driven by more or less dangerous drivers under more or less dangerous conditions.

We also limit attention to one and two vehicle accidents, ignoring the fact that many accidents only occur because of the coincidence of three or more cars.[17] We treat accidents involving two or more cars as if they all involve only two cars because multi-vehicle accidents are not separated in our accident data. Refined data would increase our estimates of the

[17] For example, one car may stop suddenly causing the car behind to switch lanes to avoid a collision—the accident occurs only if another car is unluckily in the adjacent lane.

benefits from the driving reductions associated with per-mile premiums because the size of accident externalities increase with the number of cars involved in collisions.

Let

m_i = miles traveled by driver i per year

M = aggregate vehicle miles traveled per year by all drivers

l = total lane miles

D = traffic density, or traffic volume = $M/\ l$

f_i = probability that i is driving at any given time

δ_1 = damages from one-vehicle accident

δ_2 = damages to each car in a two-vehicle accident

Holding speed constant, the fraction of the time that i is driving, f_i, will be proportional to the miles she drives, m_i; hence $f_i = \rho m_i$, for some ρ. For convenience, imagine that the l lane miles are divided into L "locations" of equal length. An accident occurs between driver i and j if they are in the same location and neither brakes or takes other successful evasive action . The chance that i is driving and j is in the same location is $f_i\,(f_j/L)$. Let q be the probability of accident conditional upon being in the same location. The expected rate of damages to i from two-car accidents with $j \neq i$ will then be

$$a_{2i,j} = \delta_2 f_i \frac{f_j}{L} q.$$

Summing over $j \neq i$ and substituting ρm_j for f_j and ρm_i for f_j yields expected damages to i from two-car accidents:

$$a_{2i} = \delta_2 \rho^2 m_i \frac{q\Sigma_{j\neq i} m_j}{L}.$$

Letting $c_2 \equiv \delta_2 \rho^2 l/L$, we have

$$a_{2i} = c_2 m_i \frac{(M - m_i)}{l},$$

or, assuming m_i is small relative to M,

$$a_{2i} \approx c_2 m_i \frac{M}{l} = c_2 m_i D.$$

Ignoring multiple-car accidents, the total expected accident damages suffered by driver i are then

$$a_i = c_1 m_i + c_2 \; m_i D.$$

The first term in the equation reflects the fact that a driver may be involved in an accident even if he is driving alone (e.g., falling asleep at night and driving into a tree), with c_1 representing the expected accident costs from driving a mile alone. The second term reflects the fact that the chance of getting into an accident with other vehicles in that mile increases as the traffic density D increases. The linearity of this model in m_i ignores the possibility that practice and experience could bring down the per-mile risk, as well as the offsetting possibility that driving experience (which is generally a safe experience) could lead to complacency and conceit. Empirical estimates of the elasticity of an individual's accidents with respect to that individual's mileage, as surveyed in Edlin [1999], range from .35 to .92, but as Edlin [1999] discusses, this work has been limited by the scarcity of reliable micro-level data pairing mileage and accidents, and probably yields downward biased estimates because of noisy mileage data and the difficulty of controlling for the factors that cause any given driver to drive very little (which are likely related to accident propensity).[18]

Summing over each driver i yields the total accident costs:

$$A = c_1 M + c_2 M D = c_1 M + c_2 M^2/l. \tag{1}$$

Observe that the cost of two-car accidents $c_2 M^2/l$ increases with the square of total

[18] For an example of such a downward bias, consider Hu et al. [1998] who study an elderly population. Omitted bad health variables seem likely to be positively correlated with worse driving and probably with less driving as well. Mileage data in that study also come from survey and seem highly susceptible to measurement error.

miles. Aggregate accident costs are quadratic in aggregate vehicle miles traveled, and this non-linearity is the source of the externality effect.

The marginal total accident cost from driving an extra mile is

$$\frac{dA}{dM} = c_1 + 2c_2D. \tag{2}$$

In contrast, the marginal cost of accidents to driver i is only

$$\frac{da_i}{dm_i} = c_1 + c_2D. \tag{3}$$

The difference between these two costs, c_2D, is the externality effect. It represents the fact that when driver i gets in an accident with another driver he is typically the " but for" cause of both drivers' damages in the sense that, "but for" him having been driving, the accident would not have happened. (Strangely enough, it is entirely possible that both drivers are the "but for" cause of *all* damages). This model could overstate the externality effect because of accident substitution: i.e., because if driver A and B collide, it is possible that driver A would have hit driver C if driver B weren't there.[19] Such a substitution effect would be captured in our regression estimates by a lower coefficient on traffic density, and hence a lower estimate of the externality effect.

A different view of the accident externality of driving is found by observing that the average cost of accidents per mile driven is:

$$\frac{A}{M} = c_1 + c_2D. \tag{4}$$

A given driver who drives the typical mile expects to experience the average damages $\frac{A}{M}$. Yet, this driver also increases D, which means that he also causes the accident rate for

[19] On the other hand, it understates the externality effect to the extent that some collisions require more than two vehicles.

others to rise at a rate of $\frac{d\frac{A}{M}}{dM} = c_2\frac{dD}{dM} = \frac{c_2}{l}$. Multiplying this figure by the M vehicle miles of driving affected again yields an externality c_2D.

The basic intuition behind the accident externality is simple. If a person decides to go out driving instead of staying at home or using public transportation, she may end up in an accident, and some of the cost of the accident will not be borne by either her or her insurance company; some of the accident cost is borne by the other party to the accident or that party's insurance company (although the average mile is not subsidized, the marginal mile is!).[20]

1.1 Gains from Per-mile Premiums.

We now compare the current insurance system, which we characterize (somewhat unfairly as footnote 3 concedes) as involving lump sum premiums, with two alternative systems: competitive per-mile premiums and Pigouvian per-mile premiums. As derived above, the break-even condition for insurance companies charging per-mile premiums is

$$p = \frac{A}{M} = c_1 + c_2M/l \tag{5}$$

This equation can be viewed as the supply curve for insurance as a function of the number of vehicle miles travelled requiring insurance. Again, in a more sophisticated model, and in practice, rates would vary by risk class i, and break-even competitive prices would be $p_i = \frac{A_i}{M_i} = c_{1i} + c_{2i}M/l$, where subscript i's have the natural meaning.

Let the utility of each of the n drivers be quasi-linear in the consumption of non-driving goods y and quadratic in miles m:

$$V(y,m) = y + am - \frac{n}{b}m^2. \tag{6}$$

[20] Another way to derive our formula for accidents, in which two-vehicle accidents are proportional to the square of miles driven, is to begin with the premise that the marginal cost of a mile of driving is the expected cost of accidents to both parties that will occur during that mile. Then the marginal cost of accidents will be twice the average: i.e., $\frac{dA_{2-car}}{dM} = 2\frac{A_{2-car}}{M}$. The unique solution to this differential equation, in which the elasticity of accidents with respect to miles is 2, is $A_{2-car} = c_2M^2$.

Then, the aggregate demand will be linear:

$$M = M_0 - bp \tag{7}$$

The equilibrium miles, M^*, and per-mile price, p^*, are found by solving equations (5) and (7):

$$M^* = \frac{M_0 - bc_1}{1 + bc_2/l}$$
$$p^* = \frac{c_1 + c_2 M_0/l}{1 + bc_2/l}.$$

If drivers continued to drive as much under per-mile premiums as they do under per-year, i.e., if b=0 so that demand were completely inelastic, then insurance companies would break-even by charging

$$p = c_1 + c_2 M_0/l.$$

however, for $b > 0$, as driving falls in reaction to this charge, the accident rate per-mile will also fall (because there will be fewer cars on the road with whom to collide). As the per-mile accident rate falls, premiums will fall in a competitive insurance industry, as we move down the average cost curve given by Equation (5).

Figure 1 depicts the situation. Let c_0 be the non-accident costs of driving (gas, maintenance, etc.) and assume that drivers pay these costs in addition to per-mile insurance premiums p. If drivers pay per year premiums so that $p = 0$, then they demand M_0 miles of driving. The social gain from charging per-mile accident premiums p^* in this model equals the reduction in accident costs less the lost benefits from foregone driving, the shaded region in Figure 1. This surplus S is given by

$$S = \frac{1}{2}\left(\left.\frac{dA}{dM}\right|_{M_0} + \left.\frac{dA}{dM}\right|_{M^*}\right)(M_0 - M^*) - \frac{1}{2}p^*\left(M_0 - M^*\right). \tag{8}$$

The first term is the reduction in accident costs that results from a fall in driving from M_0 to M^*. The second is the driving benefits lost from this reduction net of the non-accident cost savings $c_0\,(M_0 - M^*)$.

The marginal accident cost $\frac{dA}{dM}$ is given by equation (2). Note that because the marginal accident cost $\frac{dA}{dM}$ lies above the average cost $\frac{A}{M}$, the competitive per-mile premium $p^*$is less than the socially optimal accident charge which would lead to M^{**}miles driven. Socially optimal accident charges will not result from competition because of the accident externality. Government would need to impose a Pigouvian tax of $\left(\frac{\frac{dA}{dM}|_{M^{**}}}{\frac{A}{M^{**}}} - 1\right) \times 100\%$ on insurance premiums $\frac{A}{M^{**}}$. We call this sum Pigouvian per-mile premiums. By assuming quasi-linear utility, we are ignoring income effects. As a per-year premium is shifted to a per-mile charge, under other utility specifications, driving would not fall by as much as it would under a pure price change, because people would no longer have to pay a yearly premium and could use some of that money to purchase more driving than they would under a pure price change. The liklihood of such income effects are, however, overshadowed by our uncertainty about the price responsiveness of driving, so it does not seem worthwhile to consider them explicitly. We ultimately run policy simulations with elasticities of demand chosen conservatively (i.e., on the low side), so our estimates are similar to what they would be if we had a different utility assumption that allowed income effects, but chose a less conservative elasticity.

Our benefit calculation assumes that the number of drivers would remain unchanged in a switch to per-mile premiums. In fact, the number of drivers would probably increase under a per-mile system because the total price of a small amount of driving (say 2,000 miles per year) would fall. Although the extra drivers, who drive relatively little, will limit driving reductions and hence accident reductions somewhat, they would probably increase the accident savings net of lost driving benefits, and would surely do so in the case of Pigouvian per-mile premiums. The reason is that these extra drivers gain substantial driving benefits, as evidenced by their willingness to pay insurance premiums. In the case of Pigouvian per-mile premiums, the entry of these extra drivers necessarily increases the benefits from accident cost reductions net of lost driving benefits.

Pigouvian per-mile premiums could be implemented with a uniform percentage tax on competitive per-mile premiums in either a fault-based tort system or a no-fault tort system, as long as every driver stands an equal chance of being at fault. If drivers differ in fault propensity, then taxing premiums will work better in a no-fault system than in a tort system, because the optimal tax will be invariant to a driver's ability (i.e., invariant to expected share of total damages from relative negligence). To the extent that a no-fault sytem limits recovery to economic damages, as it commonly does in practice, the tax would need to be raised to account for the full externality.

1.2 Congestion

Congestion will fall if driving is reduced. In a fundamental respect, congestion is the counterpart to accidents. In the simplest model of congestion, congestion occurs when driver i and j would be in the same location at the same time except that one or both breaks to avoid an accident. The resulting delay is, of course, costly. A rudimentary model of congestion would therefore have congestion costs rising with the square of miles, holding lane miles fixed, so that

$$\text{congestion cost } C = a\frac{M^2}{l}.$$

As with accident costs, then, the average cost of congestion per-mile would equal one-half the marginal cost:

$$\frac{C}{M} = \frac{aM}{l} = \frac{1}{2}\left(\frac{dC}{dM}\right). \tag{9}$$

Equation (9) relates the average cost of delay to the marginal cost, so that we can use Schrank, Turner and Lomax's [1995] estimates of the average cost of delay in order to estimate the marginal cost of delay, and in particular the *external* marginal cost of delay.

This formulation undoubtedly understates the marginal cost (and hence the external cost) of congestion substantially, because as two vehicles slow down they generally force others to slow down as well. A cascade of such effects becomes a traffic jam. Looking at measured flow rates of traffic as a function of the number of cars travelling suggests that during periods of congestion the marginal congestion cost of driving is often many times, up to and exceeding 10 times, the average congestion experienced – at least during highly congested periods.[21] To be conservative, however, we assume that the marginal cost of congestion is twice the average cost, so that the portion of the marginal cost that is external to the driving decision equals the average cost.

Congestion cost savings that are external to the driving decision should also be added to the benefits from per-mile premiums. Assuming, that the mile foregone is a representative mile and not a mile drawn from a particularly congested or uncongested time, the person foregoing the mile will escape the average cost of delay, $\frac{C}{M}$. This savings should not be counted though among our benefits from driving reductions, because it is internalized. Viewed differently, each person derives no net benefit from her marginal mile of driving, because she chooses to drive more miles until driving benefits net of congestion cost just equal operating costs. Yet, as there is less traffic on the road, other drivers will experience reduced delays and this external effect should be added to our calculations. The external effect, as with accidents, equals the difference between the marginal and average cost of delay, so a conservative estimate of the external cost of dM extra miles driven is

$$\frac{C}{M}dM.$$

2 Data.

As a proxy for auto accident costs, we use state-level data on total private passenger auto insurance premiums from the National Association of Auto Insurance Commissioners (1998, Table 7). We subtract premiums paid for comprehensive coverage, so that we are left only

[21] Author's calculation based upon traffic flow tables. GAO, "Traffic Congestion: Trends, Measures, and Effects" GAO/PEMD-90-1, November 1989, p. 39.

with accident coverage. If the insurance industry is competitive, these figures represent the true economic measure of insured accident costs, which includes the administrative cost of the insurance industry and an ordinary return on the capital of that industry. These premium data are for private passenger vehicles, so we adjust these figures to account for commercial premiums by multiplying by 1.14, the national ratio of total premiums to noncommercial premiums.[22]

Insured accident costs do not come close to comprising all accident costs. The pain and suffering of at fault drivers is not insured, and auto insurance frequently does not cover their lost wages. (In no-fault states, pain and suffering is also not compensated below certain thresholds). These omitted damages are substantial and their inclusion would raise our estimates of the cost of driving and the benefit of driving reduction significantly. Pain and suffering is often taken to be three times the economic losses from bodily injury.

Other data come from a variety of sources. Data on the miles of lanes by state come from Table HM-60, 1996 Highway Statistics, FHWA. Annual vehicle miles by state come from Table VM-2, 1996 Highway Statistics, FHWA. Data on the distribution of fuel efficiency among vehicles in the current U.S. fleet, and the distribution of miles by fuel efficiency of car come from the 1994 Residential Transportation Energy Consumption Survey. We get gasoline prices by state from the Petroleum Marketing Monthly, EIA, Table 31 ("all grades, sales to end users through retail outlets excluding taxes") and Table EN-1 (federal and state motor gasoline taxes).

3 The traffic density-accident relationship.

The social elasticity of accidents with respect to miles of driving should substantially exceed an individual's elasticity because of the externality effect explained in the previous section. Even if the typical individual has an elasticity of .5, the elasticity of total accident costs

[22] See, p.22, the Insurance Information Institute 1998 Fact Book.

with respect to total miles driven would be close to 1 because any individual driver will cause others to have extra accidents when he drives more. One piece of evidence on the social elasticity comes from a study of California freeways from 1960-1962 (Lundy, 1964 cited in Vickrey, 1968). A group of 32 segments of four lane freeways with low average traffic had a per-mile accident rate of 1.18 per million miles compared with 1.45 per million miles on twenty segments with more traffic. The implied incremental accident rate was 1.98 accidents per million vehicle miles, suggesting an elasticity of accidents with respect to miles of 1.7=1.98/1.18. Because of the externality associated with driving pointed out in Section 1, we expect the elasticity of total accidents with respect to total miles to exceed the elasticity of an individual's accidents with respect to her driving. In fact, if an individual has an elasticity of 1 as the model assumes, the "aggregate" elasticity would be 2 if all accidents involved 2 cars. The California highway data accords roughly with what one would predict given that roughly 30% of accidents involve only one vehicle.[23]

It is worth comparing accident costs in pairs of states that have similar numbers of lane miles but very different numbers of vehicle miles traveled. For example, New Jersey and Wyoming both have approximately 75,000 lane miles. New Jersey has eight and a half times as much driving, however, and has an average insured accident cost of 7.7 cents per mile traveled instead of the 1.8 cents per mile of Wyoming. Comparing Ohio and Oklahoma we see a similar pattern. Ohio has approximately two and a half times as much driving on a similar number of lane miles and has higher average accident cost (3.6 vs. 2.6 cents per mile). Likewise, if we compare Hawaii and Delaware, which have similar numbers of vehicle miles traveled, we find that Hawaii, which has fewer lane miles and so substantially higher traffic density, has substantially higher accident costs per-mile. In general, average accident costs are much higher in states that have a lot more driving, holding lane miles fixed. This feature, which drives the high insurance rates in dense areas, is just another view of the

[23] See table 27, U.S. Department of Transportation [1997].

externality effect. The fact that marginal accident costs are higher than average accident costs is what drives up average accident costs as miles increase.

Many other idiosyncratic factors are involved, however, in a state's insurance costs. Maryland and Massachusetts, for example, have an almost identical number of lane miles and fairly similar vehicle miles traveled. However, although Massachusetts drivers only drive about 7 percent more miles per year in aggregate than Maryland drivers their average costs per-mile is 40 percent higher (6.7 cents vs. 4.8 cents), so that total insured accident costs are 45 percent higher. Whether this difference is attributable to differences between Massachusetts and Maryland drivers or differences between the roads or weather in the states is unknown. Cars may also be more expensive to repair in Massachusetts.

Here, we fit the model presented in Section 1 in order to form estimates of the marginal accident cost from driving an extra mile in each of the 50 states. As explained in Section 3, we use total auto accident insurance premiums paid in a state as a proxy for the total cost of automobile accidents. We estimate the effects of traffic density on accidents in two ways— by a calibration method and a regression method— as described below. The regression method utilizes the cross-state variation in traffic density to estimate its effect, while the calibration method relies upon the structure of the model and data on the percentage of accidents involving multiple vehicles. Each method has weaknesses, and after discussing the likely biases in each of these methods, we conclude that the true effect of density lies somewhere between the two estimates. The traffic density effect allows us to estimate the social marginal accident cost of driving and the extent to which this cost exceeds the average, or internalized marginal, cost of driving.

We modify the model of Section 1, assuming that each state's idiosyncratic errors ε_s enter multiplicatively as follows:

$$\frac{A_s}{M_s} = (c_1 + c_2 D_s)(1 + \varepsilon_s). \quad (10)$$

$$= c_{1s} + c_{2s} D_s, \quad (11)$$

where

$$c_{1s} = c_1(1 + \varepsilon_s)$$

$$c_{2s} = c_2(1 + \varepsilon_s)$$

and where s indexes states.

Once c_1 and c_2 are estimated, we can find the idiosyncratic component ε_s for each state from the above equation using the observed values of accident costs, miles traveled and lane miles in the state. We estimate the coefficients c_1 and c_2 in two ways — a calibration model and a regression model.

In our calibration model, we utilize national data on the percentage of accidents involving multiple cars. Assume that national accident costs are given by

$$A = c_1 M + c_2 M D,$$

where the costs of one- and two-car accidents are, respectively,

$$A_1 = c_1 M$$

and

$$A_2 = c_2 M D.$$

Let $\overline{a}$ be the average damage per insured vehicle from an accident, so that two-vehicle accidents have total damages of $2\overline{a}$ and one-vehicle accidents have damages $\overline{a}$. Let r denote the proportion of accidents that involve two vehicles. (Nationally, 71% of crashes were multiple-vehicle crashes in 1996, and we assume that multi-car accidents involve only two cars, since we don't have data on the number of cars in multi-car accidents and since this assumption makes our benefit estimate conservative.)[24]

If N is the total number of accidents in a state we have:

$$A = N(1-r)\,\overline{a} + 2Nr\overline{a},$$

so that

$$N\overline{a} = \tfrac{A}{1+r}.$$

This implies that the total cost of one-car accidents is

$$A_1 = \tfrac{(1-r)}{1+r}A,$$

and similarly for two-car accidents

$$A_2 = \tfrac{2r}{1+r}A.$$

The one and two-car accident coefficients can then be determined from the formulas:

$$\hat{c}_1 = \tfrac{A_1}{M} = \tfrac{(1-r)A}{1+r}\tfrac{1}{M}$$

and

$$\hat{c}_2 = \tfrac{A_2}{M^2}l = \tfrac{2r}{1+r}A\tfrac{l}{M^2},$$

Using the observed national data on accident costs (A), miles traveled (M), and lane miles (l), we estimate that the one-vehicle coefficient $\hat{c_1}$ is roughly .007 dollars per-mile,

[24] The statistic 71% is found by taking the ratio of the number of multiple vehicle crashes to total crashes in table 27, U.S. Department of Transportation [1997]. This figure understates the number of accidents that involve multiple vehicles because if a single vehicle crashes into a fixed object, for example, that is a single vehicle crash even if the vehicle swerved to avoid another car.

while $\hat{c_2}$ is 1.1 x 10^{-7} dollars per-mile squared per lane mile. This means that roughly 18% of costs are attributed to one-car accidents.

In our regression model, we estimate the coefficients c_1 and c_2 with a cross-sectional regression. Assuming that the idiosyncratic components ε_s are i.i.d. mean zero random variables that are independent of D_s, OLS estimates $\hat{c_1}$ and $\hat{c_2}$ are consistent under standard regularity conditions. Table 1 gives the results of the cross-sectional OLS regression in column 2 and the calibration method in column 1.

The estimate of the one-vehicle coefficient $\hat{c_1}$ suggests a cost of 2.2 cents per-mile. The other coefficient, $\hat{c_2}$, is 5.4 x10^{-6} cents per squared mile per lane mile. The regression model suggests that 55% of costs are attributable to one-car accidents, i.e., to the linear term.

In both models, the marginal accident cost is found by differentiating equation (10) which yields:

$$\frac{dA_s}{dM_s} = c_{1s} + 2c_{2s}D_s.$$

We find the state-specific coefficients for one and two vehicle accidents as follows:

$$\begin{aligned} \hat{c}_{1s} &= \hat{c}_1(1 + \hat{\varepsilon}_s) \\ \hat{c}_{2s} &= \hat{c}_2(1 + \hat{\varepsilon}_s) \\ \hat{\varepsilon}_s &= \tfrac{A_s}{\hat{c}_1 M_s + \hat{c}_2 M_s D_s} - 1. \end{aligned}$$

Table 2 gives the marginal accident costs estimated by the calibration and regression methods. Table 2 allows us to compare these costs with the average accident cost per-mile driven, which appears in column 3. The last row models the U.S. as a whole, treating it as a single state. As we see, accounting for the Vickrey externality appears significant regardless of which method we use, in that the marginal cost of accidents significantly exceeds the average cost. The reason is that both estimation methods put significant positive weight on the quadratic term. The elasticity of accidents with respect to miles (i.e. the ratio of marginal to average cost) is higher under the calibration model because that model puts more weight on the quadratic term. Below, we discuss several reasons why the regression estimates probably understate the density effect (and hence the marginal cost of driving), and why the calibration estimates may overstate this effect.

The calibration method might overstate accident externalities because the theoretical model does not account for accident substitution— i.e., the possibility that if one of the drivers in a two-car accident stayed home, another accident might have substituted for the one that happened. [25] (This bias could be offset, though, by the fact that many accidents require the coincidence of more than two cars at the same place at the same time). A second upward bias results because in the calibration method, $c_1$and c_2 are held constant, which does does not account for the fact that as driving becomes more dangerous, drivers and states both take precautionary measures. States react to higher accident rates with higher expenditures on safety by widening roads and lengthening freeway on-ramps. Drivers also make financial expenditures, buying air bags or anti-lock brakes, and nonfinancial expenditures, by paying more attention and slowing down to avoid accidents when driving in heavy traffic. All these precautionary measures mitigate the impact of extra traffic density on accidents. At the margin, if precautions are chosen optimally so that the marginal cost of precautions equals their marginal benefit, then the envelope theorem guarantees that the calibration method would still be properly capturing the sum of accident and prevention costs (i.e., we can treat prevention as being fixed). However, to the extent that people take too little precaution at the moment, the calibration results will overstate the accident externalities. Even if precautions are currently optimal, the calibration results will overstate accident externalities for large changes in behavior, because the marginal analysis of the envelope theorem will not be applicable.

[25] For example if vehicle A plows into a line of cars stopped at a light, removing vehicle B from the line might not affect the damage.

The regression method picks up both of the effects above, but unfortunately has several biases of its own that tend to make it understate the effects of density (accident externalities). Two reasons revolve around the fact that we use insurance premiums as our measure of accident costs. As mentioned at the paper's outset, a substantial portion of accident costs are not insured. If this fraction were constant across states, it would bias our calibration and regression estimates down equally. However, states with more miles driven per lane mile and higher accident costs have higher insurance premiums, and according to Smith and Wright (1992), states with higher premiums will have substantially more uninsured motorists.[26] With fewer drivers insured, a smaller share of total accident costs would be insured. This effect could bias our regression estimates of marginal cost downward significantly. Another potential downward bias for the regression results is that as accident rates and insurance costs rise, states tend to adopt no-fault insurance reform limiting coverage of noneconomic losses so that again the percentage of costs that are insured would be lower in high-cost states.

A third source of bias, which is probably substantial, is that our measure of traffic density for a given state is a noisy measure of the traffic density where the typical mile is driven in that state because of within-state heterogeneity. In particular, adding a lot of miles of empty rural roads would not reduce the traffic density where people drive, nor the number of accidents, but would reduce the predicted number of accidents from our regression because the average traffic density would fall. This observation may explain the large positive residuals in New York, for example. Noise in our measure of traffic density would tend to lower our estimates of the accident cost of density. A final source of downward bias is that the precautionary expenditures discussed above, which are induced by high traffic density, are not included in our measure of insured accident costs.

[26] In fact, they argue that there is a feedback loop so that high premiums cause more uninsured motorists and therefore still higher premiums.

To summarize, there are several reasons that the regression estimates underestimate the effect of density (and hence the marginal cost of accidents), while the calibration results overestimate the effect. The truth probably lies between these estimates, so we will treat them as framing the reasonable range of estimates.

4 Policy simulations.

4.1 Methodology.

This section estimates and compares the potential benefits of charging per-mile premiums with and without a Pigouvian tax. Competitive per-mile premiums are fixed in the simulations at rates just sufficient to allow insurance companies to break even, exactly covering accident costs. The Pigouvian per-mile premiums simulations assume a tax on premiums to account for the externalities of accidents. Both sets of simulations assume that an individual pays premiums in proportion to the miles she drives. As the introduction discussed, such policies would most likely be implemented so that per-mile rates varied among drivers or vehicles based upon the same territory, driving record, and other factors that are currently used to vary per-year rates. Since our estimates are based on statewide aggregates, they ignore substantial heterogeneity among regions and drivers within each state. Our estimates therefore considerably understate the potential benefits of both these policies, because if high risk drivers pay the highest per-mile rates, then driving reductions will be concentrated among these drivers, where they are most effective at reducing accidents.

Our calculations also ignore the costs and difficulty of verifying the number of miles traveled, two issues discussed in the final section. However, they do account for the cost of foregone driving benefits caused by the voluntary reduction in mileage that would result from insurance being charged by the mile, as opposed to the current system of by the year.

For each policy option we estimate the consequences under three models of accident determination—linear, calibration, and regression. The linear model assumes that accidents are proportional to miles driven, i.e. that $A_s = c_{1s} M_s$. This model takes no account of the externalities from driving, nor the related fact that as people reduce their driving, accident rates per mile should fall because there are fewer drivers on the road with whom to have an accident. The regression and calibration models include a term that is quadratic in miles to account for the externality effect. The one and two-car accident coefficients are determined for these two models as described in the previous section.

We estimate a linear model for two reasons. First, the efficiency savings under a linear model are the straightforward gains from more efficient contracting that a single company (with a small market share) and its customers could together expect to receive if they alone switched to per-mile pricing. (Once other firms followed suit all these gains would go to customers). Comparing the linear model with the calibration and regression models, therefore allows us to see how much of the accident savings are external to a given driver and his insurance company. The second reason to be interested in the linear model results is the possibility of substantial learning-by-doing in driving that is not exhausted after the first couple of years. If driving more lowers an individual's accident rate so that the typical individual has an accident elasticity with respect to miles of 1/2,[27] then after accounting for the externality effect, the aggregate elasticity of accidents with respect to miles should be approximately 1 as assumed in the linear model.

Our estimates of the results of these policies naturally depend upon the price responsiveness of driving. Estimates of the price responsiveness of driving are plentiful and generally come from observed changes in the price of gasoline.

Our benchmark case assumes that the aggregate elasticity of gasoline demand with respect to the price of gasoline is .15. This figure is 25% lower than the short-run elasticity of .2 that the two comprehensive surveys by Dahl and Sterner [1991 a,b] conclude is the most plausible estimate, and also substantially lower than the miles elasticities estimated

[27] See, for example, the estimates in Hu et al. [1998] that were discussed in Edlin [1999].

by Gallini [1983]. Goldberg [1998, p. 15] has recently made an estimate of miles elasticity near zero, though she argues that for large price changes such as those we consider here, a figure of .2 is more reasonable.[28] Goldberg's standard errors are sufficiently large that her estimate is also not statistically different from .2 at the five percent level.

>From the perspective of social policy, we should be interested in long run elasticities. Long run elasticities appear to be considerably larger than short run. Goodwin's [1992] survey suggests that time series studies give long run elasticities for petrol of .71 compared with .27 for the short run; cross section studies give .84 compared with .28 for the short run. Interpreting these long run elasticities in our context is problematic because in the long run, there is substantial substitution among vehicles to more fuel-efficient vehicles which will be driven more miles. Still, Johansson and Schipper [1997] estimate that the long run elasticity of miles per car with respect to fuel price is .2. Given vehicle substitution, this figure suggests that the benefits of per-mile premiums would, in the long run, be much larger than we estimate.

>From our assumed fleet gas price elasticity of .15, we compute the mile-price elasticity (which we assume is constant across vehicles) as follows. Let

μ_i = miles traveled by cars of fuel efficiency i miles per gallon.

e = the point elasticity of a given vehicle's miles with respect to marginal price per mile (assumed constant across vehicles).

g_i = gas price per mile.

t_i = total marginal price per mile = 4.2 cents (maintenance) + 5 cents (depreciation) + g_i(gas price) + p_i(insurance price)[29]

ε = .15 = aggregate point elasticity of gasoline demand with respect to price of gasoline.

[28] Miles elasticity and gas elasticity differ by the elasticity of fuel efficiency with respect to fuel price. In the short run, this elasticity is probably relatively small, though in the long run it could be substantial.

Note that since e is the miles elasticity for each vehicle with respect to marginal price per mile, it is also the gasoline demand elasticity for that vehicle with respect to marginal price per mile. Then $e\frac{g_i}{t_i}$ is both the mile elasticity and gasoline elasticity with respect to the price of gasoline for a vehicle with fuel efficiency i mpg. Since the proportion of gasoline bought by vehicles of fuel efficiency i is $\left(\frac{\mu_i/i}{\sum_j \mu_j/j}\right)$, we can solve for e using the following relationship:

$$.15 = \varepsilon = \sum_i \left(\frac{\mu_i/i}{\sum_j \mu_j/j}\right) e\frac{g_i}{t_i}. \tag{12}$$

Assuming that driving demand is linear, and each car of fuel efficiency i is charged the same per-mile premium $p_i = p$, driving demand becomes $M = M_0 - \sum \mu_{i0} e\frac{p}{t_{i0}}$ (where the subscript 0 denotes the value variables take on under current practice, with zero marginal insurance charges).[33]

Solving this driving demand equation simultaneously with the per-mile premium zero profit condition (equation (5)) yields the equilibrium miles M^* and per-mile premiums p^*. We first compute this equilibrium for each state. We then model the U.S. in two ways: first, in a disaggregated model where the national mile reduction is the sum of state mile reductions and second, treating the nation in an aggregated fashion as if it itself were a state. We use the equilibrium values p_s^*, M_s^* to compute surplus in each state s according to equation (8).

Finally, to simulate Pigouvian per-mile premiums, we replace the zero profit condition with the requirement that premiums equal the marginal social accident cost of driving. Thus, the "supply" equation for insured miles under Pigouvian per-mile premiums is

$$p = c_1 + 2c_2 M/l$$

[33] For a linear demand curve $D(t)$ with a point elasticity of e at price t_0, the reduction in demand from a price increase Δt is *exactly* $D(t_0)e\frac{\Delta t}{t_0}$.

We solve this equation simultaneously with the per-mile demand equation $M = M_0 - \sum \mu_{i0} e \frac{p}{t_{i0}}$ for each state to compute the equilibrium under per-mile premiums with a Pigouvian tax.

4.2 Results.

4.2.1 Per-Mile Premiums

Table 3 presents our estimates of the consequences of switching to per-mile premiums. The zero profit condition for insurance companies is that per-mile premiums equal the average insurance cost of accidents per mile driven. These premium figures are quite high and exceed the cost of gasoline in many states as Table 2 shows. Even with the modest price elasticity of .15 assumed here, the resulting driving reduction is substantial. The national reduction in vehicle miles traveled, $M_0 - M^{*,}$, is approximately 10% in all three models, and reaches 15% in high-traffic states. The reduction is somewhat less in the nonlinear models than it is in the linear ones, because in the nonlinear models, as driving is reduced, the risk of accidents also falls and with it, per-mile premiums. Since equilibrium per-mile premiums are lower in these models, the total driving reduction is lower. This effect is much more pronounced in the calibration model, because of the larger traffic density effect from two-car accidents in this model. Under the calibration models in Massachusetts, the per-mile charge falls from 6.7 cents per-mile to 5.8 cents per-mile as driving is reduced. Even with this fall, per-mile charges remain roughly comparable to the cost of gasoline, making the expected driving reduction roughly 15%.

Reductions in driving would naturally be much larger in states that currently have high insurance costs and would thus face high per-mile premiums. For example, if we compare New Jersey with Wyoming (two states with similar lane miles but very different vehicle miles traveled (VMT), we find that implementing competitive per-mile premiums would reduce New Jersey's VMT by 16.4 percent under our calibration model versus 4.4 percent in Wyoming. The reduction is much larger in New Jersey because the higher traffic density there leads to higher accident rates: the per-mile premium in New Jersey would be 6.5 cents per-mile as compared to 1.8 in Wyoming.

None of the per-mile premiums have been adjusted for uninsured drivers, because data on the percentage of uninsured drivers is poor. Estimates of the percentage of uninsured drivers are often in the neighborhood of 25% (see Khazzoom [1997], Sugarman [1993], and Smith and Wright [1992]). Our estimates of the per-mile premium are calculated by dividing estimated insured accident costs by total miles driven rather than by insured miles driven. This could substantially understate the actual per-mile premiums if total miles substantially exceed insured miles. However, it wouldn't change our estimates of aggregate driving reductions significantly because even though the per-mile premium would be higher for insured miles, it would be zero for uninsured miles.[34]

These driving reductions lead us to predict lower insurance (and accident) costs of $14 billion according to the regression model and $17 billion according to the calibration model. Even after subtracting lost driving benefits (the second term in equation (8) , the benefits we estimate for accident savings net of lost driving benefits remain substantial in all three models. Nationally, these net accident savings range from $5.3 billion to $12.7 billion, as Table 3 reports. The difference between our $5.3 billion estimate under the linear model and our $12.7 billion under the calibration model is dramatic: Accounting for accident externalities raises our estimate of benefits by 150 percent. Such a large difference makes sense. If a price change for driver A causes her to drive less, much of her reduction in accident losses is offset by her lost driving benefits. In contrast, every driver with whom she might have had an accident, gains outright from the reduced probability of having an

[34] Let u be the fraction of uninsured drivers and $\hat{p}$ be our estimate of true per-mile premiums. If premium $\frac{\hat{p}}{1-u}$ is charged on $(1-u)$ percent of miles, then the aggregate mile reduction is identical to our estimate given linear demand. Some revenue shortfall could be expected because priced miles fall by a larger *percentage* than in our estimate. However, this is approximately offset by the fact that insured accident losses could be expected to fall by more than we estimate, because driving reductions would be concentrated in the insured population.

accident with A who is driving less. Taking this externality effect into account, nationally, the net gain is $75 per insured vehicle under the calibration model, as reported in Table 3. However, since insurance companies and their customers don't take the externality benefits into account, their view of the gain from per-mile premiums is probably closer to the $31 of our linear model.[35] In high traffic density states, the gain per insured vehicle is quite high – approximately $150 in Massachusetts and New York and nearly $200 in Hawaii and New Jersey under the calibration model.

Compare the net accident reductions in the last two rows of Table 3. Accident reductions are about 10 percent higher when the U.S. is modeled in a disaggregated way. In the National Aggregated Model, heterogeneity is ignored and the U.S. is modeled as if it were a state and a uniform per-mile premium were charged in every state. This estimate therefore does not pick up one of the important benefits of allowing competition to determine the level of per-mile premiums. In a competitive insurance market, there are no cross-subsidies among territories, so high prices are charged in areas that have high accident rates, where the benefits from driving reduction will be highest. Each of our state estimates suffers from the same problem. Our benefit estimates from per-mile premiums are lower than they would be in competitive insurance markets, because there is substantial variation within a state in traffic density and accident rates. As we pointed out earlier, areas with high accident rates will be charged higher per-mile premiums and therefore experience larger driving reductions. If within-state heterogeneity is similar to across-state heterogeneity, we could expect that our estimates of net accident gains are 10 percent lower than actual gains would be. Taking into account heterogeneity among drivers, as would happen naturally under a competitive system of per-mile premiums, would increase benefits still further.

All of our benefit estimates depend critically of course on driving elasticities. Driving

[35] State Farm, the largest auto insurance carrier in the U.S., has a 20-25% market share and so captures up to a quarter of these "external" benefits – and therefore has a larger incentive to adopt premium schedules that reduce driving than does an insurance carrier with a very small market share.

reductions and net accident savings are both higher (respectively lower) if the aggregate gas demand elasticity is higher (respectively lower) than .15. The relationship between elasticity and accident savings is somewhat sub-linear, however, because the externality effect means that gains are smaller when there is less driving. Nationally, net accident benefits go from \$9 billion for an elasticity of .1 to \$16 billion for an elasticity of .2, using the calibration model.

In general, the estimates of net accident cost savings under the regression model are significantly smaller than under the calibration model. This difference results from the regression model putting little weight on the externality effect. As we have argued, this very small weight is probably due to several likely biases resulting from state errors being negatively correlated with traffic density. We therefore concentrate our attention on the calibration results.

Our calculation of net accident cost savings under the calibration model does not account for the possibility that reduced traffic density causes drivers to drive less carefully, or causes states to spend less money making roads safe. It is likely that as traffic diminishes, people will exercise less care, and so actual accident costs will not fall as much as we estimate. However, this effect is not necessarily a criticism of the calibration model estimates. At the margin, this observation simply implies that some of our estimated accident cost reductions will actually materialize as reductions in the cost of accident prevention. Assuming that the tort system is currently ensuring an optimal level of care, our calculation will be accurate for small reductions in driving. Some inaccuracy due to infra-marginal effects are possible, but these are probably small given that we are only considering driving reductions of 10-15%.

These calculations also ignore the fact that more drivers will choose to become insured once they have the option of economizing on insurance premiums by only driving a few miles. Today, some of these low-mileage drivers are driving uninsured while others are not driving at all. To the extent that per-mile premiums attract new drivers, the reduction in vehicle miles traveled will not be as large as our simulations predict. Surprisingly, though this observation does not mean that the social benefits are lower than we predict. In fact, they are probably higher. The per-year insurance system is inefficient to the extent that low-mileage drivers who would be willing to pay the true accident cost of their driving choose not to drive, because they must currently pay the accident cost of those driving many more miles. Giving them an opportunity to drive and pay by the mile creates surplus if their driving benefits exceed the social cost (their benefits would always exceed the social cost under Pigouvian per-mile premiums since they are choosing to pay the social cost, and benefits probably exceed costs under per-mile premiums since they pay most of the social cost).

4.2.2 Pigouvian Per-Mile Premiums.

Finally, consider Table 4, which presents our results for Pigouvian per-mile premiums. Pigouvian per-mile premiums would involve a tax on premiums sufficiently large that a driver pays the full accident cost of his driving accounting for accident externalities. We calculate the Pigouvian tax here under the assumption that auto insurance premiums reflect all accident costs. As we discussed in the introduction, the bulk of accident costs are not covered by auto insurance. In particular, auto insurance covers a small fraction of the value of statistical lives lost, and also doesn't cover the pain and suffering of at fault drivers. The reader should therefore keep in mind that truly optimal Pigouvian taxes would account for these costs and would be substantially higher than those we use for our estimates.[36]

For the linear model, the average cost of accidents (A/M) equals the marginal cost $\left(\frac{dA}{dM}\right)$, so the Pigouvian tax is 0. In our calibration and regression models, however, which take account of the accident externalities, the marginal cost of accidents exceeds the average cost. In consequence, the Pigouvian tax is substantial. Under the calibration model, an

[36] The fact that life insurance or other insurance serves in part to fill the compensation gap between auto insurance and full compensation does not take away from this point.

appropriate Pigouvian tax would be about 90% in high traffic density states such as New Jersey and about 40% in low density states like North Dakota. On average across the U.S., the Pigouvian tax would be 83% under the calibration model compared with 19% under the regression model. For the calibration model, the Pigouvian tax makes national driving reductions 15.7% instead of 9.2%. National net accident savings grow to $15.3 billion from $12.7 billion, as seen in Table 4.

4.3 Delay Costs from Congestion

The cost of traffic delays are a large concern,[37] and one ancillary benefit of per-mile premiums and of the Pigouvian tax would be to reduce congestion related delays as driving falls. As discussed in Section 1.2, not all of the resulting time savings should be added to the social gain calculated above, however. Some of congestion costs are already internalized by drivers and reflected in the driving demand curve. This subsection provides rough estimates of the external portion of these cost savings. As section 1.2 explained, our methodology should result in a lower bound.

A detailed study by Schrank, Turner and Lomax [1995] estimates that the cost of congestion in the form of delay and increased fuel consumption in the U.S. exceeded $49 billion in 1992 and $31 billion in 1987.[38] This study valued time at $8.50/hr. in 1987 and $10.50/hr. in 1992, which will seem a considerable undercounting to those who would far prefer to be at work than stuck in a traffic jam. If we project this figure to $60 billion in 1995, this amounts to 2.5 cents for every mile driven. As discussed in presenting our model, although the marginal cost of congestion is many times the average cost of congestion during congested periods, we conservatively assume that the marginal cost of congestion is twice the

[37] A recent poll by Mark Baldarassare shows that voters in California are "most satisfied with their jobs" and "most negative about traffic." New York Times 6/2/98, A1, "Economy Fades As Big Issue in Newly Surging California."

[38] My summation for the 50 urban areas they studied. See Table A-9, p. 13, and Table A-15, p. 19, in Shrank, Turner and Lomax [1995]. See also Delucci [1997], who estimates congestion costs at $22.5-99.3 billion.

average cost, so that the external marginal cost of congestion equals the average. Table 5 gives our estimates of the national portion of congestion reduction that is external and should be added to net accident benefits. In all models, estimated externalized gains from congestion reductions are large, ranging from \$5.5 billion to \$9.4 billion as seen in Table 5. Under per-mile premiums, congestion reductions are largest in the regression and linear models because in those models, accident rates (and hence per-mile premiums) don't fall much or at all as driving falls. In contrast, the congestion reductions for per-mile premiums with a Pigouvian tax are largest (\$9.4 billion) under the calibration model, because of the substantial driving reductions caused by the large Pigouvian tax that accounts for accident externalities from driving.

These calculations are based upon the average cost of delay. Congestion delays, of course, are concentrated during certain peak time periods and at certain locations. This fact simply means that the congestion reductions from per-mile pricing are concentrated during these time periods and these locations. Our calculations are robust provided that the elasticities of demand for congested miles and non-congested miles are comparable, and that the externalized marginal cost is a constant multiple of average cost.[39] The concentration of congestion costs simply suggest that we would be even better off if driving were priced particularly high during congested periods and somewhat lower otherwise.

4.4 Total Benefits.

Table 5 gives total estimated annual national benefits from competitive per-mile premiums and Pigouvian per-mile premiums. The total benefits are expressed both in aggregate

[39] To understand why, consider a model with two types of miles: A, B. Let the initial quantities of driving these miles be a, b, and let C_a, C_b be the total cost of delay during driving of types A, B respectively. Then, the average cost of delay is $c = \frac{C_a + C_b}{a+b}$, and the average cost of delay during driving of the two types is $c_a = C_a/a, c_b = C_b/b$. The externalized marginal congestion costs are likewise c_a, c_b. Observe that if a uniform per mile price p is charged for both types of miles, the congestion savings will be $\frac{p\varepsilon}{g}[ac_a + bc_b] = \frac{p\varepsilon}{g}(C_a + C_b)$, where g is the initial gas cost per mile of driving, and ε is the elasticity of miles with respect to the price of gasoline. This is equivalent to what we would calculate if we treated the two types of miles equivalently, with c as the externalized marginal cost of miles. Then we would estimate the congestion reduction as: $\frac{p\varepsilon}{g}[a + b]c = \frac{p\varepsilon}{g}(C_a + C_b)$.

and per insured vehicle. These annual benefits are quite high and using the regression estimates as our lower bound and the calibration estimates as our upper bound suggests that charging by the mile on a national basis would be socially beneficial if verifying miles could be achieved for less than \$91.5–\$107.5 per car each year. In some high traffic density states, per-mile premiums could be socially beneficial even if the cost of verifying miles approached \$200 per vehicle. External benefits made up \$20-\$24 billion of our estimated benefits since net accident savings were only \$5 billion under the linear model, as reported in Table 5. The gains with a Pigouvian tax were higher still at \$111-\$146 per insured vehicle. These estimates neglect environmental gains that would result if the current price of gasoline does not adequately account for emissions, noise pollution and road maintenance. Likewise, they would overstate gains if current gasoline taxes exceed those nonaccident noncongestion costs. Our estimates also did not account for underinsured and uninsured accident costs. Including these latter figures into our estimates of eliminated accident externalities would raise the estimated benefits by several billion dollars more.

The total benefits are quite large even for the linear model where accidents are proportional to mileage. Under the linear model, the total benefits of per-mile premiums are \$67 per insured vehicle. As mentioned early, this model would be roughly accurate if individual elasticities of accidents with respect to miles were .5, because then the externality effect would make the social elasticity roughly one, as in a linear model. Estimates under the regression model lie roughly halfway in between the linear model and the calibration model.

5 Conclusions and Policy Implications

In all three models, the aggregate benefits of per-mile premiums are quite large. They are concentrated in states with high traffic density where accident costs and the externality effect appear particularly large. Aggregate benefits reach \$11 billion nationally, or over \$67 per insured vehicle even under the linear model, and are substantially larger (\$15-18 billion) under our preferred regression or calibration models. In high traffic density states like New Jersey, the benefits from reduced accident costs, net of lost driving benefits could be as high as $198 per insured vehicle, as indicated in Table 3.

Why then are most premiums so weakly linked to actual mileage and closer to per-year than per-mile premiums? Standard contracting analysis predicts that an insurance company and its customers would not strike a deal with a lump-sum premium if an individual's accidents increase with his driving, and if vehicle miles is freely observable. In that case, by reducing or eliminating the lump-sum portion and charging the marginal claim cost for each mile of driving, the contract can be made more profitable for the insurance company and also more attractive to its customers: as individuals reduce their driving, the insurance carrier saves more in claims than the lost driving benefits to its customers. Hence the "mystery."

The primary reason we don't see per-mile premiums is probably monitoring costs, the reason suggested by Rea [1992] and by some insurance executives. Traditionally the only reliable means of verifying mileage was thought to be bringing a vehicle to an odometer-checking station. The twin sister of these monitoring costs is that a firm charging per-mile premiums would suffer abnormally high claims from those who committed odometer fraud. The significance of monitoring costs/fraud costs as an explanation is supported by the fact that commercial policies (where the stakes are larger) are sometimes per-mile, and now that cheap technologies exist that allow mileage verification "at a distance," at least one firm is now experimenting with per-mile premiums.[40] Adverse selection provides another explanation that tends to close the per-mile premiums market.[41]

[40] See Wall Street Journal [1999].

[41] Adverse selection is another reason that a given insurance company may not want to switch to per-mile premiums on its own. Even if the insurance company knows the average miles driven per year by drivers in a given risk pool, it does not (currently) know the miles that given individuals drive. If it charges a per-mile premium equal to the current yearly premium for the pool divided by the average number of miles driven by drivers in the pool, it will lose money. Those who drive more miles than the average will leave the pool for a firm charging per-year rates and those who drive less miles will stay with this insurance company. The remaining drivers or adversely selected, because low mileage drivers in any given per-year risk class with

If monitoring costs are what limit the use of per-mile premiums policies, then to encourage their use would seem unwise because lack of use may be a good signal that the policies' benefits do not justify their costs. The theory and empirical work here highlights another reason, though, why such policies are not common, a reason that suggests policy intervention could be valuable. In particular, the social gains from accident reduction as a driver reduces her driving could substantially exceed the private gains (realized by the driver and her insurance carrier), at least in high-traffic density states. In New Jersey, for example, we estimate that the private gains as captured by the linear model are $86 per insured vehicle as compared with social gains of $189-236 once external gains are included (see Table 3). Hence, most of the benefits from switching to per-mile premiums or some other premiums schedule that reduces driving are *external*. The accident externality is surely one big reason that insurance companies have not made such a switch. If monitoring costs and other transaction costs lie in the gap between $86 and $189-236, then per-mile premiums would be efficient in New Jersey, but might not materialize in a free market. Congestion reductions make the external benefits from per-mile premiums even larger, increasing the chance of market failure.

Mandating per-mile premiums might be unwise though, even if per-mile premiums are efficient on average, because monitoring costs are substantial and vary with an individual's cost of time. (Heterogeneity across individuals favors policy options that would allow more individual flexibility.) Even if mandates are not justified, if driving does cause substantial external accident costs as the theory and the empirical work here suggest, then some policy

a given accident experience level will tend to be worse drivers than high mileage drivers in the same risk class. (Long-run historical accident costs divided by miles driven would be a sensible measure of per-mile risk.) This adverse selection means that the insurance company will have to charge a relatively high per-mile price to break even given the selection problem and the possibility that high-mileage drivers can choose to pay fixed annual premiums with other insurance companies. In principle, the insurance company could probably find a sufficiently high per-mile price that would increase profits. However, one could understand the hesitancy of a marketing director to propose to his CEO that the insurance company change its pricing structure in a way that would make its prices less attractive than other insurance companies' to a large percentage (probably more than half) of its current customers.

action could be justified.

The simplest policy option in states such as Massachusetts that already have regular checks of automobiles for safety or emissions, would be to record odometer readings at these checks and transfer this information together with vehicle identification numbers to insurance companies. This would remove the need for special stations for odometer checking, or for installing special monitoring devices in vehicles. Private monitoring costs would also be reduced if the government increased sanctions for odometer fraud. Legislation such as the new Texas Law that legalizes or otherwise fascilitates switching the insurance risk exposure unit from the vehicle-year to the vehicle-mile can only help.

A second policy option is to impose a tax on premiums sufficient to account for the accident externality of an additional driver. If insurance companies continued to have a weak mileage-premiums link, people would at least, then, still face efficient incentives at the margin of whether to become drivers. Moreover, insurance companies would then have increased incentives to create a strong mileage-premiums link, and drivers would face second-best incentives at the margin of deciding how many miles to drive. By making insurers pay the total social accident costs imposed by each of their drivers, a tax would give insurers the incentive to take all cost-effective measures to reduce this total cost. An externality tax would align the private incentives to incur monitoring costs and to charge per-mile premiums with the social incentives, so that insurance companies would switch premium structures to per-mile or to a schedule that better reflects accident cost whenever monitoring costs and transition costs become low enough to justify the switch. Such a tax would also make per-mile premiums higher to reflect both per-mile claim costs and the tax. The consequent driving, accident, and delay reductions would likewise be larger, as shown in the Pigouvian tax portion of Table 5. An alternative to a tax that would be more difficult to administer, but perhaps easier to legislate, would be a subsidy to insurance companies that reduce their customers' driving equal to the resulting external accident cost reductions.

Another possible policy option is to require insurance companies to offer a choice of per-mile or per-year premiums (at reasonable rates) as proposed in March 1998 by the National Organization for Women. A fourth option is to facilitate the formation of an insurance clearinghouse that allowed individual per-mile premiums to be paid or billed "at the pump" when gasoline is purchased – again an attempt to lower monitoring costs.

Wisdom demands, however, that enthusiasm for costly policy changes be tempered until more research is done in this area. Our empirical estimates are only a first-cut. Our regression estimates suffer from all the potential biases we suggested and some we did not. Future research should include covariates and panel data. Our simulation estimates of the benefits from per-mile premiums and of the Pigouvian tax depend upon the size of the externality effect, the assumed linear accident/mileage profile for individuals,[42] the responsiveness of driving to price, and our use of insured accident costs. Each of these areas warrants considerably more examination. For example, if the estimates of the Urban Institute [1991] are correct, and total accident costs are 3.5 times higher than the insured costs considered here, then the true benefits of premium restructuring could be much larger than we have estimated. Finally, we note that it would also be quite informative to break down externalities by vehicle type.

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[42] Note that our estimates of the size of the accident externality effect are largely independent of the shape of the typical individual's accident profile, because these estimates are based upon cross-state comparisons of the effects of different traffic density levels on insurance premiums normalized by the amount of driving done. If an individual's elasticity of accident costs with respect to miles is closer to 1/2 instead of 1 as assumed here, then the elasticity of total (social) accident costs with respect to that individual's driving should be roughly 1, because of the externality effect. This observation suggests that if an individual's accidents are that unresponsive to driving, then the linear model should roughly predict the social gains from switching to per-mile premiums.

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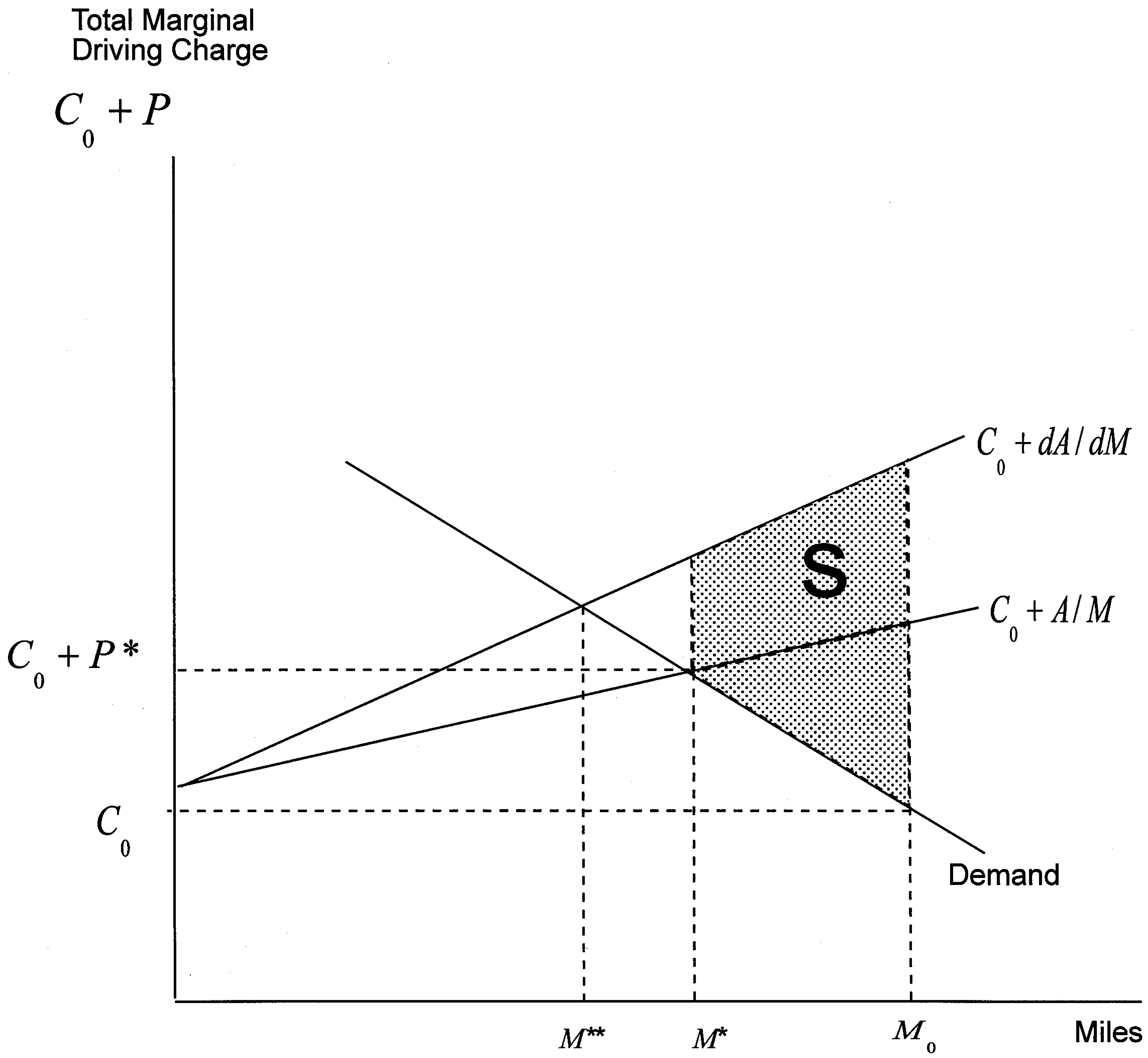
Figure 1



C_0 = non-accident cost of driving

M_0 = status quo miles driven

M^* = miles driven under competitive per-mile premiums

M^{**} = miles driven under Pigouvian per-mile premiums

Table 1

Estimates of Insured Accident Cost Function (Total State Insurance Premiums)

		Calibration Model		Regression Model (Standard Error in Parentheses)
Miles Coeff.	C_1	0.007		0.022 (0.002)
Miles*Density Coeff.	$C_2 x 10^7$	1.1		0.54 (0.06)
			R^2=	0.59

Table 2

Insured Accident Cost

3/21/2002 0:00

State	Vehicle Miles Traveled (billions per year)	Lane Miles	Avg. Cost per mile (cents)	Estimated Marginal Cost: Calibration Method (cents per mile)	Estimated Marginal Cost: Regression Method (cents per mile)
Alabama	51	193,000	2.4	4.3	3.3
Alaska	4	27,000	5.2	8.9	6.6
Arizona	40	117,000	4.4	8.2	6.4
Arkansas	27	156,000	3.0	5.2	3.9
California	276	381,000	4.1	7.8	6.6
Colorado	35	174,000	4.7	8.3	6.2
Connecticut	28	43,000	6.5	12.4	10.4
Delaware	8	12,000	4.9	9.3	7.8
Florida	128	244,000	4.3	8.2	6.7
Georgia	85	233,000	3.1	5.8	4.6
Hawaii	8	8,000	7.9	15.3	13.3
Idaho	12	121,000	2.4	3.9	2.9
Illinois	94	286,000	4.2	7.7	6.0
Indiana	65	191,000	3.0	5.6	4.4
Iowa	26	230,000	3.0	4.9	3.6
Kansas	25	271,000	3.1	5.0	3.7
Kentucky	41	151,000	3.3	6.1	4.6
Louisiana	39	126,000	4.4	8.2	6.3
Maine	13	46,000	3.0	5.5	4.2
Maryland	45	65,000	4.8	9.2	7.8
Massachusetts	48	65,000	6.7	12.9	11.0
Michigan	86	247,000	4.6	8.5	6.7
Minnesota	44	267,000	4.0	6.9	5.1
Mississippi	30	150,000	2.4	4.2	3.2
Missouri	59	250,000	3.0	5.4	4.1
Montana	9	141,000	2.6	4.0	3.0
Nebraska	16	187,000	3.0	4.8	3.5
Nevada	14	92,000	4.9	8.4	6.2
New Hampshire	11	31,000	4.3	8.0	6.3
New Jersey	61	76,000	7.7	14.8	12.7
New Mexico	21	127,000	2.9	5.0	3.7
New York	115	237,000	6.4	12.0	9.8
North Carolina	76	202,000	3.5	6.4	5.1
North Dakota	7	175,000	2.1	2.9	2.3
Ohio	101	241,000	3.6	6.8	5.4
Oklahoma	38	231,000	2.6	4.6	3.4
Oregon	30	171,000	3.8	6.7	5.0
Pennsylvania	95	247,000	5.2	9.7	7.7
Rhode Island	7	12,000	7.3	13.8	11.4
South Carolina	39	134,000	3.5	6.5	5.0
South Dakota	8	168,000	2.5	3.6	2.7
Tennessee	56	178,000	2.8	5.1	4.0
Texas	181	626,000	3.2	5.8	4.5
Utah	19	85,000	3.2	5.8	4.3
Vermont	6	29,000	3.2	5.7	4.3
Virginia	70	149,000	3.5	6.5	5.3
Washington	49	164,000	3.9	7.2	5.6
West Virginia	17	72,000	4.1	7.4	5.6
Wisconsin	51	228,000	3.0	5.3	4.0
Wyoming	7	73,000	1.8	3.0	2.2
National Aggregated Model	2423	8,158,000	4.0	7.4	5.7

Table 3
Accident Savings from Per Mile Premiums
(Net of Lost Driving Benefits)

Gas Elasticity 0.15 3/21/2002 0:00

Model	$A=c_1M$ Linear Model		$A=c_1M+c_2M^2/L$ Calibration Model		$A=c_1M+c_2M^2/L$ Regression model	
	total	per insured vehicle	total	per insured vehicle	total	per insured vehicle
States	(dollars in millions)	$	(dollars in millions)	$	(dollars in millions)	$
Alabama	36	14	89	34	63	24
Alaska	13	38	28	83	17	51
Arizona	93	33	223	79	157	56
Arkansas	31	16	70	38	48	26
California	548	34	1391	86	1111	68
Colorado	91	34	207	76	137	50
Connecticut	138	59	328	141	256	109
Delaware	22	43	54	106	44	85
Florida	306	36	752	88	615	72
Georgia	112	21	277	52	224	42
Hawaii	57	81	132	188	105	150
Idaho	8	11	18	23	11	14
Illinois	205	27	491	65	365	48
Indiana	75	18	187	45	142	34
Iowa	29	13	63	29	41	19
Kansas	32	15	66	31	44	21
Kentucky	58	21	140	50	102	37
Louisiana	96	39	227	92	167	68
Maine	14	15	34	37	24	26
Maryland	127	38	314	93	255	76
Massachusetts	263	66	622	155	511	128
Michigan	237	33	562	78	442	61
Minnesota	85	26	191	58	126	38
Mississippi	21	15	50	35	34	24
Missouri	69	19	166	45	121	33
Montana	8	11	15	22	9	13
Nebraska	18	13	36	27	23	17
Nevada	39	39	86	85	54	54
New Hampshire	24	28	59	68	43	50
New Jersey	453	86	1040	198	901	171
New Mexico	21	19	49	44	32	28
New York	574	60	1339	139	1045	109
North Carolina	114	19	282	48	211	36
North Dakota	4	7	6	13	4	8
Ohio	165	21	410	52	314	40
Oklahoma	35	15	80	34	56	24
Oregon	52	22	118	51	74	32
Pennsylvania	317	38	749	90	565	68
Rhode Island	44	68	101	157	80	124
South Carolina	63	23	151	56	113	42
South Dakota	6	10	10	18	7	12
Tennessee	55	16	136	39	99	28
Texas	230	24	559	59	409	43
Utah	23	18	55	43	36	28
Vermont	8	17	18	41	13	28
Virginia	105	21	264	54	206	42
Washington	90	27	216	64	148	44
West Virginia	37	29	86	68	61	48
Wisconsin	56	15	134	37	91	25
Wyoming	3	8	6	16	4	10
U.S. Total (disaggregated sum)	5310	31	12686	75	9762	58
National Aggregated Model	4954	29	11813	70	8476	50

Table 4
Accident Savings from Per-Mile Premiums with Pigouvian tax
(Net of Lost Driving Benefits)

Gas Elasticity 0.15 — 3/21/2002 0:00

Model	$A=c_1M$ Linear Model		$A=c_1M+c_2M^2/L$ Calibration Model		$A=c_1M+c_2M^2/L$ Regression model	
States	total (dollars in millions)	per insured vehicle $	total (dollars in millions)	per insured vehicle $	total (dollars in millions)	per insured vehicle $
Alabama	36	14	109	42	67	26
Alaska	13	38	32	96	19	58
Arizona	93	33	269	95	178	63
Arkansas	31	16	83	45	49	26
California	548	34	1719	106	1305	80
Colorado	91	34	244	90	150	55
Connecticut	138	59	396	170	301	129
Delaware	22	43	66	129	49	96
Florida	306	36	918	108	659	78
Georgia	112	21	338	64	223	42
Hawaii	57	81	159	226	129	183
Idaho	8	11	21	27	12	15
Illinois	205	27	593	79	390	52
Indiana	75	18	228	55	148	36
Iowa	29	13	72	33	42	19
Kansas	32	15	75	35	43	20
Kentucky	58	21	169	61	106	38
Louisiana	96	39	272	110	177	72
Maine	14	15	42	45	26	28
Maryland	127	38	384	114	292	87
Massachusetts	263	66	749	187	585	146
Michigan	237	33	676	94	452	63
Minnesota	85	26	224	68	133	41
Mississippi	21	15	61	42	36	24
Missouri	69	19	199	54	122	33
Montana	8	11	16	25	10	15
Nebraska	18	13	41	30	24	18
Nevada	39	39	100	99	60	59
New Hampshire	24	28	71	82	47	54
New Jersey	453	86	1241	236	991	189
New Mexico	21	19	58	52	34	30
New York	574	60	1604	167	1162	121
North Carolina	114	19	344	59	229	39
North Dakota	4	7	6	14	4	9
Ohio	165	21	501	63	341	43
Oklahoma	35	15	95	40	55	23
Oregon	52	22	139	60	83	36
Pennsylvania	317	38	900	108	616	74
Rhode Island	44	68	121	188	90	140
South Carolina	63	23	182	67	116	43
South Dakota	6	10	11	20	7	12
Tennessee	55	16	166	47	106	30
Texas	230	24	678	72	429	45
Utah	23	18	66	52	40	31
Vermont	8	17	22	49	13	29
Virginia	105	21	325	66	226	46
Washington	90	27	261	77	168	50
West Virginia	37	29	103	81	64	50
Wisconsin	56	15	161	44	97	27
Wyoming	3	8	7	19	4	10
U.S. Total (disaggregated sum)	5310	31	15319	91	10707	63
National Aggregated Model	4936	29	14174	84	9131	54

Table 5
U. S. Benefits from Other Premium Schedules

	Linear Model	Calibration Model	Regression Model
Per-Mile Premiums			
Net Accident Savings			
U.S. Total (billions of dollars)	5.3	12.7	9.8
Per Insured Vehicle (dollars)	31.4	75.0	57.7
Reduced Delay Costs (external)			
U.S. Total (billions of dollars)	6.0	5.5	5.7
Per Insured Vehicle (dollars)	35.6	32.5	33.8
Total Benefits			
U.S. Total (billions of dollars)	11.3	18.2	15.5
Per Insured Vehicle (dollars)	67.0	107.5	91.5
with Pigouvian tax			
Net Accident Savings			
U.S. Total (billions of dollars)	5.3	15.3	10.7
Per Insured Vehicle (dollars)	31.4	90.6	63.3
Reduced Delay Costs (external)			
U.S. Total (billions of dollars)	6.0	9.4	8.0
Per Insured Vehicle (dollars)	35.6	55.6	47.5
Total Benefits			
U.S. Total (billions of dollars)	11.3	24.7	18.7
Per Insured Vehicle (dollars)	67.0	146.2	110.8