Measuring Per Mile Risk for Pay-As-You-Drive Automobile Insurance

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This study examines the relationship between accident costs and annual miles driven with mileage and claims data representing approximately 3 million individual car years of insurance exposure for private passenger automobiles in Massachusetts in the 2006 policy year. Poisson and linear models relating pure premium to annual mileage estimates demonstrate that mileage is a significant predictor of insurance risk, that mileage alone cannot replace traditional rating factors such as class and territory, and that mileage gains in explanatory power when used in conjunction with those traditional rating factors. These findings provide a strong actuarial basis for pay-as-you-drive insurance, in which drivers are charged rates per mile that differ depending on the driver's class and territory. A model of consumer response to pay-as-you-drive insurance based on studies of miles elasticity to gasoline prices suggests that if all drivers in Massachusetts switched to per mile insurance policies, aggregate vehicle miles traveled in the state would drop by 5.0% to 9.5%. Greenhouse gas emissions from private passenger automobiles would be reduced by a similar amount, and the social equity implications of pay-as-you-drive insurance would be positive. On the basis of sound actuarial justification and positive social benefits, this study finds a strong argument in favor of the regulatory approval of pay-as-you-drive insurance.

Pay-as-you-drive insurance is an automobile insurance pricing model in which customers are each assigned a rate of cents per mile and billed for actual miles driven. Such a mileage-based pricing scheme was first suggested by Vickrey (*1*), and numerous researchers since then have provided evidence for the potential benefits of such a scheme: for insurers, improved actuarial accuracy; for consumers, an opportunity to save money by choosing to drive less; and for society, a reduction in automobile accidents and other negative externalities of driving (*2–6*).

In recent years there have been several experiments with pay-as-you-drive insurance in the U.S. market. In 2008, MileMeter, a start-up based in Texas, became the first U.S. company to write insurance on a pure cents-per-mile basis. For more than a decade Progressive Insurance Company and more recently General Motors Acceptance Corporation have also introduced products that verify customers' mileage and offer a deeper low-mileage discount than traditional insurance products, though the unit of exposure used is still the car year rather than the mile. Bordoff and Noel point out several factors responsible for the relatively slow acceptance of true pay-as-you-drive insurance: monitoring costs (though these are falling over time), a number of relevant patents held by Progressive, and regulatory barriers (*3*). Guensler et al. surveyed 43 state insurance commissioners and found that 16 states, including Massachusetts, do not allow pay-as-you-drive insurance (*7*).

An additional factor that may have slowed both industry adoption and regulatory acceptance of pay-as-you-drive insurance is the relative lack of evidence characterizing the mileage–risk relationship at the individual level. Most studies of pay-as-you-drive insurance have relied on correlating traffic densities with accident rates across entire highways or even U.S. states (*1–3*). Although these studies make it clear that a correlation does exist, such a correlation is not adequate for insurance companies looking to build a pricing model nor for regulators looking to assess precisely the potential impact on consumers of pay-as-you-drive insurance.

This study makes several contributions. First, it uses the largest disaggregate data set available to date: it analyzes data on $502 million worth of claims on almost 3 million individual cars driven an aggregate of 34 billion mi. Second, it classifies drivers by the traditional insurance rating factors of class and territory, thus better isolating the effect of annual mileage on individual driver risk. Third, through this classification it is able to characterize the rate levels and relativities of an actuarially accurate pay-as-you-drive pricing scheme. Finally, with this disaggregate data set it models the effect of pay-as-you-drive pricing on consumer behavior and on greenhouse gas emissions and assesses social equity impacts.

DATA

This study uses a data set released publicly by the Massachusetts Executive Office of Energy and Environmental Affairs in 2010. The data set contains insurance policy and claims data collected by Commonwealth Automobile Reinsurers and odometer readings collected by the Massachusetts Registry of Motor Vehicles. This public data set was processed to produce an analytic data set that is available online (http://mit.edu/jf/www/payd). Further details on the data-processing methodology and additional descriptive statistics are available in a report prepared for the Conservation Law Foundation by Ferreira and Minikel (*8*). This study focuses on the risk model and analytic methods used to assess the interaction of mileage with traditional automobile insurance rating factors.

Insurance Data

The Commonwealth Automobile Reinsurers data set records written transactions pertaining to insurance policies and claims. Written

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TABLE 1 Five Driver Classes with Market Share and Claims Experience

Class	Total Exposure (car years)	Percentage of All Exposure	Claim Frequency per 100 Car Years	Pure Premium per Car Year (for basic BI–PDL–PIP) ($)
Adult	2,141,668	75	5.0	160
Business	40,592	1	6.0	206
<3 years of experience	114,929	4	12.7	421
3–6 years of experience	115,008	4	9.6	314
Senior citizen	459,695	16	4.8	144
All	2,871,892	100	5.5	175

NOTE: BI = bodily injury; PDL = property damage liability; PIP = personal injury protection.

transactions for policy year 2006 were processed to derive earned exposure values for each policy and net incurred losses for each claim plus outstanding reserves as of December 2008. Claims with net incurred losses plus outstanding reserves of less than $50 were considered to have been settled without payment. Only bodily injury and property damage liability losses up to $25,000 and personal injury protection losses up to $2,000 were considered in this study. These levels of coverage are the mandatory minimum in Massachusetts and therefore should be consistent across drivers.

The compulsory bodily injury liability coverage limits in Massachusetts are relatively low compared with the cost of many accidents. The limitation of the study to only consider losses up to mandatory minimums is likely to bias results as follows. Rate groups with higher average claim costs per accident (groups with more severe accidents) are likely to appear less risky compared with other rate groups than they actually are. However, this limitation on the analysis is necessary in order to avoid the confounding influence of drivers' preferences for differing coverage levels.

The analysis used here considers just two traditional rating factors used by the insurance industry: class and territory. Class represents vehicle use and driver years of experience, and territory represents the town in which the vehicle is principally garaged. The available data set includes several dozen classes and 351 towns in Massachusetts grouped into three dozen rating territories, but for simplicity these have been grouped into five classes and six territories. The five classes used are adults, senior citizens, business use vehicles, drivers with 0 to 3 years of driving experience, and drivers with 3 to 6 years of driving experience. The six territories represent approximate sextiles of risk—Territory 6 represents the towns with the highest accident rates and insurance rates and Territory 1 represents the least risky towns. Each territory comprises approximately one-sixth of total exposure, though not exactly because the territories are constrained to contain whole towns.

Table 1 shows the distribution of exposure, claim frequency (average number of claims per unit exposure), and pure premium (average net incurred losses per unit exposure) across classes; Table 2 shows the same for territories. Because pure premium here represents direct losses only without any loading for insurance companies' expenses and is limited to mandatory coverage only, a multiplier of approximately 5.5 is appropriate to translate these pure premium values into retail prices that consumers would pay for typical comprehensive coverage products.

Mileage Data

The Registry of Motor Vehicles data set records odometer readings taken at state-mandated annual safety checks. These odometer readings were processed to derive the number of miles driven between readings for each vehicle. When scaled for the time elapsed between readings, this process provides an estimate of annual miles driven. Vehicles that changed license plates between odometer inspections were not included in the study in order to ensure that a mileage estimate and its associated claims data refer to the same driver yet do introduce some bias, since cars that changed owners during the study period are excluded.

The annual mileage estimates thus created can be joined to the insurance data set by vehicle identification number (VIN). In cases in which annual multiple mileage estimates were available through three or more odometer readings, the mileage estimate with the greatest temporal overlap with the period of earned exposure from the insurance data set was chosen. Still, the overlap is partial for most vehicles: a policy lasting from March 2006 to March 2007 might have a mileage estimate based on odometer readings in June 2006 and July 2007. This temporal mismatch introduces the possibility of regression to the mean: a vehicle estimated to have been driven fewer miles than the average based on odometer readings was probably actually driven a bit more than estimated during the actual policy year, and vehicles with high mileage estimates were probably driven a bit less than estimated. The effects of this phenomenon on this study's results are addressed further later on.

TABLE 2 Six Territories with Market Share and Claims Experience

Territory	Total Exposure (car years)	Percentage of All Exposure	Claim Frequency per 100 Car Years	Pure Premium per Car Year (for basic BI–PDL–PIP) ($)
1 (low)	547,490	19	3.9	114
2	557,705	19	4.5	139
3	322,883	11	4.8	143
4	577,956	20	5.4	170
5	533,192	19	6.6	214
6 (high)	328,249	11	9.2	314
All	2,867,474	100	5.5	175

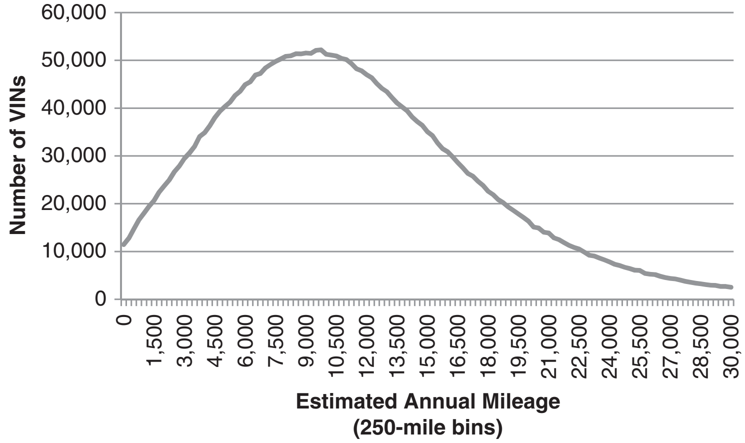

FIGURE 1 Histogram of annual mileage estimates for 3.25 million policy–vehicle combinations in Massachusetts.

Figure 1 shows the distribution of annual mileage estimates in the available data set, and the following two tables show the average annual mileage across the five classes and six territories.

Class	*Average Annual Mileage*
Adult	12,398
Business	14,173
<3 yrs experience	12,911
3–6 yrs experience	13,207
Senior citizen	7,519
All	11,695

Territory	*Average Annual Mileage*
1	12,456
2	12,149
3	12,262
4	11,798
5	10,702
6	10,523
All	11,695

Fuel Economy Data

A commercial VIN parsing service, VINquery.com, was hired to decode the VINs of vehicles in this study and provide fuel economy estimates for each. An estimate was successfully obtained for 96% of vehicles in the study sample. Fuel economy was found to average 20.0 mpg and to exhibit almost no correlation with annual mileage, class, or territory. The high-risk territories have slightly higher average fuel economy, but only by a few percent (20.4 mpg in Territory 6 versus 19.7 in Territory 1). Business use vehicles exhibit lower-than-average fuel economy (15.1 mpg), but among the age and driving experience class groupings, average fuel economy varies by only about 10% (19.8 mpg for adults versus 21.5 mpg for individuals with 3 to 6 years of driving experience).

Sample Size

After vehicles with invalid insurance data or insufficient odometer readings to produce a mileage estimate were discarded, the data set used for this study comprised 2.87 million car years of exposure earned by 3.05 million distinct vehicles (3.25 million distinct policy–vehicle combinations) with an average claim frequency of 5.6 claims per car year and an average pure premium (for only the state-mandated coverage described earlier) of \$175 per car year. This data set represents 71% of the exposure contained in the original state-released data set and so, even allowing for some uninsured drivers on the road, accounts for easily over half of the drivers, vehicles, and miles driven in Massachusetts in 2006.

METHODOLOGY AND RESULTS

To assess the correlation between mileage and accident risk, a variety of Poisson and linear regression models were fitted to the joined mileage and insurance exposure and claims data by using the generalized linear model and linear model features of the statistical software package R.

The simplest model, whose results are shown in Equation 1, considers pure premium as a function of mileage only. Equation 1 shows that when all vehicles are considered together, high mileage does correlate with high risk, but the relationship is less than linear with an exponent of only 0.36. Figure 2 plots this model against the actual data aggregated into 250-mi mileage bins for ease of graphing.

$$\text{pure premium} = \$6.53 * \left(\text{annual miles}^{0.36}\right) \tag{1}$$

The curvature of the model suggests that mileage alone, though significant, is not likely to be a satisfactory rating factor. Therefore, in subsequent models mileage is considered alongside class and territory. With these factors, the slightly more complex model shown in Equation 2 regresses pure premium on mileage, class, and territory grouping.

$$\text{pure premium} = \$2.35 * \left(\text{annual miles}^{0.40}\right) * \left(\text{class relativity}\right) * \left(\text{territory relativity}\right) \tag{2}$$

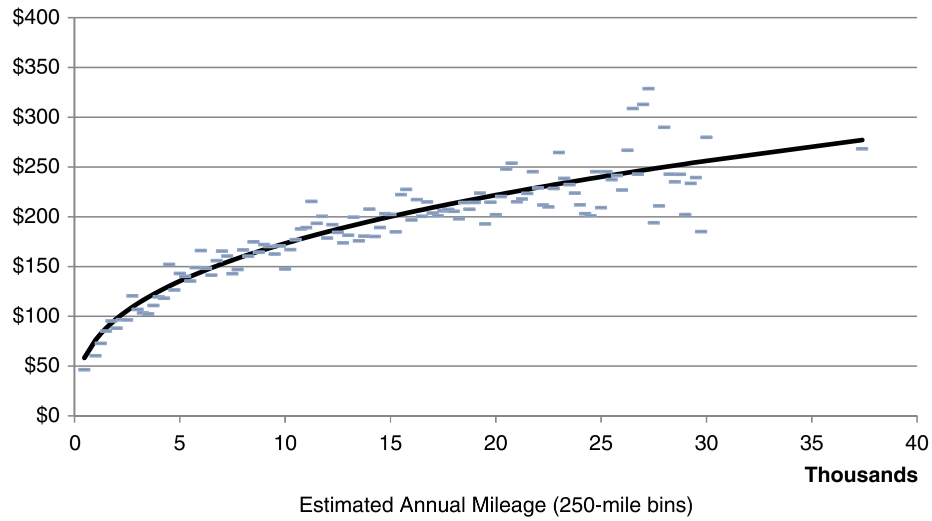

FIGURE 2 Fit of Poisson regression on pure premium per car year by annual mileage estimate: all policies.

The corresponding class relativity and territory relativity are shown in the following two tables. Relativities are considered with adults and territory 1 (the least risky group) as the reference.

Class	*Relativity*
Adult	1.00
Business	1.32
<3 yrs experience	2.65
3–6 yrs experience	1.83
Senior citizen	1.17

Territory	*Relativity*
1	1.00
2	1.24
3	1.28
4	1.55
5	2.04
6	2.98

The exponent on mileage in Equation 2 has increased compared with Equation 1, from 0.36 to 0.40. This finding means that the relationship between risk and mileage is closer to proportional once class and territory are considered. The range of relativities in Table 4 shows that even when mileage is considered, risk varies as much as threefold between different class and territory groupings.

When the same model is fitted on only those policies whose mileage estimates temporally overlap the policy period by 90% or more, the mileage exponent rises further to 0.42. This finding is suggestive that the true mileage–risk relationship is slightly more linear than that observed in Equation 2 and that part of the reason for the curvature seen in Figure 2 is regression to the mean.

However, another reason for the curved nature of the Equation 2 model fit lies in the model itself. The Poisson regression used in Equation 2 is an appropriate model in that it respects the underlying "rare event" nature of automobile accidents and allows for all policies (most of which have zero claims and zero losses) to be analyzed at a disaggregate level. However, this model is also imperfect, because the class and territory relativities affect only the magnitude of the curve, not its shape. The model is constrained to find a single exponent for mileage (in this case, 0.40) for all classes and territories. If the relationship between risk and mileage were linear within any one class or territory group but the slopes differed (to the extent that the per-mile risk differs across the class and territories), the model in Equation 2 would "compromise" between the different slopes by finding an exponent less than 1, even though a regression on any one group would find an exponent closer to 1, indicating a more proportional relationship.

Equation 3 shows the results of such a regression for only Territory 3 adults as one such example. The exponent is now 0.46, higher within this one group than for all drivers as a whole. When this same model is fitted to only the Territory 3 adult drivers whose mileage estimates temporally overlap at least 90% with their policy periods, the exponent rises to 0.54; this finding demonstrates that the role of regression to the mean is important here. Within a class–territory group, particularly when the effects of regression to the mean can be minimized, the mileage–risk relationship is more nearly linear than it is for all drivers considered together. Because insurance companies use additional rating factors as well as much finer-grained class and territory groupings than are used here, they are likely to find an even higher exponent.

$$\text{pure premium} = \$1.70 \times \left(\text{annual miles}^{0.46}\right) \qquad (3)$$

A more lengthy treatment of this subject would fit this same model for each of the 30 class–territory groupings separately. In order to treat the entire data set with a broad stroke, however, this study instead fits various linear models to the data. Vehicles are not treated at the individual level but rather are aggregated into bins by annual mileage (500-mi increments), class, and territory. In the linear regression, the bins are weighted by total earned exposure so that each vehicle counts equally even though different numbers of vehicles may be present within different bins.

Table 3 summarizes the results of three linear models fitted for these bins. The adjusted R^2 statistics reflect the proportion of the variation in risk between bins that can be explained by the model. Mileage alone explains 9% of the variation, class and ter-

TABLE 3 Results of Three Linear Models for Pure Premium on Mileage, Class, and Territory Bins

Factor Considered	Model Results	Adjusted R^2 Statistic
Mileage	Pure premium = \$111.70 + 0.55¢ × annual miles	.09
Class and territory	Pure premium = \$96.50 + class adjustment + territory adjustment	.57
Mileage, class, and territory	Pure premium = \$40.12 + class adjustment + territory adjustment + (0.43¢ + class rate + territory rate) × annual miles	.72

ritory alone explain 57%, but taken together, they explain 72%. The whole is better than the sum of the parts: mileage provides more explanatory power when coupled with class and territory. These factors likely provide a control on where and how the miles are being driven, with class as a proxy for driver skill and territory as a proxy for setting.

The results of the Poisson and linear models introduced here can be summarized as follows:

- Mileage is a significant predictor of insurance risk;
- If used alone, mileage is inferior to traditional insurance rating factors; and
- If used in conjunction with traditional insurance rating factors, mileage can substantially improve actuarial accuracy.

Because mileage is significantly correlated with insurance risk, it is natural that it should be incorporated into insurance prices in a more significant way than the minor low-mileage discounts currently offered by most insurers. One possible pricing scheme would be to rate insurance on a strictly per mile basis with no annual fee at all. In this case, the retail prices for comprehensive coverage (applying a 5.5 multiplier to the pure premiums calculated from this study's data set) would range from about 4 cents to about 34 cents per mile for the class and territory groupings considered here. The following two tables compare the relativities under such a scheme with the per-car-year relativities. No provision is made here for second-order interactions. Again, adults and territory 1 are considered as the reference group.

	Relativity	
Class	*Per Car Year*	*Per Mile*
Adult	1.00	1.00
Business	1.38	1.32
<3 yrs experience	2.72	2.65
3–6 yrs experience	1.91	1.83
Senior citizen	0.93	1.17

	Relativity	
Territory	*Per Car Year*	*Per Mile*
1	1.00	1.00
2	1.23	1.24
3	1.27	1.28
4	1.51	1.55
5	1.92	2.04
6	2.77	2.98

Another possibility would be to price insurance with an annual fee plus a lower per mile rate. The annual fee might or might not cover some number of miles—for instance, 2,000 mi. Such an annual fee could serve several functions: it would help to price some of the nonlinearity in the mileage–risk relationship by ensuring that low-mileage drivers pay enough to cover their insurance costs; it could help insurance companies to cover the fixed costs of writing an insurance policy and monitoring mileage; and depending on its structure, it could help to avoid an increase in uninsured motorists with premium payments that have not kept pace with their mileage.

ECONOMIC AND ENVIRONMENTAL IMPLICATIONS

Vehicle Miles Traveled and Greenhouse Gas Reduction Model

Potential reductions in vehicle miles traveled (VMT) due to pay-as-you-drive insurance are modeled as follows. Each vehicle is assigned a current operating cost per mile equal to the June 2010 gasoline price (\$2.70/gal) divided by its fuel economy. Each vehicle is then assigned a hypothetical future operating cost equal to its current operating cost plus a per mile insurance rate calculated for its class–territory group. The percentage increase in per mile operating cost is calculated by dividing the future cost by the current cost, and this percentage increase is multiplied by an assumed elasticity to obtain the percentage decrease in mileage for that vehicle. This percentage decrease is then multiplied by the vehicle's estimated annual mileage to obtain the vehicle's predicted annual mileage reduction. This predicted annual mileage reduction is then summed across all vehicles and divided by the aggregate annual mileage for all vehicles in the study to obtain an estimate of the statewide percentage reduction in VMT.

The elasticity value used here is based on a review of several studies of consumer VMT elasticity with respect to gasoline prices (*9–15*). When gasoline prices rise, consumers respond initially with reduced VMT but eventually respond with increased fuel efficiency as well. To isolate the effect of operating cost on VMT, this model considers the short-run elasticity from the reviewed studies, even though the intent is to model the long-run response to per mile insurance. The studies reviewed here indicate that –0.15 is an appropriate conservative figure for the elasticity of vehicle mileage with respect to operating cost (*9–15*).

This model has several limitations, including the use of a flat elasticity figure across all vehicles and drivers regardless of use or income, the exclusion of urban parking costs in assumed current operating cost, and the lack of consideration of any income effects from eliminating or reducing the yearly fee for insurance. The results obtained from this model must be considered as rough order-of-magnitude estimates for the effect of per mile insurance on VMT under simple assumptions.

The model indicates that if all drivers in Massachusetts switched to pay-as-you-drive insurance priced on a strictly per mile basis with no annual fee, an aggregate VMT reduction on the order of 9.5% could be expected. Pure premium data indicate that the best linear fit for risk as a function of mileage does not pass through the origin, and so an alternate pricing scheme, in which consumers pay a yearly fee with 2,000 mi included and then pay a lower per mile rate thereafter, is also considered. Because the per mile rate is lower than in a strictly per mile scheme, this pricing model is estimated to result in a VMT reduction of 5.0%. Because fuel economy is found to be nearly uncorrelated with class or territory in this data set, the percentage reductions in greenhouse gases from private passenger automobiles would be similar. These reduction estimates represent upper bounds for what could be achieved through the adoption of pay-as-you-drive insurance because adoption by all drivers is assumed. In reality pay-as-you-drive insurance would be offered as a consumer option and, in the near term at least, only drivers with mileage below their rate group's average mileage would switch.

Social Equity Implications

Prior studies have noted a concern among the public or regulators that pay-as-you-drive insurance might hurt a particular geographic group, such as rural drivers (*3, 7*). However, because this study finds that per mile rates need to be differentiated by class and territory groups, different geographic regions would remain separate risk pools. Risk and insurance cost would not be redistributed among regions, and so there is no basis for concern that a particular geographic group—say, rural drivers—would be hurt by the new pricing scheme. The average rural driver drives more miles than the average urban driver but would enjoy low per mile insurance rates and so would see no increase in total expenditure with the same driving habits (and would even gain an option to reduce expenditure by choosing to reduce mileage).

Indeed, the results found here suggest that the social equity implications of the introduction of pay-as-you-drive insurance would be generally positive. First, it would alleviate the cross-subsidy burden on low-mileage drivers within rate groups. Second, it would generate congestion reduction and safety benefits that would be experienced by all, including those who do not own a car, who are generally in the low-income group. The safety improvements due to mileage reduction would be particularly pronounced because the riskiest drivers would have the highest per mile rates and therefore the largest incentive to drive less. Third, it would improve fairness by rating insurance at least partly on controllable individual factors. As shown in Table 6, relativities under a per mile pricing scheme would be no lower, and in some cases would be higher, than under per-car-year pricing; however, the number of miles driven would be controllable by each driver. This aspect would offer low-income drivers an opportunity to save money by choosing to drive less. Meanwhile, the average driver in any given class–territory grouping would be no better or worse off under a pay-as-you-drive scheme than under traditional pricing if his or her driving habits did not change. Indeed, in the long run, the 5.0% to 9.5% decrease in aggregate VMT projected here would bring about a commensurate reduction in accident costs and therefore in insurance rates.

CONCLUSIONS

This study examines insurance claim costs, driver class and territory, and annual mileage estimated from odometer inspections for 2.87 million car years of earned exposure on vehicles in Massachusetts in policy year 2006. Poisson and linear regression models used to analyze the relationship between these variables demonstrate conclusively that mileage is a significant predictor of risk. Mileage provides poor explanatory power on its own and cannot substitute for class or territory as rating factors, but when coupled with these factors it substantially improves actuarial accuracy. This finding points to the actuarial justification of a pricing scheme in which drivers are assigned individualized per mile rates based on class, territory, and other rating factors.

The introduction of pay-as-you-drive insurance is not only actuarially justified, it is also socially beneficial. A model of Massachusetts consumer response to pay-as-you-drive insurance rates suggests that it could bring about reductions in aggregate miles driven and greenhouse gas emissions from private passenger automobiles on the order of 5.0% to 9.5% if all drivers switched to pay-as-you-drive. Pay-as-you-drive insurance would offer consumers a means of saving money and would have some positive effects on social equity.

Insurance regulations in Massachusetts do not currently allow pay-as-you-drive insurance. This study's key finding, that charging for insurance by the mile is both actuarially justified and socially beneficial, provides a strong argument for the legalization of pay-as-you-drive insurance provided that appropriate consumer protections can be enacted. For example, drivers should be appropriately aware of the variable cost of driving (and any financial implications of their payment plans) and should have some control over the use of tracking data about their mileage. Likewise, plans should be structured to avoid increases in uninsured motorists with lapsed insurance coverage because their mileage gets ahead of their premium payments. Technology continues to reduce the cost of measuring and monitoring when, where, and how motorists drive. Hence, it will be increasingly in the public interest both to encourage implementation of usage-based automobile insurance pricing and to evolve a regulatory structure that protects consumers from potential abuses of the new technologies.

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REFERENCES

1. Vickrey, W. Auto Accidents, Tort Law, Externalities and Insurance: An Economist's Critique. *Law and Contemporary Problems,* Vol. 33, No. 3, 1968, pp. 464–487.
2. Edlin, A. S. Per-mile Premiums for Auto Insurance. In *Economics for an Imperfect World: Essays in Honor of Joseph E. Stiglitz* (R. Arnott, B. Greenwald, R. Kanbur, and B. Nalebuff, eds.), MIT Press, Cambridge, Mass., 2003, pp. 53–82.
3. Bordoff, J. E., and P. J. Noel. Pay-As-You-Drive Auto Insurance: A Simple Way to Reduce Driving-Related Harms and Increase Equity. Brookings Institution, Washington, D.C., 2008. http://www.brookings.edu/~/media/Files/rc/papers/2008/07_payd_bordoffnoel/07_payd_bordoffnoel.ashx.

4. Parry, I. W. H. Is Pay-As-You-Drive Insurance a Better Way to Reduce Gasoline Than Gasoline Taxes? *American Economic Review,* Vol. 95, No. 2, 2005, pp. 288–293.
5. Greenberg, A. Costs and Benefits of Varying Per-Mile Insurance Premiums Based on Measured Risks Specific to Each Mile Driven. Presented at 88th Annual Meeting of the Transportation Research Board, Washington, D.C., 2009.
6. Litman, T. *Transportation Elasticities: How Prices and Other Factors Affect Travel Behavior.* Victoria Transport Policy Institute, Victoria, British Columbia, Canada, 2010. http://www.vtpi.org/elasticities.pdf.
7. Guensler, R., A. Amekudzi, J. Williams, S. Mergelsberg, and J. Ogle. Current State Regulatory Support for Pay-as-You-Drive Automobile Insurance Options. *Journal of Insurance Regulation,* Vol. 21, No. 3, 2002.
8. Ferreira, J., and E. Minikel. *Pay-As-You-Drive Auto Insurance in Massachusetts: A Risk Assessment and Report on Consumer, Industry and Environmental Benefits.* Conservation Law Foundation, Boston, Mass., 2010. http://www.clf.org/wp-content/uploads/2010/12/CLF-PAYD-Study_November-2010.pdf.
9. Dahl, C., and T. Sterner. Analyzing Gasoline Demand Elasticities: A Survey. *Energy Economics,* Vol. 13, No. 3, 1991, pp. 203–210.
10. Gallini, N. T. Demand for Gasoline in Canada. *Canadian Journal of Economics,* Vol. 16, No. 2, 1983, pp. 299–324.
11. Goldberg, P. The Effects of the Corporate Average Fuel Efficiency Standards in the U.S. *Journal of Industrial Economics,* Vol. 46, No. 1, 1998, pp. 1–33.
12. Goodwin, P. B. A Review of New Demand Elasticities with Special Reference to Short and Long Run Effects of Price Changes. *Journal of Transport Economics and Policy,* Vol. 26, No. 2, 1992, pp. 155–169.
13. Johansson, O., and L. Schipper. Measuring the Long-Run Fuel Demand of Cars: Separate Estimations of Vehicle Stock, Mean Fuel Intensity and Mean Annual Driving Distance. *Journal of Transport Economics and Policy,* Vol. 31, No. 3, 1997, pp. 277–292.
14. Parry, I. W. H., and K. A. Small. Does Britain or the United States Have the Right Gasoline Tax? *American Economic Review,* Vol. 95, No. 4, 2005, pp. 1276–1289.
15. Small, K. A., and K. Van Dender. Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. *Energy Journal,* Vol. 28, No. 1, 2007, pp. 25–51.

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