PAY-AS-YOU-DRIVE INSURANCE: IT'S IMPACTS ON HOUSEHOLD DRIVING AND WELFARE

(TRB 14-1827)

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The following paper is a pre-print, the final publication can be found in the *Transportation Research Record*, No. 2450: 76-82, 2014.

ABSTRACT

Vehicle-miles traveled (VMT) can greatly impact crash risk, and therefore insurance costs, but accurately assessing VMT has been challenging for insurance agencies. Affordable technology now allows insurance companies to better track VMT, and has prompted pilot programs and further research of mileage-based, or "pay-as-you-drive" (PAYD) insurance. Existing research agrees that PAYD programs can discourage extraneous driving, thereby directly saving drivers money (but reducing consumer welfare, although by less than consumer cost savings), reducing crash risks, insurers' costs, and externalities. Past studies consider aggregate, national or state-wide impacts of PAYD policies, with some focus on equity impacts, but much heterogeneity is ignored. This study bolsters existing work by predicting PAYD impacts using NHTS data to model driver response to driving cost changes and an insurance pricing model (per vehicle) based on actual loss data and risk factors by vehicle type. This study anticipates PAYD impact variations across a sample of NHTS households and vehicle types, and finds that on average, households save enough on reduced insurance and travel costs to cover lost welfare from VMT reductions. Results suggest that the average (light-duty) vehicle will be driven 2.7% less (237 fewer annual miles per year), with average consumer benefits of only $2.00 per vehicle with a premium that is partially fixed and partially mileage-based. Drivers with the lowest annual VMT needs are expected to receive the largest welfare benefits, thanks to a convex relationship between VMT and crash losses. This analysis provides support to existing literature that PAYD policies can reduce VMT and insurance pricing equity without harming driver welfare.

Key Words: Insurance, pay-as-you-drive, PAYD, pricing, welfare, equity, VMT

INTRODUCTION

Current automobile insurance pricing considers individual driver and vehicle risk factors to determine appropriate policy pricing, but relies on often inaccurate estimates of actual vehicle miles travelled (VMT). Without sophisticated technology or a national requirement for annual odometer readings, insurance companies usually rely on driver estimates of how much they actually drive their vehicle, leading to frequent underreporting of VMT (*1, 2*), and subsequently risk, as driver exposure to potential crashes increases with each additional mile travelled. This comes at a cost to insurance companies, but also harms low-VMT drivers who implicitly pay for increased crash rates of high-VMT drivers within the same risk class.

An alternative to lump-sum based insurance pricing (paid annually or bi-annually) is a per-mile premium approach, often called "pay-as-you-drive" (PAYD) insurance. Insurance companies, policy makers, and some drivers have shown growing interest in PAYD in recent years, especially as technology advances have made it more feasible. Over the past decade, several pilot studies (e.g., *3, 4*) and policy evaluations have considered impacts of PAYD policy implementation and reported reduced mileage and fuel use, alongside savings to drivers and insurance firms.

While results are promising, more detailed analyses should anticipate how PAYD policies might impact insurance costs and driving behaviors on a larger scale. This study expands existing PAYD analyses by estimating welfare impacts across households and accounting for heterogeneity in price elasticity of their demand for VMT and fuel-use. Driver response and insurance pricing are modeled as a function of vehicle and household characteristics using ordinary least squares (OLS) regression with the 2008 National Household Travel Survey (*5*) and insurance loss models from Massachusetts (*6*). Welfare estimates from reduced driving and insurance loss changes are then considered for each vehicle and household, and compared across households. This study expands previous work on PAYD by including more heterogeneous responses to driving costs, and disaggregated insurance costs that vary across individual vehicles and households.

LITERATURE REVIEW

Over 40 years ago, William Vickrey proposed a number of insurance pricing policy reforms, including premiums that "vary much more in proportion to the actual mileage traveled" (*7*). He argued that lump-sum pricing improperly prices insurance as a fixed cost, when crash risks depend heavily on actual miles traveled. Vickrey noted that, although drivers were assigned to risk classes based on vehicle and demographic characteristics, VMT was almost an entirely independent consideration. Risk assignment has changed little since Vickrey's original critique. Initially, accurate and affordable mile-tracking technology and data infrastructure were a limitation. When VMT is used to calculate individual premiums, it is usually classified broadly, and reported without verification, leading to frequent underestimation (*1, 2*). Therefore, within a given risk class, very few drivers are paying close to their actual risk, as proxied by miles driven (the marginal cost), and actually pay an average cost (to insurers). Litman (*8*) notes how this promotes inequity and results in wasteful driving. Drivers paying lump-sum annual insurance costs are not likely to consider the costs they impose on other drivers each time they travel and may only be concerned with gasoline and vehicle maintenance costs when evaluating the marginal costs of their driving. In general, insurance costs are often "hidden" to drivers, but generally comprise 10 to 15% of annual vehicle costs (*9*).[1]

Vickrey's (*7*) central premise is that incorporating marginal crash risk into vehicle operating costs provides more efficient pricing while perhaps reducing driving and insurance costs overall. Edlin (*10*) was one of the first to apply Vickery's thoughts, by calculating PAYD pricing impacts on crash counts and costs. Parry (*11*) followed this research with more detailed estimates of VMT and fuel-use reductions. Bordoff and Noel (*12*) extended Edlin's and Parry's work to the household level, modeling welfare impacts across individual households. Ferreria and Minikel (*6*) considered crash and welfare impacts in Massachusetts using a rich data set on actual losses to insurance firms alongside U.S. Census data. Together these studies represent a comprehensive analysis of PAYD impacts on individuals, the road network, the environment, and the economy. Each estimated significant levels of savings and reduced VMT and fuel use, but made assumptions that ignore much heterogeneity across households.

Modeling PAYD Impacts

Edlin (*10*) created one of the earliest economic models to anticipate driver response to PAYD insurance policies, and benefits gained from reduced congestion and crash risks. In applying his model to all vehicles in the U.S., he predicted just over 9% VMT reduction, yielding insurance accident cost savings of around $17 billion. His model contained numerous equations to define vehicle and road network parameters (e.g., miles driven per vehicle, lane miles, traffic density, congestion, and damages per crash), along with driving costs and consumer surplus. Per-mile insurance costs were defined as a driver's total accident costs (modeled as function of crash likelihood given roadway attributes) divided by total miles driven. Edlin (*10*) used a linear VMT-demand curve and computed surplus based on changes in VMT demand and marginal total accident costs from driving an extra mile. Edlin's marginal accident costs for individual drivers took the following linear form:

$$\left(\frac{dA}{dM}\right) = c_1 + 2c_2 D \tag{1}$$

where c_1 is expected crash costs from driving one more mile "alone," and the second term reflects increased costs from having other drivers on the road, as a function of density (*D*). Edlin (*10*) considered changes in accident costs (*A*) over miles driven (*M*) as a cost savings, which was considered alongside VMT demand to form the following consumer surplus (CS) equation:

$$CS = 0.5\left(\left.\frac{dA}{dM}\right|_{M_0} + \left.\frac{dA}{dM}\right|_{M_*}\right)(M_0 - M^*) - 0.5p^*(M_0 - M^*) \tag{2}$$

where M_0 is initial VMT and M^* is VMT with PAYD pricing (p^*). Bordoff and Noel (*12*) subsequently considered a similar calculation for individual driver savings using reduced per-mile insurance costs, along with crash-reduction benefits calculations. Both Edlin (*10*) and Bordoff and Noel (*12*) computed VMT response and insurance pricing using state-level traffic and network information and average statewide insurance costs. Edlin (*10*) also estimated marginal accident costs per mile driven, which provides the majority of social benefits. He

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[1] This assumes full coverage insurance for an average sedan in the U.S. in 2012, driving between 10,000 and 15,000 miles each year.

estimated that PAYD crash cost savings are about \$20 B per year, and congestion savings contribute another \$4 to \$9 billion annually. Bordoff and Noel (*12*) obtained similar results in their more recent study (\$21 B in crash cost savings and \$13 B in reduced congestion).

While crash cost savings are significant for an aggregate, national PAYD implementation, this study focuses on insurance (loss) savings for individual driver settings. Bordoff and Noel (*12*) estimated a total (annual) insurance cost savings (to U.S. customers) of \$7.7 B, or about \$34 per vehicle-year, based on average statewide insurance rates. This constitutes about 13% of total PAYD savings, and varies across households. Parry (*11*) estimated that PAYD returned U.S. welfare gains of nearly \$20 B with a 9% VMT reduction, using per-mile costs for VMT- and fuel-related externalities of crashes, congestion, local pollution, carbon emissions, and oil dependency. Parry (*11*) did not compare savings across households and only considered PAYD impacts relative to welfare impacts of increased fuel taxes. However, Bordoff and Noel (*12*) followed Parry's earlier methods to estimate VMT reduction as a function of fuel prices, fuel economy, and the price elasticity of gasoline (assuming drivers responded similarly to a per-mile price increase from insurance). Parry (*11*) and Bordoff and Noel (*12*) used the following approach to calculate individual (vehicle) response to PAYD policies:

$$M = M_0 \left(\frac{p_F + p_i f^0}{p_F^0}\right)^{\beta_M \beta_m \eta_p} \tag{3}$$

where p_F is fuel price, f^0 is fuel economy, η_p is gasoline price elasticity, and β_M and β_m are fractions of gasoline demand reduction from reduced VMT and from increased fuel economy, respectively. Equation 1 allowed Bordoff and Noel (*12*) to estimate VMT responses and insurance savings across households. Despite heterogeneity in each household, this equation assumed a constant gasoline demand elasticity (η_p = -0.55), which limited estimation of true household impacts. Bordoff and Noel (*12*) applied the equation to 2001 NHTS data to evaluate impacts across households. Overall, they found that about two-thirds of households saved money from reduced insurance premium costs, while the remaining third paid more. Bordoff and Noel (*12*) anticipated greatest savings for low-income households and losses beginning for households with about \$50,000 or more annual income. Despite the concentration of losses among higher-income households, Bordoff and Noel (*12*) noted that the losses and benefits as a percent of income became trivial as income increased beyond very-low income levels (of less than \$10,000 per year). Additionally, they noted that not every household gained or lost in each income bracket, but the share of households saving money was greater for lower-income households (nearly 80% in the lowest bracket) than for higher-income households (about 55% at its lowest).

Predicting Insurance Costs

Ferreria and Minkel (*6*) evaluated PAYD impacts using Massachusetts insurance claims and VMT information. Part of their study analyzed the relationship between claim frequency and VMT, as a means to optimize PAYD pricing. Generalized linear regressions of their insurance losses (versus each vehicle's annual VMT) provided an empirical equation to estimate the ideal premium that should be charged, based on vehicle VMT. Ferreria and Minikel (*6*) then modified their equation by controlling for general location within the state (6 territories) and providing a relative crash risk across driver classes (e.g., those over age 25, business travelers, those with less than three years' driving experience, and the elderly).

In summary, several studies provide meaningful starting points for evaluating PAYD policies, but rigorous evaluation of PAYD policies has been limited. While Edlin (*10*) and Parry

(*11*) developed extensive analytical methods to predict driver behavior and estimate externality impacts, the resulting models are applied to aggregate data. Bordoff and Noel (*12*) evaluated household impacts in some depth, but their model did not allow for heterogeneity in individual response to price increases. Ferreria and Minikel (*6*) provided some empirical data and applications with variable insurance costs, but their underlying model also assumes homogeneity in gasoline price response. These studies can be improved upon by allowing for more flexibility into driver response and more accurate insurance cost estimation (on a vehicle or driver basis).

METHODOLOGY

This study uses household-level data from the 2008 NHTS to model response to increased travel costs. An OLS model predicts annual VMT for each vehicle in the survey, based on household and driver characteristics, and VMT changes are estimated based on each vehicle's per-mile insurance cost estimates. Consumer surplus changes are calculated for each vehicle based on VMT and insurance loss changes (which are considered costs to the vehicle owner). Results are analyzed across households, and aggregate benefits tallied, following related work by Parry (*11*) and Bordoff and Noel (*12*). The model is applied to the entire NHTS sample, and to samples only in Massachusetts, which was the geographical focus of Fererria and Minikel's (*6*) insurance loss model.

VMT Forecasting

NHTS data provide a predictive equation for VMT, based on vehicle and household characteristics. The 2008 NHTS data contain information on household travel behaviors, demographics, vehicle ownership, and vehicle use. Here, data were evaluated at the vehicle level, and linked to all household details. The 2008 NHTS refers to nearly 300,000 unique vehicles, and most (270,728) contained sufficient data for estimation. Every surveyed vehicle has a user-reported annual VMT and a "best estimate," developed using a number of techniques, depending on which independent variables are available (*13*). The best-estimate variable was used in this analysis to provide the largest sample size, since many self-reported odometer values were unavailable and are often underreported anyway (*14*). Table 3 summarizes the NHTS data used in the model.

The model includes independent variables of vehicle age, fuel economy, number of drivers (for the vehicle of interest), household income and size, numbers of workers and adults (over age 18), and an indicator for urban location.[2] Unfortunately, NHTS data do not include insurance cost information, so some homogeneity in insurance pricing must be assumed. In reality, each vehicle and driver are placed in unique risk classes, based on demographics characteristics and owner's driving records. An additional covariate, "driving costs per mile," considers average vehicle gasoline costs (per gallon) divided by fuel economy (miles per gallon). This metric allows the model to directly consider an added PAYD marginal cost to estimate a new VMT. If the NHTS included insurance costs (and other risk metrics like crash history), researchers could more directly account for insurance costs, which – as the study and others on the subject suggest – is an important factor in evaluating travel costs and behavior.

[2] Urban location is based on 2000 Census Cartographic Boundary Files with minimum population density of 1,000 persons per square mile.

Insurance Pricing

Insurance loss estimates are based on Ferreria and Minikel's (*6*) empirically derived equations and modification factors from the Insurance Institute for Highway Safety (*16*). Though insurance costs vary significantly with demographics and accident history, there are few predictive equations or methodologies to anticipate costs by vehicle and driver characteristics. This difficulty likely explains why previous studies (*15, 11, 12*) assumed average statewide premium costs reported by the National Association of Insurance Commissioners, ignoring the heterogeneity across households. Though still limited by assumptions, this study considers individual insurance *losses* from actual claims (not premiums paid) based on model-predicted VMT and vehicle type. Total insurance losses (per vehicle) are based on Ferreria and Minikel's (*6*) examination of 2006 Massachusetts insurance claims versus each vehicle's (i) annual VMT ($x_{VMT,\, i}$), specified as follows:

(4) $$I_i = 6.53(x_{VMT,i})^{0.36}$$

Per-mile insurance losses are computed by dividing annual insurance cost (per vehicle) (I_i) by annual VMT (x_{VMT}). Equation 4 exhibits strong returns to scale, with per-mile costs falling to 22 and 17 cents at 10,000 and 20,000 VMT per year, respectively. Since crash risk (and therefore, estimated insurance losses) increase with every mile driven (for drivers of any risk class), lower-VMT drivers are paying more per mile for insurance than higher-VMT drivers, ceteris paribus. Ferreria and Minikel's (*6*) insurance cost estimates are modified using the IIHS's (*16*) relative losses across vehicle types (car, van, pickup truck, & SUV). The IIHS (*16*) provides collision losses by vehicle make, model, and year, relative to average annual losses (e.g., the average 2009-2011 Chevrolet Malibu sedan might experience 10% lower average collision losses for all vehicles with similar coverage policies). Relative losses were averaged for each of the four passenger vehicle types, yielding factors of 1.2, 0.88, 0.88, and 0.66 for cars, trucks, vans, and SUVs, respectively. Higher relative loss factors for cars could stem from their generally lighter weight and smaller physical footprint (which can increase crash severity and associated damages relative to heavier vans, SUVs, and trucks [*17*]). Car owners may also be more likely to report and collect on damages sustained, because they prefer to have fewer visual flaws on their vehicles than owners of bigger and more rugged, off-road-capable vehicles. Ferreria and Minikel's model is specific to Massachusetts drivers, so extrapolating across other states directly would lead to both over- and under-estimation. This inaccuracy can be reduced some by multiplying Eq. 4 by normalized state average collision expenditures (relative to the Massachusetts average). Such data is available from the Insurance Information Institute (*18*) for 2006 (the year from which the insurance loss model was estimated) for each state. This data indicates that average annual maximum collision losses come from Washington D.C., at $444.80 per year, and minimum losses from South Dakota at $190.96 per year. Massachusetts comes in above average ($288.29), at $353.32. These costs ($s$), normalized versus the Massachusetts average, are multiplied by Eq. 4, based on each vehicle i's state j, as well loss factors (f) by vehicle type k to compute state- and vehicle-adjusted insurance loss ($I_{i,j,k}$) as follows:

(5) $$I_{i,j,k} = 6.53(x_{VMT,i})^{0.36} \times f_k \times s_j$$

Estimating VMT Response to PAYD Insurance

Here, VMT and fuel-use changes were estimated by using NHTS VMT model results in conjunction with estimated per-mile insurance losses, added to the fuel cost term (as a function of fuel economy). Therefore, VMT under a PAYD policy was re-computed for each vehicle in the data set, with a new per-mile operating cost. This approach assumes that driver response to PAYD pricing is identical to reactions of fuel prices, since per mile driving costs are based solely on gas costs and fuel economy. This assumption is valid only for a short term analysis, since individuals may reduce their total per-mile costs by acquiring a more fuel-efficient vehicle.

Elasticity response to driving costs (η) is represented by the OLS coefficient for VMT response to change in per-mile driving costs. At a given driving cost and VMT, the elasticity can be computed as follows:

(6) $$\eta = \frac{\partial x_{VMT}}{\partial p_m}\frac{p_m}{x_{VMT}}$$

Welfare Calculations

Changes in consumer surplus are computed as follows, thanks to a linear VMT function:

(7) $$\Delta CS = -0.5\left(x_{VMT,f} + x_{VMT,0}\right)\left(p_f - p_o\right) + I_0$$

where $x_{VMT,0}$ and $x_{VMT,f}$ are initial (pre-PAYD) VMT and final VMT, respectively, and p_o and p_f are initial and final travel costs (per-mile),[3] respectively (where the difference is equal to the estimated per-mile insurance costs), and I_0 is initial (estimated) annual insurance loss. This insurance cost is considered "saved" since insurance payments are transferred as a per-mile cost in final per-mile costs (p_f).

RESULTS

VMT regression model results (Table 4) suggest lower VMT and fuel use as operating costs rise, as expected. Coefficients for vehicle age, fuel economy, vehicles per household, number of adults, and per-mile driving cost (based on fuel economy and fuel cost) are all negative, implying that VMT falls as these variables rise in value. Reduced VMT is to be expected from higher per-mile costs and from older vehicles (as they become more mechanically unreliable, more worn and thus less desirable). Additionally, an indicator variable for urban location is negative, suggesting that average urban VMT is lower than in rural settings, where lower density likely translates to longer trip lengths. Intriguingly, VMT is lower, on average, for those vehicles with higher fuel economy, which is somewhat counter to expectations but is probably due to fuel economy acting as a proxy for density and accessibility (since smaller vehicles are relatively more popular in high-density locations, where travel distances are shorter and parking more difficult to find). VMT is predicted to rise with household size, number of workers, and income as expected, based on income effects observed by Puller and Greening (*19*), Kayser (*20*), Small and Van Dender (*21*), and others.

The average estimated price elasticity of VMT is -0.14, which is very similar to Fererria and Minikel's (*6*), Parry's (*11*), and Bordoff and Noel's (*12*) model values, as well as modified values used by Parry (*11*) and Bordoff and Noel (*12*).[4] This approach provides a *range* of

[3] Initial per-mile costs (p_o) correspond to fuel costs as a function of vehicle fuel economy (from NHTS). Final per-mile costs include the per-mile insurance costs.

[4] From Eq. (3), both Parry (*11*) and Bordoff and Noel (*12*) used an effective VMT elasticity of -0.15, assuming β_M and β_m parameters of 0.4 and 0.67.

elasticities by vehicle and household characteristics, varying between the highly elastic (-1.13) and the highly inelastic (-0.04). Despite these extreme values, elasticity estimates over the sampled households are tightly distributed about the mean (with a standard deviation of just 0.065).

Applying Eq. (7) to VMT estimates across all NHTS vehicles (sample size of 219,137) suggests that PAYD pricing would decrease driving by an average of 2.7%, ranging between 1 and 52%[5], with a standard deviation of 2.6% across the household sample. Utility losses associated with that decrease were nearly equal to modeled insurance costs, with the average vehicle owner benefiting a net $2.04 per year per vehicle, with these benefits ranging between $0.19 to $26 per year, per vehicle (with a standard deviation of $1.80). Comparing results across vehicle classes suggests that owners of vehicles with higher average loss rates (cars, primarily) may be more responsive to PAYD policies, reducing their VMT at twice the rate of van owners, 4 times the rate of SUV owners, and nearly twice that of truck owners, on average, as shown in Table 1.

A similar analysis is performed, but for NHTS vehicles registered only in Massachusetts (a sample size of 13,351). This estimation provides a more focused approach using samples that better match the insurance loss model, estimated by Fererria and Minikel (*6*) using Massachusetts insurance data. These results are similar, but of slightly higher magnitude than results from all samples. Table 2 indicates that the average net welfare increase is $3.18 per driver per year (weighted by vehicle type distribution). Average VMT response for Massachusetts drivers appears slightly more dramatic than the average across all states, at 3.6% decrease, equal to around a 315 mile per vehicle per year reduction.

VMT and welfare impacts exhibit a convex relationship, with benefits rising rapidly as VMT drops beyond 5,000 miles per year, as shown in Figure 3. This form reflects the insurance cost model, which assumes an inverse relationship between VMT and insurance cost, and also shows the results of insurance cost scaling by vehicle class. This result suggests that low-VMT drivers are compensated more for reduced miles when switching to PAYD.

Extrapolating annual savings across each passenger vehicle in the United States, [6] insurance savings to vehicle owners would be on the order of $405 M (using national-level results). This calculation only considers insurance loss savings though, and does not count externalities, which are expected to offer additional benefits to society under PAYD policy (*11, 12*). Assuming Parry's (*11*) externality costs of 12 cents per mile[7], total VMT-related benefits are computed to be nearly $5.6 B per year (or about $30 per vehicle-year).

Average annual (non-externality) welfare benefits of less than $5 per vehicle are considerably lower than Bordoff and Noel's (*12*) $34 per vehicle per year average, but these estimates correspond to much lower insurance costs since they are based on a loss model, and not actual premia (which are likely higher to reflect various administrative costs, profit, risk factors or more comprehensive coverage beyond basic collision).[8] The approach used here considers the welfare impacts of transitioning from an idealized annual insurance policy based

[5] Results were trimmed to include vehicles with annual VMT no less than 1,000 miles. Prior to excluding these outliers, VMT reduction and elasticity values were unreasonably high.

[6] The Bureau of Transportation Statistics (*22*) estimates that 190.2 M light-duty, short-wheelbase vehicles were registered in the United States in year 2011. Of these, 58% are assumed to be cars, 8% vans, 17% SUVs, and 17% pickup trucks (*5*).

[7]Externalities considered here include reduced congestion costs, accident costs, and local pollution, valued at 6.5, 4.0, and 1.5 cents per mile, respectively (*11*).

[8] Bordoff and Noel (*12*) assumed average nationwide PAYD costs of 6.6 cents per mile.

on loss and VMT, to an incremental PAYD policy, with a portion of premium charges remaining fixed, following the approach of Ferreira and Minikel. These results are useful to show that although transferring fixed costs to variable costs may reduce VMT (and decrease consumer surplus), vehicles with ideally priced insurance policies will be compensated through per-mile insurance savings. However, this approach is limited and many not reflect actual premium costs since many drivers are likely paying beyond the marginal cost of coverage (based purely on anticipated losses for a certain vehicle type and annual VMT) because of previous crashes or other risk factors like age, experience, and location. Additionally, this framework excludes the administrative costs of implementing PAYD, and any premium taxes and commissions, which may erode some driver savings from PAYD. Further work should consider the implementation cost of PAYD as transferred to the driver to better understand long-term impacts.

CONCLUSIONS

This analysis considered the welfare effects of translating idealized annual insurance costs (equal to losses) into a per-mile, PAYD pricing structure. Shifting insurance costs from a fixed to partially variable structure suggests that the average vehicle may be driven about 2-4% fewer miles per year, with cars seeing the largest drops in VMT, followed by trucks, vans, and finally SUVs. Using idealized insurance losses to assign annual and per-mile PAYD costs results in small, but consistently positive net welfare benefits for all vehicles considered in the NHTS data. Though individual vehicle insurance savings from switching to PAYD appear small, at around $2.00 per year per vehicle, this equates to around $405 B in consumer savings nationwide, and as much as $15.6 B when including externality impacts of reduced driving. These impacts are considerably less than previous estimates by Bordoff and Noel (*12*), Parry (*11*), and Edlin (*15*), but all previous PAYD cost estimates have been based off statewide insurance averages, which are much higher than the loss-based policies estimated here.

This study builds on existing PAYD analyses by introducing more heterogeneity across vehicles and drivers with respect to VMT response and insurance losses. Though the insurance loss model applied here is rather limited, it establishes a precedent for more sophisticated approaches. A deficiency of the model used is that it predicts all vehicles to experience positive net changes in welfare by changing to a PAYD policy, which is quite unlikely. A high-mileage driver in the same risk class as a low-mileage driver, paying equal premiums, for instance, may well pay *more* under PAYD pricing. Bordoff and Noel (*12*) did capture this result, estimating that about a third of drivers would pay more for PAYD, using average state insurance prices, though drivers saved money on average. Since the analysis pursued here considers optimal pricing based on VMT, losses, and vehicle type only, such heterogeneity in insurance pricing is not reflected. Estimating insurance premiums from vehicle and driver attributes is challenging, due to the proprietary nature of the insurance industry; but a more realistic (non-ideal) insurance cost model is critical for anticipating welfare variations across a diverse set of risky and safe drivers and their vehicles. Additionally, externalities were not fully quantified here, since congestion, crash, and emissions and other impacts can vary significantly across regions (based on road network densities, existing congestion, and climate). Though “back-of-the-envelope” calculations offer results very similar to those from Parry (*11*) and Bordoff and Noel (*12*), a more comprehensive model of behavioral adjustments, benefits and costs would provide more detailed impact estimates and a more comprehensive view of PAYD insurance impacts.

Even without a highly sophisticated insurance loss estimation model, this work provides many valuable insights regarding VMT changes and welfare impacts of PAYD policies. The literature on this subject is somewhat sparse, despite growing interest and technological feasibility, so continuing to develop rigorous analyses on the topic is critical for evaluating PAYD policies. This study contributes further evidence that PAYD policies/programs could resolve insurance pricing inefficiencies and reduce aggregate VMT without harming social welfare.

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List of Tables and Figures

TABLE 1 Average Vehicle Insurance Costs and VMT Impact Estimates, by Vehicle Type (all Records)

	Car	***Van***	***SUV***	***Truck***	***Weighted Avg.***
Number of Samples	112,066	18,039	44,365	44,667	--
Estimated PAYD Premium (cents/mile)	1.8	1.2	0.9	1.3	1.47
Estimated Annual Insurance Losses	$185	$142	$107	$137	$156
Average Percentage Change in VMT	-3.4%	-2.1%	-1.4%	-2.3%	-2.66%
Average Change in Annual VMT (mi/yr)	-292	-198	-143	-210	-237
Average Net Welfare Increase ($/year/vehicle)	$2.94	$1.33	$0.70	$1.52	$2.01

TABLE 2 Average Vehicle Insurance Costs and VMT Impact Estimates (Massachusetts)

	Car	***Van***	***SUV***	***Truck***	***Weighted Avg.***
Number of Samples	3,795	633	7,480	1,443	--
Estimated PAYD Premium (cents/mile traveled)	2.5	1.8	1.3	1.9	1.73
Estimated Annual Insurance Losses	$228	$172	$131	$171	$165
Average Percentage Change in VMT	-5.6%	-3.6%	-2.5%	-4.4%	-3.64%
Average Change in Annual VMT (mi/yr)	-459	-323	-235	-348	-315
Average Net Welfare Increase ($/year/vehicle)	$6.22	$2.95	$1.55	$3.71	$3.18

TABLE 3 Data Summary of NHTS Data for VMT Model

Variable	***Description***	***#Obs.***	***Mean***	***Std. Dev.***	***Min***	***Max***
HHINC	HH Income	270,728	12.37	5.217	1	18
HHSIZE	Number of HH Members		2.63	1.267	1	14
URBRUR	Urban Location Indicator		0.67	0.472	0	1
WRKCOUN	Number of Workers		1.18	0.946	0	6
VEHAGE	Vehicle Age		9.13	7.276	1	35
EPATMPG	Estimated Fuel Economy		26.21	8.673	6.4	141
HHVEHCN	Number of Vehicles in HH		2.71	1.374	0	27
NUMADLT	Numbers of Adults (Age 18+) in HH		2.10	0.711	1	10
GSCOST	Average Gasoline Cost per Gallon		3.07	0.144	1.22	4.63
MILECOST	Cost/Mile (gscost/epatmpg)		0.13	0.047	0.03	0.52

TABLE 4 VMT Regression Results, using OLS

Variable	***Coefficient***	***Standard Eror***	***t***
	17,664	170.25	103.8
HHINC	74.8	4.01	18.7
HHSIZE	751.304	19.63	38.3
URBRUR	-1099.6	39.95	-27.5
WRKCOUNT	1205.8	24.45	49.3
VEHAGE	-221.9	2.76	-80.3
EPATMPG	-156.1	3.33	-46.8
HHVEHCNT	-376.2	16.30	-23.1
NUMADLT	-531.2	37.09	-14.3
MILECOST	-15,927	625.05	-25.5
R-squared	0.07		
Standard Error of Estimate	9606.4		
Sum of Squares - Regression	1.895E+12		
Sum of Squares - Residual	2.498E+13		
Sum of Squares - Total	2.688E+13		

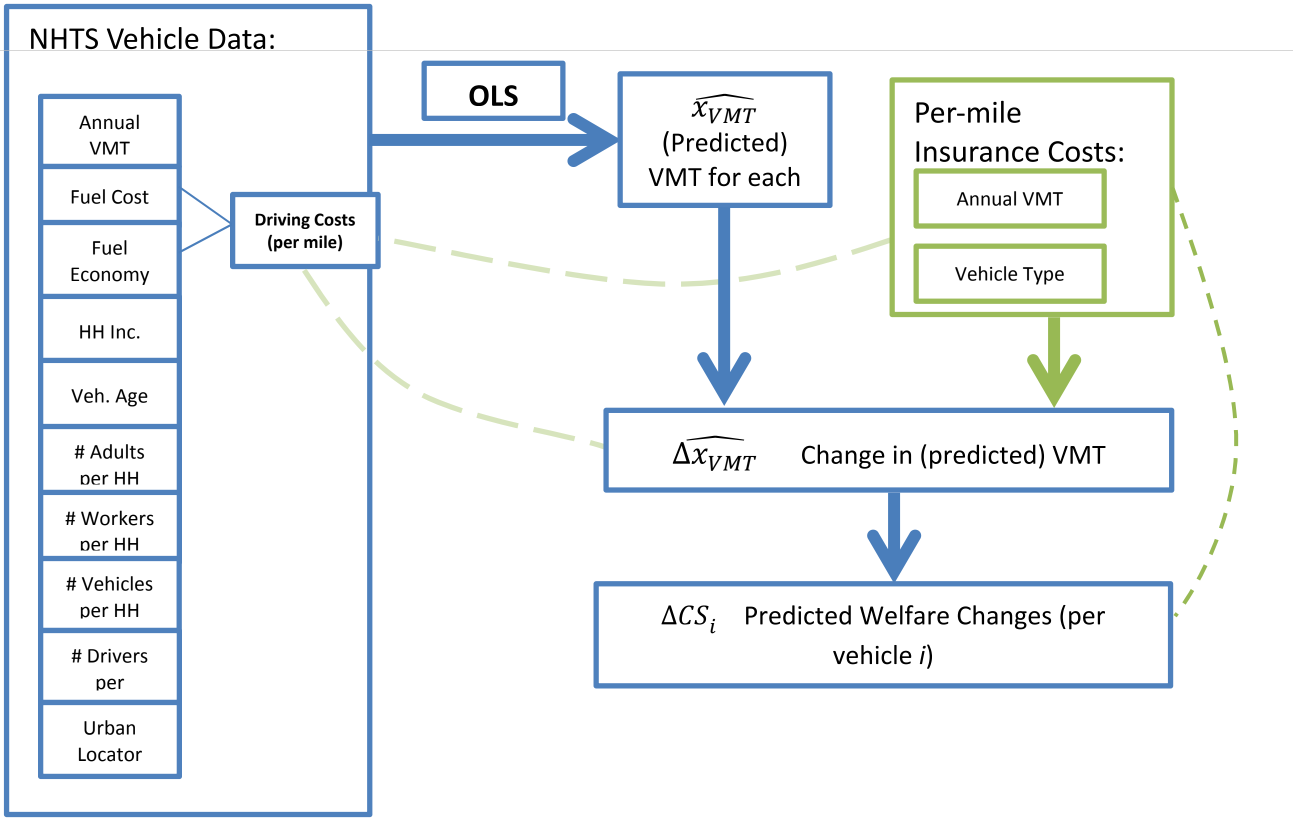

FIGURE 1 Model Specification for Predicting VMT and Welfare Impacts for Each Vehicle.

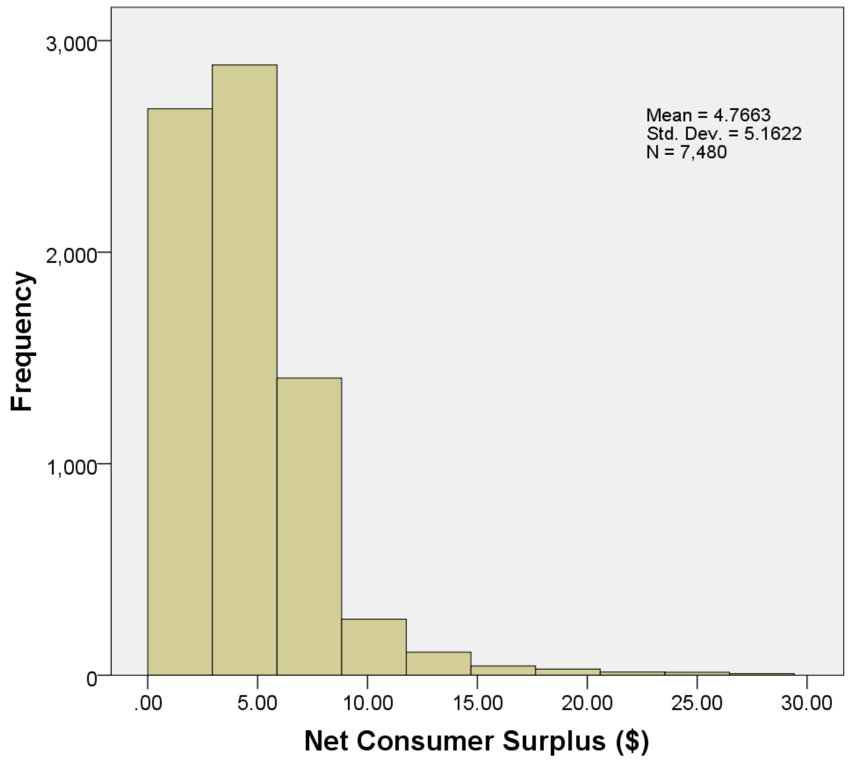

FIGURE 2 Frequency Distribution of Consumer Surplus.

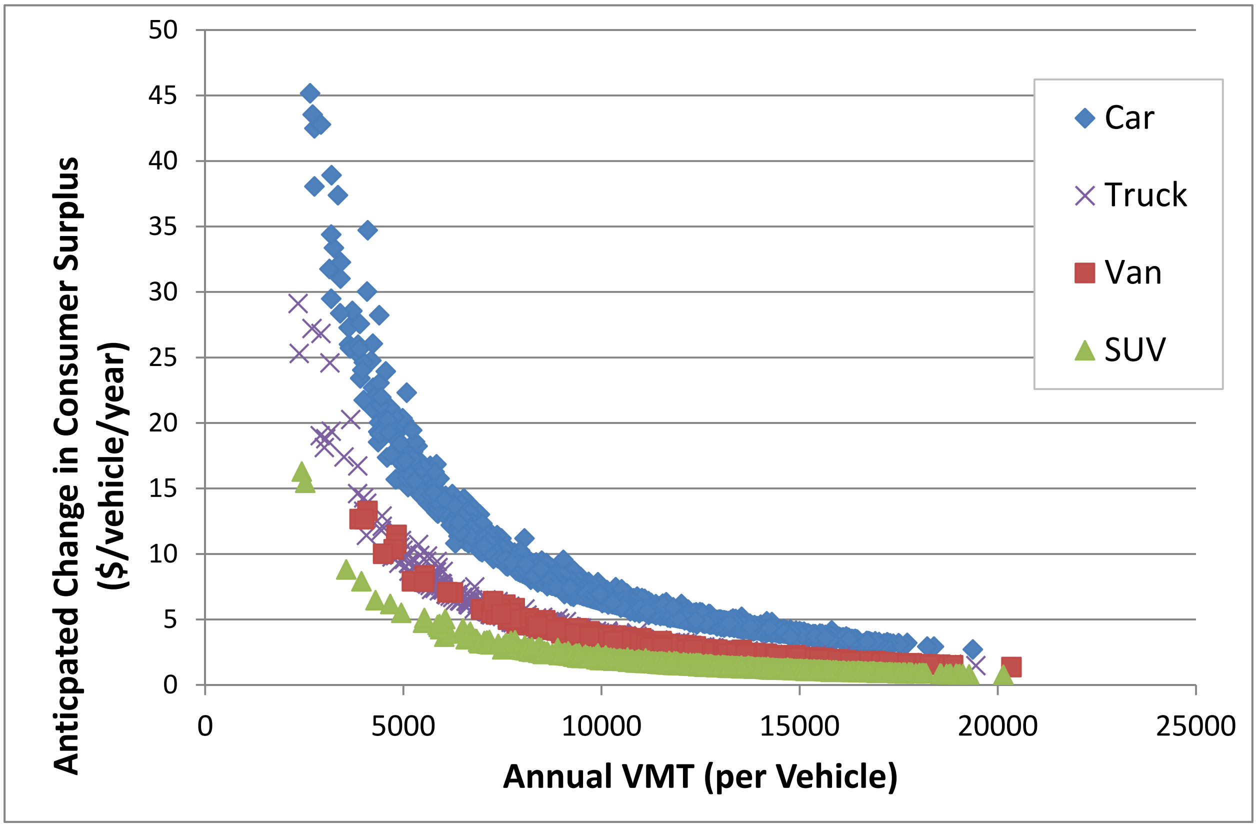

FIGURE 3 Estimated Consumer Surplus Changes vs. Annual VMT (per vehicle), by Vehicle Type.