Response of New Car Buyers to Alternative Energy Policies: The Role of Vehicle Use Heterogeneity

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Abstract

Is a fuel tax or a product tax more effective in stimulating the purchase of fuel-efficient cars for fuel savings and emissions reductions? This paper uses vehicle usage variation across drivers to show that the fuel tax outperforms the product tax because high-mileage drivers are more responsive to changes in fuel taxes than to changes in product taxes even if the vehicle usage is held fixed. It is critical to account for vehicle use heterogeneity when comparing competing policies for trimming gasoline consumption and emissions from transportation because modeling variation in vehicle use intensity changes estimates of consumer response to policies substantially. Models not accounting for vehicle use heterogeneity misinform us about the relative effectiveness of policies.

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1. Introduction

In the United States, gasoline consumption by passenger cars and light-duty trucks accounts for about 59 percent of the carbon emissions attributed to transportation activities, which collectively make up the most significant share of U.S. carbon emissions from fossil fuel consumption among all end-use economic sectors (EPA, 2018). At the local level, the ambient air pollution caused by automobile emissions has been found to affect infant health and contribute to the high rate of acute asthma attacks among young children in some urban areas (Knittel et al., 2016; Simeonova et al., 2019). Growing concerns about energy overuse, climate change, and the impact of local air pollution on public health have raised the interest in designing effective public policies to reduce motor fuel consumption in the passenger transportation sector.

This paper compares the effectiveness of a fuel tax and a product tax in stimulating the purchase of fuel-efficient cars for fuel savings and emissions reductions in the new car market. The fuel tax is an excise tax imposed on the sale of fuel, which changes the retail gasoline price. A product tax refers to policies that alter the relative purchase prices of vehicles with different fuel efficiency levels, such as fees imposed on inefficient vehicles and rebates provided for efficient vehicles according to their per-mile fuel consumption.

I investigate which policy instrument delivers the biggest reduction in the use of gasoline for a given limit on revenue raised. I show that the fuel tax outperforms the product tax in reducing gasoline consumption of new car buyers because high-mileage drivers are more responsive to a change in fuel taxes than to a change in product taxes even if the vehicle usage is held fixed. Moreover, when accounting for consumer responses on both extensive and intensive margins, the fuel tax has a clear advantage over the product tax in reducing gasoline consumption even when the magnitude of the tax change is small.

I argue that it is critical to account for vehicle use heterogeneity when comparing competing policies for trimming gasoline consumption and emissions from transportation because modeling variation in vehicle use intensity changes estimates of consumer response to policies substantially. Additionally, I show that a model not accounting for vehicle use heterogeneity not only understates the fuel-saving effects of both policies but also misinforms us about the relative effectiveness of different policies in reducing gasoline consumption of new car buyers.

This paper uses the information on observed vehicle choices and subsequent vehicle use to characterize consumer heterogeneity in annual mileage. In contrast, most studies in the literature apply information from the National Household Travel Survey (NHTS) to calculate the average annual mileage by vehicle class and by vehicle age at the national level. Grigolon et al. (2018) provide the first study treating consumers' vehicle use heterogeneity and their valuation of expected fuel cost savings in a unified empirical framework by applying vehicle kilometers traveled per year obtained from the 2007 U.K. National Travel Survey to new car markets in seven European countries. This paper employs the empirical mileage distributions constructed from the inspection logs of vehicles sold in separate new car markets. The observed annual vehicle miles traveled provide a better approximation of the car's expected lifetime mileage.[1] Furthermore, the mileage microdata allows me to investigate the effect of fuel taxes on both extensive and intensive margins at the same time, which has not been conducted in the literature according to my knowledge.

To evaluate the effectiveness of policies in stimulating the purchase of fuel-

[1] Jacobsen et al. (2019) have shown that it is critical to account for vehicle use heterogeneity for the comparison between gasoline taxation and fuel-economy standards as competing policies aimed to reduce greenhouse gas emissions from transportation.

efficient cars, it is crucial to understand whether consumers are myopic in their preferences about vehicle fuel efficiency. In the U.S., subsidies for fuel-efficient vehicles and automobile fuel economy standards have been widely implemented because the agencies believe consumers do not fully perceive the fuel-saving benefits from improved vehicle fuel efficiency. But do they? For instance, if consumers are fully rational and willing to pay for improved fuel efficiency, product taxes would not be necessary. However, if consumers are boundedly rational or have a low willingness to pay for improved fuel efficiency, product taxes will serve the same purpose as subsidies in creating price differences and stimulating more consumers to buy fuel-efficient car models than they otherwise would.

In papers employing reduced-form regressions to study how changes in fuel prices affect the equilibrium prices and quantities sold of new and used cars with different fuel economy ratings, researchers mainly rely on fuel price variations over time and hence induced fuel cost changes. However, Gillingham et al. (2015) find substantial heterogeneity in consumer response to gasoline prices by vehicle fuel economy quantiles, which implies that consumers may value a decrease in fuel price and an increase in vehicle fuel efficiency differently because the former can be seen as a relatively short-term gain in comparison to the latter. In this paper, I focus on fuel cost variations generated from heterogeneity in vehicle use intensities across drivers from different geographic regions instead of changes in gas prices over time.[2]

My estimates show that new car buyers fully value the gas cost savings generated from improved vehicle fuel efficiency. They are willing to pay an extra

[2] Bento et al. (2012) provide simulation evidence to show that ignoring consumer heterogeneity when estimating the willingness to pay for discounted future energy cost savings will result in a sorting bias, which may mistakenly lead to the conclusion of consumer undervaluation.

one dollar in the up-front purchase price of the car for a one-dollar reduction in discounted future gas cost. My calculation is closer to the full-valuation results reported by Busse et al. (2013) and Grigolon et al. (2018) than to the partial-valuation results obtained by Allcott and Wozny (2014) and Leard et al. (2017).[3]

When a product tax is applied, the relative price of vehicles with higher fuel economy ratings falls, which incentivizes consumers to choose fuel-efficient vehicles. A fuel tax influences a consumer's vehicle purchase decision by augmenting the difference in the fuel cost between vehicle models with different fuel economy ratings. The success of this mechanism depends on how many miles a consumer drives and to what extent this consumer values the future gas cost savings arising from improved vehicle fuel efficiency.

To characterize consumer heterogeneity in vehicle use intensities and preference over vehicle attributes, I assemble the vehicle ownership and inspection history for all new passenger cars sold in Massachusetts in 2011 from a dataset that contains information about every vehicle registered in Massachusetts from 2009 to 2014. I calculate the annual miles traveled of a car using the difference between odometer readings from the vehicle inspection logs.

My empirical analysis proceeds in two steps. First, I estimate a random coefficients logit demand model in the style of Berry et al. (1995). In particular, I apply the discrete choice model to define the probability of a consumer buying a specific new car model as a function of the car's attributes (including price) and the present discounted value of the car's lifetime gas cost. Previous work has paid close attention to heterogeneous consumer tastes for vehicle attributes but

[3]Consistent with my results, using housing transaction data in the state of Massachusetts between 1990 and 2011, Myers (2019) finds little evidence that home buyers are systematically undervaluing future fuel costs associated with space heating and cooling systems.

not heterogeneous vehicle use patterns. To incorporate vehicle use heterogeneity, I let the new car buyer's expected annual vehicle miles traveled and the car's fuel efficiency level jointly determine the present discounted value of a car's lifetime gas cost. Variations in car attributes and expected lifetime gas cost allow me to identify flexible substitution patterns for new car buyers. I model unobserved car attributes as random effects, and I employ price shifters as instrumental variables to address price endogeneity.

In the second step, I conduct policy simulations to understand the effects of alternative energy policies on gasoline conservation. I compare the amount of fuel savings resulting from applying a fuel tax and a product tax on the per-mile fuel consumption of a car model, holding revenues equivalent. By accurately capturing heterogeneous consumer response to alternative policies, my policy simulations show that drivers in the top half of the annual vehicle miles traveled distribution are more responsive to the fuel tax than to the product tax. Therefore, the fuel tax incentivizes high-mileage drivers more to choose fuel-efficient car models and to substitute away from conventional gasoline-powered cars toward hybrid and electric vehicles.

By estimating the price elasticity of driving from the microdata and predicting new annual mileage, I allow consumers in my model to adjust their vehicle use decisions after applying new fuel taxes while previous work has kept vehicle use patterns fixed before and after implementing taxes based on the assumption of perfectly inelastic demand for driving. My result shows that when accounting for consumer responses on both extensive and intensive margins, a change in fuel taxes is more effective than a change in product taxes in reducing gasoline consumption of new car buyers even when the magnitude of the tax change is small.

The paper proceeds as follows. The next section develops the demand model.

Section 3 describes the data. In section 4, I introduce the empirical framework and state the identification strategy. Section 5 presents the results from demand estimation and discusses the implied consumer valuation of expected future gas cost savings. Section 6 carries out the policy simulation. Section 7 gives the robustness check to address induced travel. Section 8 concludes.

2. An Empirical Model of New Car Demand

In this section, I present a random coefficients discrete choice model of the demand for new passenger cars in the style of Berry et al. (1995) and Petrin (2002). I let the present discounted value of a car's lifetime gas cost enter the consumer's decision of which new car to purchase as in Grigolon et al. (2018). Since consumers may differ in expected vehicle miles traveled and hence in their expected gas costs, I incorporate the empirical distribution of annual mileage when constructing the expected gas cost variable.

I employ a sample of new car buyers and estimate the conditional choice of buying a new passenger car directly as in Train and Winston (2007). In a complete vehicle choice model, the consumer can choose to buy a new vehicle, buy a used vehicle, continue using her current vehicle, or not own any vehicle. I restrict my model's choices to buying a new conventional vehicle or a new clean vehicle because I only observe new car purchase prices.[4] I define the inside good as gasoline-powered passenger cars excluding SUVs. The outside good contains both hybrid and electric cars.[5]

[4]The further difficulty is that information for correctly inferring the conditional density of tastes that affects both which new car the consumer chooses and whether the consumer chooses other alternatives is not available.

[5]I drop diesel-powered vehicles because the number of new diesel cars sold in a single month is small. Among all passenger vehicles registered in Massachusetts as of 2017, only 1.07 percent are powered by diesel fuel.

My sample for the demand estimation comes from a regional market (Massachusetts) and covers six months.[6] Thus, I model and analyze the effects of alternative energy policies on the demand system in the short run. In my model, the product offering is exogenous to policy changes, so the supply side is not specified and estimated.[7]

2.1. Model Formulation

There are T markets with I_t buyers of new passenger cars in each market t. The conditional indirect utility function of consumer i for car v is

$$u_{ivt} = \alpha_i \; x_v + \beta \; (p_v + \gamma \; G_{ivt}) + \zeta_{vt} + \epsilon_{ivt}, \tag{1}$$

in which x_v is a vector of observed car attributes, p_v is the purchase price of car v, and G_{ivt} is the present discounted value of expected future gas cost associated with consumer i choosing to buy car v in market t.[8] Coefficients included in vector α_i identify the individual-specific valuation of observed car attributes, while β is the price sensitivity. The unobserved (to the econometrician) vehicle attributes of model v in market t are denoted ζ_{vt}. The unobserved component of

[6] Records of almost all vehicles registered in Massachusetts from 2009 to 2014 are available. I form my sample to avoid model year 2010 and earlier model years because of the automotive industry crisis of 2008 - 2010. I choose to use the model year overlapping months during which both new model year 2011 and 2012 cars are for sale because these observations have the longest inspection histories within the feasible time frame for me to trace mileage records.

[7] Using the MaritzCX New Vehicle Customer Survey for the years 2010 through 2015, Leard et al. (2019) analyze the welfare effects of regulations on new vehicle buyers in the short run while treating fuel economy and vehicle performance as exogenous. In addition, Grigolon et al. (2018) show, when the supply side is included, similar policy changes as I'm considering in this paper have only a small impact on average new car prices which implies a high degree of tax pass-through.

[8] This indirect utility does not include the income of consumer i because the income is common to all options in her choice set and drops out of the equation eventually (Nevo, 2000; Train, 2009).

the utility function ϵ_{ivt} follows the Type I Extreme Value Distribution, and it is independent and identically distributed over all consumers i, cars v, and markets t. I normalize the utility of the outside good to zero so that my estimates are in terms of the difference between the utility of purchasing a specific conventional car v and the utility of choosing to buy the outside good.

Coefficient γ is the "valuation factor" introduced by Allcott and Wozny (2014). Rational consumers should be indifferent between spending a dollar on the up-front car purchase price and a dollar in present discounted value on total gasoline consumed (Allcott and Greenstone, 2012). Therefore, a value of $\gamma = 1$ implies that the consumers weigh the gas costs against the up-front car purchase prices in a fully rational way. A value of $\gamma < 1$ suggests that the consumers undervalue expected future gas costs at the time they initially purchase their cars. An overvaluation is indicated if $\gamma > 1$.

I define the present discounted value of a car's lifetime gas cost as an expectation over the annual mileage and the gas price

$$G_{ivt} = E\left[\sum_{s=1}^{S} \frac{1}{(1+r)^s}\, m_{it}\, \frac{g_t}{mpg_v}\right], \tag{2}$$

in which m_{it} is the expected annual vehicle miles traveled of consumer i in market t, g_t is the market-specific per-gallon gas price, and mpg_v is the car-specific fuel economy rating. The ratio g_t/mpg_v gives the per-mile fuel cost of a specific vehicle model v because the fuel economy rating is measured in miles per gallon. The interest rate at which consumers discount future gas costs is denoted r, and S is the length of time over which consumers value gas cost savings generated from improved vehicle fuel efficiency.[9]

[9]Although I am using a static setup, following Allcott and Wozny (2014), I assume a forward-looking new car buyer will divide this G_{ivt} into two parts: the present discounted value of gas costs during her holding period, and the

According to equation 2, G_{ivt} is heterogeneous across new car buyers if the individual-specific expected annual mileage is applied. I employ the market-specific empirical distribution of annual vehicle miles traveled D_t and draw m_{it} from corresponding D_t for each simulated driver in demand estimation. Incorporating vehicle use heterogeneity in this way helps avoid the endogenous sorting bias identified by Bento et al. (2012) because consumers who drive more are likely to have a higher valuation of gas cost savings arising from improved vehicle fuel efficiency.

There could be multiple sources of consumer heterogeneity when modeling the present discounted value of the expected gas cost, such as a discount rate that varies across consumers and across time.[10] In this paper, I concentrate on heterogeneous annual mileage, so I assume the same interest rate r and time horizon S for all consumers.[11] By imposing such a simplifying assumption, I express the present discounted value of expected lifetime gas cost of car v as

$$G_{ivt} = \rho \; m_{it} \; \frac{E\left[g_t\right]}{mpg_v}, \tag{3}$$

in which $\rho \equiv \sum_{s=1}^{S} (1+r)^{-s}$ is a common "capitalization factor" that measures how consumers trade off the up-front car purchase price against the expected annual gas cost over S years. A fully myopic consumer will assign no weight to

present discounted value of gas costs over the remainder of the car's life after it is resold. In this model, car owner i knows the payout of selling this car to its next owner will be the present discounted value of the resale price plus that present discounted value of the remaining gas costs.

[10] Multiple factors may affect consumer optimization in this context: a present bias, a systematically biased belief about the relative energy costs of products with different energy efficiency levels, or inattention. DellaVigna (2009) provides a review of both the psychology and economics literature relevant here.

[11] As both low discount rate and long vehicle lifetime tend to result in consumer undervaluation, I employ different assumptions on these parameters so a list of alternative estimates of the valuation factor γ can be presented and analyzed.

annual gas cost, in which case the present discounted value of expected lifetime gas cost in equation 3 would be zero.

2.2. Individual Choice Probability and Market Share

Using equation 1 and equation 3, I rewrite the conditional indirect utility of consumer i for car v in market t as follows:

$$u_{ivt} = \alpha_i \ x_v + \beta \ p_v + \beta\gamma\rho m_{it} \ \frac{E\left[g_t\right]}{mpg_v} + \zeta_{vt} + \epsilon_{ivt}. \tag{4}$$

I use available data on x_v, p_v, m_{it}, mpg_v and $E[g_t]$ to estimate α_i, β, and the coefficient of expected annual gas cost $\beta\gamma\rho$. After that, I divide $\beta\gamma\rho$ by the price sensitivity β to obtain $\gamma\rho$ which is the product of the valuation factor and the capitalization factor.

I take two steps to compute γ as in Grigolon et al. (2018). First, I apply assumptions on interest rate r and time horizon S to calculate ρ. Next, I divide the product $\gamma\rho$ by the capitalization factor ρ to reveal γ. Given the interest rate, the relevant time horizon, and the gas price expectation, γ depends on the individual-specific expected annual mileage m_{it} and the fuel economy rating of car v.

I let each new car buyer choose to purchase the alternative that delivers the highest level of utility relative to all other options in her choice set. I assume α_i and m_{it} come from a distribution $F(\theta)$ where θ includes all parameters of this distribution. Based on equation 4, and let δ be the linear mean utility component of u_{ivt}, the individual choice probability of consumer i for car v in market t is

$$s_{ivt}(\delta, \rho, \theta) = \frac{\exp(\alpha_i \ x_v + \beta \ p_v + \beta\gamma\rho m_{it} \ \frac{E[g_t]}{mpg_v} + \zeta_{vt})}{1 + \sum_{v'=1}^{J} \exp(\alpha_i \ x_{v'} + \beta \ p_{v'} + \beta\gamma\rho m_{it} \ \frac{E[g_t]}{mpg_{v'}} + \zeta_{v't})}. \tag{5}$$

Then the predicted market share of car v in market t is

$$S_{vt}(\delta, \theta) = \int_{(\alpha_i, m_{it})} s_{ivt}(\delta, \rho, \theta) \; dF(\theta). \tag{6}$$

2.3. Heterogeneous Consumer Response to Alternative Policies

The individual choice probability described in equation 5 can be used to show that differentiated consumer response to alternative energy policies comes from different vehicle use patterns. I let τ^g denote a new excise tax on retail gasoline sales, which generates the change in fuel tax. Alternatively, I place a product tax on a car's per-mile fuel consumption (in gallons/mile). Because the per-mile fuel consumption is the inverse of a car's fuel economy rating (in miles/gallon, i.e., MPG), I write this product tax as τ^{mpg}/mpg_v. Given these notations, the expected post-tax gas price is $E[g_t] + \tau^g$ per gallon and the post-tax vehicle purchase price becomes $p_v + \tau^{mpg}/mpg_v$.

Plugging new prices into equation 5, the probability of consumer i choosing model v in market t becomes

$$s_{ivt} = \frac{\exp(\alpha_i \; x_v + \beta \; (p_v + \frac{\tau^{mpg}}{mpg_v}) + \beta\gamma\rho m_{it} \frac{E[g_t]+\tau^g}{mpg_v} + \zeta_{vt})}{1 + \sum_{v'=1}^{J} \exp(\alpha_i \; x_{v'} + \beta \; (p_{v'} + \frac{\tau^{mpg}}{mpg_{v'}}) + \beta\gamma\rho m_{it} \frac{E[g_t]+\tau^g}{mpg_{v'}} + \zeta_{v't})}.$$

To inspect the consumer response to the implementation of a new fuel tax and a product tax, I differentiate the individual choice probability with respect to τ^g and τ^{mpg} following Grigolon et al. (2018). When holding vehicle use fixed, consumer i's response given the change in fuel tax is

$$\frac{\partial s_{ivt}}{\partial \tau^g} = \beta\gamma\rho m_{it} \; s_{ivt} \; \left(\frac{1}{mpg_v} - \sum_{v'=1}^{J} \frac{s_{iv't}}{mpg_{v'}} \right). \tag{7}$$

Similarly, consumer i responds to the product tax by adjusting her choice probability such that

$$\frac{\partial s_{ivt}}{\partial \tau^{mpg}} = \beta\ s_{ivt}\ \left(\frac{1}{mpg_v} - \sum_{v'=1}^{J} \frac{s_{iv't}}{mpg_{v'}} \right). \tag{8}$$

Since the price sensitivity β is negative, the common part in the parentheses of equations 7 and 8 implies that, when implementing either tax, the probability of consumer i choosing car v will decrease if the per-mile gasoline consumption of car v is higher than the sales-weighted average per-mile gasoline consumption of all new car models in the market. This result fits intuition because the cost of purchasing and operating a car with high fuel economy rating will be lower than that cost for a less fuel-efficient car model after applying either τ^g or τ^{mpg}, all else equal.

The difference between consumers' responses to alternative policies lies in the term outside of the parentheses. The fuel tax influences the individual choice probability differently because the combination $\beta\gamma\rho m_{it}$ relates a consumer's response to her valuation of the expected gas cost savings. Moreover, this effect varies when there is heterogeneity in vehicle use intensity across new car buyers.

3. Data

With the model and its assumptions in mind, this section presents the sample I construct using several data sources. The primary data used in this paper is the Massachusetts Vehicle Census (MAPC, 2015). It is based on the Automated License and Registration System and a separate database containing records of vehicle inspections, both of which are administrative data sets maintained by the Massachusetts Registry of Motor Vehicles (Reardon et al., 2016).

3.1. Vehicle Choices

In Massachusetts, passenger vehicle registration renewal is valid for two years while vehicles are required to be inspected annually and within seven days of sale. When constructing the Massachusetts Vehicle Census (MAVC), registration records are split where a vehicle inspection record, which delivers the mileage reading, begins or ends. So each record in the MAVC covers a defined period when the specified vehicle had a unique combination of owner, garaging address, and average daily mileage (Reardon et al., 2016).

Vehicle manufacturer, model, fuel type, fuel economy rating, curb weight, and the manufacturer suggested retail price (MSRP) of each vehicle are included in the MAVC data. Vehicle identification number (VIN) and ZIP Code of garaging address are also available from the MAVC researcher files.

I apply a highly disaggregated definition of the vehicle model to capture the variation in fuel efficiency and engine performance as much as possible. Each vehicle recorded in the MAVC is a manufacturer/model/model year (MY) combination, e.g., "Volkswagen Jetta 2011". I use VINs and the VIN decoder provided by the National Highway Traffic Safety Administration (NHTSA) to retrieve the trim level information of each vehicle.[12] Also, I use the trim level information to collect extra vehicle attributes such as vehicle body type, vehicle passenger volume, and interior cargo volume from Cars.com and Ward's Automotive Yearbook. The unit of observation in my sample is at the very detailed level, e.g., "Volkswagen Jetta 2011, 2.5 liter, 170 hp, 3,045 lbs, 27 MPG, 94.1

[12]Manufacturers use trim levels to identify a vehicle's level of equipment or special features. For models that use several trim choices, automakers usually offer three or four versions. For example, the gasoline-powered 2011 Volkswagen Jetta comes in three versions: S, SE, and SEL. The Jetta S is the base model, which includes the fewest features and has the lowest price of the three. The SE is in the middle of the range in both price and equipment, and the SEL is the most luxurious and feature-rich version.

ft^3 passenger volume, and 15.5 ft^3 cargo volume".

3.2. New Car Markets

In Massachusetts, thirteen Metropolitan Planning Organization (MPO) regions cover all municipalities of the state. An MPO is a federally required regional transportation policy-making organization made of representatives from local government, regional transit operators, and state transportation agencies. MPOs are responsible for coordinating and managing transportation projects and services carried out in different regions across the state. Following the Massachusetts Travel Survey published by the Massachusetts Department of Transportation in 2012, I employ MPO regions to define geographic new car markets to capture heterogeneous vehicle use patterns.

Numbers of vehicle registration in MAVC were 25% and 32% lower than the count of registered vehicles published by the Massachusetts Department of Revenue for 2009 and 2010 (Reardon et al., 2016). So I exclude MAVC data from calendar years 2009 and 2010. I also avoid MY 2010 and previous ones because of the automobile industry crisis from 2008 to 2010. After dropping earlier observations, new passenger cars registered in the second half of the calendar year 2011 have the longest inspection history within the MAVC time frame for me to trace mileage records. Therefore, I use new car registration records of MY 2011 and MY 2012 from ten MPO regions in Massachusetts between July 2011 and December 2011 to construct the new car market.[13]

[13] Based on disaggregated new vehicle transaction data, Copeland et al. (2011) point out that for about half the calendar year, automakers simultaneously sell two vintages of the same model. During the second half of 2011, almost all new passenger registrations are for MY 2011 and MY 2012. I drop three MPO regions when building the sample because there are very few observations in each of them. See the Appendix for a detailed data cleaning procedure.

3.3. Prices

The expected gasoline price of consumers plays a vital role in my model. Based on the Michigan Survey of Consumers (MSC), Anderson et al. (2011) conclude that households in the MSC typically form expectations about the inflation-adjusted price of gasoline using a simple no-change model. Specifically, households surveyed in MSC expect the nominal gasoline price to grow at the same rate as inflation, which is equivalent to expecting the real price of gasoline in the future to be the same as the current price of gasoline. Although the inflation expectations data in the MSC is limited to selected horizons, this no-change model is valid when advanced methods of inflation forecasting are employed (Baumeister and Kilian, 2016). I adopt this simple rule of thumb in my analysis. Therefore, the gas price expectation in my model is the average of the statewide average midgrade gasoline price in Massachusetts over six months from July 2011 to December 2011 for all new car buyers.[14]

I use MSRPs for new car purchase prices because transaction prices are not available. Market dummies are included in the mean utility term to account for manufacturer and dealer incentives offered to the new car buyers and other market fixed effects.

3.4. Empirical Distributions of Annual Vehicle Miles Traveled

I construct the ownership and inspection history for observations in my sample from the vehicle registration and inspection records contained in the MAVC. Each valid vehicle inspection record in the MAVC reports the number of days

[14] In addition to applying this no-change model, I evaluate several alternative behavioral models of consumers' gas price expectations following Kilian and Sims (2006). These alternative models of consumers' expected gas prices give similar results to the no-change model. I also apply the prices of the regular grade gasoline for robustness checks. The results are nearly identical. Refer to the Appendix for further discussion and the results.

between two inspections and the average daily miles traveled during that period. I weight the daily miles using the length of the time span between two inspections, and apply this weighted average daily mileage to calculate the expected annual vehicle miles traveled for each vehicle.

From the new car market sample (the demand sample), I select all registered new cars with complete inspection records over three consecutive years to create the mileage sample.[15] Table 1 presents the numbers of observations in both the demand sample and the mileage sample by markets. Summary statistics of daily vehicle miles traveled by markets reported in table 1 illustrate the variation in vehicle use patterns of consumers from different MPO regions.

[15] Forming the mileage sample using cars with three consecutive inspection records helps produce accurate *annual* mileage estimates. Overall, *the average number of the days between two inspections* is 379, and the standard deviation is 32. When using cars with two inspections, these numbers are 408 and 110. For a mileage sample with cars having four inspection records, these numbers are 379 and 142.

Table 1: Demand Sample and Mileage Sample

	(1) Num. of	(2) Demand	(3) Mileage	(4) Daily Veh. Miles Traveled			
MPO Market	**Towns/Cities**	**Sample Obs.**	**Sample Obs.**	**Mean**	**Median**	**Max.**	**S.D.**
Berkshire	32	180	114	34.55	31.36	90.80	17.77
Boston Region	97	5,104	3,532	31.20	29.32	124.53	15.46
Cape Cod	15	297	197	39.77	37.66	153.63	22.37
Central MA	40	717	493	39.80	36.90	120.13	19.30
Merrimack Valley	15	409	297	41.51	40.49	119.83	18.40
Montachusett	22	281	197	44.24	39.24	113.01	21.98
Northern Middlesex	9	402	277	36.94	34.59	111.64	17.90
Old Colony	17	461	323	38.88	37.48	109.68	18.57
Pioneer Valley	43	645	444	35.94	33.05	136.01	18.48
Southeastern MA	27	633	440	40.97	37.36	130.00	21.69
Total	**317**	**9,129**	**6,314**	**34.75**	**31.93**	**153.63**	**17.93**

Notes: MPO stands for Metropolitan Planning Organization. I drop three MPO regions when building the sample because there are very few observations in each of them. The number of towns and cities in column (1) shows how many municipalities are included in a corresponding MPO. Column (2) reports the number of observations involved in demand estimation. Column (3) tells the number of observations that have three consecutive mileage records starting from the second half of 2011 to the end of 2014. Mean Daily Mileage column shows the mean value of average daily miles traveled per vehicle.

4. Empirical Implementation

I employ a sequence of T markets to estimate the taste parameters in a system of market shares using the Generalized Method of Moments (GMM). The data I am using has three main components: car attributes including price, market shares, and market-specific empirical distributions of the annual mileage.

4.1. Specification of the Taste Parameters

To achieve flexible substitution patterns for new car buyers, I allow the marginal utilities of some observed car attributes and the expected gas cost to vary at the individual level. The conditional indirect utility of consumer i for car v in market t becomes

$$u_{ivt} = \bar{\alpha}\ x_v + (\Sigma^K \nu_i)'\ x_v^K + \beta\ p_v + \beta\gamma\rho\ m_{it}\ \frac{g}{mpg_v} + \zeta_{vt} + \epsilon_{ivt} \tag{9}$$

in which $\bar{\alpha}$ is a vector of mean valuations for observed car attributes, ν_i is a $K \times 1$ vector of unobserved (to the econometrician) idiosyncratic tastes for K observed car attributes x_v^K, and Σ^K is a matrix with parameters σ^k on the diagonal.[16] I apply K independent $\chi^2(3)$ distributions truncated at 95 percent for ν_i following Petrin (2002).[17] Parameters σ^k capture the heterogeneity in unobserved tastes ν_i for x_v^K in the population.

The MSRP of new car model v is p_v. I apply the average Massachusetts midgrade gasoline price over the sample period to all consumers. This approximation implies $E[g_t] = g$ for every new car buyer in each MPO market. I specify

[16] I restrict the covariances of all random coefficients to be zero as in Nevo (2000).

[17] This distributional assumption implies that the heterogeneity of unobserved consumer tastes in the population is skewed in the positive direction. I also apply the standard normal distribution for ν_i for a robustness check. The results obtained from this alternative distributional assumption are similar.

g/mpg_v as the per-mile gas cost of driving (in dollars per mile). The product $\beta\gamma\rho$ is estimated as one random coefficient with random draws m_{it} from corresponding market-specific mileage distribution D_t. Therefore, the variation in car attributes allows me to identify taste parameters $\bar{\alpha}$ and σ^k, while empirical mileage distributions provide extra information to ensure the identification of $\beta\gamma\rho$.

The term ζ_{vt} represents unobserved car attributes. It does not have a random coefficient. The inclusion of this term allows the model to rationalize patterns of market shares observed from the data. I define this term of unobserved car attributes as

$$\zeta_{vt} = \zeta_t + \tilde{\zeta}_{vt} \tag{10}$$

in which ζ_t captures the market fixed effects, and $\tilde{\zeta}_{vt}$ are random effects accounting for any remainder of unobserved product attributes that vary across different car models and markets.

4.2. Identification and the GMM Estimator

To incorporate vehicle use heterogeneity, I apply the discrete choice model to define the individual choice probability and hence the market share of a particular new car model as a function of the car attributes (including price) and the new car buyer's expected gas cost. In my model, a consumer knows what tasks her newly purchased passenger car will perform before she buys it. Therefore, her expected annual mileage is the same as the actual annual mileage observed from the data.[18] The variation in the up-front purchase price and the expected gas cost across different car models allows me to identify how much new car buyers value the expected fuel cost savings arising from improved vehicle fuel efficiency when they initially purchase their cars.

[18] I test alternative assumptions in section 7.

To pin down the parameters governing the substitution patterns of the new car buyers, I need variations in expected gas cost across consumers and attributes across new car models. As summarized in table 1, market-specific empirical mileage distributions help capture the variation in vehicle use patterns among consumers in different regional markets. The variation in the expected car lifetime gas cost across drivers in my sample comes from the difference in the model-specific vehicle fuel efficiency and the individual-specific expected annual vehicle miles traveled rather than from changes in gasoline prices because the gasoline price is the same for all new car buyers. Additionally, I include car purchase price, performance ratio (i.e., horsepower/curb weight), interior passenger volume, and premium features for demand estimation. Car attributes that vary at the vehicle trim level have higher dispersion around the mean than attributes changing at the nameplate-model level.[19]

Following the seminal work Berry (1994), I define the product-specific linear mean utility component of u_{ivt} as

$$\delta(S_{vt}, \theta) \equiv \bar{\alpha}\ x_v + \beta\ p_v + \zeta_t + \tilde{\zeta}_{vt} \tag{11}$$

in which S_{vt} is the market share of model v in market t. Given the distributional assumption on consumer taste for car attributes and the expected gas cost, Berry (1994) demonstrates that there is a unique $\delta_{vt}(\theta)$ that solves $S_{vt}^{data} - S_{vt}(\delta, \theta) = 0$ for each θ, in which S_{vt}^{data} is the observed market share.

I address price endogeneity by using price shifters z_{vt} in market t as instrumental variables. In particular, for car v, the squares of its own attributes, the sum of each attribute of car models made by the same manufacturer, and that

[19] Refer to the Appendix for detailed information about attributes of new car models purchased by consumers.

of car models made by competing manufacturers are employed as instrumental variables. These instruments are introduced by Pakes (1996), and have been used by Berry et al. (1995) and subsequent work. By applying this group of instruments, I assume that the unobserved car attributes $\tilde{\zeta}_{vt}$, although correlated with the car purchase price, are mean independent of those observed nonprice car attributes and the gas price expectation.[20]

I compute $\delta(S_{vt}, \theta)$ numerically using the contraction mapping procedure developed by Berry et al. (1995).[21] Given the mean utility term and the assumption $E(\tilde{\zeta}_{vt}(\theta)|z_{vt}) = 0$, equation 11 becomes a standard linear regression model. The primary set of moments that I use for the GMM estimator is $E(\tilde{\zeta}_{vt}(\theta)z_{vt}) = 0$. The GMM estimator $\hat{\theta}_{gmm}$ is the solution to this following criterion function

$$\hat{\theta}_{gmm} = \underset{\theta}{\operatorname{argmin}}\, \tilde{\zeta}(\theta)' Z W^{-1} Z' \tilde{\zeta}(\theta) \tag{12}$$

in which Z is the instrument matrix and I set the weighting matrix W to be $Z'Z$ following Nevo (2000). I take into account both sampling error and simulation error to estimate the standard errors of the parameter estimates following Hansen (1982).

[20] This set of price shifters are the standard instruments used in random coefficients logit demand applications (Gandhi and Houde, 2019). They have been proved very effective in the study of many industries such as automobiles, computers, and pharmaceutical drugs (Nevo, 2000). For automobiles, previous papers applying price shifters as instrumental variables include Petrin (2002), Berry et al. (2004), and Train and Winston (2007).

[21] I code analytical gradients to implement the nonlinear GMM estimation based on numerical optimization with a set of starting values and stopping rules for termination. Using the quasi-Newton method and MultiStart function in MATLAB, I set the tolerance at 1E-14 for the fixed-point iterations and test twenty starting values (Knittel and Metaxoglou, 2014). For the demand model accounting for vehicle use heterogeneity, fourteen of twenty starting values reach the same minimum value of the objective function while the rest produce suboptimal values.

5. Consumer Valuation of Expected Gas Cost Savings

Correctly accounting for consumer heterogeneity has been recognized as an essential modeling feature when estimating the demand for differentiated products in general (Ackerberg et al., 2007). When examining the consumer valuation of expected gas cost savings, I show that accounting for vehicle use heterogeneity is at least as important as accounting for taste heterogeneity among consumers. To do so, I compare parameter estimates and corresponding valuation factors from three different demand models.

The *IV Logit Mean Miles* model is an instrumental logit model combining price shifters as instrumental variables to address the price endogeneity. In this simple logit model, the expected annual vehicle miles traveled equals the mean of the observed mileage distribution for consumers in each market, and there is no heterogeneity in consumer taste for observed car attributes.

To investigate changes in the demand estimation and the valuation factor resulted from including different types of heterogeneity, I develop the *IV RCLogit Mean Miles* model and the *IV RCLogit EPD Miles* model to account for taste heterogeneity and vehicle use heterogeneity accordingly.[22] The IV RCLogit Mean Miles model adapts random coefficients for consumer preference over some of the observed car attributes as laid on in the previous section while still using mean mileage. The IV RCLogit EPD Miles model introduces mileage heterogeneity by incorporating random draws from the market-specific empirical mileage distributions when forming the individual-specific expected gas cost variable. Therefore, heterogeneous annual vehicle miles traveled are employed to calculate the expected future gas cost while the valuation of car attributes remains homogeneous.

[22]RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution.

5.1. Demand Estimation

Table 2 reports parameter estimates from three demand models. Results from the IV Logit Mean Miles model (column 1 in table 2) are intuitive. New car buyers have strong disutility from high car purchase prices, and they penalize high expected car lifetime fuel costs. Parameter estimates on market dummies (not shown) have consistent patterns across all three demand models. They suggest that residents living in any MPO regions but Boston are more likely to buy gasoline-powered cars relative to consumers living in the Greater Boston area. When applying the price shifters as instruments, the F-statistic from the first-stage mean utility regression is 124. I reject weak instruments at the 95% confidence level according to the bias method introduced by Stock and Yogo (2005).

Both the IV RCLogit Mean Miles model (column 2 in table 2) and the IV RCLogit EPD Miles model (column 3 in table 2) deliver the price sensitivity parameter close to that from the IV Logit Mean Miles model.[23] When allowing for heterogeneity in annual mileage and hence in the valuation of expected gas cost in the IV RCLogit EPD Miles model, the impact of expected gas cost on utility entirely varies with the individual-specific annual mileage. The expected gas cost again has a negative and significant effect on consumer utility. According to previous literature, horsepower and size are essential attributes for U.S. consumers to consider when buying new vehicles. The estimated mean valuations in column 3 indicate that new car buyers in Massachusetts also favor cars with rapid acceleration and large interior passenger volume.

[23]However, when comparing both random coefficients logit models to the IV Logit model, the estimation is less precise without extra information being used. This is particularly true in a multiple random coefficients case when a higher dimensional integral needs to be computed (Reynaert and Verboven, 2014).

Table 2: Parameter Estimates from Alternative Models

	(1) IV Logit Mean Miles	(2) IV RCLogit Mean Miles	(3) IV RCLogit EPD Miles
	Average Utility		
Constant	-6.74	-6.40	-6.60
	(0.38)	(2.26)	(0.41)
Car MSRP	-0.46	-0.40	-0.44
	(0.13)	(0.21)	(0.11)
Gas Cost	-5.92	-6.29	-
	(1.82)	(2.20)	-
Horsepower/Weight	0.78	-1.89	0.78
	(0.30)	(7.27)	(0.28)
Passenger Volume	3.94	3.60	3.95
	(0.46)	(19.35)	(0.48)
Premium Features	0.67	0.49	0.61
	(0.41)	(0.69)	(0.33)
European Automaker	0.44	0.48	0.46
	(0.20)	(0.26)	(0.22)
Japanese Automaker	-0.03	-0.02	-0.03
	(0.11)	(0.13)	(0.11)
Korean Automaker	0.08	0.13	0.09
	(0.12)	(0.21)	(0.12)
Utility that Varies over Consumers Related to Mileage Distributions			
Gas Cost	-	-	-6.56
	-	-	(1.88)
Utility that Varies over Consumers Following $\chi^2(3)$			
Horsepower/Weight	-	0.60	-
	-	(1.17)	-
Passenger Volume	-	0.10	-
	-	(5.81)	-

Notes: Standard errors in parentheses. RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. Coefficients for market fixed effects are omitted. 5,000 Monte Carlo draws and quasi-Newton method are used for random coefficients models.

5.2. Valuation Factor

In this subsection, I calculate consumer valuation of expected gas cost savings arising from improved vehicle fuel efficiency using parameter estimates obtained from demand models that employ different mileage information. I show that vehicle use heterogeneity must be included to reveal the true valuation factor γ if a bias is likely caused by the endogenous sorting of low-mileage drivers into less fuel-efficient car models.

I divide the gas cost coefficient $\beta\gamma\rho$ by the price coefficient β to obtain $\gamma\rho$ which is the product of the valuation factor and the capitalization factor. Then I apply assumptions on the discount rate and the time horizon to compute the capitalization factor ρ. Finally, I take the ratio of $\gamma\rho$ over ρ to reveal the valuation factor γ. My calculation of the valuation factor is closer to the full-valuation results reported by Busse et al. (2013) and Grigolon et al. (2018) than to the partial-valuation results obtained by Allcott and Wozny (2014) and Leard et al. (2017).

A reasonable estimate of the valuation factor γ relies on choices carefully made for the interest rate r and the time horizon S. Allcott and Wozny (2014) calculate the average discount rate weighted over used vehicle buyers using different payment methods (i.e., financed, leased, and cash) and set the discount rate as 6%. I adopt this value of the discount rate for analysis. The vehicle sustainability and travel mileage schedules published by the NHTSA suggests that the average maximum vehicle age of passenger cars is 25 in the U.S. (Lu, 2006). Using the 2009 NHTS data, Leard et al. (2017) update the maximum lifespan for cars to 35 years as better technology and overall vehicle quality improvements have been driving up the average vehicle age over time. I assume that cars have a maximum lifespan of 35 years but still apply the original NHTSA estimate (25 years) for comparison.[24]

The first row of column 1 in table 3 shows that the product $\gamma\rho$ calculated

[24] A relatively long average vehicle lifetime tends to conclude consumer undervaluation. The definition of the capitalization factor is $\rho \equiv \sum_{s=1}^{S} (1+r)^{-s} = \frac{1}{r}[1-(1+r)^{-s}]$. When the product $\gamma\rho$ is fixed, a lower r or a larger S (i.e., higher ρ) leads to a smaller γ.

Table 3: Consumer Valuation of Expected Gas Cost Savings

	(1) **IV Logit** **Mean Miles**	**(2)** **IV RCLogit** **Mean Miles**	**(3)** **IV RCLogit** **EPD Miles**
Gas Cost/MSRP			
$\gamma\rho$	12.93	15.64	14.97
	(6.51)	(12.46)	(6.86)
Valuation Factor			
γ (r = 6%, S = 35)	0.89	1.08	1.03
	(0.45)	(0.86)	(0.47)
γ (r = 6%, S = 25)	1.01	1.22	1.17
	(0.51)	(0.97)	(0.54)
Implicit Discount Rate (%)			
r (γ = 1, S = 35)	7.01	5.37	5.73
r (γ = 1, S = 25)	5.88	3.99	4.41

Notes: Standard errors in parentheses. RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. The combination $\gamma\rho$ is computed using parameter estimates from the demand estimation. The discount rate is denoted r, and S is the maximum car lifetime. Refer to the Appendix for valuation factors under the assumption $r = 4\%$.

from the IV Logit Mean Miles model is noticeably smaller than those obtained from models accounting for either type of heterogeneity among consumers. Consequently, when assuming the maximum car lifetime to be 35 years (the second row of column 1 in table 3), the valuation factor computed from the IV Logit Mean Miles model predict a modest consumer undervaluation of expected gas cost savings arising from improved vehicle fuel efficiency. This corresponds to the conclusion reached by Bento et al. (2012) through a simulation study: when the undervaluation of energy costs is not present in the true data generating process, the simple logit model could erroneously suggest undervaluation while the random coefficients logit model recovers the actual value.

When choosing time horizon as 35 years (the second row of columns 2 and 3 in table 3), models accounting for heterogeneity in either consumer preference over car attributes or expected annual mileage indicate that consumers fully value the benefits of improved vehicle fuel efficiency when they initially purchase their cars (i.e., $\gamma = 1$). I compare the IV RCLogit Mean Miles model and the IV RCLogit EPD Miles model in policy simulations. Although these two models produce almost identical valuation factors, model setup incorporating distributional miles reveals differentiated effectiveness of fuel taxes and product taxes in gasoline conservation while the former doesn't.

I also calculate the implicit discount rate for new car buyers following Hausman (1979). This implicit discount rate is the interest rate at which consumers discount the future, assuming that they value the expected gas cost savings to the full extent over a given value of the car lifetime. In the second-to-last row of table 3, when assuming 35 years as the maximum lifespan for passenger cars, the implicit discount rate obtained from the IV Logit Mean Miles model is larger than the discount rate calculated by Allcott and Wozny (2014) as this simple logit model does not account for any heterogeneity among consumers. Model setups incorporating either type of consumer heterogeneity deliver implicit discount rates closer to 6%.

Although the gasoline price was trending down during the sample period, it was still at a high position relative to gasoline prices during the previous years. In this case, consumers seem to behave rationally by assigning a full valuation to expected gas cost savings. Hassett and Metcalf (1993) argue that high energy expenditure increases the return to an energy saving investment because the return to the investment is the energy cost avoided. Similarly, Busse et al. (2016) suggest that, if consumers experience an adjustment cost to changing their vehicle choices or vehicle use patterns, they may not respond to changes in gasoline prices until the price crosses a threshold at which it becomes worthwhile to make the necessary switch.

6. Policy Simulations

At the root of designing effective policies in producing fuel savings and emissions reductions in passenger transportation is the influence of policies on consumer behavior. In this section, I carry out policy simulations to show that accounting for vehicle use heterogeneity is critical when evaluating such policies. To do so, I compare the amounts of fuel savings resulting from implementing alternative policies calculated from random coefficients demand models using different mileage information. The result shows, although producing almost identical valuation factors, a model applying mean mileage leads to similar fuel-saving effects for the fuel tax and the product tax while a model employing distributional mileage suggests the fuel tax is more effective in gasoline conservation even if the vehicle usage is held fixed.

6.1. Perfectly Inelastic Demand for Driving

Policy simulations conducted in this subsection investigate the effects of a fuel tax and a product tax on consumers' vehicle choice decisions but not on how many miles to drive. Although the fuel tax may directly affect consumers' demand for vehicle miles traveled because it changes the cost of driving, I fix the expected annual mileage before and after applying new fuel taxes for every simulated new car buyer based on the finding of inelastic consumer demand for vehicle miles traveled with respect to changes in gasoline prices from the literature (Gillingham, 2014; Davis and Kilian, 2011). Also, according to the "weak rebound effect" result in the context of transportation services from recent literature studying the energy efficiency gap, I assume an improvement of the vehicle fuel efficiency doesn't influence the vehicle use pattern of consumers (Gillingham et al., 2016).

In column 1 of table 4, I report the current average annual gasoline consumption of new car buyers in Massachusetts calculated from observed new car market shares and mileage distributions. Columns 2 and 3 of table 4 present the amounts of expected average annual gasoline consumption per driver when I in turn apply a counterfactual increase of the fuel tax by \$0.25/gallon to the average midgrade gasoline price in Massachusetts, which was \$3.69/gallon over the sample period, and a revenue-equivalent product tax on the per-mile gasoline consumption of a car model.[25]

The first row in Panel A of table 4 shows that, in a model accounting for heterogeneity in consumer preference over car attributes but not vehicle usage, a 25 cents increase in the fuel tax has a negligible and almost identical effect as a revenue-equivalent product tax in reducing gasoline consumption of new car buyers. The expected gasoline consumption decreases to about 474 gallons per driver per year in both scenarios. However, the second row in Panel A suggests that in a model properly accounting for vehicle use heterogeneity, a fuel tax reduces the expected average annual gasoline consumption by 1.54 percent while a revenue-equivalent product tax reduces the consumption by only 0.96 percent.

To investigate the mechanism that generates this relative effectiveness result, I examine the impacts of alternative policies on different groups of drivers. I assign simulated new car buyers who land in the top half of the mileage distribution to the "High Miles" group and the rest to the "Low Miles" group. When considering only low-mileage drivers (the first row in Panel B of table 4), the counterfactual fuel tax reduces about the same annual gasoline consumption on average as the product tax does. However, the fuel tax has a substantial fuel-saving effect on high-mileage drivers. When applying an extra fuel tax \$0.25/gallon, the second row in Panel B of table 4 shows high-mileage drivers reduce their average annual gasoline consumption from about 611 gallons to roughly 598 gallons

[25]Refer to the Appendix for the calculation of a revenue-equivalent product tax.

by switching to fuel-efficient cars. Although a revenue-equivalent product tax also leads to trimming in average annual gasoline consumption of high-mileage drivers, the cutback is smaller.

This set of comparisons yields important insights. When consumers fully value the gas cost savings arising from improved vehicle fuel efficiency (i.e., $\gamma = 1.03$), a fuel tax and a product tax incentivize different groups of consumers to substitute toward more fuel-efficient car models and therefore generate differentiated fuel-saving results. When breaking down the impacts of alternative policies by mileage group, I show that high-mileage drivers are more responsive to policy changes relative to low-mileage drivers. More importantly, high-mileage drivers are more responsive to a change in fuel taxes than to a change in product taxes, while low-mileage drivers are more responsive to product taxes.

I have shown that when the same set of policies is considered, a model not employing heterogeneous miles not only understates the fuel-saving effects of both policies but also misinforms us about the relative effectiveness of two policies in reducing gasoline consumption of new car buyers. From this set of policy simulations, it seems the aggregate fuel savings and emissions reductions generated from correctly implementing fuel taxes could be considerable at the national level even when the demand for driving is held fixed before and after applying taxes.

Table 4: Expected Average Annual Gasoline Consumption, Fixed VMT

	Expected Average Annual Gasoline Consumption (gal.)			**Percentage Change from the Current Level**	
	(1)	(2)	(3)	(5)	(6)
	Current	Extra Fuel Tax \$0.25/gal.	Revenue Equivalent Product Tax	Extra Fuel Tax \$0.25/gal.	Revenue Equivalent Product Tax
Inelastic Demand for VMT					
***Panel A**: Mean Miles vs. Heterogeneous Miles*					
IV RCLogit Mean Miles ($\gamma = 1.08$)	477.77	473.65	473.96	-0.86%	-0.80%
IV RCLogit EPD Miles ($\gamma = 1.03$)	458.84	451.77	454.44	-1.54%	-0.96%
***Panel B**: Low Miles vs. High Miles in IV RCLogit EPD Miles Model ($\gamma = 1.03$)*					
IV RCLogit EPD Miles (Low Miles)	306.24	304.93	304.55	-0.43%	-0.55%
IV RCLogit EPD Miles (High Miles)	611.03	598.23	603.93	-2.10%	-1.16%

Notes: RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. Consumers with expected annual vehicle miles traveled in the top half of the mileage distribution are in the "High Miles" group, and the rest are assigned to the "Low Miles" group. The product tax is calculated according to a car's per-mile fuel consumption.

6.2. *Elastic Demand for Vehicle Miles Traveled*

In the previous subsection, I assume a perfectly inelastic demand for driving to show that a fuel tax is more effective in reducing gasoline consumption as it incentivizes high-mileage drivers more to choose fuel-efficient cars. In this subsection, I allow consumers to respond to changes in fuel prices by adjusting how much to drive. Therefore, the second set of policy simulations carried out in this subsection also accounts for the effect of fuel taxes on consumer response on the intensive margin.

I estimate the elasticity of driving with respect to gasoline prices and predict new mileage after applying the counterfactual fuel tax that changes the retail gasoline price.[26] In the meantime, for the revenue-equivalent product tax scenario, I stick to the "weak rebound effect" result from recent energy efficiency literature. It indicates that consumers do not drive more after switching to more fuel-efficient vehicles, so new car buyers' decisions about how much to drive are held fixed after implementing the product tax.

[26] Using mileage information obtained from the MAVC vehicle registration and inspection records, I create a vehicle level panel dataset that includes about 6,000 new passenger cars over three years. I define the vehicle-driving period as the unit of observation following recent papers in the literature that explore vehicle odometer readings (Gillingham et al., 2015; Knittel and Sandler, 2018). Applying a log-linear specification, I regress the average daily miles traveled of a car during the period between two inspections on the average gasoline price over the same vehicle-driving period using the fixed effects estimator. I instrument the local gas price using the Brent crude price. I include average municipality-specific unemployment rate, average national Consumer Confidence Index, and the percentage of summer months during corresponding vehicle-driving period as control variables. Additionally, I account for vehicle-driving period start year and end year fixed effects and the number of months between two inspections. Refer to the Appendix for estimation results.

Table 5: Expected Average Annual Gasoline Consumption, Predicted VMT

	Expected Average Annual Gasoline Consumption (gal.)			**Percentage Change from the Current Level**	
	(1)	(2)	(3)	(5)	(6)
	Current	Extra Fuel Tax $0.25/gal.	Revenue Equivalent Product Tax	Extra Fuel Tax $0.25/gal.	Revenue Equivalent Product Tax
The Elasticity of Demand for VMT Equals -0.57					
Panel A: *Mean Miles vs. Heterogeneous Miles*					
IV RCLogit Mean Miles ($\gamma = 1.08$)	477.77	467.71	474.09	-2.11%	-0.77%
IV RCLogit EPD Miles ($\gamma = 1.03$)	458.84	447.32	454.56	-2.52%	-0.93%
Panel B: *Low Miles vs. High Miles in IV RCLogit EPD Miles Model* ($\gamma = 1.03$)					
IV RCLogit EPD Miles (Low Miles)	306.24	299.46	304.59	-2.21%	-0.54%
IV RCLogit EPD Miles (High Miles)	611.03	594.15	604.13	-2.76%	-1.13%

Notes: RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. Consumers with expected annual vehicle miles traveled in the top half of the mileage distribution are in the "High Miles" group, and the rest are assigned to the "Low Miles" group. The product tax is calculated according to a car's per-mile fuel consumption.

I follow the same procedure conducted in the previous subsection but apply new mean mileage numbers and new mileage distributions accordingly after implementing the extra fuel tax. Numbers in the first row in Panel A of table 5 suggest that, even when not accounting for heterogeneous vehicle usage among consumers, an extra fuel tax of \$0.25/gallon reduces more gasoline consumption relative to a revenue-equivalent product tax when drivers are allowed to switch vehicles *and* to adjust mileage in response to changes in fuel taxes.

In a model properly accounting for heterogeneity in vehicle usage, the new fuel tax again reduces more gasoline consumption per driver per year compared to the product tax. When looking into different driver groups in Panel B of table 5, both low-mileage drivers and high-mileage drivers make pronounced responses to an increase in the fuel tax. This set of policy simulations indicates that when accounting for its effects on consumer responses on both extensive and intensive margins, a change in fuel taxes has a clear advantage over a change in product taxes in reducing gasoline consumption of new car buyers, even when the magnitude of the tax increase is small.

7. Addressing Induced Travel

My model assumes a consumer knows what tasks her newly purchased passenger car will perform before she buys it so the vehicle use pattern is predetermined. Following this assumption, I use observed odometer readings as expected annual mileage in demand estimation and apply the same observed mileage data for policy simulations.

However, a consumer may adjust her driving according to the fuel efficiency level of the car she bought. Specifically, a consumer may drive more if she ends up with a fuel-efficient car, which is associated with a lower overall cost of driving, and vice versa otherwise. Analysis carried out in this section shows if it is true that consumers are smoothing out car purchase decisions with their driving patterns, my model underestimates consumers' valuation of expected fuel cost savings and hence produces a conservative estimate of the fuel-saving effect of fuel taxes. I use simulations to demonstrate such one-sided bias.[27]

From the mileage sample described in section 3.4, I observe what car was purchased by a consumer and how many miles were driven. My model assumes this observed mileage is the amount used by this consumer to calculate the expected annual gas cost when she purchases this car. If this consumer has adjusted her driving behavior according to the fuel efficiency level of the car since she bought it, the *true expected annual mileage* of consumer i considering buying car model v in market t can be approximated as

$$tm_{it} = m_{it} - c \times mpg_v \tag{13}$$

in which tm_{it} is the true expected annual mileage, m_{it} is the mileage observed from the data when consumer i drives car v, and c is a correction constant. Using this equation, I pick a positive number for c and subtract the extra mileage associated with a car's fuel-efficiency level from observed mileage m_{it} to obtain tm_{it}.[28] I then apply a new mileage distribution that consists of the true expected annual mileage for demand estimation but still use observed mileage for policy simulations.

[27]Intuitively, the fact that a consumer drives more when she bought a fuel-efficient car implies she does value the fuel cost savings arising from improved vehicle fuel efficiency.

[28]This correction constant c is applied here to adjust the scale. A more fuel-efficient car with lower per-mile driving cost has a larger miles-per-gallon number (mpg_v). For example, if c equals 100 and the observed annual mileage is 10,000 miles for both car x (30 MPG) and car y (15 MPG), the true expected annual mileage for consumers driving these two cars would be 7,000 miles and 8,500 miles accordingly.

Table 6: Addressing Induced Travel, Fixed VMT

	Expected Average Annual Gasoline Consumption (gal.)			**Percentage Change from the Current Level**	
	(1)	(2)	(3)	(5)	(6)
	Current	Extra Fuel Tax \$0.25/gal.	Revenue Equivalent Product Tax	Extra Fuel Tax \$0.25/gal.	Revenue Equivalent Product Tax
Inelastic Demand for VMT with Mileage Correction (c=100)					
***Panel A**: Mean Miles vs. Heterogeneous Miles*					
IV RCLogit Mean Miles ($\gamma = 1.32$)	477.77	455.82	457.37	-4.59%	-4.27%
IV RCLogit EPD Miles ($\gamma = 1.39$)	453.73	423.52	429.50	-6.66%	-5.34%
***Panel B**: Low Miles vs. High Miles in IV RCLogit EPD Miles Model ($\gamma = 1.39$)*					
IV RCLogit EPD Miles (Low Miles)	309.81	301.35	301.54	-2.73%	-2.67%
IV RCLogit EPD Miles (High Miles)	597.25	545.35	557.10	-8.69%	-6.72%

Notes: Mileage used in this set of policy simulations is constructed from the mileage correction equation 13. RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. Consumers with expected annual vehicle miles traveled in the top half of the mileage distribution are in the "High Miles" group, and the rest are assigned to the "Low Miles" group. The product tax is calculated according to a car's per-mile fuel consumption.

Table 6 presents the simulation results with the correction constant equals 100. The policy recommendation does not change given this robustness analysis. When maintaining assumptions on the interest rate and the maximum car lifetime, valuation factor estimates from demand models using corrected mileage are larger than those estimated from applying observed mileage data. As reported in Panel A of table 6, a new fuel tax is still more effective in reducing total gasoline consumption relative to a revenue-equivalent product tax in either a model employing mean mileage or a model using distributional mileage. In Panel B of table 6, low-mileage drivers respond to different taxes in a similar way while high-mileage drivers are more responsive to a change in the fuel tax, which is consistent with earlier results.

8. Concluding Remarks

In this paper, I have shown that accounting for vehicle use heterogeneity is critical when evaluating the effectiveness of a fuel tax and a product tax in generating fuel savings and emissions reductions by analyzing models employing distributional mileage and models considering only mean mileage. I construct the ownership and inspection history for new passenger cars using vehicle registration and inspection records contained in the MAVC, which covers almost every single vehicle registered in Massachusetts between 2009 and 2014. This high-quality vehicle level microdata allows me to form and apply distributions of expected annual mileage in demand estimation and policy simulations. The observed annual vehicle miles traveled during years after the new car purchase provide a better approximation of the car's lifetime mileage and facilitate the decomposition of the impacts of alternative energy policies on new car buyers.

I find that it is crucial to account for vehicle use heterogeneity when comparing the effectiveness of alternative energy policies aimed to reduce gasoline consumption and greenhouse gas emissions from transportation. My demand estimation indicates that consumers fully value gas cost savings arising from improved vehicle fuel efficiency when they initially purchase their cars. My policy simulations suggest that high-mileage drivers are more responsive to a change in fuel taxes than to a change in product taxes. By capturing such heterogeneous consumer responses to policy changes, I show that a fuel tax is more effective than a revenue-equivalent product tax in reducing the total gasoline consumption of new car buyers. Moreover, a model not accounting for vehicle use heterogeneity understates the fuel-saving effects of both policies and misinforms us about the relative effectiveness of these two policies. Furthermore, when accounting for consumer response on both extensive and intensive margins, the fuel tax has a clear advantage over the product tax in reducing gasoline consumption even when the magnitude of the tax change is small.

Declarations of interest

Declarations of interest: none

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Appendix A. Data Appendix

Appendix A.1. Sample Construction

After obtaining records of all non-commercial and non-diesel vehicles, I use the vehicle identification number (VIN) to construct a vehicle history sequence for every vehicle. I also use the combination of VIN and plate identifier to construct an owner history sequence for each vehicle. I mark a vehicle as a newly purchased one if its first vehicle history record is also the first owner history record, *and* the starting odometer reading of this record is smaller than 300 miles.[29]

I apply two criteria to flag low-quality observations. In MAVC, registration records are split where a mileage estimate begins or ends (Reardon et al., 2016). Registration periods without a corresponding mileage estimate are retained but assigned a "false" value for inspection matching. In addition, the temporal overlap between the mileage estimate and the registration record is compared to the length of the mileage estimate period as a measure of data reliability. A high value for the percentage of overlapping period suggests that the vehicle had the same owner and was garaged in the same location for a large portion of the mileage estimate period; a low value means that a substantial portion of the estimated mileage may have been driven while the vehicle was owned by another person or garaged in a different location. I flag a vehicle as a bad observation if there is a "false" value assigned *or* the percentage of overlapping period is smaller than 90% for any of its inspection records.

Dividing all new vehicles registered in 2011 which have no low-quality ob-

[29]When not applying restrictions on the starting odometer readings, the observation pool constructed from matching two sequences includes brand new vehicles, vehicles released from commercial fleet, used vehicles came from other states, and those missed in previous census data. 200 miles is the other starting odometer reading tested for robustness. The results are similar.

servation flags into two groups by registration time, I report the vehicle count by model year (MY) and by vehicle type in table A.7. Almost all passenger cars registered in the second half of 2011 are MY 2011/2012, while only 88% for new car registrations during the first half of calendar year 2011 are for MY 2011/2012.

I employ all MY 2011/2012 new passenger cars registered during the second half of 2011 without any low-quality observation flags as the demand sample for analysis. From this demand sample, I select vehicles with exactly three consecutive inspection records since their first registration to form the mileage sample. The average number of days between two inspections is 379 for cars included in the mileage sample, and the standard deviation is 32 days.[30] Using the market-specific mileage sample, I construct the empirical distribution of expected annual vehicle miles traveled for new car buyers in each new car market.

In Massachusetts, thirteen Metropolitan Planning Organization (MPO) Regions showed in figure A.1 cover all 351 municipalities of the state. An MPO is a federally required regional transportation policy-making organization made of representatives from local government, regional transit operators, and state transportation agencies. Each MPO creates a fair and impartial setting for effective regional decision making in the metropolitan area to effectively engage communities and stakeholders.[31] Following the Massachusetts Travel Survey published by the Massachusetts Department of Transportation in 2012, I employ MPO regions to define the geographic new car market. Tables A.8 and A.9

[30] About 70% vehicles included in the demand sample show up in the mileage sample. The standard deviation of days between two inspections for vehicles with two or four consecutive inspection records is much larger.

[31] Refer to this website for more information about MPOs in Massachusetts: https://www.mass.gov/service-details/regional-planning

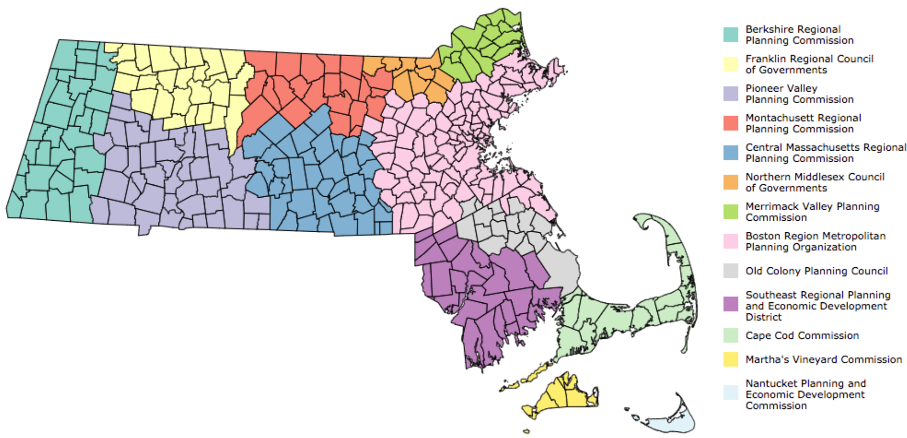
Table A.7: New Vehicle Registration Counts in 2011

	Jan - Jun 2011				**Jul - Dec 2011**			
Model Year	**Car**	**SUV**	**Truck**	**Van**	**Car**	**SUV**	**Truck**	**Van**
2010 and earlier	1,078	178	106	77	64	17	7	2
2011	7,788	4,882	1,120	549	5,119	3,488	1,091	405
2012	364	34	0	28	4,631	2,131	274	275
Total	9,230	5,094	1,226	654	9,814	5,636	1,372	682

Notes: Numbers of vehicle registration in MAVC were 25% and 32% lower than the count of registered vehicles published by the Massachusetts Department of Revenue for 2009 and 2010 (Reardon et al., 2016). So I exclude MAVC data from calendar years 2009 and 2010. I also avoid Model Year 2010 and previous ones because of the automobile industry crisis from 2008 to 2010. After dropping earlier observations, new passenger cars registered in the second half of calendar year 2011 have the longest inspection history within the MAVC time frame for me to trace mileage records.

present vehicle counts by MPO and by registration month for demand sample and mileage sample accordingly.

Figure A.1: Metropolitan Planning Organization Regions



Notes: An MPO is a federally required regional transportation policy-making organization made of representatives from local government, regional transit operators, and state transportation agencies. Each MPO creates a fair and impartial setting for effective regional decision making in the metropolitan area to effectively engage communities and stakeholders. Source: Massachusetts MPO Website Finder

Table A.8: Vehicle Counts by Region and by Month, Demand Sample

MPO	07/2011	08/2011	09/2011	10/2011	11/2011	12/2011	Total
Berkshire	29	26	32	32	26	35	180
Franklin County	8	12	6	13	12	9	60
Pioneer Valley	100	115	115	95	106	114	645
Montachusett	48	51	52	46	39	45	281
Central Massachusetts	114	104	146	114	123	116	717
Northern Middlesex	65	76	59	72	67	63	402
Merrimack Valley	70	91	73	74	55	46	409
Metro Boston	735	958	890	805	842	874	5,104
Old Colony	75	74	96	73	73	70	461
Southeastern Massachusetts	103	122	113	104	95	96	633
Cape Cod	41	40	62	45	57	52	297
Martha's Vineyard	3	7	1	2	1	6	20
Nantucket	1	0	2	1	1	1	6
Total	**1,392**	**1,676**	**1,647**	**1,476**	**1,497**	**1,527**	**9,215**

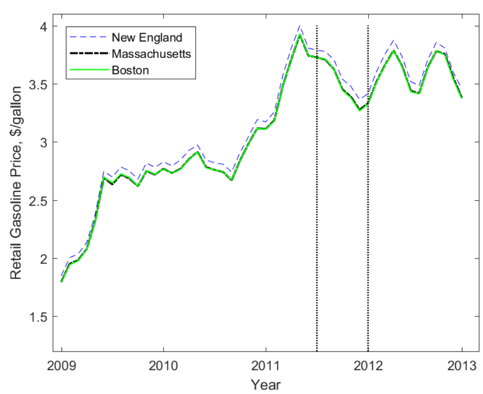
Table A.9: Vehicle Counts by Region and by Month, Mileage Sample

MPO	07/2011	08/2011	09/2011	10/2011	11/2011	12/2011	Total
Berkshire	16	15	20	22	16	25	114
Franklin County	8	9	4	12	7	7	47
Pioneer Valley	74	85	75	67	70	73	444
Montachusett	28	33	41	33	30	32	197
Central Massachusetts	81	77	93	85	80	77	493
Northern Middlesex	50	52	39	48	43	45	277
Merrimack Valley	50	72	57	57	31	30	297
Metro Boston	501	680	665	548	575	563	3,532
Old Colony	55	55	69	56	42	46	323
Southeastern Massachusetts	74	89	78	70	68	61	440
Cape Cod	25	25	45	32	38	32	197
Martha's Vineyard	2	6	1	1	0	3	13
Nantucket	0	0	2	0	1	0	3
Total	**964**	**1,198**	**1,189**	**1,031**	**1,001**	**994**	**6,377**

Appendix A.2. Expected Fuel Prices

The EIA uses a regional classification that divides the U.S. into seven Petroleum Administration for Defense Districts (PADD). It provides gas price information for these seven regions, and also for ten states and nine cities separately. Figure A.2 shows that the monthly average price of the midgrade gasoline in the New England area (PADD1A), the statewide average price of Massachusetts, and the citywide average price of Boston share the similar pattern. The latter two overlap because these two average prices are very close to each other. I employ the average price of midgrade motor fuel in Massachusetts from the U.S. Energy Information Administration (EIA) to form the consumer expectation of future gasoline prices.

Figure A.2: Monthly Average Price of the Midgrade Gasoline



Notes: The monthly average price of the midgrade gasoline in the New England area, the statewide average price of Massachusetts, and the citywide average price of Boston are plotted in this figure. The latter two are visually indistinguishable because these two average prices are similar. Prices that used for empirical analysis lie between two vertical dotted lines. All prices are normalized to 2011 dollars. Source: EIA Monthly Gasoline Prices Table.

Appendix A.3. Variation in Car Attributes

Table A.10: Vehicle Attributes

Variable	**Mean**	**Std. Dev.**
Vehicle Price ($\times 10^4$)	2.33	0.70
Fuel Economy (MPG)	27.49	7.07
Engine Horsepower (bhps)	171.71	51.59
Engine Size (liter)	2.28	0.61
Curb Weight(1,000 lbs)	3.15	0.39
Passenger Volume (ft^3)	98.19	8.39
Premium Features (0-1)	0.04	0.20
Number of Observations	**9,129**	

Notes: Following the literature, I use the ratio of horsepower to weight as a proxy for passenger car performance in demand estimation. The 2010-2014 Wards Automotive Yearbook describes lower luxury cars as those with MSRP higher than $34,000, and upper luxury cars as those cost more than $42,000. The “premium features” here refers to new cars that cost more than $38,000.

Appendix B. Empirical Appendix

Appendix B.1. Valuation Factors with 4% Interest Rate and Midgrade Fuel

Table B.11: 4% Interest Rate for Consumer Valuation of Expected Gas Cost Savings

	(1) **IV Logit** **Mean Miles**	**(2)** **IV RCLogit** **Mean Miles**	**(3)** **IV RCLogit** **EPD Miles**
Gas Cost/MSRP			
$\gamma\rho$	12.93	15.64	14.97
	(6.51)	(12.46)	(6.86)
Valuation Factor			
γ (r = 4%, S = 35)	0.69	0.84	0.80
	(0.35)	(0.67)	(0.37)
γ (r = 4%, S = 25)	0.83	1.00	0.96
	(0.42)	(0.80)	(0.44)
Implicit Discount Rate (%)			
r (γ = 1, S = 35)	7.01	5.37	5.73
r (γ = 1, S = 25)	5.88	3.99	4.41

Notes: Standard errors in parentheses. RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. The combination $\gamma\rho$ is computed using parameter estimates from the demand estimation. The discount rate is denoted r and S is the maximum car lifetime.

Appendix B.2. Results from Using the Price of Regular Grade Fuel

Table B.12: Regular Grade Fuel Price Parameter Estimates from Alternative Models

	(1) IV Logit Mean Miles	**(2) IV RCLogit Mean Miles**	**(3) IV RCLogit EPD Miles**
	Average Utility		
Constant	-6.74	-6.40	-6.74
	(0.38)	(2.26)	(0.39)
Car MSRP	-0.46	-0.40	-0.46
	(0.13)	(0.21)	(0.13)
Gas Cost	-6.19	-6.58	-
	(1.90)	(2.30)	-
Horsepower/Weight	0.78	-1.89	0.78
	(0.30)	(7.27)	(0.30)
Passenger Volume	3.94	3.60	3.94
	(0.46)	(19.35)	(0.46)
Premium Features	0.67	0.49	0.67
	(0.41)	(0.69)	(0.41)
European Automaker	0.44	0.48	0.44
	(0.20)	(0.26)	(0.20)
Japanese Automaker	-0.03	-0.02	-0.03
	(0.11)	(0.13)	(0.11)
Korean Automaker	0.08	0.13	0.08
	(0.12)	(0.21)	(0.12)
Utility that Varies over Consumers Related to Mileage Distributions			
Gas Cost	-	-	-6.19
	-	-	(1.90)
Utility that Varies over Consumers Following $\chi^2(3)$			
Horsepower/Weight	-	0.60	-
	-	(1.17)	-
Passenger Volume	-	0.10	-
	-	(5.81)	-

Notes: Standard errors in parentheses. RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. Coefficients for market fixed effects are omitted. 5,000 Monte Carlo draws and quasi-Newton method are used for random coefficients models.

Table B.13: Regular Grade Fuel for Consumer Valuation of Expected Gas Cost Savings

	(1) **IV Logit** **Mean Miles**	**(2)** **IV RCLogit** **Mean Miles**	**(3)** **IV RCLogit** **EPD Miles**
Gas Cost/MSRP			
$\gamma\rho$	13.52	16.35	15.65
	(6.81)	(13.03)	(7.17)
Valuation Factor			
γ (r = 6%, S = 35)	0.93	1.13	1.08
	(0.47)	(0.90)	(0.49)
γ (r = 6%, S = 25)	1.06	1.28	1.22
	(0.53)	(1.02)	(0.56)
γ (r = 4%, S = 35)	0.72	0.88	0.84
	(0.36)	(0.70)	(0.38)
γ (r = 4%, S = 25)	0.87	1.05	1.00
	(0.44)	(0.83)	(0.46)
Implicit Discount Rate (%)			
r (γ = 1, S = 35)	6.61	5.01	5.36
r (γ = 1, S = 25)	5.42	3.57	3.98

Notes: Standard errors in parentheses. RCLogit stands for Random Coefficients Logit Model. EPD is short for Empirical Distribution. The combination $\gamma\rho$ is computed using parameter estimates from the demand estimation. The discount rate is denoted r and S is the maximum car lifetime.

Appendix B.3. Revenue-equivalent Product Taxes

Once a new gasoline tax is applied to the original level τ, the change of total gas tax paid by consumer i driving car v becomes $\rho\frac{m_i}{mpg_v}\tau^g$ over the car's lifetime. The expected revenue from the new gasoline tax over all cars in the choice set per consumer in market t turns to

$$g_{it}(\zeta_{vt}, \tau, \tau^g; \alpha_i, \beta, \beta\gamma\rho^{m_{it}}) = \sum_{v=1}^{J} s_{ivt}(\zeta_{vt}; \alpha_i, \beta, \beta\gamma\rho^{m_{it}})\ \rho\ \frac{m_{it}}{mpg_v}\ (\tau+\tau^g). \quad \text{(B.1)}$$

The revenue generated from the fuel tax in market t is

$$R_t = \int_\theta g_{it}(\zeta_{vt}, \tau, \tau^g; \alpha_i, \beta, \beta\gamma\rho^{m_{it}})\ dF(\theta) I_t. \quad \text{(B.2)}$$

To compute a revenue-equivalent product tax, I derive an equation of expected revenue per consumer over all available car models for the product tax similar to equation B.1 and integrate that to the market-specific total revenue. Algorithm 1 explains this process in details.

Algorithm 1: Compute Tax Revenue

1. Set the new fuel tax and hence the new gas price;
2. Apply the same set of simulated individuals as used for the demand estimation;
3. Load the vector of residual error terms ζ_{vt} obtained from the demand estimation to hold the demand system constant;
4. Simulate new consumer choices given the change in gas prices, and compute the new choice probability for each car in the choice set of individual i;
5. Calculate the expected tax revenue over all cars per consumer using equation B.1, and take an average of the expected tax revenue over all consumers in market t;
6. Multiply the average expected tax revenue per consumer by the number of potential buyers in each market I_t to get the total expected tax revenue in market t as described in equation B.2;
7. Solve for a revenue-equivalent product tax by the market and obtain corresponding individual choice probability vectors.

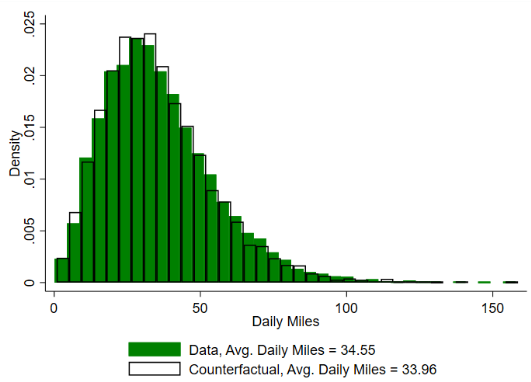
Appendix B.4. Estimate the Elasticity of Driving

Table B.14: The Elasticity of Driving in Mileage Sample

	Fixed Effects with IV
ln(midgrade gas price)	-0.57
	(0.23)
ln(unemployment rate)	-0.21
	(0.11)
ln(national CCI)	1.71
	(1.43)
ln(summer months)	0.91
	(0.20)
ln(months between inspections)	0.05
	(0.03)
Constant	-3.63
	(6.53)
Driver-vehicle FE	Yes
Record-start-year FE	Yes
Record-end-year FE	Yes
R-square	0.04

Notes: The estimation follows Gillingham (2014) and Gillingham et al. (2015). The dependent variable is ln(average daily VMT). VMT stands for vehicle miles traveled. CCI is the Consumer Confidence Index. The number of observational units is 6,377. F-statistic for the first stage regression is 1.5×10^6 when the Brent crude price is used to instrument for local gasoline prices. Values in parentheses are robust standard errors clustered at the MPO level. Gillingham (2014) estimates a medium-run elasticity of driving that equals -0.22 using new vehicle registrations in California during 2001-2003. Gillingham et al. (2015) point out consumer responsiveness became greater in the late 2000s when gasoline prices were rapidly changing. A relatively elastic consumer response estimated from my sample could also be due to within-household switching of vehicles.

Figure B.3: Counterfactual Mileage for Policy Simulations



Appendix C. Theory Appendix

Appendix C.1. Consumer Response to Policy Changes

Plugging new prices into equation 4, the deterministic part of the conditional indirect utility of consumer i for car model v in market t is now

$$\phi_{ivt} \equiv \alpha_i \ x_v + \beta \ (p_v + \frac{\tau^{mpg}}{mpg_v} + \gamma\rho \ \frac{m_{it}}{mpg_v} \ (E[g_t] + \tau^g)) + \zeta_{vt}.$$

The probability of consumer i choosing model v in market t becomes

$$s_{ivt} = \frac{\exp(\phi_{ivt})}{1 + \sum_{v'=1}^{J} \exp(\phi_{iv't})}.$$

To inspect the consumer response to the implementation of a new gasoline tax and a product tax, following Grigolon et al. (2018), I differentiate the individual choice probability with respect to both τ^g and τ^{mpg}. Consumer i's response given the change in gasoline tax is

$$\begin{aligned} \frac{\partial s_{ivt}}{\partial \tau^g} &= s_{ivt} \frac{\partial \phi_{ivt}}{\partial \tau^g} - s_{ivt} \sum_{v'=1}^{J} s_{iv't} \frac{\partial \phi_{iv't}}{\partial \tau^g} \\ &= \beta_i \gamma \rho m_{it} \ s_{ivt} \ (\frac{1}{mpg_v} - \sum_{v'=1}^{J} \frac{s_{iv't}}{mpg_{v'}}). \end{aligned}$$

Similarly, consumer i responds to the product tax by adjusting her choice probability such that

$$\begin{aligned} \frac{\partial s_{ivt}}{\partial \tau^{mpg}} &= s_{ivt} \frac{\partial \phi_{ivt}}{\partial \tau^{mpg}} - s_{ivt} \sum_{v'=1}^{J} s_{iv't} \frac{\partial \phi_{iv't}}{\partial \tau^{mpg}} \\ &= \beta_i \ s_{ivt} \ (\frac{1}{mpg_v} - \sum_{v'=1}^{J} \frac{s_{iv't}}{mpg_{v'}}). \end{aligned}$$