Title

Elasticity of Vehicle Miles of Travel to Changes in the Price of Gasoline and the Cost of Driving in Texas

Author
Wenzel, TP

Publication Date
2023-12-11

Peer reviewed

ERNEST ORLANDO LAWRENCE
BERKELEY NATIONAL LABORATORY

LBNL-2001138

Elasticity of Vehicle Miles of Travel to Changes in the Price of Gasoline and the Cost of Driving in Texas

Tom Wenzel and K. Sydny Fujita

Energy Technologies Area
Lawrence Berkeley National Laboratory
Berkeley, CA 94720

March 2018

This work was supported by the Office of the Director for Energy Policy and Systems Analysis, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

Acknowledgements

We would like to thank those who reviewed earlier drafts of this report, and provided helpful comments and insights: Sarah Garman and Thomas White, Office of Energy Policy and Systems Analysis, U.S. Department of Energy; Kevin Bolon and Michael Shelby, Office of Transportation and Air Quality, U.S. Environmental Protection Agency; and Anna Spurlock of LBNL. Youness Bennani of LBNL provided valuable assistance in matching the EPA certification fuel economy values with the Texas vehicle data.

The report was funded by the Office of Energy Policy and Systems Analysis of the U.S. Department of Energy. We are grateful for their support of this research.

This work was supported by the Office of the Director for Energy Policy and Systems Analysis of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

Executive summary

This report examines the sensitivity of annual vehicle miles of travel (VMT) of light-duty vehicles to the price of gasoline, commonly referred to as the elasticity of demand for VMT to the price of gasoline; the fuel-economy-related rebound effect is generally assumed to be of the same magnitude as the VMT elasticity of gas price or driving cost. We use detailed odometer readings from over 30 million vehicles in four urban areas of Texas, over a six-year period. We account for economic conditions over this period, as well as vehicle age. Following the literature we include fixed effects by vehicle make and individual vehicle, as well as the effect of adding an instrument to predict monthly gasoline price independent of any influences of demand for gasoline on its price.

We estimate that the elasticity of demand for VMT in Texas is -0.09 after accounting for differences in vehicle models: in other words, a one percent increase in the price of gasoline is associated with a 0.09% decrease in annual VMT. Adding variables to account for the median household income or population density of the zip code in which the vehicle is registered, or including an instrument to address potential endogeneity in gas prices, slightly reduces this estimate. Our result suggests that the rebound effect in Texas is slightly lower than that in California and Pennsylvania using similar vehicle-level data.

We find that vehicles registered in zip codes with lower median household income have a larger decrease in VMT associated with an increase in gas prices than vehicles in zip codes with a higher median income. Surprisingly vehicles in zip codes with the lowest population density exhibit the largest decrease in VMT associated with an increase in the price of gasoline, even though we suspect households in such areas have fewer transportation options than the average household. As we expect, vehicles registered in the densest urban areas also are associated with large decreases in VMT induced by gas price increases. Drivers in Austin are more sensitive to increases in gas price than drivers in Dallas or Houston, despite Austin having an overall lower Walk and Transit Scores, and a higher average median income, than Dallas and Houston.

Increases in the price of gasoline are associated with increases in annual VMT for two-door cars, and especially full size vans, but with relatively large decreases in VMT in car-based crossover utility vehicles (CUVs,) and truck-based sport utility vehicles (SUVs), and to a lesser extent in small (compact and ½-ton) and large (3/4- and one-ton) pickups. We suspect that the low fuel economy of the light trucks makes their drivers particularly sensitive to increases in the price of gasoline; this sensitivity may be muted for the large pickups which are often used for specific work-related tasks. However, we were surprised to find that drivers of CUVs are equally as sensitive to high gasoline prices as drivers of light trucks, despite their relatively higher fuel economy. We plan to investigate the extent to which households switch their travel to a different vehicle in response to changes in the price of gasoline in a future analysis at the household level.

For most vehicle types, vehicles with relatively low fuel economy have a larger decrease in VMT in response to an increase in the price of gasoline than vehicles with relatively high fuel economy; the relationship is strongest in CUVs, followed by small pickups/SUVs, with drivers of cars the least responsive to an increase in the price of gasoline. VMT actually increases in large pickups with high fuel economy in response to an increase in the price of gasoline.

Minivans and full vans have the opposite effect of the other vehicle types, where increasing fuel economy results in decreases in VMT; an increase in the price of gasoline is associated with relatively large increases in VMT in full vans, regardless of their rated fuel economy. By effectively decreasing the price of gasoline, fuel economy standards are likely to induce drivers of new, relatively high MPG vehicles to increase their VMT. Our analysis by rated fuel economy suggests that increased fuel economy standards will induce drivers of high MPG vehicles to increase their VMT, by 15% in CUVs, 10% in small pickups and SUVs, 7% in minivans, and less than 1% in cars. We estimate the weighted average VMT increase in new high MPG vehicles to be 5.2%.

Most researchers analyze the VMT elasticity in response to a change in the price of gasoline as a proxy for the response to a change in the cost of driving. We used the rated combined city/highway fuel economy of each vehicle to calculate the cost of driving, in cents per mile, since the vehicle's previous inspection (price of gasoline divided by the vehicle's fuel economy). Across all vehicle types, the average cost of driving was 12.5 cents per mile during our analysis period, with cars having the lowest (10.5 cents per mile), and large pickups the highest (19 cents per mile), average cost of driving. We find that a one percent increase in the cost of driving is associated with a decrease in VMT (0.16% decrease) nearly twice as large as a one percent increase in the price of gasoline (0.09% decrease in VMT), after accounting for vehicle make and model.

Table of Contents

List of Tables

List of Figures

1 Introduction

The U.S. employs joint fuel economy and greenhouse gas emission standards on new light-duty vehicles as a policy instrument to reduce energy use from personal transport.[1] Fuel economy/emission standards trade off an increase in the initial cost of new vehicles (from incorporating mass reduction or other technologies which improve vehicle efficiency) with lower operating costs (from reduced fuel consumption); as a result, the higher initial costs are offset by the future fuel savings after only a few years of operation.

One potential concern regarding new vehicle fuel economy standards is that consumers may respond to the lower per-mile cost of driving by increasing the number of vehicle miles of travel (VMT), thereby delaying the point at which the fuel savings exceed the increased initial cost, and reducing the expected fuel savings and emission reductions of the standards. This phenomenon is referred to as Jevons paradox or the rebound effect. Due to data limitations, the rebound effect is often assumed to be of the same magnitude as the gas price or driving cost elasticity of VMT demand (i.e., a driving cost or fuel price elasticity of -0.2 is commonly taken to imply a fuel economy driven rebound effect of -0.2), as noted in Gillingham (2014).

We analyze a detailed dataset of annual odometer readings of millions of vehicles in Texas over a six-year period to estimate the relationship between retail gas price and VMT demand. This dataset is well-suited to analyze this issue because of the number of vehicles included, and the time series of measurements available. Given that a gas price decrease and fuel economy increase can have an identical impact on the cost of driving, we interpret our findings as a proxy for the extent to which consumers may increase their travel in response to, and reduce the expected benefits of, recent and upcoming fuel economy standards.[2] We merge the detailed vehicle odometer data with vehicle registration records, which provide the address of each vehicle, in order to examine what effect location factors, such as median household income or population density by zip code, have on the elasticity of demand for VMT. We also examine several other factors that may contribute to the rebound effect, including vehicle type and timing of changes in the price of gasoline.

When calculating the cost-effectiveness of the model year 2017 to 2025 standards for light-duty vehicles, NHTSA and EPA assumed a rebound effect of -0.10; that is, for every 1% decrease in the per-mile cost of driving, consumers are expected to increase their miles traveled by 0.10%.

2 Recent estimates of the magnitude of VMT rebound

This section summarizes the recent literature on similar analyses conducted by others, for application to our data from Texas. In this report, we follow the practice of estimating the fuel

[1] The fuel economy standards, known as Corporate Average Fuel Economy (CAFE) standards, are set by the National Highway Transportation Administration (NHTSA) while the greenhouse gas emission standards are set by

[2] We plan to model the effect of a change in the cost of driving on VMT at a later time, after assigning the rated fuel economy for each vehicle in our dataset and calculating the cost of driving in dollars per mile by dividing the price of gas by the rated miles per gallon of each vehicle.

price (or per-mile cost of driving) elasticity of VMT.[3] Numerous previous studies, as discussed below, have noted that a straight-forward regression of VMT on cost of driving as estimated through fuel price changes is likely to produce a biased estimate of the rebound effect associated with a fuel economy increase. Some sources of potential bias can be mitigated through the choice of regression model, while others have to be noted and evaluated qualitatively.

Since the formal introduction of the concept of rebound to energy efficiency (Khazzoom 1980), many researchers have investigated rebound following fuel economy changes in the U.S. private vehicle fleet. Previous estimates of fuel price elasticity primarily fall in the range of -0.10 to -0.80, with the majority of estimates between -0.10 and -0.30 (with the rebound effect assumed to have the same magnitude). Some studies have distinguished between short- and long-run fuel price or driving cost elasticity, or between VMT elasticity and rebound. Actions households can take in response to changes in fuel price in the short-run include changing driving patterns, or reallocating the total VMT of a household among the different vehicles already owned by the household. Long-run responses to changes in fuel price include purchasing a replacement vehicle, or changing home or work location. Studies that distinguish between the short- and long-run responses tend to find a larger impact in the long-run.

We summarize recent estimates of rebound relevant to our work in the following sections. The primary findings from these studies are summarized in Table 2.1.

2.1 State-level data

Small and Van Dender (2007) estimate rebound using pooled cross sectional annual data of U.S. states for the period of 1966-2001 (later updated through 2009 in Hymel and Small (2015)). Their use of two- and three-stage least squares simultaneous aggregate demand modeling for VMT, vehicle stock, and fuel economy allow them to account for endogenous changes in fuel efficiency.[4] Additionally, they distinguish between autocorrelation and lagged effects, include a measure of the stringency of fuel-economy standards, and allow their estimate of the rebound magnitude to vary with household income, degree of urbanization, calculated fuel cost per mile, and retail gas price. While their choice of model specification and their underlying data are quite different from what we are currently working with, Small and Van Dender's (2007) study provides useful insights into sources of potential bias and connections between variables. In particular, Small and Van Dender (2007) note that ignoring the dependence of fuel economy on fuel price may cause the rebound effect to be overestimated if unobserved factors that cause VMT to be large (e.g. an unusually long commute) also cause fuel economy to be high (e.g. commuter chooses fuel-efficient vehicles to reduce their commute costs), as also discussed in Goldberg (1998) and West (2004). Small and Van Dender (2007) also address the impact of the built environment at the state level on VMT, including the variables "adults/road-mile" (a

[3] In future work, we plan to separately estimate a coefficient on fuel economy or to perform the analysis with fixed effects for fuel economy.

[4] Endogeneity occurs when the independent or an explanatory variable of interest is correlated with the model error term. In our context that would occur if, when regressing VMT on fuel price, there is some factor that is not observed or controlled for in the model that is correlated with both VMT and fuel price. If unaddressed, the estimated coefficient on fuel price is likely to be biased.

measure of traffic congestion) and "fraction of population served by rail transit" in their system of equations. Hymel et al. (2010) is an extension of Small and Van Dender (2007), which adds a fourth equation accounting for the interrelationship between travel and congestion; the resulting estimate of the rebound effect was found to remain similar to that found in Small and Van Dender (2007).

Hymel and Small (2015) revisit the simultaneous-equations methodology of Small and Van Dender (2007), adding data through 2009 to evaluate any differences between the 2000s and the time period analyzed in the original study. The tumultuous gas market of the 2000s provides ideal data to test the symmetry of consumer response to changes in the cost of driving. Of note, they find that the price elasticity of VMT is much greater in magnitude in years when gasoline prices are rising than when they are falling. Since light-duty vehicle standards would be expected to lower the cost of driving, this would suggest that the lower estimate of the price elasticity of VMT would likely be the appropriate elasticity to use when analyzing the impacts of light-duty vehicle standards. Additionally, Hymel and Small (2015) test the hypothesis of the correspondence of VMT response to driving cost changes induced by fuel price changes versus fuel economy changes. Gillingham (2011) and Greene (2012) also find that changes to fuel economy have a lesser impact on miles driven than do changes to fuel price. Looking at the timing of VMT response to fuel price changes, Hymel and Small (2015) find that response to price rise is quick (i.e., largest in year of and year following the change) and adjustment following a price drop occurs more slowly (i.e., small in year of and larger in year following the change). This suggests that there is some "stickiness" in consumer behavior that could potentially mitigate rebound following a fuel-economy-driven decrease in the cost of driving. This notion of VMT "inertia" is also supported by findings of Knittel and Sandler (2013) and Molloy and Shan (2013).

Greene (2012) uses U.S. time series data (1966-2007), aggregated to the level of total light-duty vehicles due to data source constraints, to investigate rebound associated with increasing fuel economy. Greene tests for but does not find evidence of simultaneity bias among his measures of VMT, gas price, and fuel consumption, so his primary model specifications are log-linear and log-log regressions without instrumental variables. Due to the importance of CAFE standards in shaping the trajectory of manufacturer-provided fuel economy options, Greene includes a measure of the stringency of CAFE in his models. Greene also tests the use of a lagged dependent variable, based on the notion that fleet fuel economy is largely locked-in in the short term. Greene notes that when fuel economy increases due to regulation, it comes at an increased capital cost, which, if included in drivers' assessments of the total cost of driving, will potentially mitigate rebound.

Fairly uniquely among the literature, Greene's findings allow him to reject the hypothesis that elasticity of gas price is equal to elasticity of fuel consumption at sample means (i.e., the driving response to a fuel economy increase is not equal but opposite to the response to a gas price increase). Combining this finding with the insignificance of his models' coefficients on fuel consumption, Greene concludes that, analyzed at the level of the aggregate U.S. light-duty fleet, VMT is not subject to direct fuel economy-related rebound.

2.2 Micro (individual vehicle) data

Linn (2013) uses the Department of Transportation's 2009 National Household Travel Survey (NHTS) to estimate VMT elasticity and long-run rebound, based on detailed travel diaries conducted by tens of thousands of households. The 2009 NHTS extrapolates annual VMT based on self-reported VMT on the day of the travel diary. Linn identifies three common modeling assumptions that he aims to relax in his analysis: 1) fuel economy is uncorrelated with other vehicle attributes, 2) fuel economy of vehicles in a household's fleet are uncorrelated with each other, and 3) the rebound effect is the same magnitude as VMT gas price elasticity. Linn (2013) expands a simple log-log regression model, initially estimating VMT as a function of driving-cost-per-mile, to a log-log regression measuring separate coefficients on fuel price and fuel economy, as well as including vehicle model fixed effects, instruments for vehicle fuel economy, demographic variables, and the average fuel economy of a household's other vehicles. After decomposing the cost-per-mile variable in this way, he arrives at a higher estimate of long run rebound in the range of -0.20 to -0.40.[5] Linn (2013) notes that controlling for the fuel economy of other vehicles owned by the household reduced the estimated magnitude of the rebound effect for multi-car households.

Leung (2015) explores the role that VMT allocation across a household's fleet can play in the overall demand response to a gas price increase. This is a unique approach, as compared to others who consider potential changes to fuel economy only via new vehicle purchase (long-run) or altered driving behavior of a constant vehicle (e.g., shift to more highway and less city miles driven, less aggressive acceleration). Leung uses National Household Travel Survey data to evaluate differences between annual average daily household driving and the day captured in a 24-hour travel diary for each household (specifically, total household VMT, total fuel consumption, average MPG). His model specification allows him to decompose household decreased demand for gas in response to gas price shock into: 1) changes to VMT, 2) changes to fuel economy or MPG (via a household reallocating its VMT to a different vehicle with a different MPG). Leung finds that gas price is positively correlated with fuel use and VMT, and negatively correlated with MPG; elasticities for the full sample are: gasoline use (-0.11), VMT (-0.09), and MPG (0.02). These elasticities imply that 17 percent of the fuel use elasticity can be attributed to increases in average MPG, a consideration that is generally not accounted for in the literature. Leung also finds significant differences for heterogeneous/homogenous fleets (heterogeneous fleets demonstrate more switching with greater gains from switching), urban/rural (rural have higher VMT elasticity and a higher MPG elasticity and decrease VMT proportionally more than urban), income groups (low income households were twice as responsive as other households in fuel use and more than twice as responsive in terms of VMT), and trip composition (high gas prices do not substantially alter number of trips, but do decrease trip length).

Knittel and Sandler (2013) discuss the VMT elasticity to gas price in the context of the gas tax as an emission reduction policy tool, looking at CA light duty vehicles over the period of 1998-2008. They begin with a log-log regression model, include time, vehicle age, and location fixed

[5] Note that this appears to run counter to the Gillingham (2011) and Greene (2012) findings of a smaller response of VMT to fuel economy as compared to gas price.

effects, and add make-model and individual vehicle fixed effects in subsequent runs. From the model specification including individual vehicle fixed effects, they estimate a VMT elasticity of -0.15. Aiming to reveal any underlying heterogeneity in VMT elasticity, they note the yearly quartile into which each vehicle falls based on its emissions, fuel economy, and weight; they include a linear interaction of the percentiles of these variables and the log of gasoline prices in their regressions. Knittel and Sandler (2013) also examine three vehicle age groups (4 to 9 years old, 10 to 15 years old, and 16 to 27 years old), finding that middle-aged and older vehicles are more elastic than new vehicles on average, though within each age bin, there is still substantial heterogeneity. Knittel and Sandler (2012) used odometer readings from thirteen years of California emissions inspection test result data to investigate whether the cost of driving (in dollars per mile, calculated as the gasoline price divided by the MPG rating) influences the fuel economy of vehicles that are scrapped (extensive margin) or the miles per day vehicles are driven (intensive margin). Knittel and Sandler model the natural log of daily vehicle miles of travel (VMT) as a function of the natural log of the cost of driving (DPM), a dummy variable for whether the vehicle is a light-duty truck, and fixed effects for the calendar year and month of measurement, vehicle age, and the vehicle owner demographics (using zip code where the vehicle is registered). They use three different fixed effects to capture differences in vehicles: vehicle make, vehicle model year/make/model, and individual vehicles. They also investigate whether VMT varies by the rated fuel economy of vehicles, using rated fuel economy quartiles. They find that accounting for vehicle make reduces the VMT elasticity from -0.40 to -0.14, and ranges from -0.29 for vehicles with the lowest fuel economy (16.7 MPG) to -0.15 for vehicles with the highest (30.3 MPG). Accounting for individual vehicles increases the overall VMT elasticity to -0.26, ranging from -0.31 to -0.20 based on fuel economy.

Gillingham (2014) combines registration and emission inspection data for approximately 5 million California vehicles purchased between 2001 and 2003. One limitation of these data is that California requires vehicles to be inspected every other year, so the effect of changes in gas prices on VMT is muted. Vehicles are required to be inspected starting six years after initial registration (or at the time of resale for vehicles four years old or older). Odometer readings from the first inspection for this set of vehicles were combined with information on vehicle types, county-level demographics, and when possible, consumer income data (in the cases where the buyer applied for a loan during the vehicle purchase process). Gillingham's primary model is a log-log regression incorporating county fixed effects (time-invariant differences in driving necessity across counties) and month-of-year-of-purchase fixed effects (assuming that different types of consumers may purchase vehicles at different times of year).

Gillingham (2014) also investigates the VMT elasticity implications of various types of consumer heterogeneity. He performs quantile regression and k-means cluster analysis to compare estimated rebound differences across specific subsets of vehicles and drivers in his data. He finds that responsiveness increases with the median household income by zip code, starting at about -0.22 for lower brackets, peaking at -0.45 for $75-100k/year, and then dropping back to -0.40 for the wealthiest drivers. It is suspected that high elasticity at higher incomes relates to several interconnected factors: wealthier households having more discretionary driving; wealthier households may be more likely to switch from driving to flying for long trips; wealthier households tend to own more vehicles (i.e., within-household fleet switching is a likely response to fuel price change). Based on the heterogeneity in VMT elasticity that his models reveal, Gillingham (2014) points out the importance of awareness of the differential effectiveness of greenhouse gas reduction policies and distributional differences in policy impact across groups of drivers.

Gillingham et al. (2015) apply similar techniques to those of Gillingham (2014) to a dataset composed of Pennsylvania registration and annual emissions inspection records from 2000 to 2010, combined with demographic and geographic information. The dataset includes odometer readings, zip codes, and extensive vehicle characteristics. From their primary model specification (a log-log regression incorporating fixed effects), they estimate a short-run gasoline price elasticity of driving demand of -0.10, which they note is consistent with the Knittel and Sandler (2013) estimate of a "two-year" gasoline price elasticity of driving for all but the newest vehicles of -0.15.[6]

As in Gillingham (2014), they explore heterogeneity of elasticity across groups of vehicles and drivers, finding that quantile regressions by elasticity (using a randomly drawn sample of 10%) reveal a high percentage of vehicles are largely inelastic to gasoline price changes, and the aggregate elasticity estimate is strongly influenced by low fuel economy (less than 20 miles/gallon highway) and mid-age (3 to 7 year old) vehicles. Among key findings, Gillingham et al. (2015) state that one of their study's primary contributions to the literature is establishing support for the notion that the price elasticity of VMT and the rebound effect may be heterogeneous and relatively close to zero in the short run.

2.3 Difference-in-difference analysis

De Borger et al. (2016) analyze Danish odometer data for 350,000 individual vehicles over a ten-year period, including very detailed information on each household (i.e., income, education level, number and ages in household, employment status, commute distance, etc.).[7] Uniquely among the papers we have reviewed, this analysis focuses on the effect of changes in fuel economy on annual VMT, holding gas prices constant (rather than inferring rebound using the gas price demand elasticity). This is the most relevant model specification in the context of estimating what degree of VMT rebound to anticipate in the case of new fuel economy/emission standards.

The authors examine only those households that owned exactly one vehicle over the entire time period; over 90% of households in Denmark own only one vehicle, so this restriction does little to limit their data set and remains representative of the majority of the study population. De Borger et al. (2016) use a difference-in-difference approach to identify the impact of a change in fuel economy on household VMT. Households that do not replace their vehicle act as a control group on the effect of changes in gas prices (and other broad economic factors) on VMT. The effect of changes in vehicle fuel economy on VMT can be estimated by comparing the change in VMT over the course of the study period of the households that do not replace their vehicle

---

[6] Considering the differences in location (California versus Pennsylvania), this estimate of the short-term (i.e. one-year) elasticity is not inconsistent with the -0.22 medium-term (i.e. two-year) elasticity estimated by Gillingham (2014).

[7] Note that this study was conducted in Denmark, so the magnitude of rebound found by De Borger et al. (2016) may not be directly applicable to the U.S. However, the techniques employed remain of interest to us.

versus those that do replace their vehicle (i.e., the *difference* in VMT *difference* over time and across household types).

Table 2.1. Recent estimates of VMT elasticity or magnitude of the rebound effect

Paper	Values	Notes
Small and Van Dender, 2007	-0.045 short run, -0.222 long run at sample averages; -0.022 short run, -0.107 long run at 1997-2001 average values	US state-level data
Hymel and Small, 2015	-0.178 long run Price falling: -0.04 long run Price rising: -0.04 to -0.25 long run 2000 - 2009 average values	US state-level data
Linn, 2013	-0.20 to -0.40 long run	US National Household Travel Survey
Knittel and Sandler, 2012	-0.14 to -0.40 long run	CA emission inspection and registration data
Knittel and Sandler, 2013	-0.15 medium run across sample, but variation by vehicle type	CA emission inspection and registration data
Gillingham, 2014	-0.22 medium run at sample average; by quantile: -0.33 lowest, -0.24 middle, -0.17 highest	CA emission inspection data
Gillingham et al, 2015	-0.10 short run	PA emission inspection data
De Borger et al., DeBorger et al, 2016	-0.075 to -0.10 short to medium run	Denmark microdata

2.4 Response to gas taxes

Li et al. (2012) use state level annual data to explore the consumer response to gasoline taxes as distinct from total retail gas prices, relaxing the common assumption that consumers react to changes in gas taxes the same way they react to changes in gas price (i.e., gas price elasticity and gas tax elasticity are often assumed equal). Li et al. identify two key reasons to expect a differential consumer reaction to gas taxes as compared to gas price changes driven by underlying oil prices: persistence (new gas taxes will remain in effect for the foreseeable future; oil prices fluctuate) and salience (media coverage of gas tax changes is substantial). They track three variables to reflect consumer response to gas tax and total price changes: VMT, gas consumption, and fuel economy. Li et al. estimate the gas price elasticity of VMT demand at -0.39 in the short run, -0.27 when the gas tax is excluded.[8] We note that their estimate of consumer response to an increase in the gas tax is three times as large as other researchers' estimates of consumer response to an increase in the price of gas, supporting Li et al.'s suggestion that consumers respond differently to gas price and gas tax signals.

[8] Note that we cannot use our Texas microdata to address this issue because the Texas state tax rate on motor fuel ($0.20/gallon) has been in place since 1991 and does not change during our analysis period (http://www.fhwa.dot.gov/policyinformation/statistics/2011/mf121t.cfm)

2.5 Gasoline demand elasticity

While not directly analyzing rebound or VMT elasticity, Levin et al. (2013) investigate the related issue of very short run consumer price response to gas price, using credit card expenditures on gasoline aggregated across all consumers in a metropolitan area (i.e., own-price elasticity of gasoline demand). Using daily variation across 243 U.S. cities over approximately 3 years, they find a daily price elasticity of demand for gasoline of -0.30 to -0.47. While it is important to note that daily gasoline purchase decisions and daily VMT decisions are not perfectly aligned, this paper provides an estimate of elasticity at a higher level of temporal granularity than is commonly investigated. Levin et al. also estimate gas price elasticity at differing levels of spatial and temporal aggregation, finding that elasticity estimates decrease in magnitude as time steps or geographical units increase in size, finding a national monthly price elasticity of -0.13.[9] Based on this finding, Levin et al. posit that the tendency of researchers to use aggregated data sets (e.g. monthly or annual data at the state or national level) could lead to a downward bias in estimates of the price elasticity of gasoline demand.[10] Of additional interest, Levin et al. explore the role of persistence of price changes, finding strongest responses in the day following a price increase, a return almost to the original level within the next few days; price response becomes slightly stronger (though not to the degree of the one-day impact) ten to twenty days after the change. This adjustment after ten to twenty days could plausibly reflect driver adaptations such as altering VMT or relying more heavily on a particular vehicle in a household's fleet. Daily gasoline purchases allow Levin et al. to examine price elasticity of demand for gasoline at extremely short time scales; however, the data do not allow analysis of elasticity of individual vehicles, nor the effect of vehicle type or age on VMT.

Lin and Prince (2013) examine the role of gas price volatility in consumers' price elasticity of demand for gasoline, finding that during periods of high price volatility, consumers are less responsive to a given shift in price as compared to an identical price shift during a period of low price volatility. Applying a dynamic model to national monthly gas price and per capita gasoline demand between 1990 and 2012, Lin and Prince estimate a gas price elasticity of -0.03 to -0.24 when gas price variance is high and from -0.04 to -0.29 when gas price variance is low. Given that the Texas microdata we use cover the same period of extreme gas price volatility, applying general insights from Lin and Price suggests that we may arrive at an estimate of the lower bound on gas price elasticity of VMT.

3 Data and methods

In this section we describe the data we used in our analysis, and the analysis methodology.

[9] This national-level estimate (or the state-level monthly estimate of -0.295) is likely to be most appropriate for comparison to our own work, although we again note that a distinction must be made between the gas price elasticities of gasoline demand and VMT demand.

[10] In terms of takeaways for our current work, this suggests that we ought to explore the time-step and geographic information available in our Texas microdata (e.g., month as opposed to year; fixed effects by ZIP code), as well as remaining aware that our estimate of gas price elasticity of VMT demand may be lower than if our data included more frequent odometer readings.

3.1 Data

In order to perform our analysis, we merged detailed data on light-duty vehicles up to 10,000 pounds gross vehicle weight rating (GVWR)[11] in Texas with Texas retail gas prices over time, as well as numerous control variables, as described in Table 3.1. We include variables for the population density and the median household income of the zip code in which the vehicle was registered; a variable for economic conditions, the monthly unemployment rate in Texas; vehicle age; and dummy variables for the month and calendar year in which the inspection occurred.

Table 3.1. Variables included in regression models

Price of gasoline	LNPRICE05	Natural logarithm of the average price per gallon since last inspection ($2005 per gallon; from Texas Regular All Formulations Retail Gasoline Prices, EMM_EPMR_PTE_STX_DPG, http://www.eia.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_dpgal_m.htm)
Unemployment rate (U)	LNUERATE	Natural logarithm of average unemployment rate since last inspection (Bureau of Labor Statistics, Texas Statewide, Seasonally Adjusted)
Income (D)	LNZIPINC	Natural logarithm of average median household income in zip code (000s; from 2000 U.S. Census)
Density (D)	LNZIPDEN	Natural logarithm of average population density in zip code (population/acre) in zip code (000s; from 2000 U.S. Census)
Vehicle age (V)	LNVEHAGE	Natural logarithm of vehicle age, in years (Year of inspection – MY + 1)
	VEHAGEMOS	Vehicle age in months, based on the month of the current emission inspection, assuming each vehicle placed in service October 1 of its model year
	LNVEHAGEAVG	Natural logarithm of midpoint between VEHAGEMOS and VEHAGEMOS at previous inspection
	MONTH	Month of inspection (1 to 12)
	MON1-MON12	Dummy variable for month of inspection, with MON6 (June) as the default
Calendar year	CY05-CY10	Dummy variable for calendar year, with 2008 as the default

We obtained over six years of emission inspection results from the vehicle information database (VID) data from the Texas emission inspection and maintenance (I/M) program, from January 2005 through December 2010. Emissions inspections are required every year in Texas, starting when a vehicle is two years old, in the seventeen counties surrounding Austin, Dallas, El Paso, and Houston; an annual safety inspection is required for all other vehicles registered in the state.[12] The dataset includes the full 17-digit vehicle identification number (VIN), which can be used to determine vehicle year, make and model, as well as the odometer reading at the time of inspection. We subtract the odometer reading from the previous inspection by the odometer reading in the current inspection, divide by the number of days between annual inspections, and multiply by 365.25 days to estimate the annual VMT for each vehicle. During the inspection the

[11] For regulatory purposes EPA and NHTSA define light-duty trucks as pickups with a GVWR of less than 8,500 pounds, but SUVs and full size vans with a GVWR of less than 10,000 pounds.

[12] The safety inspection data are collected by the Texas Department of Public Safety (DPS). These data are available in electronic format starting in 2008; however, DPS only retains historical records for the previous 26 months. These data will be used to analyze average VMT of vehicles outside of the Texas I/M areas in a future analysis.

vehicle odometer is read visually and entered into the computer system by the test technician; as a result, it is possible that the odometer reading is misread. We exclude vehicles with an estimated annual VMT of zero or less than zero (3.0% of the sample), or greater than 50,000 miles (1.3% of the sample), under the assumption that at least one of the odometer readings was recorded incorrectly.

For our initial analysis we included pickup trucks between 8,500 and 10,000 pounds GVWR; however, since these vehicles are not considered light-duty vehicles by NHTSA or EPA, in subsequent analyses we excluded these pickup trucks.

We also obtained seven snapshots of the Texas Department of Motor Vehicles registration database, including vehicle owner name and address, in January of 2005 through 2011. We merged the odometer readings with the DMV registration records based on the VIN. We also merged population density and median household income by zip code from the 2000 U.S. Census.

Our dataset includes VMT records on 32,179,232 vehicles that meet the following criteria: 1) calculated annual VMT was greater than zero but less than 50,000 miles; 2) age was between two and fifteen years; 3) registered in zip codes in Texas; 4) emissions inspection occurred between January 2005 and December 2010.

We analyze data from the 17 counties included in the emissions inspection program, which comprise the metropolitan areas of Austin, Dallas, El Paso, and Houston. Figure 3.1 shows the cumulative distribution of population in 2000 in Texas by the population density in each county. Nine of the 11 most urban counties are included in the emission inspection program; the remaining two most urban counties, Bexar and Gregg Counties, are in the San Antonio metropolitan area. The 17 counties included in this analysis (indicated by open squares in Figure 3.1) accounted for just over half of the total population in Texas in 2000.[13] The 17 counties included in our analysis accounted for nearly 60% of the population and the vehicle population in Texas in 2013.

---

[13] Odometer readings from vehicles registered in the remaining counties of Texas are available from the state Department of Public Safety, which performs a similar annual safety inspection; however, those data are only available going back to July 2010. We plan to analyze the odometer data from the vehicle safety inspections in the future, to understand how gas prices affect driving in more rural areas of Texas.

Figure 3.1. Cumulative distribution of Texas population by county population density

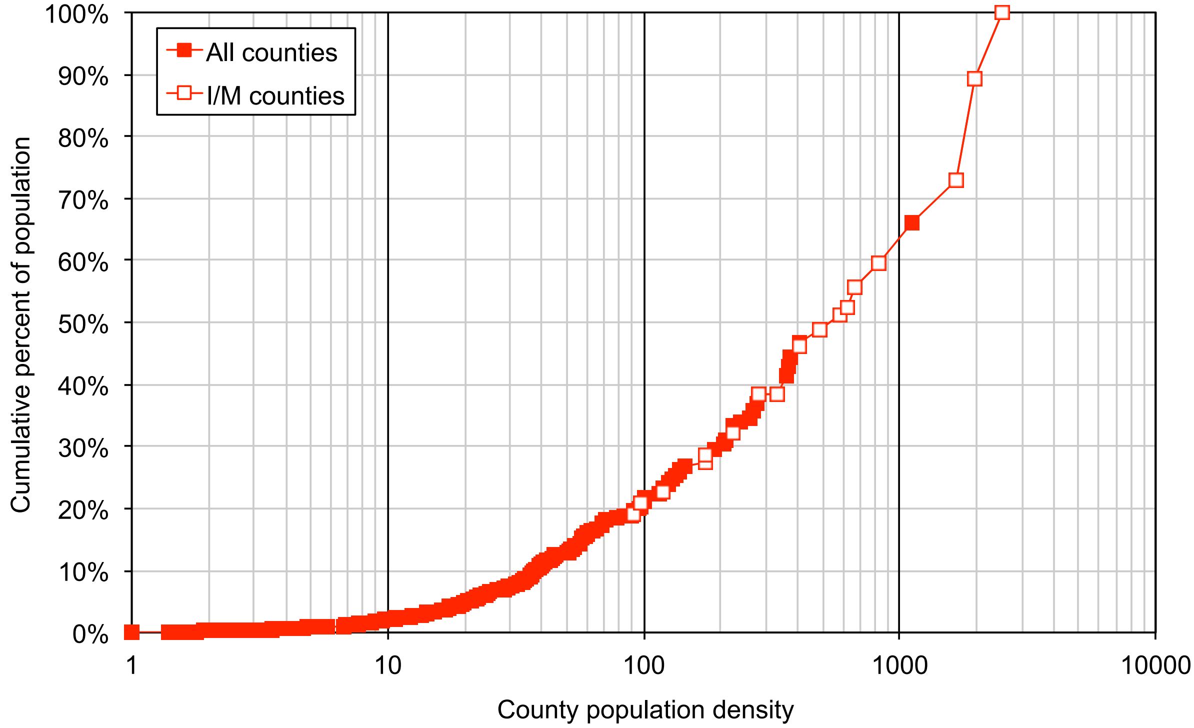


Figure 3.2 and Figure 3.3 compare the actual monthly price of gasoline (Figure 3.2) and unemployment rate (Figure 3.3) with the average values faced by each vehicle since its previous inspection, normalized to that value in January 2005. The figures indicate that there is a lot more month-to-month variation in the monthly data than in the average values (approximately annual) faced by each vehicle since its previous inspection, especially for the price of gasoline. Figure 3.2 indicates that the price of gasoline increased consistently from $1.50 per gallon in January 2005 to $4.00 per gallon in November 2008, an 88% increase, with two intervening declines in late 2005 to early 2006, and mid-2006 to early 2007. The price then declined to a low of $1.50 per gallon in November 2009, then increased again to $3.00 per gallon by February 2011. Figure 3.3 indicates that the unemployment rate decreased from just over 6.0% in January 2005 to a low of 4.3% in March 2008, then rapidly increased to a high of over 8.0% in July 2009 before beginning to decline slightly.

Comparing Figure 3.2 and Figure 3.3 indicates that as gasoline price increased the unemployment rate decreased, until late 2008 when gasoline price decreased and the unemployment rate increased. There is a small period of time, between roughly late 2009 and early 2010, when both gasoline price and unemployment rate increased.

Figure 3.2. Texas monthly gasoline price and log of average since previous inspection normalized to January 2005

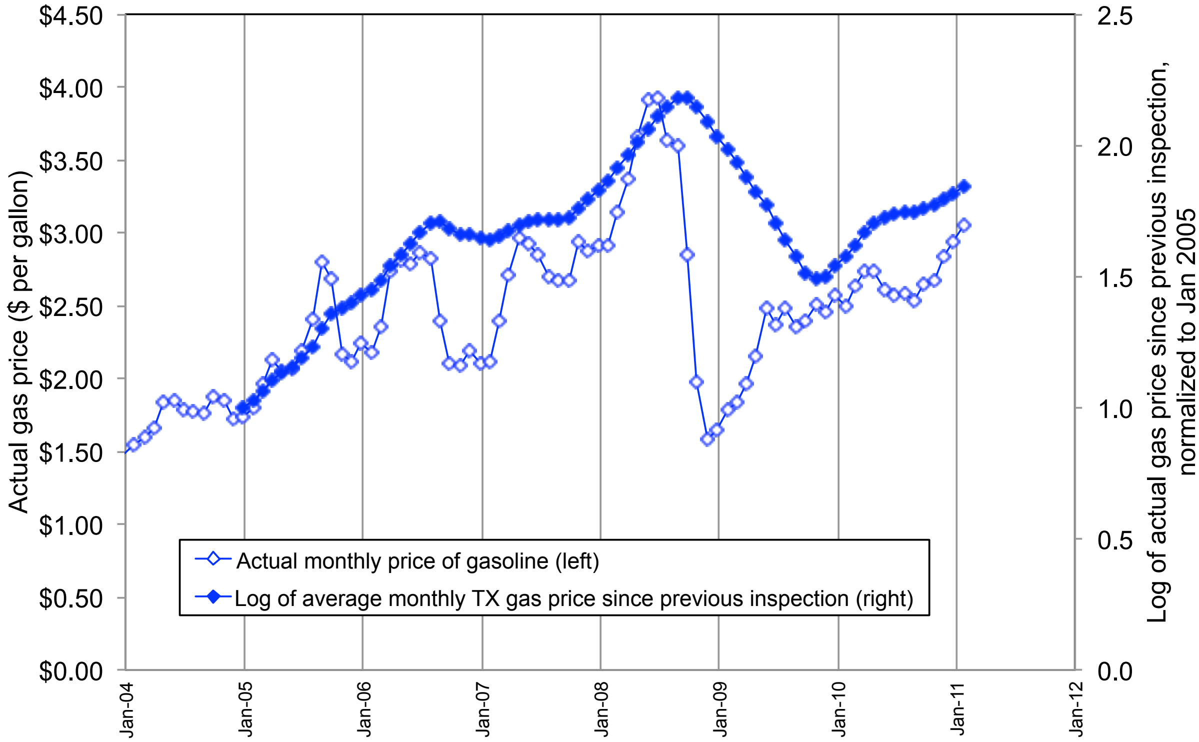


Figure 3.3. Texas monthly unemployment rate and log of average since previous inspection normalized to January 2005

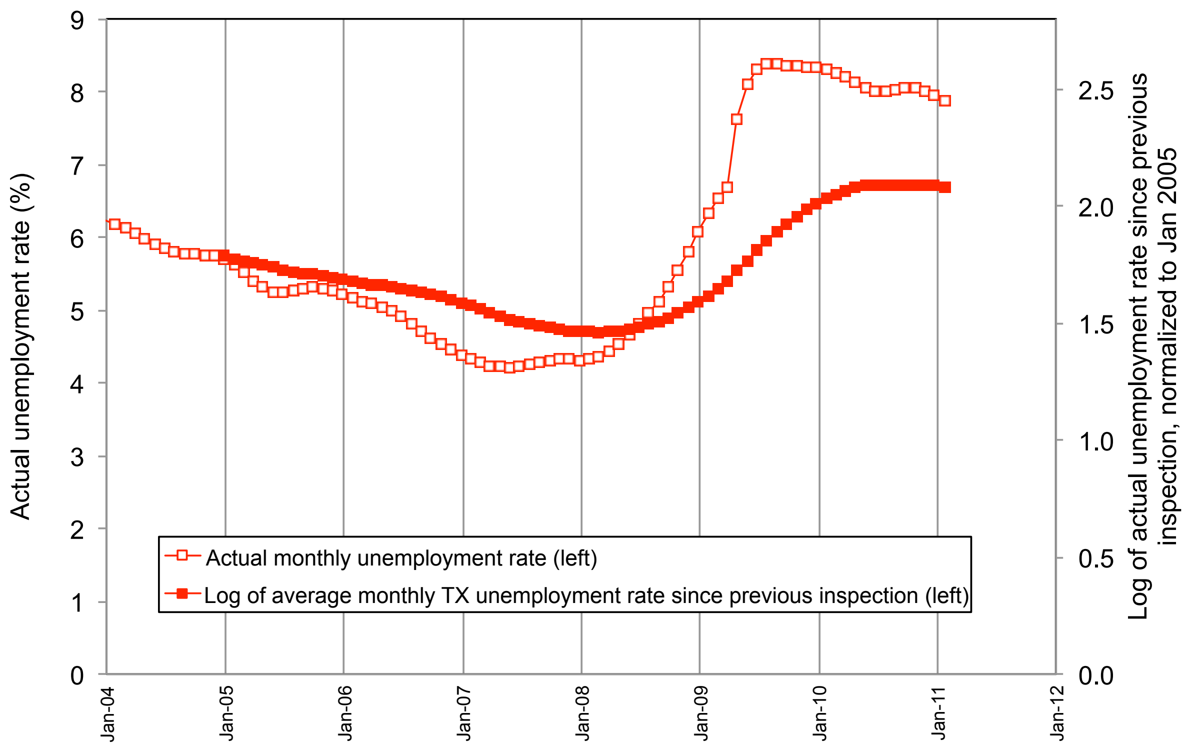


Figure 3.4 shows the average annual VMT by year between 2005 and 2010, for a MY02 car. For cars of a given model year, average annual VMT decreases as vehicles age; reading down the curve for MY02 cars, average annual VMT decreases between 500 and 1,000 miles every successive calendar year. However, there is much less fluctuation in average annual VMT for cars of a given age; average annual VMT is fairly constant for 4- and 7-year old cars (both shown in green) over time. Note that in Figure 3.4 the average VMT of a MY02 car (in gold) matches the average VMT of a 4-year old car in 2005, and that of a 7-year old car in 2008 (both in green).

Figure 3.5 indicates that, on average, annual VMT also decreases by month of the year; for example, a 2002 vehicle tested in December 2009 was driven almost 500 fewer miles on average since its last inspection than a 2002 vehicle tested in January 2009. Similarly, a 4-year old car tested in December 2008 was driven almost 500 fewer miles on average since its last inspection than a 4-year old car tested in January 2008. The exception tends to be vehicles tested in the last few months of the year; it is not clear why these vehicles have slightly higher VMT than those tested one or two months earlier in a given year. As in Figure 3.4, the average VMT of a MY02 car (in gold) matches the average VMT of a 4-year old car in 2005, and that of a 7-year old car in 2008 (both in green).

Note that we define vehicle age as the calendar year minus the model year; we do not know the month in which an individual vehicle was first placed into service, and therefore its actual age in months. Initially the month of inspection indicates when the vehicle was first registered and placed into service. However, over time the month of inspection for an individual vehicle in each subsequent year can vary from the month of initial registration, for several reasons. First, an additional inspection is required when a vehicle is sold, which resets the month of subsequent annual inspections. And the first month of inspection/registration does not correspond to the month in which the vehicle was purchased for vehicles that were registered in Texas after being moved from another state. Nearly two-thirds of the vehicles in our dataset are from model year 2002 or older, whose initial inspection occurred prior to 2005, the first year of our dataset. Of the remaining vehicles, half were tested in the same month as their initial inspection, and 40% were tested in a different month; 10% had their initial inspection test after they were four years old, which indicates that they were moved into Texas after their initial registration in another state.[14] Therefore, for the majority of vehicles (half of 2003 and newer vehicles, and 82% of all vehicles), the month of inspection does not reflect the month of initial purchase. Rather, the month of inspection is a rough measure for vehicle age: vehicles tested in December 2005 are on average eleven months older than vehicles tested in January 2005.

[14] For vehicles that were initially registered in Texas, 88% of all three-year old vehicles were tested in the same calendar month as their initial inspection one year earlier. However, the percentage tested in the same calendar month consistently declines over time to only 15% of all eight-year old vehicles that were initially registered in Texas.

Figure 3.4. Average vehicle miles of travel since last annual inspection, by year

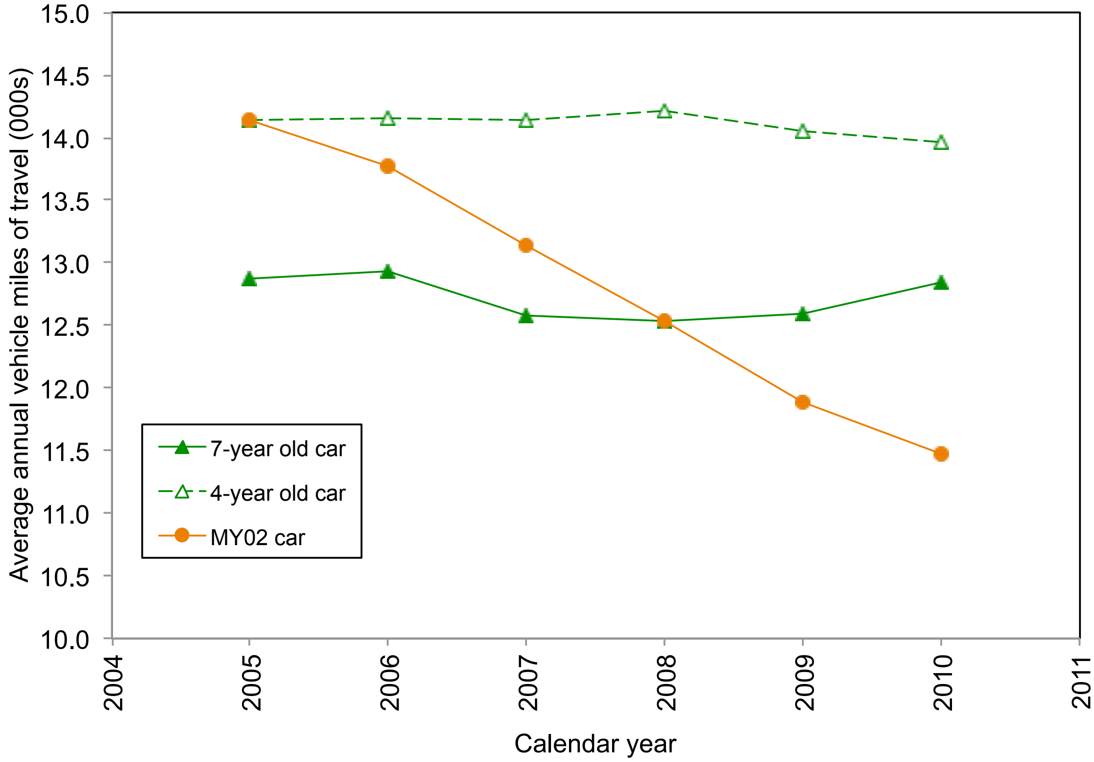
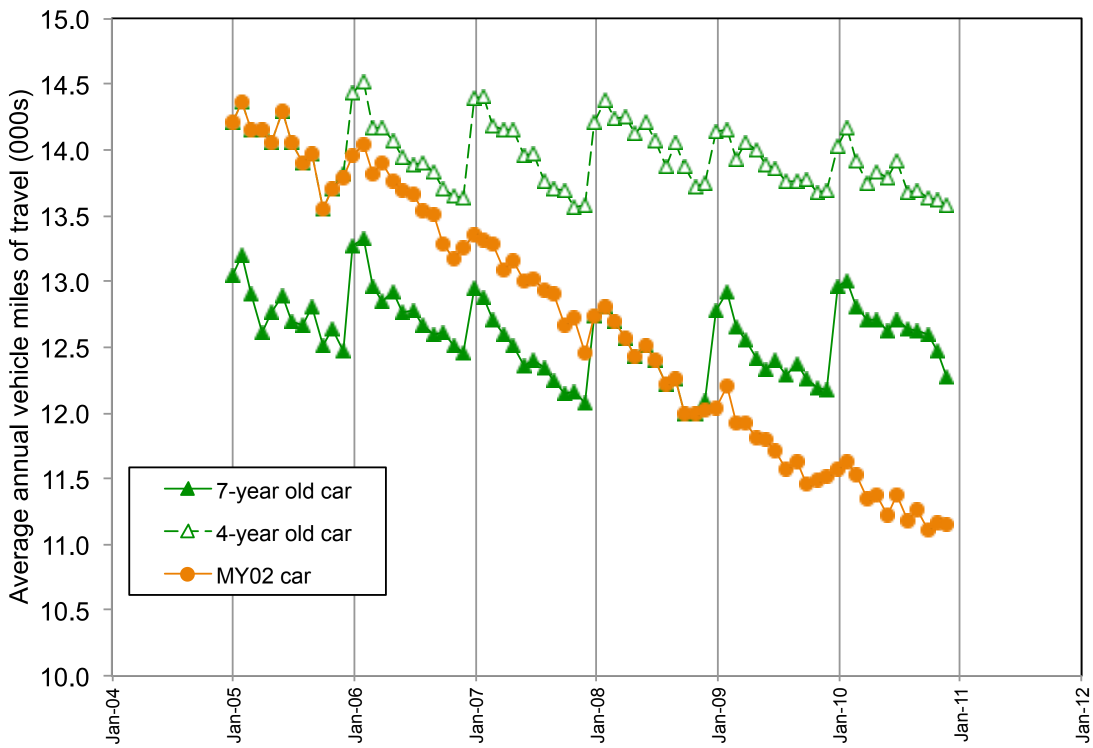


Figure 3.5. Average vehicle miles of travel since last annual inspection, by month



Gillingham et al. (2015) accounted for vehicle age using a continuous variable in years, comprised of the calendar year of the inspection minus the model year, and added a second term where this value was squared.[15] We tested three measures of vehicle age on VMT: 1) discrete dummy variables for the age in years, based on the formula: test year – model year +1; 2) the discrete age in years and a continuous variable for the month the vehicle was tested (ranging from 1 to 12); and 3) the discrete age in years and discrete month variables. We included all vehicles between 2 and 15 years of age in our analysis. We also included discrete dummy variables for each calendar year between 2005 and 2010 (with 2008 as the default).

3.2 Methods

To estimate the gas price elasticity of VMT demand, we move through a sequence of increasingly rigorous regressions: ordinary least squares (OLS) with vehicle model or individual vehicle fixed effects, and two stage least squares (2SLS) with make-model or individual vehicle fixed effects.

3.2.1 Ordinary least squares (OLS) regression model

We begin our analysis of the effect of gas price on VMT by specifying several ordinary least squares regression models. The simplest of these models uses only gas price to explain VMT variation, while additional specifications include vehicle age, calendar year, and economic and demographic variables.

The ordinary least squares models are broadly defined as follows:

$$VMT_{it} = \beta_0 + \beta_p p_t^g + \boldsymbol{\mu U_t} + \boldsymbol{\alpha V_{it}} + \boldsymbol{\delta D_i} + \varepsilon_{it}$$

Where:
VMT_{it} = vehicle miles traveled,
p_t^g = monthly TX gas retail price variable,
$\boldsymbol{U}_{t}$ = monthly TX unemployment rate,
$\boldsymbol{V_{it}}$ = vehicle age,[16]
$\boldsymbol{D_i}$ = demographic variables (population density and median household income by zip code),
ε_{it} = residual,
i = vehicle index (unique VIN), and
t = time index (month).

The coefficient β_p provides a naive estimate of the gas price elasticity of VMT demand. However, this estimate is quite likely to be biased. We run variations of this regression model where we control for vehicle make-model and individual vehicle fixed effects, as discussed below.

[15] They also ran three separate regressions for one of three vehicle ages: less than three, three to seven, and greater than seven years old, which accounted for 6%, 33%, and 50% of the total sample of vehicles.
[16] Vehicle age is represented either as a continuous variable in years or months, or as discrete year and month dummy variables, in different model specifications.

3.2.2 Fixed effects

Fixed effects are used to control for anything unobserved about a unit of observation, such as a given vehicle make-model or a given vehicle, that doesn't change over time but may vary across units. Make-model fixed effects will control for any time invariant factors associated with each make-model that influence VMT, allowing the coefficient on gas price in the regression model to isolate the variation in VMT response to gas price over time within each make-model combination, averaged across all make-model combinations in the dataset. VIN fixed effects achieve a comparable impact in terms of holding constant all time-invariant factors associated with an individual vehicle.[17] This can also be accomplished by demeaning all of the variables within each unit of observation (e.g., make-model or VIN), or equivalently, adding a dummy variable for each make-model, or each individual vehicle, as appropriate.

The ordinary least squares models with fixed effects are defined as follows:

$$VMT_{it} = \beta_0 + \beta_p p_t^g + \boldsymbol{\mu U_t} + \boldsymbol{\alpha V_{it}} + \boldsymbol{\delta D_i} + \boldsymbol{\gamma}_i + \varepsilon_{it}$$

Where:
VMT_{it} = vehicle miles traveled,
p_t^g = monthly TX gas retail price variable,
$\boldsymbol{U}_t$ = monthly TX unemployment rate,
$\boldsymbol{V_{it}}$ = vehicle age,
$\boldsymbol{D_i}$ = demographic variables (population density and median household income by zip code),
$\boldsymbol{\gamma}_i$ = fixed effect (make-model or VIN),
ε_{it} = residual,
i = vehicle index (unique VIN), and
t = time index (month).

3.2.3 Two stage least squares (2SLS) regression model

We next proceed to two-stage least squares regression (2SLS), using instrumental variables to isolate supply-related changes in gas price (i.e., supply shocks) with the goal of obtaining an unbiased estimate of the gas price elasticity of VMT demand. We also run regression models that combine 2SLS with make-model and vehicle-specific fixed effects.

In general, the instruments should be correlated with the explanatory variable of interest (in our case the actual price of gasoline), but not with the unobserved variation captured in the error term of the linear model. Ideally, there will be a strong correlation between the instrument and the instrumented explanatory variable (the actual price of gasoline), and no correlation between the instrument and the dependent variable (VMT), except through the instrumented explanatory variable (the predicted price of gasoline).

[17] Note, however, that this can be problematic if a particular vehicle is sold between owners or its role within a household fleet changes. If there are substantial changes to household occupant and fleet compositions over the time period we are analyzing, VIN fixed effects will act to hold constant something that is in fact not constant over time. As our data set does not currently account for the household vehicle fleet associated with each VIN in each data entry, we prefer to rely on the results of model specifications using vehicle make-model fixed effects.

Several previous analyses used weather-related oil supply disruptions in the U.S. Gulf Coast area to predict the retail price of gasoline. Because of its location near the Gulf Coast, gasoline demand in Texas may not be fully independent of extreme weather events that disrupt oil production in the Gulf Coast; in other words, extreme weather events in the Gulf Coast may simultaneously disrupt oil production and cause changes in demand for VMT and gasoline in much of Texas. Therefore we use U.S. crude oil price as our supply instrument. Appendix A provides more details on instrumental variables, and how we chose crude oil price as our instrument.

We construct several versions of 2SLS fixed effects regression models, in which we use U.S. crude oil price to predict Texas gas prices. Two-stage least squares regression uses the exogenous variation in an explanatory variable (retail gas price) to provide an unbiased estimator of its impact on the dependent variable (VMT).

In the first stage, we regress the endogenous explanatory variable, Texas retail gas price (p_t^g), on the other explanatory variables and the instruments.[18] Using the coefficients obtained from the first stage regression, we calculate fitted values of the endogenous explanatory variable ($\widehat{p_t^g}$); given a strong instrument, these fitted values will now be exogenous to VMT demand.

Stage one:

$$p_t^g = \propto_0 + \propto_{\boldsymbol{z}} \boldsymbol{z_t} + \mu U_t + \boldsymbol{\alpha_v V_{it}} + \boldsymbol{\delta D_i} + \boldsymbol{\gamma}_i + \varepsilon_{it}$$

Where:
p_t^g= monthly TX gas retail price variable,
$\boldsymbol{z_t}$= gas price instruments,
$\boldsymbol{U}_\mathrm{t}$ = monthly TX unemployment rate,
$\boldsymbol{V_{it}}$= vehicle age,
$\boldsymbol{D_i}$**=** demographic variables (population density and median household income by zip code),
$\boldsymbol{\gamma}_i$= fixed effect (make-model or VIN),
ε_{it} = residual,
i = vehicle index (unique VIN),
t = time index (month), and

Following stage one, we calculate the instrumented gas price ($\widehat{p_t^g}$) for each entry in the data set. The second stage then proceeds as usual for OLS with fixed effects, with the exception that instrumented gas price ($\widehat{p_t^g}$) is included instead of our original endogenous gas price variable (p_t^g).[19]

Stage two:

$$VMT_{it} = \beta_0 + \beta_p \widehat{p_t^g} + \boldsymbol{\mu U_t} + \boldsymbol{\beta_v V_{it}} + \boldsymbol{\delta D_i} + \boldsymbol{\gamma}_i + \epsilon_t$$

---

[18] Note that this can be done in models with or without fixed effects.

[19] We perform several versions of these regressions, each with different sets of explanatory variables. This requires separate computations of first stage coefficients, such that the explanatory variables and fixed effects of each first stage match those of its second stage.

Where:
VMT_{it} = vehicle miles traveled,
$\widehat{p_t^g}$ = predicted monthly TX gas retail price,
$\boldsymbol{U}_t$ = monthly TX unemployment rate,
$\boldsymbol{V_{it}}$ = vehicle age,
$\boldsymbol{D_i}$ = demographic variables (population density and median household income by zip code),
$\boldsymbol{\gamma}_i$ = fixed effect (make-model or VIN),
ϵ_t = residual,
i = vehicle index (unique VIN), and
t = time index (month).

After conducting these analyses using the price of gasoline as an explanatory variable, we recreate each analysis after replacing the price of gasoline with the cost of driving; i.e. the price of gasoline divided by each vehicle's rated fuel economy in miles per gallon, or dollars per mile.

3.2.4 Additional analyses

After evaluating the results of the sequence of regressions defined above, we select several preferred specifications that we believe provide an accurate model of the "baseline" relationship between VMT and retail gas prices or the cost of driving in Texas. Using subsets of the overall dataset, we run separate models to estimate the effect of changes in gas price or the cost of driving on VMT by: vehicle type; metropolitan area; rising or falling gas prices; and quantiles of median household income (by zip code), zip code population density, and rated vehicle fuel economy; all analyses are run both with and without vehicle make-model fixed effects, and with and without the supply instrument variable. Comparing the coefficients on these variables provides insight into driving differences and the relative degree of gas price response across vehicle type.

4 Results

4.1 Primary model results

Table 4.1 shows the estimated effect of changes in the gas price on annual VMT, for five separate regression models. The rows in Table 4.1 are different combinations of some of the variables described in Table 3.1 : unemployment rate, calendar year, and four different measures of vehicle age. The left-hand panel of Table 4.1 shows the estimated effect of changes in the actual gas price on annual VMT, whereas the right-hand panel shows the estimated effects after adding U.S. oil price as an instrument to predict the gas price. Columns A and D show the estimates with no fixed effects, Columns B and E show the estimated effects after accounting for make-model fixed effects, and Columns C and F show the results after accounting for individual vehicle fixed effects.

We suspect that drivers respond differently to changes in gas prices based in part on the type of vehicle they drive, in particular if their vehicle is inherent to the functions of their job (i.e. as a pickup truck would be to a home contractor), or how sensitive the cost of driving is to the price of gasoline (i.e. the fuel economy of their vehicle).[20] We first ran ordinary least squares regressions (labeled "No FE" in the table), then added fixed effects for vehicle models, based on a make-model code developed by NHTSA ("M-M FE"), and for individual vehicles, based on their vehicle identification numbers, or VINs ("VIN FE"). The models with no fixed effects have an R^2 ranging from 0.00 to 0.07, and the models including vehicle model fixed effects have an R^2 ranging from 0.06 to 0.11; however, the models including individual vehicle fixed effects all have an R^2 of 0.71 or 0.72.

Table 4.1. Estimated elasticity of VMT demand to changes in gas price, 5 regression models

	Control variables used				Without supply instrument			With supply instrument		
Model	Unem-ployment	CY	Age	Month	A. No FE	B. M-M FE	C. VIN FE	D. No FE	E. M-M FE	F. VIN FE
1	n	n	n	n	-0.086*	-0.161*	-0.217*	-0.131*	-0.279*	-0.392*
2	y	y	cont	n	0.063*	0.018*	-0.129*	0.070*	0.021*	-0.128*
3	y	y	disc	n	-0.204*	-0.215*	-0.075*	-0.211*	-0.224*	-0.076*
4	y	y	disc	cont	-0.075*	-0.082*	0.004	-0.082*	-0.092*	0.000
5	y	y	disc	disc	-0.065*	-0.075*	0.005*	-0.076*	-0.087*	0.001

* Estimate is statistically significant at the 95% confidence level.

We next added an instrument to estimate the change in gasoline prices as a function of monthly U.S. oil production, which is highly correlated with monthly gasoline price in Texas but unlikely to be influenced by changes in demand to gasoline in Texas (an analysis of several other supply variables is included in Appendix A). For the non-fixed effect models we used the Proc Model procedure in SAS, which compared the OLS results without the instrument with the two-stage

[20] Recall that Gillingham (2014) used fixed effects to account for different vehicle makes and models, whereas Gillingham et al. (2015) used fixed effects to account for differences among individual vehicles, based on the vehicle identification number (VIN); Knittel and Sandler (2013) analyzed both vehicle model and individual vehicle fixed effects.

least squared results with the instrument, and reports a Hausman value. In all 5 regression models without fixed effects shown in Table 4.1 the Hausman value was statistically significant, indicating that the regression models including the instruments were preferable to the models without the instruments. The Proc Model procedure does not allow simultaneous computation of two-stage models that include fixed effects variables (and subsequently calculation of the Hausman value); therefore, for the regressions adding fixed effects for vehicle models and individual vehicles we separately ran the first stage with the instruments and the second stage with predicted gasoline prices based on the estimates from the first stage model. The model R^2 of the first stage regression models was quite high, 0.87 for Model 1 and 0.99 for Models 2 through 5, for models using either vehicle model or individual vehicle fixed effects. The model R^2 of the second stage regression models was similar to that of the models without supply instruments: lowest R^2 (from 0.00 to 0.07) for models with no fixed effects, followed by models including vehicle model fixed effects (R^2 from 0.06 to 0.11) and models including individual vehicle fixed effects (R^2 of 0.71 or 0.72). The estimated effects of predicted gasoline price on VMT using the supply instrument are shown in the right-hand panel of Table 4.1 (Columns D through F).

Table 4.1 indicates that a simple regression model that only accounts for gasoline price (Model 1) estimates that a 1% increase in gas price is associated with a 0.09% decrease in annual VMT without fixed effects, a 0.16% to 0.28% decrease using make-model fixed effects, and a 0.22% to 0.39% decrease using individual vehicle fixed effects. Model 2, which adds the log of the average monthly unemployment rate since the previous inspection, calendar year dummy variables, and a single continuous vehicle age variable, estimates that an increase in price is associated with a 0.13% decrease in annual VMT using individual vehicle fixed effects (Columns C and F), but increases in annual VMT in with no fixed effects and using make- model fixed effects (Columns A and D, and B and E). Using the 15 discrete age variables rather than a single continuous age variable (Model 3) results in an increase in the price of gasoline being associated with a 0.20% or larger decrease in VMT, either with no fixed effects (Columns A and D) or vehicle model fixed effects (Columns B and E), and a 0.08% decrease in VMT using individual vehicle fixed effects (Columns C and F). Using the discrete age variables and including a continuous variable (ranging from 1 to 12) for the month of the year in which the vehicle was tested (Model 4) greatly reduces the estimated decrease in annual VMT, to 0.08% or 0.09% for the models with no fixed effects or vehicle model fixed effects. Replacing the continuous month variable with eleven discrete month variables (using June as the default) slightly reduces the estimated effect of an increase in the price of gas on annual VMT, ranging from 0.07% to 0.09%, in the models with no fixed effects or vehicle model fixed effects.

The right-hand panel of Table 4.1 indicates that adding the supply instrument has little effect on the elasticities estimated by Models 2 and 3 using individual vehicle fixed effects, but increases the elasticities estimated by Models 4 and 5 with no fixed effects and vehicle model fixed effects by one to two percentage points, and dramatically increases the estimated elasticities in Model 1.

We investigated the sensitivity of Models 2 through 5 in Table 4.1 to adding continuous variables for population density and median household income by zip code. Adding the median household income, or the median household income and population density, variables has little effect on the elasticities estimated by Models 2 and 3, but slightly decreases the elasticities of

Models 4 and 5 when using no fixed effects or make-model fixed effects (but not when using individual vehicle fixed effects), both with and without the supply instrument.

Note that in Models 1 and 2 accounting for VIN fixed effects (Columns C and F) estimate a much larger sensitivity in VMT in response to changes in fuel price than the models with no fixed effects (Columns A and D) or vehicle model fixed effects (Columns B and E). On the other hand, Model 3 estimates a much larger VMT sensitivity when using random effects or vehicle model fixed effects than when using VIN fixed effects.

We select Model 5 in Table 4.1, using vehicle model fixed effects and including the supply instrument, as our preferred model of the effect of an increase in the price of gasoline on annual VMT in Texas. The full regression results for the 30 models in Table 4.1 are included in Appendix B.

As noted above, EPA and NHTSA define light-duty trucks as pickups with a GVWR of less than 8,500 pounds, but SUVs and full size vans with a GVWR of less than 10,000 pounds. We reran the 30 models in Table 4.1 after excluding pickup trucks with a GVWR over 8,500 pounds, based on the VIN of each vehicle;[21] 53% of large pickups are rated over 8,500 pounds GVWR, and were excluded from the analysis. Excluding the large pickups with GVWR over 8,500 pounds had minimal effect on the estimates shown in Table 4.1, revising individual estimates by a maximum of 0.002.

We suspect that the large difference in price elasticity between the regression models using vehicle model and individual vehicle fixed effects are due in part to the number of observations for each vehicle. Only vehicles of model year 1996 through 2004 are between two and fifteen years old in each of the six years of our study period (2005 through 2010); vehicles of earlier and later vintage cannot be tested in each of the six years of our analysis. In addition, many vehicles left or entered Texas throughout the study period, such that they were not registered in the state for all six years between 2005 and 2010. Table 4.2 shows the number of odometer measurements for each vehicle over the six-year period; only 17% of all model years, and only 23% of model year 1996 to 2004 vehicles, were tested in each of the six years between 2005 and 2010.

We also suspect that the large difference in price elasticity between the regression models using vehicle model and individual vehicle fixed effects may be due to large changes in how a vehicle is driven in a given year. This can occur when a vehicle is sold or otherwise transferred to a new owner, when a household moves, when the size of the household changes (from a birth, a death, etc.) or when the travel patterns of the household otherwise change (when a member changes jobs, begins school, etc.) We can identify when a household moves by comparing the registered address over time; we can identify when a vehicle is sold by comparing the registered owner name over time; however, we cannot identify when a household makes substantial changes to its travel patterns from other events. Table 4.3 indicates that 61% of all vehicles remained in the same household at the same location, 28% were sold to a new owner, and 11% were owned by a

[21] The VIN identifies GVWR in 1,000-pound increments, e.g. 8,000 to 9,000 pounds GVWR; we assumed that pickups with a GVWR of 8,000 to 9,000 pounds in the VIN had an actual GVWR of less than 8,500 pounds, and included them in this analysis.

household that moved at some point during the six-year period. For model year 1996 to 2004 vehicles that were tested in each of the six calendar years, 54% remained in the same household at the same location, 34% were sold to a new household, and 13% were owned by a household that moved to a new location.

Table 4.2. Distribution of vehicles by number of tests per vehicle

	All model years		Model years 1996 to 2004	
Number of tests per vehicle	Number of vehicles	Distribution	Number of vehicles	Distribution
1	2,625,689	8.4%	1,033,825	4.5%
2	4,358,301	13.9%	1,940,167	8.5%
3	5,455,779	17.5%	3,044,957	13.3%
4	6,251,260	20.0%	4,789,436	20.9%
5	6,947,618	22.2%	6,465,887	28.3%
6	5,348,447	17.1%	5,329,974	23.3%
7	240,670	0.8%	239,753	1.0%
8+	18,079	0.1%	17,664	0.1%
Total	31,245,843	100.0%	22,861,663	100.0%

Table 4.3. Distribution of vehicles by number of tests per vehicle

	All vehicles		Model year 1996 to 2004 vehicles with 6 tests per vehicle	
Category	Number	Percent	Number	Percent
No change	18,764,837	60.6%	2,863,848	53.6%
Household moved	3,453,799	11.1%	681,040	12.8%
Vehicle sold	8,768,458	28.3%	1,785,086	33.6%
Total	30,987,094	100.0%	5,329,974	100.0%

Table 4.4 shows the estimated elasticities for all model year 1996 to 2004 vehicles, and after accounting for vehicles that were tested in each of the six calendar years, as well as for vehicles that moved or were sold at any point over the six-year period, using the control variables indicated in Model 5 of Table 4.1 (that is, monthly unemployment rate since the previous test, as well as discrete variables for calendar year, the age of the vehicle in years, and the month in which the vehicle was tested). Row 1 of Table 4.4 indicates that an increase in gas prices is associated with decreases in annual VMT when no fixed effects or make-model fixed effects are used, but is associated with increases in annual VMT when using fixed effects for individual vehicles, as noted previously in Model 5 of Table 4.1. However, if only vehicles that were tested in each of the six calendar years are included (Row 2), the estimated elasticity using individual vehicle fixed effects is quite similar to that when no fixed effects or vehicle model fixed effects are used. This suggests that using individual vehicle fixed effects will bias the estimated VMT elasticity to changes in the price of gasoline, unless one accounts for vehicles that are not observed the same number of times in the dataset. For this reason we discount the estimates using the individual vehicle fixed effects in Table 4.1, and focus on the estimates using no fixed effects or make-model fixed effects.

Table 4.4. Estimated effect of change in gas price on annual VMT by vehicle type, Model 5

	Without instrument			With instrument		
	No fixed effects	Vehicle model fixed effects	Individual vehicle fixed effects	No fixed effects	Vehicle model fixed effects	Individual vehicle fixed effects
1. MY96-04	-0.056	-0.063	0.048	-0.073	-0.082	0.041
2. MY96-04, tested in all 6 years	-0.094	-0.092	-0.103	-0.120	-0.118	-0.126
3. Not moved or sold	-0.043	-0.042	-0.074	-0.057	-0.054	-0.083
4. Ever moved	-0.126	-0.120	-0.126	-0.174	-0.170	-0.175
5. Ever sold	-0.046	-0.051	-0.085	-0.054	-0.057	-0.091

Note: All estimates are statistically significant at the 95% confidence level.

Rows 3 through 5 in Table 4.4 indicate that vehicles that were sold at some time in the six-year study period have very similar VMT elasticities for changes in the price of gasoline to vehicles that were not moved or sold during the study period; a 1% increase in the price of gasoline is associated with a 0.04% to a 0.09% decrease in annual VMT for these vehicles. However, the vehicles that belonged to households that moved during the study period are much more responsive to changes in the price of gasoline, with a 1% increase in the price of gasoline reducing annual VMT between 0.12% and 0.18%.

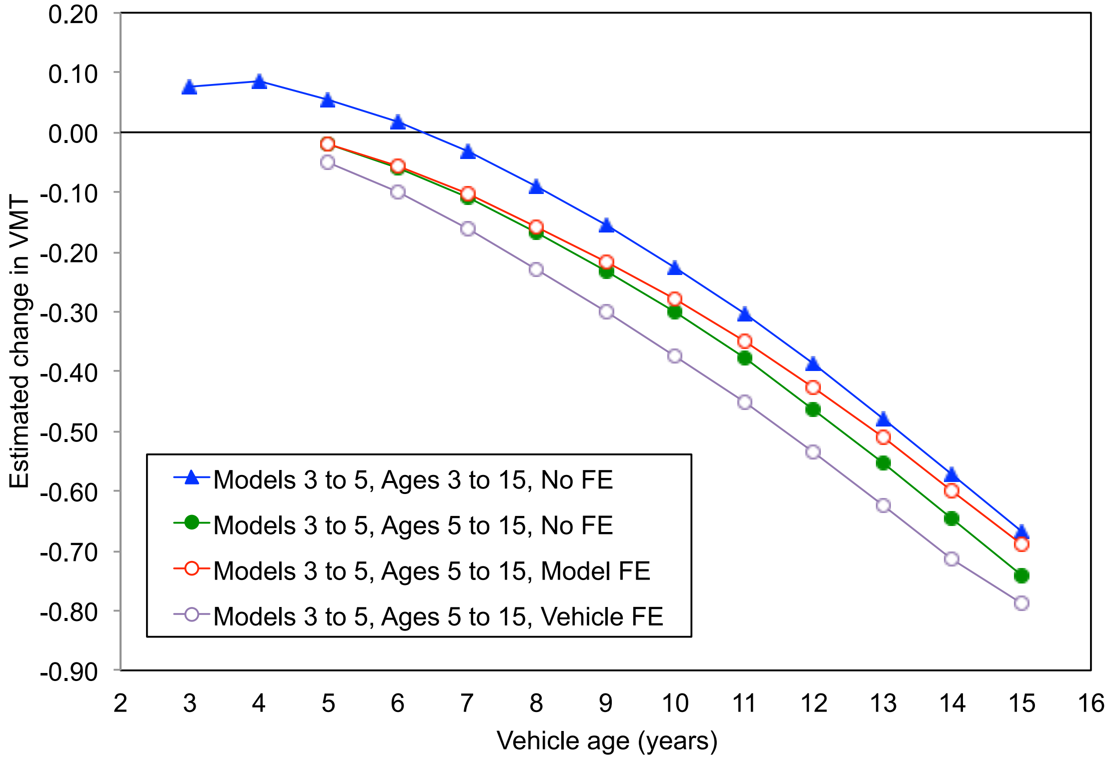
4.2 Estimated effect of control variables

In this section we discuss how sensitive the estimated values for some of the other control variables are to the variables included in the regression models shown in Table 4.1.

4.2.1 Vehicle age

Figure 4.1 shows the estimated effect of vehicle age (using the discrete years of age) on annual VMT, from Models 3 through 5 in Table 4.1. We originally used 13 discrete age variables, age of three to fifteen years, with 2-year-old vehicles as the default; the estimated effect of these 13 discrete age variables on annual VMT are indicated by the blue triangles in the figure. Note that three- to six-year old vehicles are associated with an increase in VMT relative to 2-year-old vehicles, and that only starting with vehicles 7-years-old and older is VMT estimated to decrease relative to that of 2-year-old vehicles. We then ran an additional set of regression models using only 11 discrete age variables: age of five to fifteen years, with 2- to 4-year old vehicles as the default. The range in estimates from these models are indicated by the green circles in Figure 4.1; when 2- to 4-year old vehicles are grouped together, all vehicles 5-years old and older are associated with lower VMT, as expected.

Figure 4.1. Estimated change in VMT by vehicle age, using 13 or 11 discrete age variables

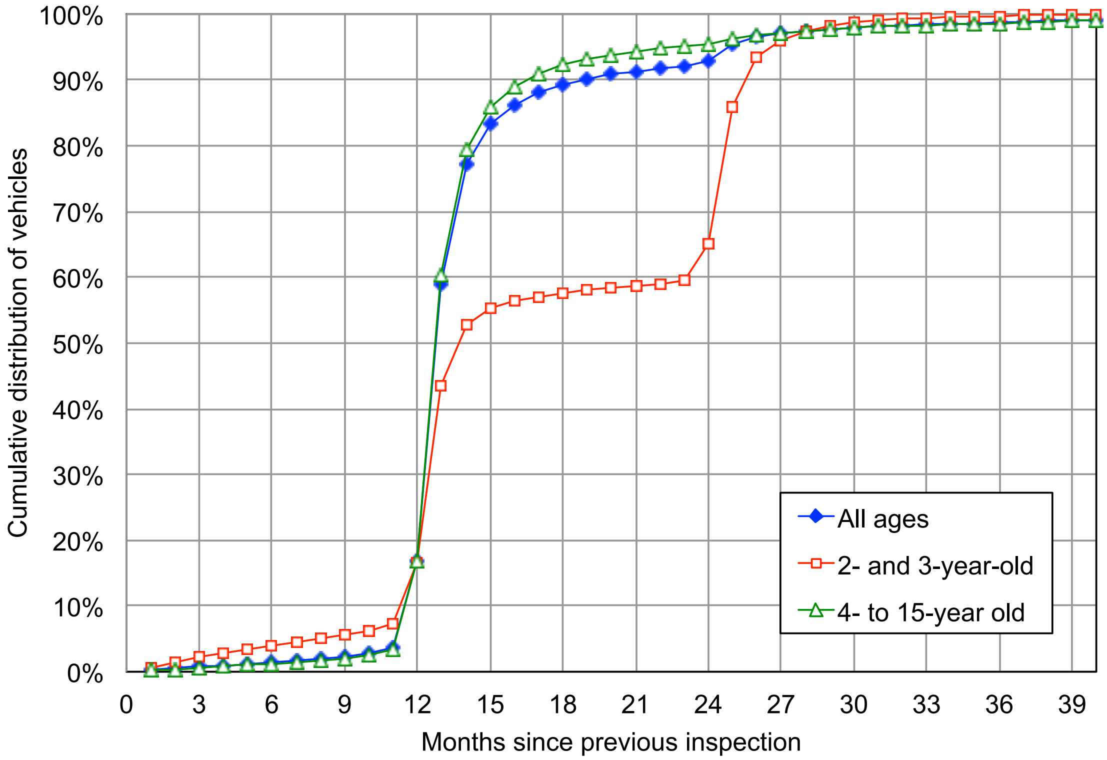


The estimated effect of vehicle age is nearly identical across all three regression models, including Models 4 and 5 which use a combination of discrete age variables in years and either a continuous variable or 11 discrete variables for the month of the year; and is nearly identical whether supply instruments are used or not. The estimated effect of age varies somewhat whether fixed effects for vehicle models or individual vehicles are used, as indicated by the open circles in Figure 4.1; however, the general trends are as expected. This change in how vehicle age is treated in Models 3 through 5 in Table 4.1 has only a very small effect on the estimated effect of gasoline price on VMT.

4.2.2 Time since previous inspection

Figure 4.2 shows the cumulative distribution of vehicles by the number of months since the previous inspection, for all vehicles as well as 2- to 3-year-old vehicles and 4- to 15-year old vehicles. As noted above, Texas requires an annual inspection, as well as an inspection when a vehicle is transferred to a new owner if the previous inspection occurred more than 180 days from the date of resale; one would expect that the majority of vehicles were tested around twelve months after the previous inspection. The blue diamonds in Figure 4.2 indicate that 3% of all vehicles were tested less than 12 months after their previous inspection, likely because they were transferred to a different owner, while 14% were tested more than 15 months after their previous inspection, likely because some owners allow their vehicle registration to lapse for a few months. Texas requires that vehicles receive their initial emissions inspection after they are two years old; the red open squares in the figure indicate that only about half of 2- and 3-year-old vehicles were inspected up to 15 months after their initial inspection; most of the remaining 2- and 3-year-old vehicles were inspected about two years after their initial inspection.

Figure 4.2. Cumulative distribution of vehicles by number of months since previous inspection and vehicle age



4.2.3 Other control variables

Table 4.5 shows the estimated association between annual VMT and the other continuous control variables (i.e., model coefficients estimated for control variables): unemployment rate since the previous inspection, vehicle age in continuous months, and the month of the year of the inspection. Only those regression models that include each of these control variables are shown in Table 4.1. The average unemployment rate since the last inspection is associated with an increase in annual VMT in Model 1 with no fixed effects or vehicle model fixed effects (but with a decrease in Model 1 using individual vehicle fixed effects), but a decrease in annual VMT in the other models, especially Model 3 with a 0.16% to 0.17% decrease in VMT for every increase in the unemployment rate. Table 4.8 also indicates that continuous vehicle age in months is associated with decreased annual VMT, as expected, using no fixed effects or vehicle model fixed effects in Model 2 (but an increase in annual VMT using individual vehicle fixed effects in Model 2). The opposite signs on the unemployment rate and continuous age variables in Table 4.1 is another indication that the results using individual vehicle fixed effects may be biased.

The estimated effect of the month of the year on annual VMT, when combined with annual age, is consistent across all versions of Model 4, with annual VMT decreasing slightly for each successive month in a given calendar year.

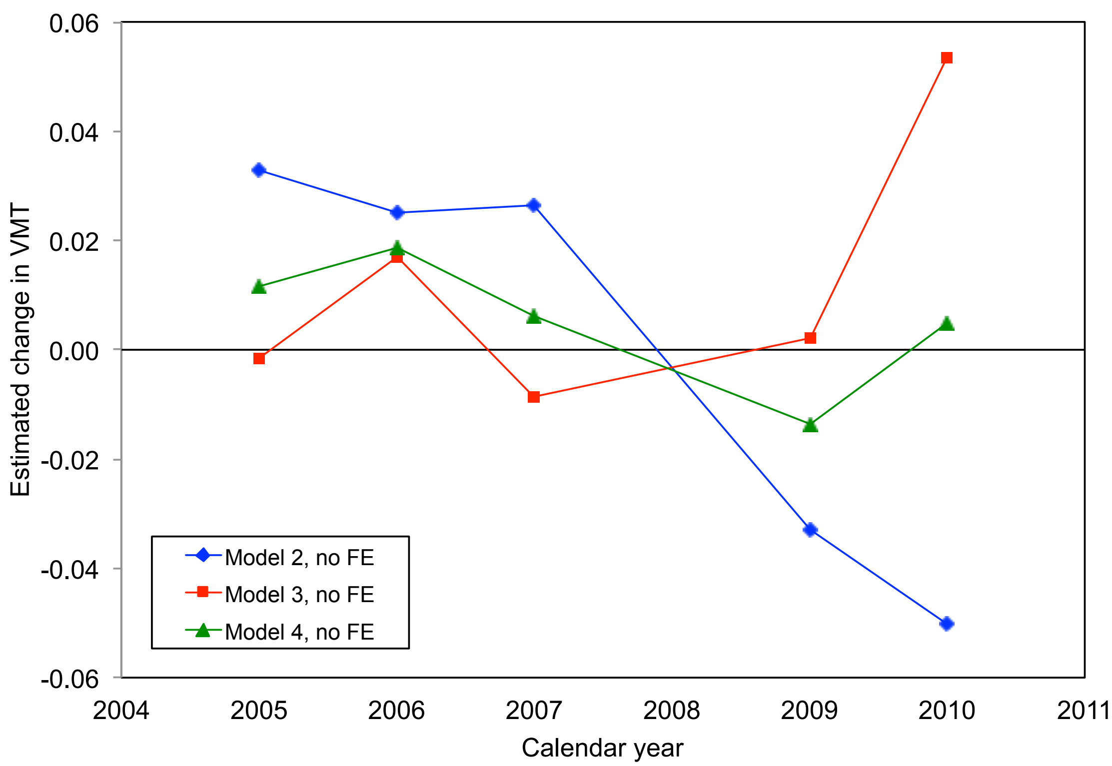
Table 4.5 Estimated effect of other continuous control variables on annual VMT

		Without instrument			With instrument		
Variable	Model	No fixed effects	Vehicle model fixed effects	Individual vehicle fixed effects	No fixed effects	Vehicle model fixed effects	Individual vehicle fixed effects
Unemployment rate	2	0.111	0.067	-0.014	0.115	0.069	-0.014
	3	-0.160	-0.169	0.026	-0.164	-0.174	0.026
	4	-0.028	-0.033	0.110	-0.033	-0.039	0.107
	5	-0.021	-0.028	0.110	-0.029	-0.036	0.107
Vehicle age	2	-0.299	-0.264	0.126	-0.299	-0.264	0.126
Month	4	-0.005	-0.005	-0.004	-0.004	-0.005	-0.004

Note: all estimates are statistically significant at the 95% confidence level.

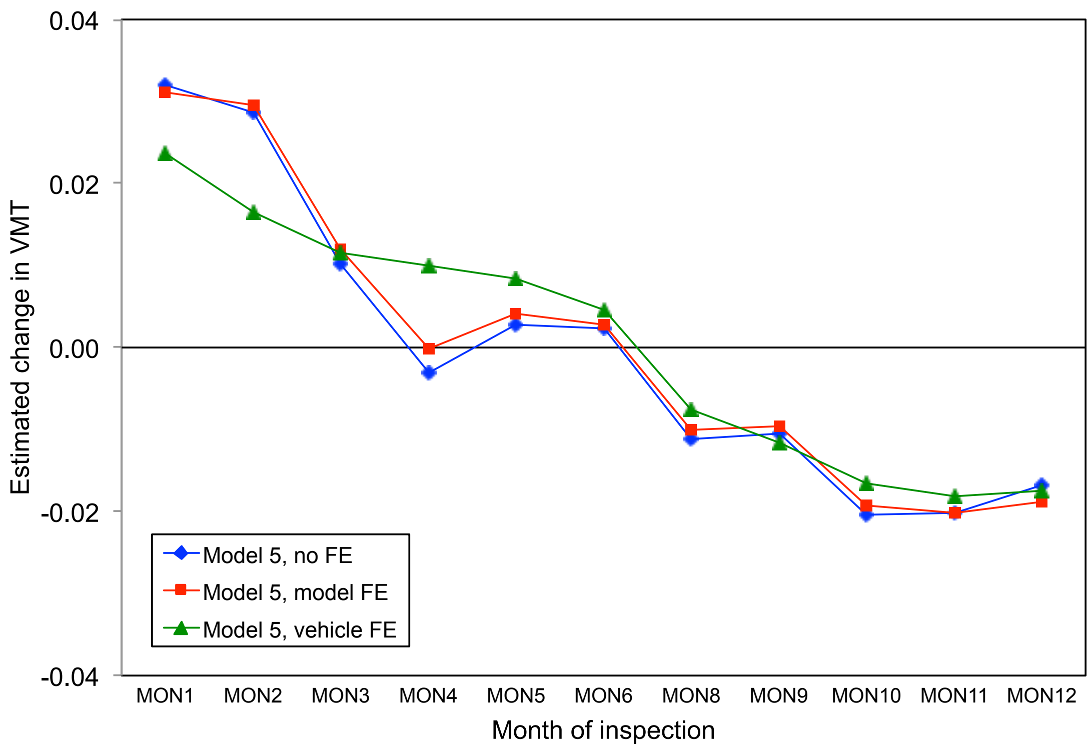
Figure 4.3 shows the estimated effect of the dummy variables for calendar year, which are included in Models 2 through 4 of Table 4.1, using no fixed effects and without the supply instrument; the estimated effect of calendar year on annual VMT in Model 5 is identical to that in Model 4. The estimated effect of the calendar year variables on annual VMT is downward sloping for the most part, with larger decreases in VMT in later calendar years, for Models 2 and 4. However, there is no consistent trend in the estimated effect of successive calendar years on annual VMT for Model 3. The trends shown in Figure 4.3 are similar when using either vehicle model fixed effects, or including the supply instrument.

Figure 4.3. Estimated effect of dummy calendar year variables on annual VMT



Recall that Figure 3.4 suggests that, for a vehicle of a given age or model year, average annual VMT decreases in each successive month of the year in which a vehicle is inspected. Figure 4.4 shows the estimated effect of the dummy variables for the month of the year in which the vehicle was inspected, from Model 5 of Table 4.1, without the supply instrument. The estimated effect of the month variables on annual VMT also is downward sloping for the most part, with larger decreases in VMT in later months of the year, regardless of whether fixed effects are used or not. The trends shown in Figure 4.4 are similar when the supply instrument is included in Model 5. Because the decrease in VMT in successive months is not always consistent or linear, we prefer Model 5, which assigns dummy variables to each month, over Model 4, which uses a single continuous variable, ranging from 1 to 12, for months of the year.

Figure 4.4. Estimated effect of dummy month of year variables on annual VMT



4.3 Additional analyses

In this section we introduce several additional variables to our preferred model specification (Model 5 in Table 4.1) in order to understand how the sensitivity of annual VMT to gas prices is related to household income, population density, vehicle type, metropolitan area, rated fuel economy, and whether gas prices are rising or falling.

4.3.1 Estimates by zip code median household income

We expect that consumers will be less responsive to an increase in the gas price as their income increases, in that fuel purchases represent a smaller portion of a wealthier household's income.

However, wealthier households are more likely to have other transportation options, such as a second vehicle or substituting airplane travel for driving long distances.

Recall that the association between fuel price elasticity and household income is mixed in the literature. Leung (2015), using NHTS survey data, found that a 1% increase in the price of gasoline was associated with a decrease in VMT twice as large in lower income households (0.16%) than in other households (0.07%). Knittel and Sandler (2013), using vehicle registration address with their California micro data, estimated that an increase in the price of gasoline was associated with slightly larger decreases in VMT in lower income households (0.07%) than higher income households (0.05%). However, Gillingham (2014), using a subset of new vehicle purchases that included the income of the individual household, found that the lowest income households had a much smaller decrease in VMT (0.22%) than the highest income households (0.40%).

To estimate the effect of an increase in the price of gasoline on annual Texas VMT by household income, we divided our sample into five equal bins by the median household income of the zip code in which the vehicle was registered, taken from the 2000 U.S. Census. Table 4.6 suggests that in response to a 1% gas price increase, lower income households tend to reduce their VMT (by 0.10% to 0.11%) more than higher income households (only 0.07%), using Model 5 from Table 4.1 with vehicle model fixed effects and the supply instrument. These results are consistent with using no fixed effects, with or without the supply instrument. These differences are similar to those found by Leung, and Knittel and Sandler.

Table 4.6. Estimated effect of change in gas price on annual VMT by median household income by zip code, Model 5

	Without instrument		With instrument	
Median household income by zip code	No fixed effects	Vehicle model fixed effects	No fixed effects	Vehicle model fixed effects
< \$35,320	-0.071	-0.082	-0.089	-0.101
\$35,320-\$43,600	-0.086	-0.093	-0.104	-0.113
\$43,600-\$53,600	-0.065	-0.068	-0.074	-0.078
\$53,600-\$68,620	-0.048	-0.059	-0.055	-0.068
> \$68,620	-0.048	-0.066	-0.049	-0.069

Note: all estimates are statistically significant at the 95% confidence level.

4.3.2 Estimates by zip code population density

Next we examine what effect urban form has on consumers' response to increasing gas prices. We use a simple measure, the population density by zip code, as a proxy for more dense development of a mixture of residential, commercial, and industrial land uses; urban density generally enables greater choices in travel modes other than a single occupant vehicle (e.g., public transit, taxis, cycling and walking). We expect that households in less dense, more rural areas have fewer transportation options than those in more dense, urban areas, and therefore will exhibit a smaller change in VMT associated with an increase in fuel prices.

We divided our sample into five equal bins by the population density of the zip code in which the vehicle was registered, taken from the 2000 U.S. Census. Table 4.7 suggests that households in the least dense areas reduce their VMT the most in response to a 1% increase in gas prices compared with households in an area with average population density (a 0.14% decrease compared to a 0.04% decrease, using individual vehicle fixed effects with the supply instrument); this is counter to our initial expectation that households living in rural areas are less responsive to changes in gas prices because of fewer transportation options. However, Table 4.7 suggests that the VMT response is u-shaped; households in the most dense, most urban areas also are associated with larger reductions in VMT than households in areas of the average density (a 0.10% decrease compared to a 0.04% decrease, using individual vehicle fixed effects with a supply instrument).

Table 4.7. Estimated effect of change in gas price on annual VMT by zip code population density, Model 5

	Without instrument		With instrument	
Zip code population density (population / sq miles of land area)	No fixed effects	Make-model fixed effects	No fixed effects	Make-model fixed effects
< 565	-0.112	-0.122	-0.126	-0.138
565-1670	-0.034	-0.047	-0.040	-0.055
1670-2870	-0.021	-0.033	-0.031	-0.044
2870-4350	-0.050	-0.056	-0.060	-0.066
> 4350	-0.075	-0.084	-0.089	-0.098

Note: all estimates are statistically significant at the 95% confidence level.

4.3.3 Estimates by vehicle type

Figure 4.5 shows the change in average annual VMT since 2005 by vehicle type, for vehicles that were two to eight years old in any of the calendar years;[22] during this period gas prices were generally increasing, except for the large decrease between mid-2008 and mid-2009. All vehicle types but CUVs reduced annual VMT over this time period, with annual VMT in two-door cars, small and large pickups, and SUVs being reduced the most, over 5% between 2005 and 2009. Annual VMT increased between 2009 and 2010 for almost all types of vehicles.

To explore differences across vehicle types, we ran eight versions of regression Model 5 in Table 4.1, one for each vehicle type shown in Figure 4.5. Table 4.8 and Figure 4.6 indicate that a 1% increase in the price of gasoline is associated with an increase in VMT in two-door cars and a large decrease in VMT in CUVs, and larger decreases in VMT in SUVs (0.20% or larger) than in pickups (0.08% to 0.18%), all of which are contrary to the trends shown in Figure 4.5. Full size vans are associated with a much higher increase in VMT from an increase in gas price in Table 4.8 and Figure 4.6 (over 0.30%) than in Figure 4.5. Four-door cars and minivans are associated with the smallest decrease in VMT in both Table 4.8 and Figure 4.6 (with an elasticity between -0.01 and -0.03) and Figure 4.5.

[22] We show the trends in two- to eight-year old vehicles because vehicles of those ages are present in each of calendar years 2005 through 2010.

Figure 4.5. Average VMT of two- to eight-year-old vehicles since 2005, by vehicle type

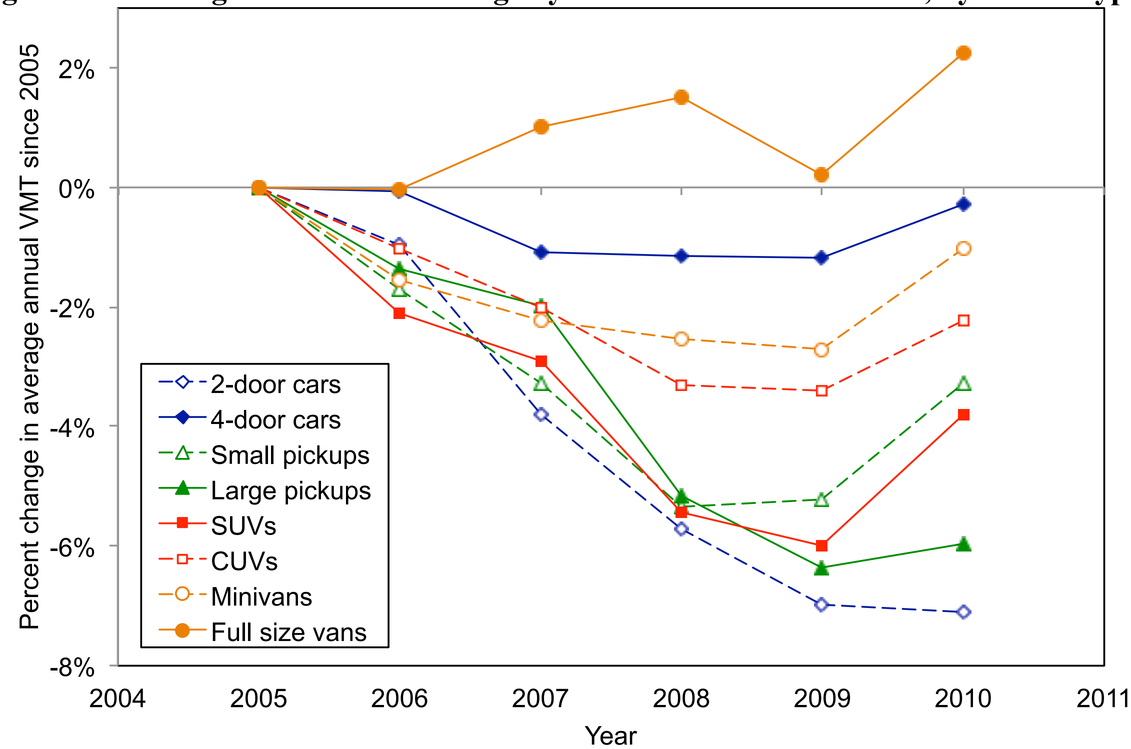


Table 4.8. Estimated effect of change in gas price on annual VMT by vehicle type, Model 5

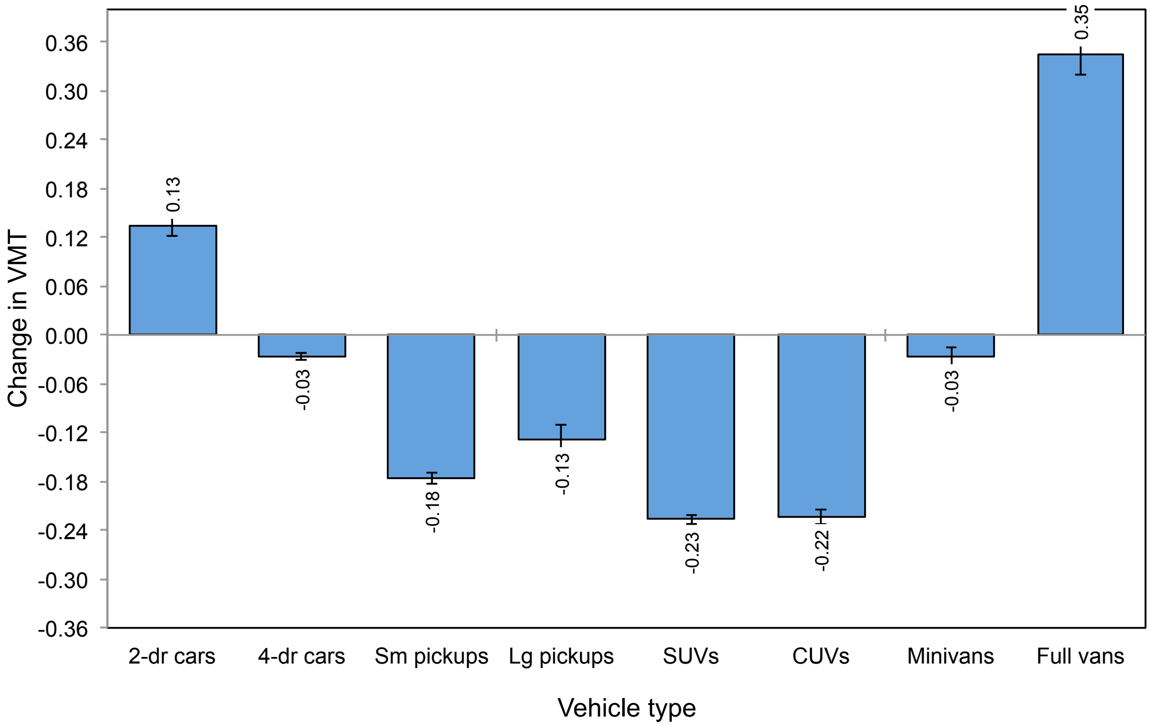
		Without instrument		With instrument	
Vehicle type	Distribution of vehicles	No fixed effects	Make-model fixed effects	No fixed effects	Make-model fixed effects
Two-door cars	7%	0.130*	0.132*	0.132*	0.134*
Four-door cars	40%	-0.015*	-0.023*	-0.016*	-0.026*
Small pickups	18%	-0.145*	-0.150*	-0.170*	-0.176*
Large pickups†	3%	-0.075*	-0.084*	-0.120*	-0.129*
SUVs	19%	-0.194*	-0.209*	-0.211*	-0.226*
CUVs	6%	-0.218*	-0.214*	-0.229*	-0.224*
Minivans	5%	-0.012	-0.018	-0.021	-0.027*
Full vans	2%	0.350*	0.354*	0.335*	0.346*

* Estimates are statistically significant at the 95% confidence level.

† Large pickups exclude pickups with GVWR greater than 8,500 pounds.

The average change in VMT from an increase in the price of gasoline in the last column of Table 4.8, weighted by the distribution by vehicle type, is -0.087, identical to the -0.087 elasticity estimated without accounting for vehicle type (using Model 5E in Table 4.1).

Figure 4.6. Estimated effect of change in gas price on annual VMT by vehicle type, Model 5



4.3.4 Estimates by metropolitan area

We next ran four versions of regression Model 5 in Table 4.1, one for each of the four metropolitan areas included in the Texas emission inspection program. Table 4.9 indicates that drivers in Austin are most sensitive to an increase in the price of gasoline, with an elasticity of -0.19 using vehicle model fixed effects and the supply instrument, followed by drivers in Houston (with an elasticity of -0.08), and by drivers in El Paso and Dallas (with an elasticity of -0.04). Drivers in Austin are more sensitive to increases in gas price than drivers in Dallas or Houston, despite Austin having an overall lower Walk Score (39.2 vs. 45.4 and 47.8) and Transit Score (33.5 vs. 39.5 and 36.8) than Dallas and Houston[23], and a higher average median income than Dallas (14% higher) and Houston (9% higher).[24]

[23] Although Austin does have a better Bike Score than Dallas and Houston (51.7 vs. 43.7 and 49.3). Walk, Transit, and Bike Scores from https://www.walkscore.com/cities-and-neighborhoods/. Last accessed March 2017.
[24] 2015 median household income by county from: http://www.txcip.org/tac/census/morecountyinfo.php?MORE=1013. 2015 population by county from: https://www.tsl.texas.gov/ref/abouttx/popcnty2010-11.html. Both last accessed March 2017.

Table 4.9. Estimated effect of change in gas price on annual VMT by metro area, Model 5

	Without instrument		With instrument	
Metropolitan area	No fixed effects	Make-model fixed effects	No fixed effects	Make-model fixed effects
Austin	-0.157	-0.169	-0.172	-0.187
Dallas	-0.027	-0.037	-0.032	-0.043
Houston	-0.049	-0.062	-0.060	-0.075
El Paso	-0.044	-0.037	-0.049	-0.043

Note: all estimates are statistically significant at the 95% confidence level.

4.3.5 Estimates by fuel economy

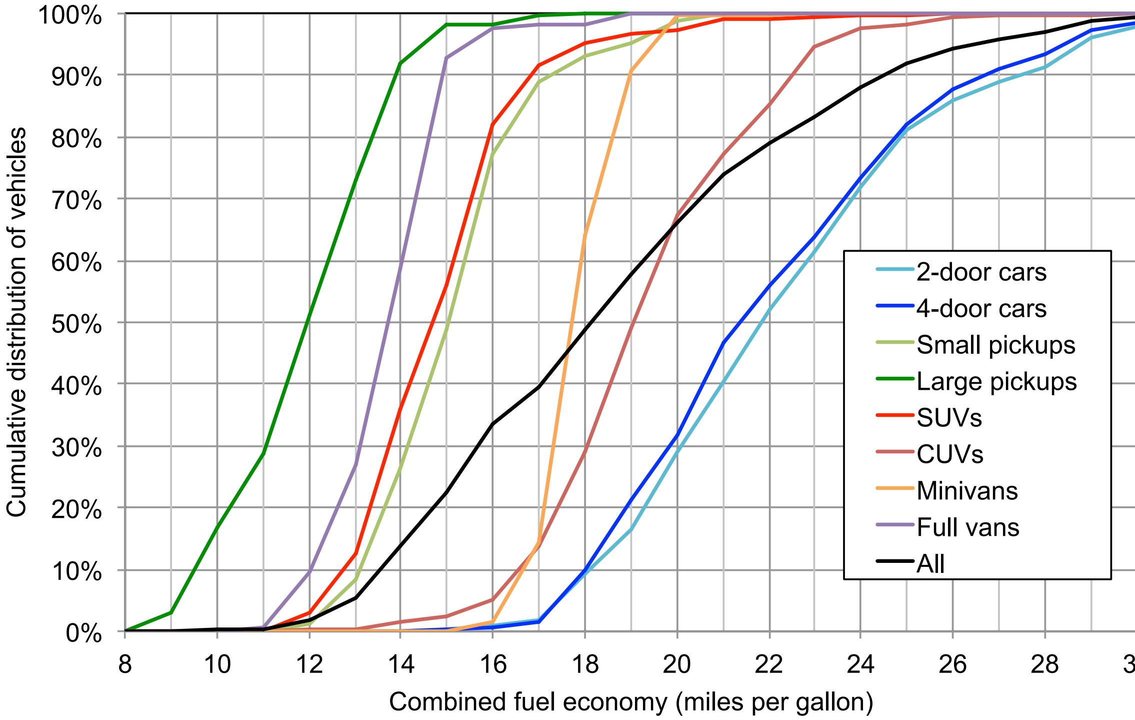
Gillingham (2015) accounted for vehicle fuel economy by running three regressions based on rated highway fuel economy: less than 20, 20 to 30, and greater than 20 miles per gallon. These three bins accounted for 48%, 51%, and 1%, respectively, of the total observations. We merged the odometer readings with rated fuel economy values by vehicle year, make and model, drive type (two- vs four-wheel drive), engine size (cylinders and displacement), and fuel type, from the certification values in EPA's Fuel Economy Guide (FEG). We were able to match 95% of the vehicles in our dataset to a city/highway combined fuel economy value in the FEG; over two-thirds of those vehicles not matched were pickup trucks with a GVWR of over 8,500 pounds, according to the VIN, and therefore not subject to the light-duty fuel economy standards.

Figure 4.7 shows the cumulative distribution of combined city/highway fuel economy, by vehicle type, for model year 1991 to 2010 light-duty vehicles. Large pickups have the lowest median combined fuel economy (12 miles per gallon), followed by full vans (13 miles per gallon), small pickups and SUVs (15 miles per gallon), minivans (18 miles per gallon), and CUVs (19 miles per gallon); cars have the highest median combined fuel economy, 22 miles per gallon. We ran eighteen separate regression models, based on three roughly equal bins of combined fuel economy for six vehicle types; because the distribution of combined fuel economy of two- and four-door cars, and small pickups and SUVs, are very similar, we combined them into two groups.

Table 4.10 shows the distribution of vehicles in low, medium, and high combined fuel economy bins, by vehicle type. Because EPA reports fuel economy as whole integers, three fuel economy bins cannot be defined for small pickups/SUVs, large pickups, and minivans such that vehicles are evenly distributed among the three bins. About half of small pickups/SUVs, large pickups, and minivans have to be assigned to the medium fuel economy bin, resulting in relatively few vehicles assigned to one of the other two bins (only 16% of small pickups/SUVs, and 19% of large pickups, are assigned to the high fuel economy bin, while only 13% of minivans are assigned to the low fuel economy bin.)

We expect that annual VMT in vehicles with relatively low fuel economy would be more responsive, and VMT in vehicles with high fuel economy be less responsive, to an increase in the price of gasoline. Table 4.10 indicates that, for the most part, this is the case, particularly for regression models using a supply instrument and accounting for vehicle make-model fixed

Figure 4.7. Cumulative distribution of combined fuel economy by vehicle type



effects (the last column of Table 4.10, and Figure 4.8). The relationship between relative fuel economy and the elasticity of VMT to changes in fuel price is strongest in CUVs, followed by small pickups/SUVs, and cars. For example, a 1% increase in the price of gasoline is associated with 0.29%, 0.24%, and 0.15% decreases in VMT, respectively, in CUVs with low, medium, and high fuel economy. VMT in low fuel economy cars is more responsive (a 0.015% decrease) to a change in the price of gasoline than in cars with medium or high fuel economy (a 0.007% and 0.004% decrease, respectively). Note that the VMT of large pickups with relatively low fuel economy is associated with a 0.32% decrease in VMT for a 1% increase in the price of gasoline, while the VMT of large pickups with relatively high fuel economy is associated with a 0.09% increase in VMT from an increase in gasoline price. As noted in Figure 4.6 above, an increase in the price of gasoline is associated with an increase in VMT in full vans; this increase in VMT is stronger in full vans with relatively low fuel economy (a 0.40% increase) than in full vans with medium or relatively high fuel economy (a 0.26% increase). Minivans have the opposite effect of the other vehicle types, where an increase in the price of gasoline is associated with a 0.04% increase in VMT in minivans with relatively low fuel economy, and a 0.07% decrease in VMT in minivans with relatively high fuel economy. The average change in VMT from an increase in the price of gasoline in the last column of Table 4.10, weighted by the distribution of each group within the entire fleet, is -0.095, comparable to the -0.087 elasticity estimated without accounting for vehicle type or relative fuel economy (using Model 5E in Table 4.1).

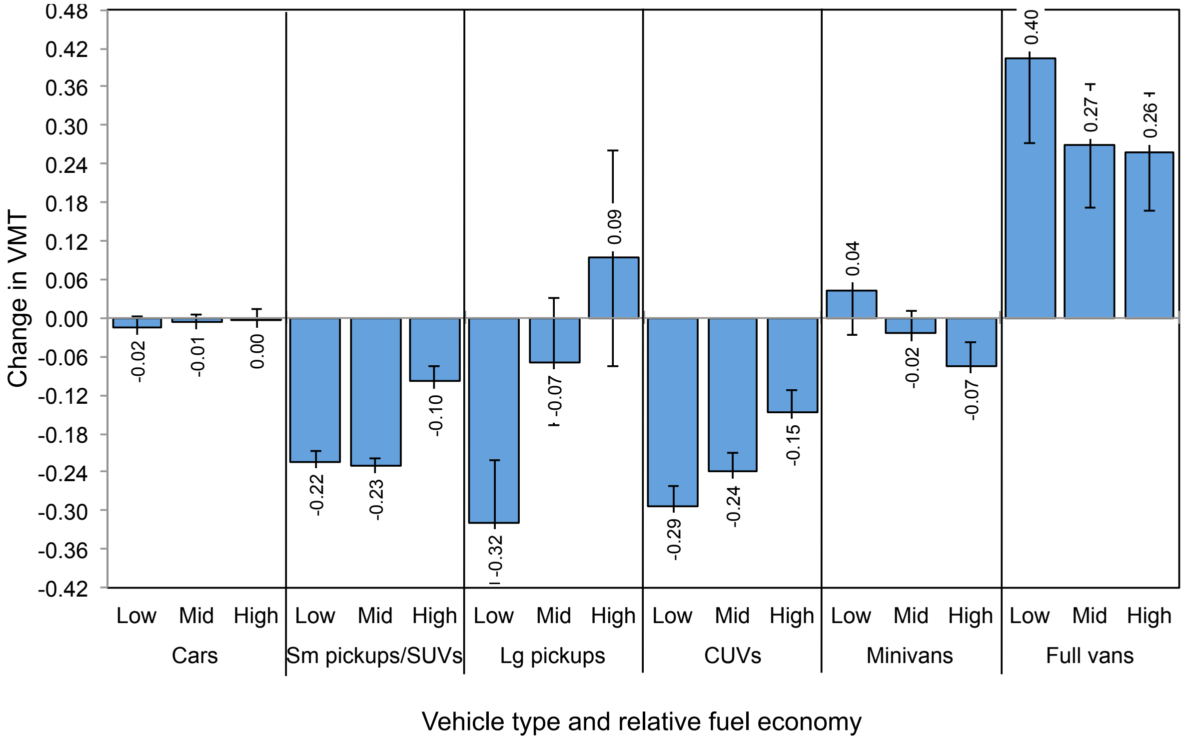
Table 4.10. Estimated effect of change in gas price on annual VMT by vehicle type, Model 5

Vehicle type	Distribution: In group	Distribution: Of all	Without instrument: No fixed effects	Without instrument: Make-model fixed effects	With instrument: No fixed effects	With instrument: Make-model fixed effects
Cars, < 21 MPG	36%		0.001	-0.015	0.003	-0.015
Cars, 21 to 23 MPG	34%	49%	0.005	-0.007	0.009	-0.007
Cars, > 23 MPG	30%		0.018*	0.008	0.005	-0.004
Sm pickups/SUVs, < 15 MPG	34%		-0.187*	-0.196*	-0.214*	-0.223*
Sm pickups/SUVs, 15 to 16 MPG	50%	37%	-0.197*	-0.205*	-0.221*	-0.230*
Sm pickups/SUVs, > 16 MPG	16%		-0.067*	-0.093*	-0.074*	-0.099*
Lg pickups, < 12 MPG	31%		-0.260*	-0.263*	-0.315*	-0.318*
Lg pickups, 12 to 13 MPG	50%	1%	-0.031	-0.037	-0.061	-0.068
Lg pickups, > 13 MPG	19%		0.122	0.115	0.100	0.093
CUVs, < 19 MPG	34%		-0.272*	-0.276*	-0.287*	-0.292*
CUVs, 19 to 20 MPG	38%	6%	-0.233*	-0.225*	-0.249*	-0.239*
CUVs, > 20 MPG	28%		-0.148*	-0.144*	-0.152*	-0.145*
Minivans, < 18 MPG	13%		0.068	0.048	0.064	0.044
Minivans, 18 MPG	46%	5%	-0.011	-0.013	-0.023	-0.025
Minivans, > 18 MPG	41%		-0.059*	-0.064*	-0.070*	-0.075*
Full vans, < 14 MPG	27%		0.351*	0.379*	0.374*	0.404*
Full vans, 14 MPG	34%	1%	0.259*	0.271*	0.249*	0.268*
Full vans, > 14 MPG	39%		0.252*	0.269*	0.234*	0.259*

* Estimate is statistically significant at the 95% confidence level.

Consequently, a decrease in the price of gasoline is expected to have effects on VMT opposite those shown in Table 4.10 and Figure 4.8. By effectively decreasing the price of gas, fuel economy standards are likely to induce drivers of new, relatively high MPG vehicles to increase their VMT. Table 4.10 and Figure 4.8 suggest that increased fuel economy standards will induce drivers of CUVs with relatively high fuel economy to increase their VMT by 15%, drivers of relatively high MPG small pickups/SUVs by 10%, drivers of relatively high MPG minivans by 7%, and drivers of cars less than 1%. Weighted by the distribution of vehicle types in the entire fleet, this translates into a 5.2% average increase in VMT from new relatively high MPG vehicles, assuming no changes in VMT for large pickups and full vans (adding in the decreases in VMT in relatively high MPG large pickups and full vans translates into a 4.7% increase in VMT from new relatively high MPG vehicles).

Figure 4.8. VMT elasticity by vehicle type and relative fuel economy, using supply instrument and make-model fixed effects



4.3.6 Estimates by rising/falling gas prices

Using annual state level data, Hymel and Small (2015) found that drivers' VMT is twice as sensitive to a 1% increase in the price of gasoline as to a 1% decrease (a 0.06% vs. a 0.03% change in VMT). As indicated in Figure 4.2 above, monthly gasoline prices can be quite volatile, making it difficult to categorize drivers' response when prices are rising versus when they are falling.

We adopted a similar approach to Hymel and Small, by comparing the average price of gasoline since the previous inspection of the current observation with the average price since the previous inspection of the previous observation, usually about 12 months prior. Figure 4.9 compares the log of the monthly trend in the price of gasoline since the previous inspection, in 2005 constant dollars, with the distribution of vehicles observed in each month by the ratio of the average price faced since the previous inspection to the average price faced over the preceding year. 28% of the vehicles faced an average price that was 10% higher at the time of the current observation than at the time of the previous observation (shown in red in the figure), only 15% faced an average price that was 10% lower than at the time of the previous observation (shown in green), and the remaining 58% faced an average price that was between 10% lower and 10% higher than at the time of the previous observation (shown in blue in the figure). Figure 4.9 indicates that 50% to 80% of vehicles inspected between February and December 2006, and between and March and December 2008 faced an average price that was higher than in their previous inspection, while 50% to 80% of vehicles inspected between June 2009 and April 2010 faced an average price that was lower than the average price at the time of their previous inspection.

We ran separate regression models for the three price regimes: if a vehicle faced an average price that was higher, lower, or about the same as during its previous inspection. We excluded the calendar year dummy variables from the regression model, as vehicles in the "lower than previous" price regime are largely confined to 2009 and 2010 (as shown in Figure 4.9).

Figure 4.9. Fraction of vehicles facing rising, falling, or steady average gas price since previous inspection

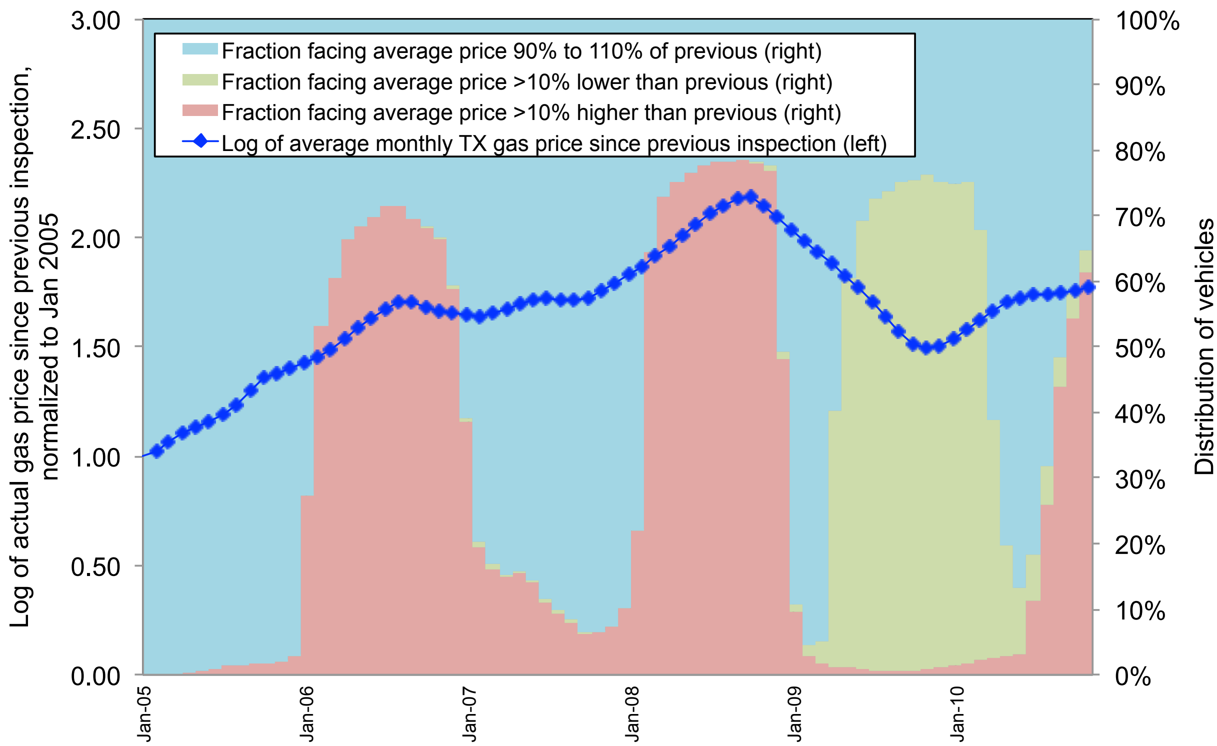


Table 4.11 indicates that consumers decrease their VMT up to 20% when gasoline prices are more than 10% higher than in the previous year, but increase their VMT over 30% when prices are more than 10% lower than in the previous year.

Table 4.11. Estimated effect of change in gas price on annual VMT by whether gas price was falling or rising, Model 5

Average price at time of current inspection relative to average price at previous inspection	Without instrument		With instrument	
	No fixed effects	Vehicle model fixed effects	No fixed effects	Vehicle model fixed effects
Higher than previous (>1.10)	-0.120	-0.187	-0.127	-0.197
Lower than previous (<0.90)	0.338	0.317	0.388	0.362
Similar to previous (0.90 to 1.10)	0.948	0.912	1.225	1.174

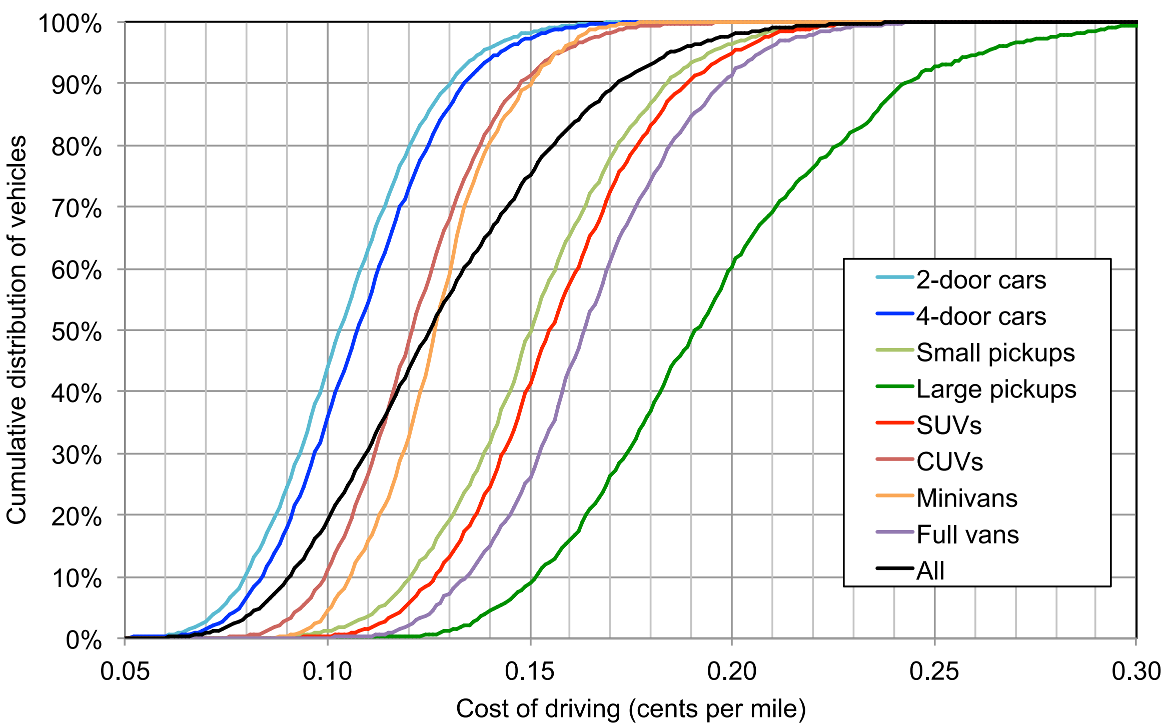
Note: all estimates are statistically significant at the 95% confidence level.

4.3.7 Estimates of VMT elasticity to a change in the cost of driving

As discussed above, much of the literature uses the VMT elasticity in response to a change in the price of gasoline as a proxy for the response to a change in the cost of driving. We used the combined fuel economy of each vehicle to calculate the cost of driving, in cents per mile, since the vehicle's previous inspection. The cost of driving is simply the cost of gasoline ($ per gallon) divided by the vehicle's combined fuel economy (miles per gallon).[25]

Figure 4.10 shows the cumulative distribution of the cost of driving, by vehicle type. The curves are smoother than the fuel economy curves shown in Figure 4.7, as the calculated cost of driving is calculated to greater precision than whole numbers. In general, the trends in the cost of driving by vehicle type in Figure 4.10 are similar to those for fuel economy in Figure 4.7, with cars having the lowest average cost of driving (around 10.5 cents per mile), followed by CUVs/minivans (12 cents per mile), small pickups and SUVs (15 cents per mile), full vans (16 cents per mile), and large pickups (19 cents per mile).

Figure 4.10. Cumulative distribution of the cost of driving, by vehicle type



The top panel of Table 4.12 repeats the estimated effect of an increase in the price of gasoline on annual VMT for 30 regression models in Table 4.1, while the bottom panel of Table 4.12 shows

[25] The actual cost of driving also includes other components, including vehicle depreciation, maintenance and repairs, registration and inspection fees, etc.

the estimated effect of an increase in the cost of driving.[26] The regression models with no fixed effects (columns A and D) estimate that an increase in the cost of driving is associated with consistent increases in annual VMT (bottom panel of Table 4.8), whereas an increase in the price of gasoline is associated mostly with decreases in annual VMT (top panel of Table 4.12). The models using vehicle make-model fixed effects (columns B and E) estimate that an increase in the cost of driving is associated with a larger decrease in annual VMT than an increase in the price of gasoline, for all five regression models except Model 3. For example, Models 4 and 5 using vehicle make-model fixed effects estimate that an increase in the cost of driving is associated with a decrease in VMT (a 15% to 16% decrease) that is nearly twice that associated with an increase in the price of gasoline (an 8% to 9% decrease in VMT), regardless of whether a supply instrument is used. For the models using individual VIN fixed effects (columns C and F), an increase in the cost of driving has about the same estimated effect on annual VMT as an increase in the price of gasoline.

Table 4.12. Estimated elasticity of VMT demand to changes in the price of gasoline or the cost of driving, 5 regression models

Model	Control variables used				Without supply instrument			With supply instrument		
	Unem-ployment	CY	Age	Month	A. No FE	B. M-M FE	C. VIN FE	D. No FE	E. M-M FE	F. VIN FE
Change in the price of gasoline										
1	n	n	n	n	-0.086*	-0.161*	-0.217*	-0.131*	-0.279*	-0.392*
2	y	y	cont	n	0.063*	0.018*	-0.129*	0.070*	0.021*	-0.128*
3	y	y	disc	n	-0.204*	-0.215*	-0.075*	-0.211*	-0.224*	-0.076*
4	y	y	disc	cont	-0.075*	-0.082*	0.004	-0.082*	-0.092*	0.000
5	y	y	disc	disc	-0.065*	-0.075*	0.005*	-0.076*	-0.087*	0.001
Change in the cost of driving										
1	n	n	n	n	0.054*	-0.284*	-0.213*	0.049*	-0.403*	-0.382*
2	y	y	cont	n	0.155*	-0.164*	-0.128*	0.156*	-0.167*	-0.126*
3	y	y	disc	n	0.124*	-0.209*	-0.074*	0.125*	-0.212*	-0.074*
4	y	y	disc	cont	0.134*	-0.154*	0.001	0.134*	-0.160*	-0.001
5	y	y	disc	disc	0.135*	-0.152*	0.001	0.135*	-0.159*	-0.001

* Estimate is statistically significant at the 95% confidence level.

Figure 4.11 demonstrates why the regression models with no fixed effects (columns A and D in Table 4.12) estimate that an increase in the cost of driving is associated with an increase in annual VMT. Figure 4.11 shows the average annual VMT by the cost of driving, for each vehicle type; vehicle types are shown in color, while all vehicle types combined are shown in black. Note that for all types of vehicles except large pickups, annual VMT decreases as the cost of driving increases (shown in colored lines), especially when the cost of driving is at its highest; the effect is strongest for cars (shown in blue). Annual VMT in large pickups, however, increases strongly as the cost of driving increases (shown in green). The trend in annual VMT for all vehicles combined (shown in black), however, is u-shaped, with VMT decreasing as cost of driving increases when the cost of driving is low (on the left hand side of the figure), where

[26] There are 4.2% fewer observations used in the models of the cost of driving than the models of the price of gasoline, for vehicles with missing rated fuel economy data; most of those vehicles with missing fuel economy data are large pickups with a gross vehicle weight rating over 9,000 pounds.

cars with relatively high fuel economy dominate the overall trend (blue dashed line for 4-door cars), and VMT increasing as the cost of driving increases when the cost of driving is high (on the right hand side of the figure), where large pickups with relatively low fuel economy dominate the overall trend (green dashed line). The net result for all vehicle types combined is that annual VMT increases slightly as the cost of driving increases (black dashed line).

Figure 4.11. Average annual VMT by cost of driving, by vehicle type

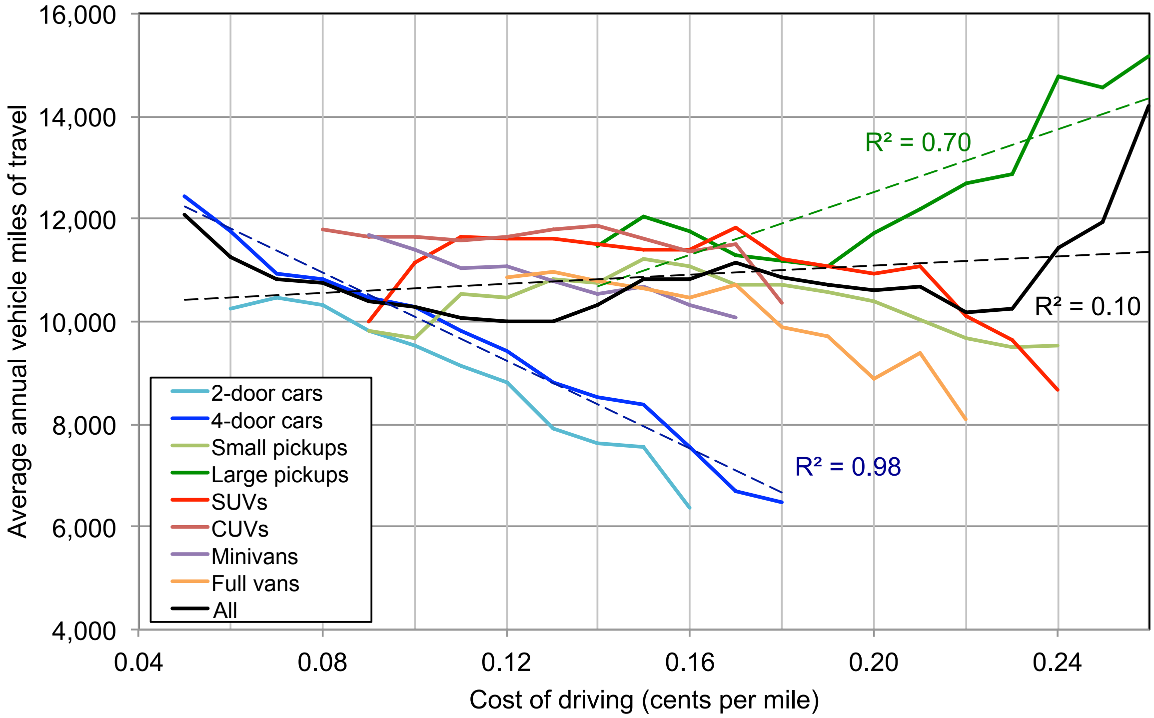


Table 4.13 confirms the trends shown in Figure 4.11. Table 4.13 shows the slope of the simple linear correlation between annual VMT and the cost of driving, by vehicle type, without accounting for any other explanatory variables. For every \$0.10 increase in the cost of driving, annual VMT decreases for almost all vehicle types, especially for cars (over 3,400 miles), full vans (over 1,900 miles), and minivans (over 1,700 miles). The exception is large pickups, whose annual VMT increases over 2,000 miles as the cost of driving increases \$0.10. However, for all vehicle types combined, annual VMT increases slightly (760 miles) as the cost of driving increases.

Table 4.13. Relationship between cost of driving and annual VMT by vehicle type

Two-door cars	-3728*
Four-door cars	-3406*
Small pickups	-265*
Large pickups†	2306*
SUVs	-623*
CUVs	-433*
Minivans	-1734*
Full vans	-1903*
All	760*

* Estimate is statistically significant at the 95% confidence level.
† Excludes pickups with GVWR greater than 9,000 pounds.

As with the price of gasoline in Table 4.5, we ran eight versions of regression Model 5E in Table 4.8, one for each vehicle type, using the cost of driving instead of the price of gasoline as an explanatory variable. Table 4.14 indicates that a 1% increase in the cost of driving is associated with a decrease in VMT in all vehicle types, except for small pickups and SUVs with no fixed effects, and full vans with vehicle model fixed effects. The average change in VMT from an increase in the cost of driving in the last column of Table 4.14, weighted by the distribution by vehicle type, is -0.167, comparable to the -0.159 elasticity estimated without accounting for vehicle type (using Model 5E in the bottom panel of Table 4.12).

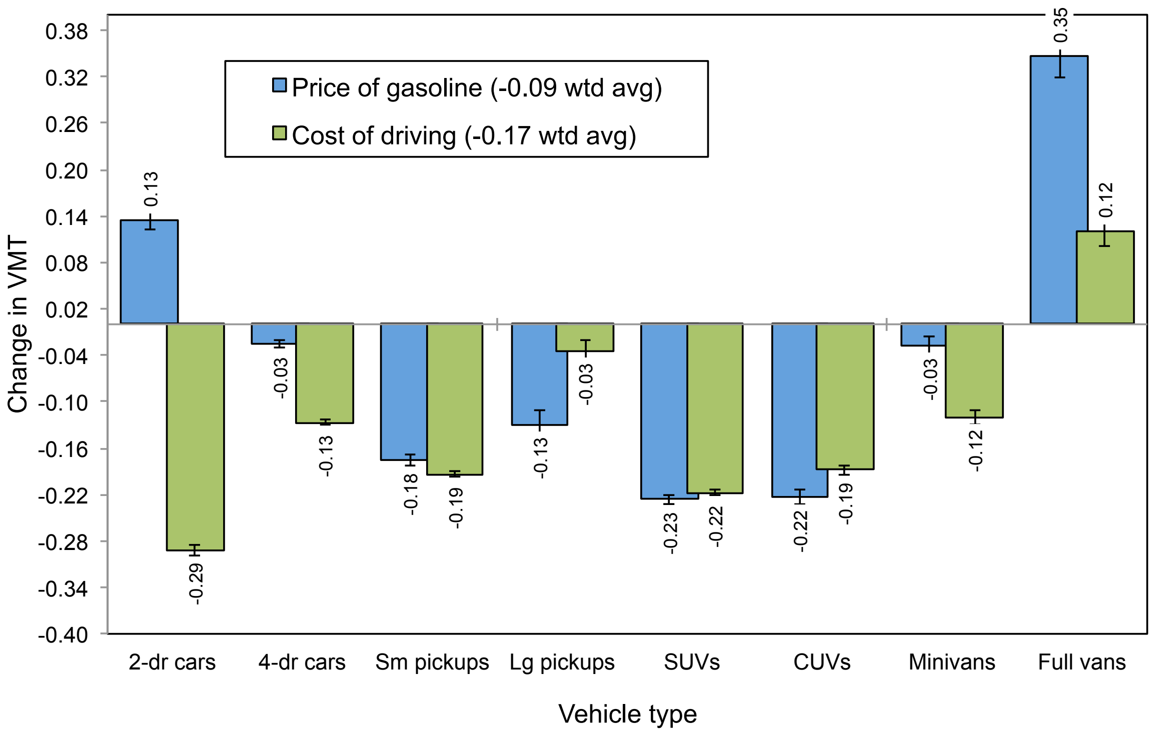
Table 4.14. Estimated effect of change in cost of driving on annual VMT by vehicle type, Model 5

		Without instrument		With instrument	
Vehicle type	Distribution of vehicles	No fixed effects	Make-model fixed effects	No fixed effects	Make-model fixed effects
Two-door cars	7%	-0.621*	-0.280*	-0.626*	-0.291*
Four-door cars	42%	-0.451*	-0.122*	-0.454*	-0.127*
Small pickups	18%	0.145*	-0.185*	0.145*	-0.194*
Large pickups†	1%	-0.074*	-0.028	-0.080*	-0.034*
SUVs	19%	0.114*	-0.209*	0.115*	-0.218*
CUVs	6%	-0.051*	-0.183*	-0.051*	-0.188*
Minivans	5%	-0.158*	-0.109*	-0.168*	-0.120*
Full vans	1%	-0.272*	0.125*	-0.284*	0.120*

* Estimates are statistically significant at the 95% confidence level.
† Large pickups exclude pickups with GVWR greater than 8,500 pounds.

Figure 4.12 compares the last columns (using the supply instrument and vehicle model fixed effects) in Tables 4.14 (cost of driving) and 4.8 (price of gasoline), by vehicle type. Note that the average of the estimates for each vehicle type weighted by the distribution of vehicles by type roughly corresponds to the overall estimates from Model 5E in Table 4.12: a 0.09% decrease in VMT from an increase in the price of gasoline, and a 0.17% decrease in VMT from an increase in the cost of driving. The figure indicates that the estimated effect of a 1% increase in the cost of driving is associated with nearly the same decrease in annual VMT as a 1% increase in the price of gasoline, for small pickups, SUVs, and CUVs (between 0.18% and 0.23%, depending on vehicle type). However, an increase in the cost of driving is associated with a larger decrease in annual VMT than an increase in the price of gasoline, for four-door cars and minivans (a 0.13% vs. 0.3% decrease), and a smaller increase in annual VMT for full vans (a 0.12% vs. 0.35% increase); an increase in the cost of driving for two-door cars is associated with a 0.29% decrease in VMT, as opposed to a 0.13% increase in VMT from an increase in the price of gasoline. An increase in the cost of driving is associated with a smaller decrease (a 0.03% decrease) in annual VMT in large pickups than an increase in the price of gasoline (a 0.13% decrease).

Figure 4.12. Estimated effect of change in cost of driving on annual VMT by vehicle type, Model 5



Since the elasticity of VMT with respect to the cost of driving accounts for the fuel economy of each driver's vehicle, the miles driven by car and minivan drivers appear to be more sensitive to the rated fuel economy of their vehicle than drivers of other types of vehicles.

4.4 Comparison with analysis of microdata from Pennsylvania

Gillingham et al. 2015 recently conducted a similar analysis using microdata from Pennsylvania from 2000 to 2010. We replicated the regression models in Gillingham 2015; Table 4.15 compares the baseline regression model results from Pennsylvania with those from Texas from 2005 to 2010, using the same control variables and supply instruments in Gillingham et al. 2015. Gillingham shows monthly U.S. GDP; we interpolated monthly U.S. GDP from quarterly GDP, and converted U.S. GDP and Texas gasoline price into 2005 dollars using the monthly CPI. As in our baseline regression models in Table 4.1, we used 2008 as the default calendar year value, and July as the default month of year value; for the time since previous inspection dummies we used inspections between 11 and 13 months since the previous inspection as the default value.

While an increase in gas price is consistently associated with a decrease in annual VMT in Pennsylvania, using Gillingham's model specifications, that is not the case in Texas; only Model G3 in Table 4.15 estimates a decrease in VMT from an increase in Texas gasoline price, and the estimated effects on VMT tend to be smaller in Texas than in Pennsylvania. An increase in GDP is consistently associated with large increases in VMT in Pennsylvania, but is associated with smaller effects in Texas. In both states increases in the unemployment rate are associated with increases in annual VMT, although the increases are much smaller in Texas than in Pennsylvania in Models G1 and G2; while older vehicles are associated with lower annual VMT in each state.

Table 4.15. Comparison of results from Pennsylvania (Gillingham 2015) and Texas

	Pennsylvania 2000-2010 (Gillingham 2015)				Texas 2005-2010			
Variable	(G1) Time Controls	(G2) Vehicle FE	(G3) All + Vehicle FE	(G4) All + vehicle FE + IV	(1) Time Controls	(2) Vehicle FE	(3) All + Vehicle FE	(4) All + vehicle FE + IV
Ln(gas price)	-0.143	-0.132	-0.219	-0.099	0.018	-0.027	0.060	0.100
Ln(US GDP)	6.320	2.090	3.850	3.180	0.747	0.555	1.031	1.125
Ln(unemp rate)	0.765	0.213	0.311	0.328	0.122	0.081	0.248	0.286
Vehicle age	-0.011	-0.059	-0.008	-0.091	-0.007	-0.030	-0.068	-0.074
Vehicle age^2	-0.003	-0.002	-0.002	-0.002	-0.004	-0.002	-0.002	-0.002
Vehicle FE	–	y	y	y		y	y	y
CY05	y	–	y	y	0.034	–	-0.110	-0.120
CY06	y	–	y	y	0.023	–	-0.083	-0.093
CY07	y	–	y	y	0.011	–	-0.038	-0.040
CY09	y	–	y	y	-0.020	–	0.005	0.009
CY10	y	–	y	y	-0.039	–	0.000	0.000
January	y	–	y	y	0.042	–	0.035	0.038
February	y	–	y	y	0.039	–	0.027	0.030
March	y	–	y	y	0.020	–	0.020	0.023
April	y	–	y	y	0.005	–	0.016	0.019
May	y	–	y	y	0.007	–	0.013	0.014
June	y	–	y	y	0.004	–	0.007	0.008
August	y	–	y	y	-0.013	–	-0.010	-0.010
September	y	–	y	y	-0.015	–	-0.016	-0.017
October	y	–	y	y	-0.027	–	-0.024	-0.025
November	y	–	y	y	-0.029	–	-0.027	-0.029
December	y	–	y	y	-0.028	–	-0.028	-0.030
<11 months	y	–	y	y	-0.299	-0.327	-0.331	-0.332
13-21 months	y	–	y	y	0.065	-0.020	-0.018	-0.018
>21 months	y	–	y	y	-0.021	-0.092	-0.086	-0.084
N (millions)	30.622	30.622	30.622	30.622	31.246	31.246	31.246	31.246
R^2	0.18	0.71	0.71	0.05*	0.08	0.72	0.72	0.72

* Gillingham reported the R^2 value of the OLS model, rather than the second stage of the 2SLS model (personal communication, Feb 2017).

Note: all estimates are statistically significant at the 95% confidence level.

Table 4.15 indicates that the discrete variables for the month of inspection are consistently associated with decreases in annual VMT for each month later in the calendar year. Additionally, vehicles whose last inspection was less than 11 months earlier, or more than 13 months earlier are associated with substantially larger annual VMT than vehicles whose last inspection was between 11 and 13 months earlier (i.e. on the regular annual inspection cycle). Because Texas also requires an inspection immediately prior to a vehicle changing ownership, the 3% of vehicles that were last tested less than 11 months ago were likely sold shortly after the previous inspection, and the current inspection is a "change of ownership" inspection. As mentioned above, we assume that consumers substantially reduce the VMT of vehicles that they are planning to sell; Table 4.14 indicates that vehicles that are about to be sold have substantially (30%) lower VMT than vehicles that were not about to be sold, and that the 9% of vehicles that delayed their annual inspection by more than nine months also had 3 to 10% lower VMT than the 46% of vehicles that reported for inspection on schedule. Gillingham does not report the estimated coefficients for the discrete year, month, or time since previous inspection variables.

We suspect that much of the difference in the results for Pennsylvania and Texas in Table 4.15 can be attributed to some of the control variables Gillingham used, and also his choice of Gulf Coast oil supply disruptions as the supply instrument to predict gas price. As discussed above, because of Texas' proximity to the Gulf Coast, hurricane and tropical storms would likely influence VMT demand in addition to oil production and gasoline supply, and thus would be a poor choice to isolate the effects of supply on gasoline prices in Texas. For this reason we use a different supply instrument in our baseline regressions for Texas. In addition, the Pennsylvania analysis spans a different time period (2000 through 2010) than the Texas analysis (2005 through 2010). Cultural, geographic, and industrial differences between the two states could also plausibly contribute to differential responses to gas price changes.

5 Conclusions

Using a large dataset of individual odometer readings from nearly every vehicle registered in four urban areas of Texas, we have examined the change in annual vehicle miles of travel attributable to an increase in the price of gasoline. Our analysis period spans from 2005 through 2010, a period when gas prices generally increased with a large decrease between mid-2008 and mid-2009, corresponding to a similar decline in economic conditions. We find that during this period Texans reduced their annual VMT by approximately 0.09% for every one percent increase in the price of gasoline. However, the sensitivity of annual VMT to the cost of driving, calculated by multiplying the price of gasoline by each vehicle's fuel economy, is nearly twice the sensitivity to the price of gasoline: a 0.16% reduction in VMT for every one percent increase in the cost of driving, in cents per mile. These estimates account for differences between vehicle models using fixed effects, and removes any effect of increased local travel on the local price of gasoline by using an instrument to predict the price of gasoline based changes in the supply of gasoline.

Regression results that account for individual vehicles (based on their vehicle identification number, or VIN) are quite different from our baseline results. We determined that this is because not all of the vehicles in our dataset have the same number of observations over our six-year analysis period, because vehicles frequently transfer into and out of Texas. When we restrict the analysis to only those vehicles that were observed six times over the six-year period we obtain essentially the same results using no fixed effects, vehicle model fixed effects, and individual vehicle fixed effects.

Following the literature we use an instrumental variable to address retail gas price endogeneity; however, we use the U.S. price of crude oil rather than weather-related supply disruptions in the Gulf Coast, which are likely correlated with travel and industry in Texas, particularly in the Houston region which borders the Gulf Coast.

Our baseline regression model controls for monthly changes in the unemployment rate in Texas; we find that an increase in the unemployment rate is associated with a decrease in annual VMT. Our results are highly sensitive to how we account for vehicle age. Average VMT tends to decrease not only by each year of annual age but by each successive month as well. As a result we use dummy variables for each year of vehicle age, as well as for the month in which the vehicle was observed. We also account for the calendar year in which the vehicle was observed.

We used quantile analyses to examine several variables that are expected to influence how much a vehicle is driven. We find that vehicles registered in zip codes with lower median household income have a larger decrease in VMT associated with an increase in gas prices than vehicles in zip codes with a higher median income. Surprisingly vehicles in zip codes with the lowest population density exhibit the largest decrease in VMT associated with an increase in the price of gasoline, even though we suspect households in such areas have fewer transportation options than the average household. As expected, vehicles registered in the densest urban areas also are associated with large decreases in VMT induced by gas price increases. Drivers in Austin are more sensitive to increases in gas price than drivers in Dallas or Houston, despite Austin having an overall lower Walk and Transit Score, and a higher average median income, than Dallas and Houston.

Increases in the price of gasoline are associated with increases in annual VMT for two-door cars, and especially full size vans. Two-door cars tend to have the highest fuel economy, so perhaps households switch their travel to those vehicles when gasoline prices are high; however, we had not anticipated that drivers of full vans would increase their travel the most in response to high gasoline prices. Regarding other types of vehicles, an increase in the price of gasoline is associated with relatively large decreases in VMT in car-based crossover utility vehicles (CUVs,) and truck-based sport utility vehicles (SUVs), and to a lesser extent in small pickups and large pickups. We suspect that the low fuel economy of the light trucks makes their drivers particularly sensitive to increases in the price of gasoline; this sensitivity may be muted for the large pickups which are often used for specific work-related tasks. However, we were surprised to find that drivers of CUVs are equally as sensitive to high gasoline prices as drivers of light trucks, despite their relatively higher fuel economy; perhaps CUVs tend to be owned by households with other, more efficient vehicles (i.e. cars) that can be used as substitutes when gas prices are high. We plan to investigate the extent to which households switch their travel to a different vehicle in response to changes in the price of gasoline in a future analysis at the household level.

For most vehicle types, vehicles with relatively low fuel economy have a larger decrease in VMT in response to an increase in the price of gasoline than vehicles with relatively high fuel economy; the relationship is strongest in CUVs, followed by small pickups/SUVs, with drivers of cars the least responsive to an increase in the price of gasoline. VMT actually increases in large pickups with high fuel economy in response to an increase in the price of gasoline. Minivans and full vans have the opposite effect of the other vehicle types, where increasing fuel economy results in decreases in VMT; an increase in the price of gasoline is associated with relatively large increases in VMT in full vans, regardless of their rated fuel economy. By effectively decreasing the price of gasoline, fuel economy standards are likely to induce drivers of new, relatively high MPG vehicles to increase their VMT. Our analysis by rated fuel economy suggests that increased fuel economy standards will induce drivers of high MPG vehicles to increase their VMT, by 15% in CUVs, 10% in small pickups and SUVs, 7% in minivans, and less than 1% in cars. We estimate the weighted average VMT increase in new high MPG vehicles to be 5.2%.

In potential future work, we plan to expand our analysis in two ways. First, we plan to use the vehicle registration data to aggregate individual vehicles into household fleets, based on common addresses. This enhancement will allow us to potentially account for number, and type, of vehicles in the household when estimating a household's combined VMT in response to a change in gas prices. It also will allow us to conduct an analysis of change in VMT for a subset of households that acquired a new vehicle during the study period, to examine the sensitivity of VMT to the replacement with a higher fuel economy, similar to De Borger et al. (2016). Second, we will extend the analysis with updated vehicle odometer and registration data through 2017; the updated dataset will also include odometer data for vehicles outside of the four metropolitan areas (from the Texas annual safety inspection program) starting in January 2012, data which were not available for the current analysis.

References

Angrist, J. and A. Krueger (1991). "Does Compulsory School Attendance affect Schooling and Earnings?" The Quarterly Journal of Economics **106**(4): 979-1014.

DeBorger, B., I. Mulalic, et al. (2016). "Measuring the rebound effect with microdata : A first difference approach." Journal of Environmental Economics and Management **79**(2016): 1-17.

Durbin, J. (1954). "Errors in Variables." Review of the International Statistical Institute **22**: 23-32.

Gillingham, K. (2011). The Consumer Response to Gasoline Price Changes: Empirical Evidence and Policy Implications Ph.D. Dissertation, Stanford University.

Gillingham, K. (2014). "Identifying the elasticity of driving: Evidence from a gasoline price shock in California." Regional Science and Urban Economics **47**(2014): 13-24.

Gillingham, K., A. Jenn, et al. (2015). "Heterogeneity in the Response to Gasoline Prices: Evidence from Pennsylvania and Implications for the Rebound Effect." Energy Economics **51**(S1): S41-S52.

Goldberg, P. K. (1998). "The Effects of the Corporate Average Fuel Economy Standards in the US." The Journal of Industrial Economics **46**: 1-33.

Greene, D. L. (2012). "Rebound 2007: Analysis of National Light - Duty Vehicle Travel Statistics." Energy Policy **41**: 14-28.

Greene, W. H. (2008). Instrumental Variables Estimation. Econometric Analysis. Upper Saddle River, New Jersey, Pearson Prentice Hall.

Hughes, J. E., C. R. Knittel, et al. (2006). Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand. Cambridge, MA, National Bureau of Economic Research. **NBER Working Paper 12530**.

Hymel, K., K. A. Small, et al. (2010). "Induced demand and rebound effects in road transport." Transportation Research B: Methodology **44**(10): 1220–1241.

Hymel, K. M. and K. A. Small (2015). "The rebound effect for automobile travel: Asymmetric response to price changes and novel features of the 2000s." Energy Economics **49**(2015): 93-103.

Khazzoom, J. D. (1980). "Economic Implications of Mandated Efficiency in Standards for Household Appliances." The Energy Journal **1**(4): 21-40.

Knittel, C. R. and R. Sandler (2012). Carbon Prices and Automobile Greenhouse Gas Emissions: The Extensive and Intensive Margins. The Design and Implementation of U.S. Climate Policy. Don Fullerton and Catherine Wolfram, National Bureau of Economic Research**:** 287-299.

Knittel, C. R. and R. Sandler (2013). The Welfare Impact of Indirect Pigouvian Taxation: Evidence from Transportation. NBER Working Paper Series, National Bureau of Economic Research. **No. 18849**.

Levin, L., M. S. Lewis, et al. (2013). High Frequency Evidence on the Demand for Gasoline. Working Paper.

Li, S., J. Linn, et al. (2012). Gasoline Taxes and Consumer Behavior. NBER Working Paper Series, National Bureau of Economic Research. **Working Paper 17891**.

Lin, C.-Y. C. and L. Prince (2013). "Gasoline price volatility and the elasticity of demand for gasoline." Energy Economics **38**(2013): 111-117.

Linn, J. (2013). The Rebound Effect for Passenger Vehicles. RFF Discussion Paper, Resources for the Future. **RFF DP 13-19**

Molloy, R. and H. Shan (2013). "The Effect of Gasoline Prices on Household Location." Review of Economics and Statistics **95**(4): 1212-1221.

Reiersøl, O. (1941). "Confluence Analysis by Means of Lag Moments and Other Methods of Confluence Analysis." Econometrica **9**(1): 1-24.

Small, K. A. and K. V. Dender (2007). Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. Economics Working Paper, University of California, Irvine **#05-06-03**.

Wald, A. (1940). "The Fitting of Straight Lines if Both Variables are Subject to Error." Annals of Mathematical Statistics **11**: 284-300.

West, S. E. (2004). "Distributional Effects of Alternative Vehicle Pollution Control Technologies." Journal of Public Economics **88**(3-4): 735-757.

Wright, S. (1928). The Tariff on Animal and Vegetable Oils. New York, P.G. Wright, MacMillan.

Appendix A. Instrumenting for price of gasoline in Texas

This appendix provides additional discussion of the rationale behind instrumental variables and two-stage least squares regression models. Some of the results presented here are duplicated from the primary results section to provide a cohesive discussion of the instrumental variables process in one location for ease of reference for readers unfamiliar with such statistical techniques.

A.1 Why use instrumental variables?

Explanatory variables can be endogenous, that is correlated with the error term in a regression model. For example, in a model predicting the quantity of a good sold based on its price, unobserved attributes of the good which are demanded by the consumer may increase the good's price. The demand for a more expensive good may be partially explained by its higher quality rather than strictly its price. In our case increased demand to travel may reduce the supply of gasoline, thereby increasing its price. Ignoring this endogeneity leads to biased estimates of regression coefficients in ordinary least-squares (OLS) regression. Some sources of endogeneity can be addressed through the use of fixed effects, which hold constant unobservable factors associated with the fixed effect variable; in our case, vehicle makes and models, or individual vehicles based on identification numbers (VINs). However, the very nature of time series data makes it likely that some endogeneity bias remains.

When we look at a sample of time series data, what we observe are pairings of gas price and VMT (p_t, VMT_t) at different points in time (see Figure A.1, panel A). Straightforward OLS regression on such a data set will produce an estimate of the gas price elasticity of VMT demand (elasticity of VMT with respect to gas price), but this estimate is likely to be biased (due to endogeneity, etc), and as demonstrated in the figure, bias can be strong enough to falsely predict a positive relationship between gas price and VMT if unrelated factors are influencing the supply of gasoline, and therefore its price (see fitted line with slope β_p). While we only observe the points in panel A, these pairs actually represent the instantaneous equilibria conditions at various points in time, as supply and demand shift (panel B). In estimating the price elasticity of VMT demand, we are interested in the slope of the demand curve as price changes, and not any shifts to the curve as other factors influence the supply of gasoline, and therefore its price.

Economists use instrumental variables in two-stage least squares regression in order to remove any supply-related changes in price when estimating the demand curve, leaving an unbiased (or at least less biased) estimate of the effect of a change in gas price on annual VMT (see Figure A.2).

Figure A.1. Bias in demand elasticity estimated from time series data

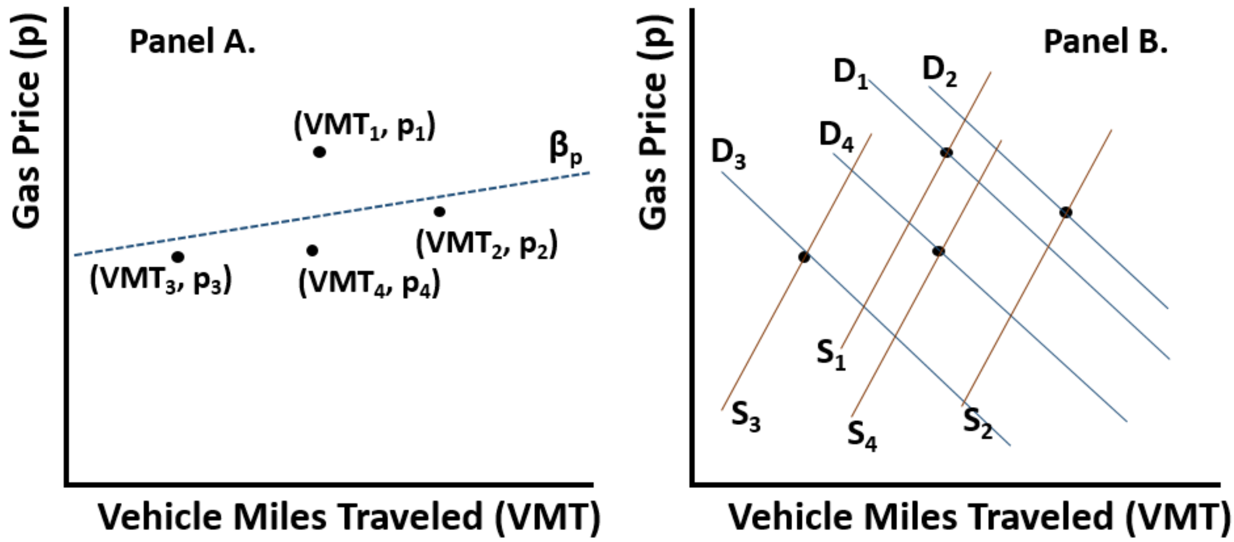
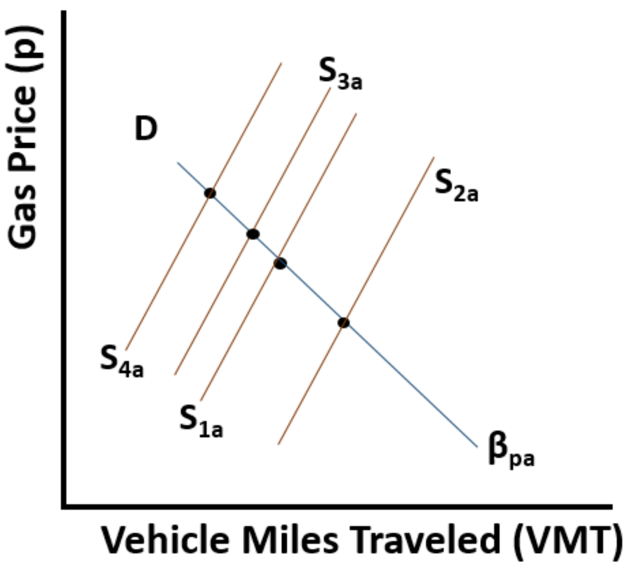


Figure A.2. Supply shocks reveal the demand curve



Instrumental variables can be used to address several forms of regression bias: 1) issues arising from simultaneous causality between the dependent variable and an independent variable of interest (see, e.g., Wright 1928; Reiersøl 1941); 2) bias from measurement error in regression models (see, e.g., Wald 1940; Durbin 1954); and 3) omitted variable bias (see, e.g., Angrist and Krueger 1991). Greene (2008) provides a through discussion of the theory underlying instrumental variables estimation. In our current focus on VMT in Texas, bias source 1) refers to the codetermination of the supply and demand for gasoline; changes in the price of gasoline are expected to influence consumers' choice of driving distance, but fluctuations in driving distance and the associated quantity of gasoline purchased could conceivably influence the price of gasoline (additionally, both gas price and VMT may be influenced by outside factors we are unable to account for). In time series data such as we use in this analysis, we view snapshots of the equilibria between demand for and supply of gasoline at different points in time. By using an instrumental variable to identify supply-related shifts in gas price, we aim to more accurately estimate the relationship between VMT and the exogenous variation in gas price.

Previous analyses of the gas price elasticity of VMT demand (including those framed as estimates of the rebound effect) have instrumented key regressors, such as gas price (Hughes, Knittel et al. 2006; Gillingham 2014; Gillingham, Jenn et al. 2015), vehicle characteristics (DeBorger, Mulalic et al. 2016), and vehicle fuel economy (Linn 2013).

A.2 Two-stage least squares (2SLS) regression model

We construct several versions of a two-stage least squares (2SLS) fixed effects regression model, in which we use instruments to predict monthly gas prices in Texas. Two stage least squares regression uses the exogenous variation in an explanatory variable (gas price) to provide an unbiased estimator of its impact on the dependent variable (VMT).

In the first stage, we regress the endogenous explanatory variable, retail gas price (p_t^g), on the other explanatory variables and the instruments.[27] Using the coefficients obtained from the first stage regression, we calculate fitted values of the endogenous explanatory variable ($\widehat{p_t^g}$); if the instrument is strong, these fitted values will now be exogenous.

Stage one:

$$p_t^g = \propto_0 + \propto_z \boldsymbol{z_t} + \mu U_t + \boldsymbol{\alpha_v V_{it}} + \boldsymbol{\delta D_i} + \gamma_i + \varepsilon_{it}$$

Where:
p_t^g= monthly TX gas retail price variable,
$\boldsymbol{z_t}$= gas price instruments,
U_t = monthly TX unemployment rate,
$\boldsymbol{V_{it}}$= vehicle age,
$\boldsymbol{D_i}$= demographic variables (population density and median household income by zip code),
γ_i= fixed effect (make-model or VIN),
ε_{it} = residual,
i = vehicle index (unique VIN),
t = time index (month).

Following stage one, we calculate the instrumented gas price ($\widehat{p_t^g}$) for each entry in the data set. The second stage then proceeds as usual for OLS with fixed effects, with the exception that instrumented gas price ($\widehat{p_t^g}$) is included instead of our original endogenous gas price variable (p_t^g).[28]

[27] Note that this can be done in models with or without fixed effects.
[28] We perform several versions of these regressions, each with different sets of explanatory variables. This requires separate computations of first stage coefficients, such that the explanatory variables and fixed effects of each first stage match those of its second stage.

Stage two:

$$VMT_{it} = \beta_0 + \beta_p \widehat{p_t^g} + \mu U_t + \boldsymbol{\beta_v V_{it}} + \boldsymbol{\delta D_i} + \gamma_i + \epsilon_t$$

Where:
VMT_{it} = vehicle miles traveled,
$\widehat{p_t^g}$= predicted monthly TX gas retail price,
U_t = monthly TX unemployment rate,
$\boldsymbol{V_{it}}$= vehicle age,
$\boldsymbol{D_i}$**=** demographic variables (population density and median household income by zip code),
γ_i= fixed effect (make-model or VIN),
ϵ_t = residual,
i = vehicle index (unique VIN), and
t = time index (month).

A.3. Instrument choice

In general, instruments should be correlated with the explanatory variable of interest (in our case the Texas retail price of gasoline), but not with the unobserved variation captured in the error term of the linear model. Ideally, there will be a strong correlation between the instrument and the instrumented explanatory variable (retail price of gasoline), and no correlation between the instrument and the dependent variable (VMT), except through the instrumented explanatory variable (predicted price of gasoline).

We considered five instruments for monthly Texas retail gasoline price based on several supply variables: U.S. crude oil price),[29] quantity of OPEC crude oil output,[30] U.S. oil refinery distillation utilization factor (i.e., the ratio of refined oil output to refinery capacity,[31] and, as in Hughes et al. (2006), Gillingham (2014), and Gillingham et al. (2015), weather-related oil supply disruptions in the U.S. Gulf Coast area.[32] Because of its location near the Gulf Coast, gasoline demand in Texas may not be fully independent of extreme weather events that disrupt oil production in the Gulf Coast; in other words, extreme weather events in the Gulf Coast may simultaneously disrupt oil production and cause changes in demand for VMT and gasoline in much of Texas. Therefore we also examine OPEC surplus production capacity[33] as a potential supply instrument.

Note that Texas has a substantial oil production sector, so in theory U.S. oil prices may not be entirely exogenous to circumstances that might simultaneously influence demand for gasoline

[29] U.S. EIA, Petroleum & Other Liquids, Texas Total Gasoline Retail Sales by All Sellers (Dollars per Gallon).
[30] U.S. EIA Short-Term Energy Outlook, Table 3c. OPEC Crude Oil (excluding Condensates) Supply, Crude Oil, OPEC Total.
[31] U.S. EIA Short-Term Energy Outlook, Table 4b. U.S. Petroleum Refinery Balance, Refinery Distillation Utilization Factor.
[32] U.S. EIA, Short-Term Energy Outlook Supplement: 2014 Outlook for Hurricane-Related Production Outages in the Gulf of Mexico, Table A1. Shut-in Production Caused by Gulf of Mexico Tropical Storms and Hurricanes, 1995-2013, https://www.eia.gov/forecasts/steo/special/pdf/2014_sp_02.pdf. Crude oil "shut-in production" is the anticipated production that has been "shut-in", i.e. left in the ground, because of hurricanes or tropical storms.
[33] U.S. EIA Short-Term Energy Outlook, Table 3c. OPEC Crude Oil (excluding Condensates) Supply, Crude Oil, OPEC Total Surplus Crude Oil Production Capacity.

and the price of crude oil. However, Figure A.3 indicates that the spot price for West Texas Intermediate crude oil extracted from the U.S. Midwest and Gulf Coast is nearly identical to that of Brent crude extracted from the North Sea, over the time period of our analysis, suggesting that global and national oil prices are largely unaffected by local demand for gasoline.

Figure A.3. Monthly crude oil spot prices, West Texas Intermediate and Brent crude

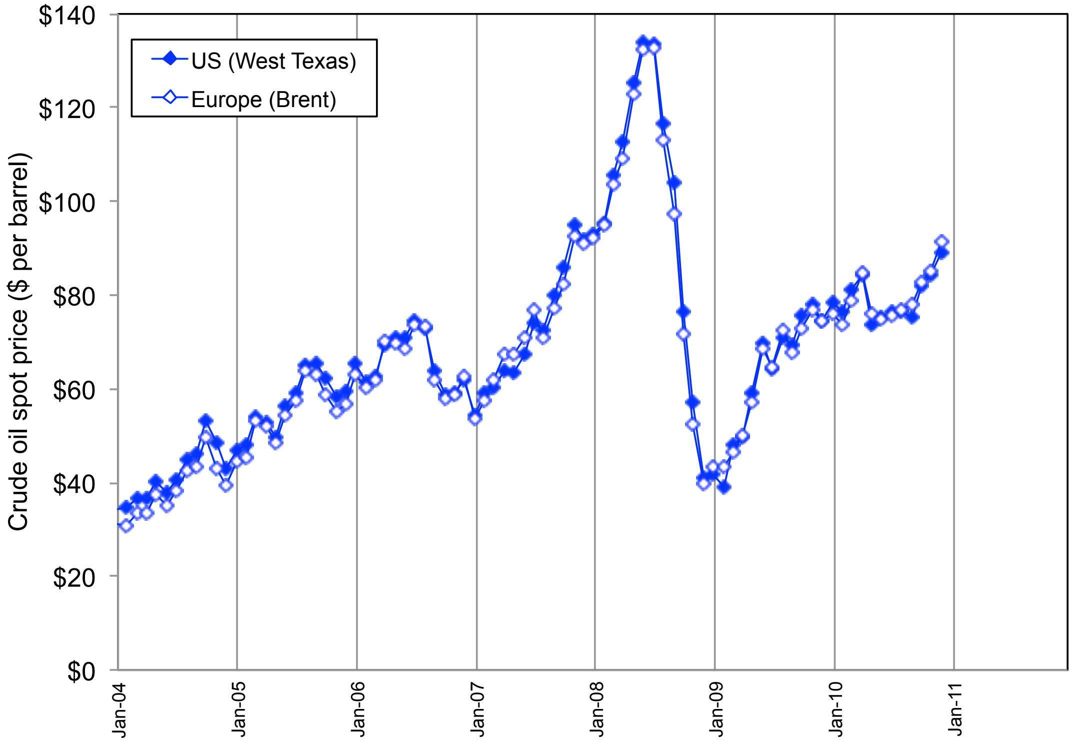


Table A.1 indicates that only the U.S. crude oil price (USOIL) is highly correlated with Texas gas price (TXGAS), with a correlation coefficient (r) of 0.93. The other four supply variables have much lower correlations with the price of gasoline in Texas (correlations above 0.30 are italicized).

Table A.1. Correlation matrix of Texas gas price and five supply variables

Variable	TXGAS	USOIL	DIST	OPEC	HURR	SURP
TXGAS (TX gas price)	1.00	–	–	–	–	–
USOIL (U.S. crude oil price)	*0.93*	1.00	–	–	–	–
DIST (distillation utilization factor)	-0.23	*-0.49*	1.00	–	–	–
OPEC (OPEC production)	0.28	0.09	*0.64*	1.00	–	–
HURR (production distruption)	-0.08	-0.17	0.27	*0.65*	1.00	–
SURP (OPEC surplus capacity)	-0.04	0.22	*-0.80*	*-0.92*	*-0.61*	1.00

Figure A.4 presents the price of gasoline in Texas and the five supply instrument variables we considered, by month; each monthly value represents the average monthly value since the previous inspection for each vehicle (roughly over the previous twelve months for most vehicles), converted to a normal log, and indexed to the value as of January 2005. Figure A.4 indicates that the trend in the U.S. average price of crude oil (shown in green) mirrors that of the price of gasoline in Texas, while shut-in production during hurricanes or tropical storms in the Gulf of Mexico (shown in orange) is quite volatile, even after taking the average monthly value since the previous inspection. The trend in OPEC crude oil production (shown by open triangles, right scale) is very similar to that of Texas gasoline price and U.S. oil price, but indicates an overall decline over the study period, while the trend in OPEC crude oil surplus capacity (shown in teal) is very nearly opposite that of Texas gasoline price and U.S. oil price. In contrast to the other supply variables, the distillation utilization factor in U.S. refineries (shown by open circles, right hand scale) does not vary much by month.

Figure A.4. Trend in average gas price and four supply instruments by month, averaged since the previous inspection, converted to normal log, and indexed to January 2005

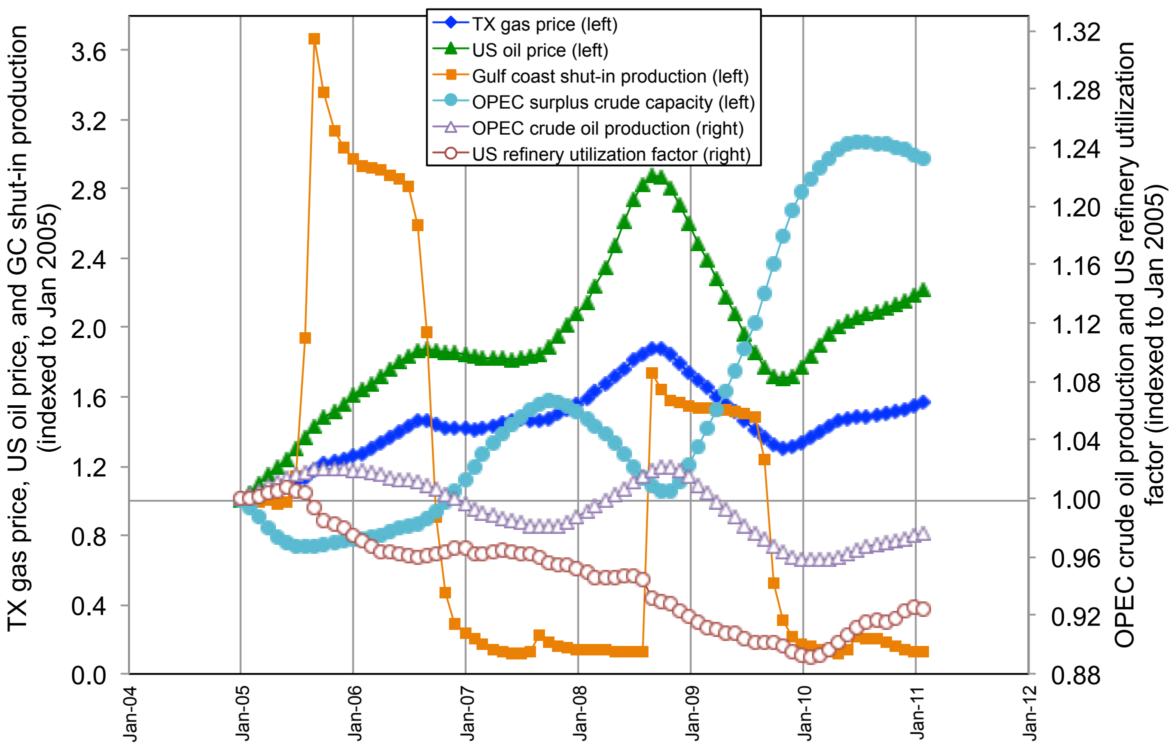


Table A.2 shows the model R^2 and the Hausman test score (divided by 1000) of 17 regression models using different combinations of the four supply variables in Table A.1. A Hausman test value of over 40 (or 0.04 in Table A.2) indicates that using the predicted gas price based on the supply instruments is preferable to using the retail gas price at the 95% confidence level for 20 degrees of freedom. The other control variables used in each model in Table A.1 are: the unemployment rate since the previous inspection, five calendar year dummy variables, eleven vehicle age dummy variables, and a continuous variable for the month of inspection (i.e. Model 4 in Table 4.1 above).

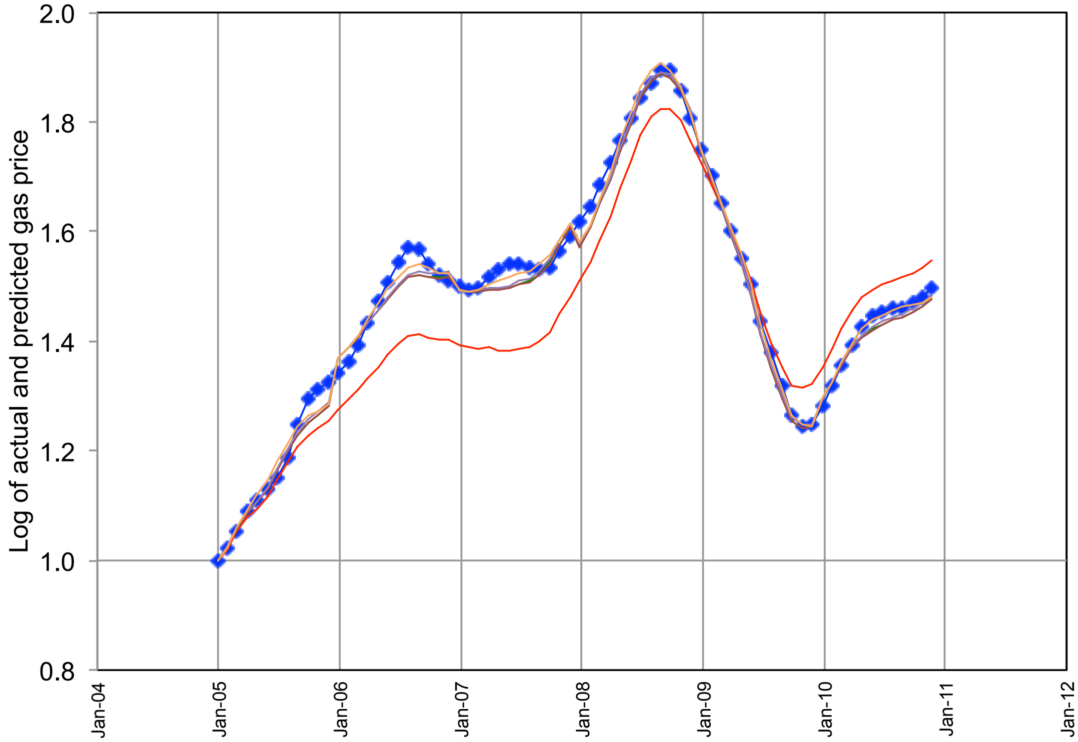
Table A.2 indicates that the models that include the U.S. oil price have the highest R^2, but not necessarily the highest Hausman scores. The high R^2 values are expected, as the U.S. oil price has a very high correlation with Texas gasoline price, as indicated in Table A.1. Models 15, 5, and 13 also have very high Hausman scores, which indicate that the instruments used to predict gasoline price are preferable to using retail gasoline price. We chose U.S. crude oil price as our instrument to predict Texas gas price, because of its high correlation with the price of gasoline, and its statistically significant Hausman test result, and because we do not believe this variable is itself strongly impacted by endogeneity in our model. We do not include any other supply variables as instruments.

Table A.2. Comparison of OLS regression of annual VMT as a function of actual Texas gas price vs. two-stage least squares regression of annual VMT as a function of predicted Texas gas price using instrumental supply variables

Model	USOIL	OPEC	HURR	DIST	SURP	Model R^2	Hausman (000s)
1	y	n	n	n	n	0.988	0.07
2	n	n	n	y	n	0.851	3.63
3	n	y	n	n	n	0.931	1.12
4	n	n	y	n	n	0.875	1.20
5	y	n	n	y	n	0.988	-4401
6	y	y	n	n	n	0.989	1.09
7	y	n	y	n	n	0.989	0.89
8	n	y	n	y	n	0.932	0.39
9	n	n	y	y	n	0.877	1.07
10	n	y	y	n	n	0.931	0.36
11	y	y	y	n	n	0.990	652
12	y	n	y	y	n	0.989	-65.4
13	y	y	n	y	n	0.989	-2347
14	n	y	y	y	n	0.933	6.64
15	y	y	y	y	n	0.992	-8353
16	n	n	n	n	y	0.906	-1.18
17	y	n	n	n	y	0.989	-1.13

Figure A.5 compares the trend in the actual price of gasoline (shown in blue diamonds) with the trends predicted using the supply instrument variable from the first stage regression for the five regression models in Table 4.1, without including fixed effects for vehicle make-models or individual vehicles (i.e. column D in Table 4.1). Figure A.5 indicates that the predicted price of gasoline based on U.S. oil price is nearly identical to the actual price of gasoline. The exception is the predicted price of gasoline from Model 1 in Table 4.1 (shown in red), which is as much as 10% lower than the actual price of gasoline in mid-2006 through mid-2007, and is as much as 6% higher than the actual price of gasoline starting in late 2009.

Figure A.5. Comparison of actual and predicted gas price under 20 regression models, prices averaged since previous inspection, converted to normal log, and indexed to January 2005



Appendix B. Detailed regression results from primary models

The detailed results for the regression models shown in Table 4.1 are presented in Tables B.1 through B.5, for Models 1 through 5, respectively.

Table B.1 Estimated elasticity of VMT demand to a change in the price of gasoline, Model 1

Control variable	Without supply instrument A. No FE	B. M-M FE	C. VIN FE	With supply instrument D. No FE	E. M-M FE	F. VIN FE
Intercept	9.324	—	—	9.555	—	—
LOGPRICE05	-0.086	-0.161	-0.217	-0.131	-0.279	-0.392
Observations	31.246	31.238	31.246	31.246	31.238	31.246
Model R^2	0.00	0.06	0.71	0.00	0.06	0.71

Note: All estimates are statistically significant at the 95% confidence level.

Table B.2 Estimated elasticity of VMT demand to a change in the price of gasoline, Model 2

Control variable	Without supply instrument A. No FE	B. M-M FE	C. VIN FE	With supply instrument D. No FE	E. M-M FE	F. VIN FE
Intercept	9.546	—	—	9.444	—	—
LOGPRICE05	0.063	0.018	-0.129	0.070	0.021	-0.128
LNUERATE	0.111	0.067	-0.014	0.115	0.069	-0.014
CY05	0.027	0.048	0.203	0.028	0.048	0.203
CY06	0.022	0.037	0.148	0.023	0.037	0.148
CY07	0.024	0.025	0.066	0.025	0.026	0.066
CY09	-0.030	-0.030	-0.096	-0.030	-0.030	-0.096
CY10	-0.043	-0.035	-0.141	-0.044	-0.035	-0.141
LNAVGAGE	-0.299	-0.264	0.126	-0.299	-0.264	0.126
Observations	31.246	31.238	31.246	31.246	31.238	31.246
Model R^2	0.05	0.09	0.72	0.05	0.09	0.72

Note: All estimates are statistically significant at the 95% confidence level.

Table B.3 Estimated elasticity of VMT demand to a change in the price of gasoline, Model 3

Control variable	Without supply instrument A. No FE	B. M-M FE	C. VIN FE	With supply instrument D. No FE	E. M-M FE	F. VIN FE
Intercept	9.879	—	—	10.162	—	—
LOGPRICE05	-0.204	-0.215	-0.075	-0.211	-0.224	-0.076
LNUERATE	-0.160	-0.169	0.026	-0.164	-0.174	0.026
CY05	-0.008	0.007	-0.045	-0.009	0.005	-0.045
CY06	0.014	0.024	-0.020	0.014	0.023	-0.020
CY07	-0.012	-0.009	-0.012	-0.013	-0.010	-0.012
CY09	0.005	0.002	-0.013	0.005	0.002	-0.013
CY10	0.062	0.059	0.017	0.063	0.060	0.017
AGE5	-0.019	-0.019	-0.049	-0.019	-0.019	-0.049
AGE6	-0.059	-0.056	-0.101	-0.059	-0.056	-0.101
AGE7	-0.108	-0.103	-0.162	-0.108	-0.103	-0.162
AGE8	-0.167	-0.157	-0.230	-0.167	-0.157	-0.230
AGE9	-0.231	-0.216	-0.301	-0.231	-0.216	-0.301
AGE10	-0.300	-0.279	-0.376	-0.300	-0.279	-0.375
AGE11	-0.378	-0.349	-0.451	-0.378	-0.349	-0.451
AGE12	-0.463	-0.428	-0.533	-0.463	-0.428	-0.533
AGE13	-0.552	-0.511	-0.623	-0.552	-0.511	-0.623
AGE14	-0.645	-0.600	-0.713	-0.645	-0.600	-0.713
AGE15	-0.741	-0.690	-0.789	-0.741	-0.690	-0.789
Observations	31.246	31.238	31.246	31.246	31.238	31.246
Model R^2	0.07	0.11	0.72	0.07	0.11	0.72

Note: All estimates are statistically significant at the 95% confidence level.

Table B.4 Estimated elasticity of VMT demand to a change in the price of gasoline, Model 4

	Without supply instrument			With supply instrument		
Control variable	A. No FE	B. M-M FE	C. VIN FE	D. No FE	E. M-M FE	F. VIN FE
Intercept	9.583*	—	—	9.698*	—	—
LOGPRICE05	-0.075*	-0.082*	0.004	-0.082*	-0.092*	0.000
LNUERATE	-0.028*	-0.033*	0.110*	-0.033*	-0.039*	0.107*
CY05	0.006*	0.021*	-0.030*	0.005*	0.019*	-0.031*
CY06	0.016*	0.026*	-0.015*	0.015*	0.025*	-0.015*
CY07	0.004*	0.007*	0.000	0.003*	0.006*	0.000
CY09	-0.011*	-0.015*	-0.026*	-0.011*	-0.015*	-0.026*
CY10	0.012*	0.007*	-0.020*	0.014*	0.009*	-0.019*
AGE5	-0.022*	-0.021*	-0.047*	-0.022*	-0.021*	-0.047*
AGE6	-0.061*	-0.058*	-0.096*	-0.061*	-0.058*	-0.096*
AGE7	-0.111*	-0.105*	-0.154*	-0.111*	-0.105*	-0.154*
AGE8	-0.170*	-0.160*	-0.220*	-0.169*	-0.159*	-0.220*
AGE9	-0.234*	-0.218*	-0.288*	-0.234*	-0.218*	-0.289*
AGE10	-0.303*	-0.281*	-0.360*	-0.303*	-0.281*	-0.360*
AGE11	-0.381*	-0.351*	-0.433*	-0.381*	-0.351*	-0.433*
AGE12	-0.465*	-0.430*	-0.513*	-0.465*	-0.430*	-0.513*
AGE13	-0.555*	-0.513*	-0.600*	-0.555*	-0.513*	-0.600*
AGE14	-0.648*	-0.602*	-0.687*	-0.648*	-0.602*	-0.687*
AGE15	-0.743*	-0.692*	-0.759*	-0.743*	-0.692*	-0.760*
MONTH	-0.005*	-0.005*	-0.004*	-0.004*	-0.005*	-0.004*
Observations	31.246	31.238	31.246	31.246	31.238	31.246
Model R^2	0.07	0.11	0.72	0.07	0.11	0.72

* Estimate is statistically significant at the 95% confidence level.

Table B.5 Estimated elasticity of VMT demand to a change in the price of gasoline, Model 5

Control variable	Without supply instrument A. No FE	B. M-M FE	C. VIN FE	With supply instrument D. No FE	E. M-M FE	F. VIN FE
Intercept	9.534*	—	—	9.648*	—	—
LOGPRICE05	-0.065*	-0.075*	0.005	-0.076*	-0.087*	0.001
LNUERATE	-0.021*	-0.028*	0.110*	-0.029*	-0.036*	0.107*
CY05	0.008*	0.023*	-0.030*	0.006*	0.020*	-0.030*
CY06	0.017*	0.026*	-0.015*	0.016*	0.025*	-0.015*
CY07	0.005*	0.008*	0.000	0.004*	0.007*	0.000
CY09	-0.011*	-0.015*	-0.026*	-0.011*	-0.015*	-0.026*
CY10	0.010*	0.005*	-0.020*	0.012*	0.008*	-0.019*
AGE5	-0.022*	-0.021*	-0.047*	-0.022*	-0.021*	-0.047*
AGE6	-0.061*	-0.058*	-0.095*	-0.061*	-0.058*	-0.095*
AGE7	-0.111*	-0.105*	-0.154*	-0.110*	-0.105*	-0.154*
AGE8	-0.169*	-0.159*	-0.219*	-0.169*	-0.159*	-0.219*
AGE9	-0.234*	-0.218*	-0.288*	-0.234*	-0.218*	-0.288*
AGE10	-0.303*	-0.281*	-0.359*	-0.303*	-0.281*	-0.359*
AGE11	-0.381*	-0.351*	-0.432*	-0.381*	-0.351*	-0.432*
AGE12	-0.465*	-0.430*	-0.512*	-0.465*	-0.430*	-0.512*
AGE13	-0.555*	-0.513*	-0.599*	-0.554*	-0.513*	-0.599*
AGE14	-0.648*	-0.602*	-0.686*	-0.647*	-0.602*	-0.686*
AGE15	-0.743*	-0.692*	-0.758*	-0.743*	-0.692*	-0.758*
MON1	0.033*	0.032*	0.024*	0.032*	0.031*	0.023*
MON2	0.030*	0.030*	0.017*	0.029*	0.030*	0.016*
MON3	0.011*	0.012*	0.012*	0.010*	0.012*	0.011*
MON4	-0.002*	0.001	0.010*	-0.002*	0.000	0.010*
MON5	0.003*	0.004*	0.009*	0.003*	0.004*	0.008*
MON6	0.003*	0.003*	0.005*	0.003*	0.003*	0.004*
MON8	-0.011*	-0.010*	-0.008*	-0.011*	-0.010*	-0.008*
MON9	-0.010*	-0.009*	-0.012*	-0.010*	-0.009*	-0.012*
MON10	-0.020*	-0.019*	-0.017*	-0.020*	-0.019*	-0.017*
MON11	-0.020*	-0.021*	-0.019*	-0.020*	-0.020*	-0.018*
MON12	-0.017*	-0.019*	-0.018*	-0.017*	-0.019*	-0.018*
Observations	31.246	31.238	31.246	31.246	31.238	31.246
Model R^2	0.07	0.11	0.72	0.07	0.11	0.72

* Estimate is statistically significant at the 95% confidence level.