The Rebound Effect for Passenger Vehicles

*Joshua Linn**

ABSTRACT

The United States and many other countries are dramatically tightening fuel economy standards for passenger vehicles. Higher fuel economy reduces per-mile driving costs and may increase miles traveled, known as the rebound effect. The magnitude of the elasticity of miles traveled to fuel economy is an important parameter in welfare analysis of fuel economy standards, but all previous estimates from micro data impose at least one of three behavioral assumptions: (a) fuel economy is uncorrelated with vehicle and household attributes; (b) for multi-vehicle households, each vehicle can be treated as an independent observation in statistical analysis; and (c) the effect of gasoline prices on vehicle miles traveled is inversely proportional to the effect of fuel economy. Two approaches to relaxing these assumptions yield a large estimate of the rebound effect; a one percent fuel economy increase raises driving 0.2 or 0.4 percent, depending on the approach, but the estimates are not statistically significantly different from one another.

Keywords: Fuel economy standards, Passenger vehicles, Vehicle miles traveled, Household driving demand

http://dx.doi.org/10.5547/01956574.37.2.jlin

1. INTRODUCTION

Motivated by a desire to reduce gasoline consumption and the associated external energy security and climate costs, the U.S. fuel economy and greenhouse gas emissions rate standards for new passenger vehicles will dramatically increase average new vehicle fuel economy. The current standards, which the U.S. Environmental Protection Agency (U.S. EPA) and the U.S. Department of Transportation set jointly, raise average fuel economy to about 35 miles per gallon (mpg) by 2016. This level represents a roughly 40 percent increase compared to the standards in the mid-2000s. Further standards to 2025 could raise fuel economy by an additional 50 percent, past 50 mpg. The U.S. policy developments are part of a larger trend in which many countries and regions are tightening standards for fuel economy or greenhouse gas emissions rates (which vary inversely with fuel economy).

A large literature has compared the cost of reducing gasoline consumption by using fuel economy or greenhouse gas emissions rate standards with the cost of using the gasoline tax (e.g., Jacobsen 2013). A central conclusion has been that the gasoline tax is much less costly to vehicle producers and consumers per gallon of gasoline saved. An important difference between fuel economy standards and a gasoline tax is that they create different incentives for driving. A gasoline tax can be used to internalize externalities that scale with gasoline consumption, such as greenhouse gas emissions. A gasoline tax also creates incentives to reduce driving, which reduces associated congestion, accidents, and local air pollution. Fuel economy standards, on the other hand, reduce

* Senior Fellow, Resources for the Future, 1616 P St., NW, Washington, DC, 20036. E-mail: linn@rff.org.

The Energy Journal, Vol. 37, No. 2.

gasoline consumption by raising fuel economy, but exacerbate the gap between the private and social cost of driving. The greater is the effect of driving costs on vehicle use—i.e., the rebound effect—the smaller the fuel savings from the standards and the associated greenhouse gas emissions reductions, and the higher are the external costs from traffic congestion, accidents, and local air quality.[1] Thus, welfare analysis depends crucially on the magnitude of the rebound effect—that is, the elasticity of miles traveled to fuel economy.

The vast rebound literature has reported a wide range of estimates of this elasticity, which imply that a 1 percent fuel economy increase raises driving 0.1 to 0.8 percent. Most estimates fall in the range of 0.1 to 0.3, and many recent estimates have fallen toward the lower end (UKERC 2007 and US EPA 2011). Based on the results of several recent studies, the U.S. government used an elasticity of 0.1 for estimating the fuel savings of the upcoming fuel economy standards.

In the context of rising fuel economy standards, I define the fuel economy rebound effect as the percent change in miles traveled caused by a 1 percent increase in fuel economy (in this context, with fuel prices held constant, this definition is equivalent to the response to a 1 percent reduction in fuel costs; for a broader discussion of the rebound effect see Gillingham et al. 2013 and Borenstein, 2015). Much of the rebound literature has used micro data (household or vehicle-level data) to estimate the magnitude of the rebound effect and has faced several major challenges. First, because households choose the fuel economy of their vehicles, fuel economy may be correlated with other attributes of the vehicle or household that are hard to control for and which may bias econometric estimates of the rebound effect (Dubin and McFadden 1984). Second, the short-run rebound effect probably differs from the long-run rebound effect because higher fuel economy may induce gradual responses—such as carpooling, moving, or changing jobs. The long-run rebound effect, rather than the short-run effect, is relevant to welfare analysis of fuel economy standards, but estimating long-run rebound introduces the typical challenges of estimating long run responses while controlling for other factors that affect VMT, such as income.

In this paper, I argue that, to avoid these challenges, every study in the rebound literature using micro data has made at least one of three assumptions about consumer behavior. The paper's contribution is to compare the estimates when imposing these assumptions with estimates that simultaneously relax these assumptions. The first assumption is that fuel economy is uncorrelated with vehicle or household attributes that affect a consumer's utility from driving. Studies using micro data that do not control for other vehicle characteristics, such as engine power or reliability, implicitly assume that fuel economy is uncorrelated with the other vehicle characteristics. However, Klier and Linn (2012) argue that because of the vehicle design process, fuel economy is likely to be correlated with attributes that can be measured (such as power) and attributes that are harder to measure (such as reliability). If they are correlated with miles traveled, failing to control for these attributes would bias empirical estimates of the rebound effect. Likewise, many studies using micro data fail to account for unobserved household characteristics, which would bias the results if such characteristics are correlated with miles traveled.

The second assumption maintained in nearly all of the rebound literature is that, for multivehicle households, the VMT for one vehicle is independent of the VMT for another vehicle belonging to the same household. Or, in other words, the fuel economy of one vehicle is uncorrelated with the fuel economy and other attributes of the household's other vehicle(s). This seems unlikely,

1. This is often referred to as the "direct" rebound effect, which is distinct from the "indirect" rebound effect that arises from the income increase for households that spend less on energy services after adopting technology that raises energy efficiency (Gillingham et al. 2013).

however, if the use of a vehicle for a particular purpose depends on its fuel economy. For example, a household may use a small car for a long commute and a large sport utility vehicle (SUV) for local shopping trips. With the exceptions of Greene et al. (1999), Feng et al. (2013), and Spiller (2012), econometric analysis of the demand for VMT and gasoline treats each of a household's vehicles as an independent observation; some studies, such as Frondel and Vance (2012) confine their analysis to single-vehicle households.

The third assumption is that VMT responds similarly to gasoline prices and fuel economy. Recent and careful analysis of consumer driving behavior (e.g., Gillingham 2013 and Knittel and Sandler 2013) account for unobserved vehicle and household characteristics but their focus is on the elasticity of driving to fuel prices as opposed to fuel economy. Such an analysis only yields an accurate estimate of the fuel economy rebound effect if consumers respond by equal and opposite amounts to fuel prices and fuel economy. This assumption may not hold in practice for a variety of reasons such as differences in the persistence or uncertainty of gasoline price or fuel economy shocks. For example, if consumers expect gasoline price shocks to be temporary and changing VMT (e.g., by arranging for carpooling) has fixed costs, VMT would respond less to a gasoline price decrease than to a proportional fuel economy increase. Of the few studies that estimate the effect of fuel economy on VMT, Gillingham (2012) finds that fuel economy affects VMT less than fuel prices; Greene et al. (1999) and Frondel et al. (2012) report no difference.

It is noteworthy that a simple approach to accounting for unobserved vehicle characteristics—including vehicle fixed effects in the estimation—cannot be used to estimate the fuel economy rebound effect unless the third assumption is valid. Many recent studies (e.g., Knittel and Sandler 2013) include vehicle fixed effects to control for unobserved vehicle characteristics. In such cases, the effect of fuel costs on driving is identified entirely by fuel price variation; this causes no problems if the objective is to estimate the effects of fuel prices on driving behavior, but it only yields unbiased estimates of the fuel economy rebound effect if consumers respond by equal and opposite amounts to fuel prices and fuel economy.

In short, recent analysis of gasoline prices and household-level driving behavior, while addressing the first assumption and in some cases the second, does not provide an accurate estimate of the fuel economy rebound effect unless the third assumption is valid. Past studies that attempt to directly estimate the fuel economy rebound effect impose at least one of the first two assumptions. Greene et al. (1999) is perhaps the closest to relaxing all three simultaneously, but nevertheless does not account for unobserved vehicle characteristics.[2]

This paper illustrates the empirical consequences of simultaneously relaxing these assumptions. All three assumptions introduce bias for previous estimates of the rebound effect, and the direction of the bias in each case is theoretically ambiguous. I use recent household survey data to relax the three assumptions. Using the 2009 National Household Travel Survey (NHTS), I estimate the effects on VMT of gasoline prices and fuel economy. The dependent variable is a vehicle's VMT, and the independent variables include the current gasoline price, the vehicle's fuel economy, and household and vehicle characteristics. I compare two approaches to relaxing the first assumption about the correlations between fuel economy and unobservables. First, a few studies (e.g., Gillingham 2013) control for vehicle characteristics or include vehicle model fixed effects in a linear regression. However, I report evidence that, in the NHTS sample, fuel economy is correlated with

2. More specifically, the variables Greene (1999) use as instruments for fuel economy—the level of the CAFE constraint and the vehicle's number of cylinders—are highly likely to be correlated with unobserved vehicle characteristics (Klier and Linn 2012), as well as unobserved household characteristics.

household characteristics after including such controls, which suggests that omitted household characteristics may also be correlated with fuel economy. This possibility motivates a second approach, which is to instrument for fuel economy using the gasoline price at the time the vehicle was obtained. This approach, which is similar to that of Allcott and Wozny (forthcoming), rests on the strong correlation between fuel prices and vehicle fuel economy documented by Li et al. (2009) and Busse et al. (2013), among others.

Turning to the other two assumptions on consumer behavior, similar to Feng et al. (2013), I account for the effects of the household's other vehicles (and their characteristics) by controlling for their average fuel economy. Finally, to relax the third assumption, I estimate separate coefficients on gasoline prices and vehicle fuel economy.

I find that VMT responds much more strongly to vehicle fuel economy than to gasoline prices. Across specifications, the elasticity of VMT to gasoline prices is -0.09 to -0.2, but the estimates are seldom statistically significant across regression models. Because the analysis includes multi-vehicle households, the definition of the rebound effect is the percentage VMT change caused by a 1 percent increase in the fuel economy of all vehicles belonging to a household. The rebound effect ranges from 0.2 (OLS) to 0.4 (IV), and the estimates are statistically indistinguishable from one another. The effect of fuel economy on VMT is statistically significant in most specifications.

I also quantify the importance of relaxing the three assumptions that the rebound literature has imposed. The rebound effect is much larger after addressing the potential correlations between fuel economy and other vehicle characteristics. Controlling for other vehicles' fuel economy reduces the estimated rebound effect for multivehicle households. There is mixed evidence on the effect of imposing the third assumption. Imposing the first two assumptions has large effects on the point estimates although in many cases the estimates are statistically indistinguishable. The point estimate is smaller when imposing all three assumptions simultaneously.

Finally, I use the results to estimate the effect on VMT and gasoline consumption of future fuel economy increases caused by tighter standards. I use the fuel economy changes for each vehicle model predicted by the National Highway Traffic Safety Administration in its analysis of the 2016 fuel economy standards (US EPA 2011). Such increases would reduce gasoline consumption by about 31 percent in the absence of a rebound effect. The baseline estimates suggest that VMT increases 9–18 percent and erodes up to one-third of the reduction in gasoline consumption.

The discussion has focused on estimates of the rebound effect using household-level data, but a subset of the rebound literature has used aggregate—for example, state-level—data (e.g., Small and van Dender 2007 and Hymel and Small 2013). Using aggregate data, controlling for other vehicles' fuel economy is not a concern as with the household data, and several studies (e.g., Greene 2012) allow gasoline prices and fuel economy to have independent effects on miles traveled. However, addressing the endogeneity of fuel economy is particularly challenging using aggregate data. Controlling for average household characteristics, such as income or education, is insufficient because these variables may have nonlinear effects on miles traveled (as turns out to be the case with the NHTS data). In addition, geographic factors, such as the urban environment, are hard to control for using aggregate data. Some studies have attempted to instrument for fuel economy using fuel economy standards, but such instruments are likely to be correlated with unobserved vehicle attributes (Klier and Linn 2012). An additional concern with the aggregate data is that miles traveled is almost always measured with significant error—there are measurement concerns with the NHTS data. Nonetheless, the estimates reported in this paper are best viewed as complementary to the estimates obtained from aggregate data, given the differing empirical models and underlying sources of variation used to identify the rebound effect.

2. ESTIMATION STRATEGY

As defined in the Introduction, the fuel economy rebound effect is the effect on VMT of a 1 percent increase in the fuel economy of all of a household's vehicles. In the remainder of the paper, in unambiguous cases, I use the term rebound effect for convenience. The objective is to estimate the rebound effect while relaxing the three assumptions discussed in the Introduction.

I begin with an equation that specifies the *VMT* of vehicle *i* belonging to household *h* as a function of its fuel costs and household characteristics:

$$\ln(VMT_{hi}) = \delta_0 + \delta_1 \ln\left(\frac{p_h}{m_{hi}}\right) + X_h\beta + \varepsilon_{hi} \tag{1}$$

where p_h is the price of gasoline; m_{hi} is the vehicle's fuel economy; X_h is a vector of characteristics of household *h*; and δ_0, δ_1 and β are parameters to be estimated. The parameter δ_1 is the elasticity of *VMT* to the vehicle's per-mile fuel costs. This equation could be derived from a simple model in which a household has Cobb-Douglas preferences over *VMT* and all other goods. The log-log relationship represents an approximation to a more complex relationship.

Estimating equation (1) would yield biased estimates of the rebound effect for three reasons. First, per-mile fuel costs are correlated with the error term if the vehicle's fuel economy is correlated with other characteristics of the vehicle or with household characteristics that are not included in equation (1). For example, a household with high expected *VMT* may be more likely to choose a vehicle with high fuel economy than a household with low expected *VMT* because the high-*VMT* household would save more money from the high fuel economy (fuel savings are proportional to *VMT*). Second, per-mile fuel costs are correlated with the error term if the vehicle's fuel economy is correlated with the fuel economy or quality of other vehicles belonging to the household. Third, *VMT* may respond differently to gasoline prices than to fuel economy, in which case δ_1 does not correspond to the fuel economy rebound effect. Anderson et al. (2013) conclude that households believe gasoline price shocks are fully persistent on average, but evidence from gasoline futures markets suggest that price shocks are sometimes expected to be less than fully persistent (Allcott and Wozny forthcoming). Consumers could respond to fuel prices and fuel economy differently because of differences in expected persistence or for other reasons.

I address the three assumptions in turn. Some previous studies include vehicle characteristics or vehicle model fixed effects to account for omitted vehicle characteristics that may be correlated with fuel economy. This approach may yield biased results for several reasons, however. First, some vehicle characteristics, such as performance, may vary within a model (e.g., across trims or model-years) and may be correlated with fuel economy—in which case, fuel economy would still be correlated with the error term in equation (1) even after including model fixed effects. For example, the 2003 Honda Civic achieved 34 mpg whereas the 2009 Honda Civic achieved 29 mpg. This mpg variation would help identify the fuel cost coefficient, but including model fixed effects would not control for other attributes that differ between the two versions. More generally, within-model changes in fuel economy likely occur during model redesigns when manufacturers change multiple characteristics at the same time (Klier and Linn 2012). Second, controlling for vehicle characteristics does not address the potential correlations between fuel economy and the characteristics of the household's other vehicles. Third, the model fixed effects do not address the possible correlations between fuel economy and omitted household characteristics. Fourth, including model fixed effects causes the fuel cost coefficient to be identified largely by gasoline price variation, which yields unbiased estimates of the fuel economy rebound effect only under assumption (c).

Besides concerns about omitted variables bias, including vehicle model fixed effects does not address the possibility of measurement error for fuel economy—and may even exacerbate measurement error. Therefore, estimating equation (1) and including model fixed effects may still yield biased estimates.

Consequently, I compare results using model fixed effects with the results if I instead instrument for the vehicle's fuel economy using the gasoline price at the time the household obtained the vehicle, $\hat{p}_{hi}$. This gasoline price is different from p_h in equation (1), which is the gasoline price at the time that VMT_{hi} is measured. For example, if VMT_{hi} is measured in April 2009 and the household obtained the vehicle in April 2002, p_h is the price of gasoline faced by the household in April 2009 and $\hat{p}_{hi}$ is the price of gasoline faced by the household in April 2002. The gasoline price at the time the vehicle was obtained is used to predict fuel economy, and the predicted value is used in place of the actual value.

The validity of the fuel economy instrument rests on three arguments. The first is that the price of gasoline affects the fuel economy of the vehicle. Klier and Linn (2010) and Busse et al. (2013) demonstrate a strong relationship between gasoline prices and the fuel economy of new vehicle purchases, and Allcott and Wozny (forthcoming) use a similar instrumental variables (IV) approach to estimate consumer demand for fuel economy. Note that $\hat{p}_{hi}$ would not predict the fuel economy of used vehicles if used vehicle supply were perfectly inelastic. In practice, for both new and used vehicles the effects of $\hat{p}_{hi}$ on vehicle fuel economy are statistically significant, but the effect is larger for vehicles obtained new than for those obtained used. The positive effect of the instrument on used vehicle fuel economy is consistent with Li et al. (2009) and Jacobsen and van Benthem (2012), who report large effects of gasoline prices on vehicle scrappage—suggesting that the supply of used vehicles is not perfectly inelastic.[3]

The second argument for the price instrument is that the correlation between p_h (the current price) and $\hat{p}_{hi}$ (the price at the time the vehicle was obtained) is sufficiently low to identify the coefficients in the second stage. In fact, despite the persistence of gasoline prices, the correlation between the two gasoline price variables is close to zero after controlling for the other variables in equation (1).

The third argument is that the gasoline price at the time the vehicle was obtained is likely to be uncorrelated with vehicle and household characteristics not included in the estimating equation. Because equation (1) includes geographic controls, the first stage is identified by temporal gasoline price variation (see, e.g., Klier and Linn 2010). The underlying argument is that the month in which the vehicle was obtained is uncorrelated with omitted variables. Although the gasoline price at the time the vehicle was obtained may affect disposable income (because higher gasoline prices raise fuel costs for any vehicle), the IV approach is valid as long as gasoline prices are uncorrelated with other determinants of disposable income. A concern with this argument is that gasoline prices may be correlated with business cycles, in which case the composition of households obtaining a vehicle when gasoline prices are high may differ in important ways from households obtaining a vehicle when gasoline prices are low. However, I document below that business cycles do not seem to be driving the first stage in the IV estimates.

3. Consumers likely choose vehicles based on expected fuel prices rather than the current price alone. Data are not available to estimate expected prices for all vehicles in the sample, and I use the gasoline price at the time the vehicle was obtained as a proxy for expected prices. Anderson et al. (2013) provide evidence that the current price is strongly correlated with expected prices.

Turning to the second assumption in equation (1), I control for the fuel economy of the household's other vehicles. For one- or two-vehicle households, controlling for other vehicle fuel economy is straightforward: for one-vehicle households the variable equals zero, and for two-vehicle households the variable equals the other vehicle's fuel economy. For households with three or more vehicles, theory does not suggest a particular functional form. I use the average fuel economy of the other vehicles, but consider alternatives such as controlling for the fuel economy of the other vehicles individually.

To address the third assumption in equation (1), I simply allow for a separate coefficient on the contemporaneous gasoline price and the vehicle's fuel economy. These modifications yield the following equation:

$$\ln(VMT_{hi}) = \delta_0 + \delta_1 \ln(p_h) + \delta_2 \ln(m_{hi}) + \delta_3 \ln(\bar{m}_{h,-i}) + f(\eta_j, X_h) + \varepsilon_{hi} \tag{2}$$

where $\ln(\bar{m}_{h,-i})$ is the log of the average fuel economy of the household's other vehicles; the variable equals zero for one-vehicle households. The function $f(\eta_j, X_h)$ includes an extensive set of controls for household and vehicle characteristics. Specifically, the regressions contain controls for demographics including income group, education group, age group, household size, number of drivers, and number of vehicles; geography including urban area type, metropolitan statistical area (MSA) size, urban area size, consolidated MSA (CMSA), population density, and household density; survey month and vehicle age. Note that the household controls are far more extensive than those used in most previous estimates of the rebound effect. The ability to include so many control variables is an advantage of the simple regression approach employed in this paper.

Equation (2) is estimated either by OLS, in which case $f(\eta_j, X_h)$ also includes model fixed effects interacted with fixed effects for the number of household vehicles, or by IV, in which case model fixed effects and interactions are omitted. The first stage equation for the vehicle's fuel economy is

$$\ln(m_{hi}) = \theta_0 + \theta_1 \ln(\hat{p}_{hi}) * X_h + \theta_2 \ln(\hat{p}_{hi}) * V_i + \theta_3 \ln(\overline{p}_{hi}) * X_h + \theta_4 \ln(\overline{p}_{hi}) * V_i + f(\eta_j, X_h) + \varepsilon_{hi}$$

where V_i is the vehicle's age group and a similar first stage equation applies to the other endogenous variable in (2), $\ln(\bar{m}_{h,-i})$. The instruments include the interaction of household characteristics, X_h, with the gasoline price at the time the vehicle was obtained, $\hat{p}_{hi}$, as well as interactions with the average gasoline price at the time the household's other vehicles were obtained, $\overline{p}_{hi}$ (the price instruments have a subscript hi because the instruments vary across vehicles within the same household). The vehicle and household characteristics used in these interactions include vehicle age group, household number of vehicles, income group, household size, number of adults, respondent age group, household number of drivers, and education group. Including the household interactions is motivated by recent papers showing substantial consumer heterogeneity in vehicle demand (e.g., Jacobsen 2013).[4] Because the first stage does not include vehicle characteristics (other than age group), the coefficients on $\hat{p}_{hi}$, and the associated interactions, are identified by the effect of fuel prices on consumer substitution when obtaining a vehicle. For example, when gasoline prices are high, if consumers are more likely to obtain a Honda Civic (about 32 mpg in 2005) than a Honda

4. Including the interactions with household attributes improves the fit of the first stage and reduces the estimated rebound effect in the second stage. As shown below, the instruments are jointly strong predictors of the endogenous fuel economy variables.

Accord (about 24 mpg), the predicted fuel economy is therefore higher. Thus, the IV estimates are identified by variation in predicted fuel economy that is driven by variation in gasoline prices at the time the vehicles were obtained. The interactions of $\hat{p}_{hi}$ with household characteristics allows for the possibility that fuel economy responds more to gasoline prices for some types of households than for others.

Despite relaxing the three assumptions, some potential concerns remain for equation (2). First, although I instrument for the fuel economy of all vehicles in equation (2), I assume that the contemporaneous gasoline price, p_h, is exogenous. Li et al. (forthcoming) provide evidence supporting the validity of this assumption.

Second, equation (2) imposes a log-log relationship between the independent variables and *VMT*. I interpret the specification as an approximation of a more complicated functional relationship. Section 4.2 reports additional specifications of equation (2) that allow the elasticity to vary across households.

Turning to the interpretation of the main coefficients, because of the sources of variation used to identify the coefficients in equation (2), the coefficient on the current gasoline price (δ_1) has a different interpretation from the coefficients on fuel economy (δ_2 and δ_3). The gasoline price coefficient is identified by within-state variation over the time spanned by the survey. For example, the coefficient is identified by comparing *VMT* of a household surveyed in January 2009 with the *VMT* of different household in the same CMSA but surveyed in the following February. Because the survey was conducted over about a year, δ_1 represents a short-run response to the gasoline price. On the other hand, the fuel economy coefficient is identified by comparing households within and across regions, as well as over time. In the sample, the average vehicle has been held for about 5 years, which allows households longer periods of time to respond to fuel economy than to gasoline prices; therefore, the fuel economy coefficients can be interpreted as representing longer-run consumer responses than the gasoline price coefficient. Because of these interpretations, the fact that the fuel economy coefficient turns out to be larger in magnitude than the gasoline price coefficient does not necessarily suggest that consumers respond more to fuel economy than to gasoline prices; it could simply be the case that one is a long-run elasticity and the other is a short-run elasticity. Because of this ambiguity, in the following analysis I compare estimates of the rebound effect derived from δ_2 and δ_3 with rebound estimates in the literature.

Before proceeding, I note that an alternative to equation (2) would be to jointly estimate the vehicle choice and *VMT* decisions. In principle, the joint estimation, of which the literature includes many examples (e.g., Bento et al. 2009), has two advantages over a standard reduced-form *VMT* equation (which imposes the three assumptions). First, the joint estimation makes it possible to control for unobserved household attributes that affect both vehicle choice and *VMT*. For example, households with members who like high-performance cars may purchase cars with low fuel economy, and they may also like to drive more miles than members of other households. This heterogeneity could be accounted for by estimating a vehicle choice equation and using the predicted choice as controls in the *VMT* choice equation (West 2004). Second, by deriving the estimating equations from a household utility function, joint estimation enables an analysis of the welfare effects of policies such as gasoline taxes or fuel economy standards.

As with joint estimation, IV estimates of equation (2) allows for potential correlations between fuel economy and unobserved household characteristics. An advantage of equation (2) over joint estimation is that it is much simpler to relax the three assumptions without making modeling compromises that are typically made in joint estimation. For example, for computational reasons, most other studies aggregate across vehicle models to reduce the choice set. The primary downside to equation (2) is that welfare analysis of particular policies, such as a gasoline tax increase, is not possible. Nevertheless, equation (2) is suitable for the paper's primary objective, which is to estimate the rebound effect.

3. DATA AND SUMMARY STATISTICS

3.1 Data

The 2009 NHTS is the primary data source. The unit of observation is the household and vehicle. I include all observations without missing values for household characteristics, geographic information, and vehicle information; the final data set contains 229,851 observations. The data set includes categorical variables for income, household size, number of adults, and education level. The geographic information includes categorical variables for urban area type, MSA size, CMSA, and urban area size. The geographic information also includes continuous variables for population density and household density.

The vehicle information includes the estimated VMT of the vehicle for the previous year, the vehicle's age, its fuel economy, and its make and model. The survey data include the year and month in which the vehicle was obtained. To construct the gasoline price instruments, I merge retail gasoline prices from the Energy Information Administration (EIA) for the corresponding year, state, and month.

Equation (2) includes the current gasoline price. The NHTS provides gasoline prices, but after including CMSA fixed effects and survey month fixed effects, there is little remaining gasoline price variation. In an attempt to increase the variation of the gasoline prices, instead of using the NHTS prices I impute the retail gasoline prices from the American Chamber of Commerce Researchers' Association (ACCRA) and EIA prices. The ACCRA prices vary by city and quarter, whereas the EIA prices vary by state and month.

For many households, the NHTS provides the CMSA in which the household resides. For those observations I use the ACCRA prices after adjusting them by the monthly deviation from the state-quarter mean, as estimated from the EIA price data (i.e., assuming that monthly prices throughout the state vary over time in proportion to one another). For the remaining observations I use the EIA prices.[5] Because of this imputation procedure, the gasoline price varies across households that were surveyed at the same time within the same state, and the price varies across households in the same CMSA that were surveyed at different times. All gasoline prices are converted to 1983 dollars using the Consumer Price Index.

The Introduction noted that the VMT data are self-reported. It would be preferable to use VMT data obtained from odometer readings, but the 2009 NHTS does not provide such data. The 1995 and 2001 versions of the NHTS do provide odometer-based VMT estimates, but the earlier versions of the NHTS do not provide the month in which the vehicle was obtained, making it impossible to construct the instrumental variables for equation (2).

Li et al. (forthcoming) compare the self-reported and odometer-based VMT data in the 1995 and 2001 NHTS and conclude that the self-reported estimates are unbiased on average, but that the estimates are compressed; high-VMT households tend to under-report and low-VMT households tend to over-report. Such misreporting would bias estimates of equation (2) if it is correlated with the independent variables, but I offer two arguments that such bias is unlikely to be large in

5. Because VMT is estimated for the 12 months prior to the survey, I have also used the average price over the previous 12 months, which yields similar results.

magnitude. First, Li et al. (forthcoming) report similar results using the self-reported and odometer-based data in their analysis of the effects of gasoline prices and taxes on VMT. Second, the 2009 NHTS data include trip diaries, in which respondents record the duration and distance of each trip they take during a 24-hour period. The VMT estimates from the trip diaries probably have much less measurement error than the annual VMT estimates (e.g., a respondent is likely to know the precise distance traveled between the house and workplace). I obtain broadly similar estimates of the rebound effect using the trip diary data, further suggesting that measurement error in the annual VMT estimate does not create substantial bias.[6]

There are some tradeoffs to using the NHTS as compared to other sources of micro-data, such as the California Smog Check data used in Gillingham (2013) and Knittel and Sandler (2013). On the one hand, the NHTS is a nationally representative sample. The data include an extensive set of vehicle characteristics and information about each vehicle the household uses, which enables an analysis of the effects of one vehicle's fuel economy on the VMT of another vehicle used by the same household (Knittel and Sandler (2013) can perform this analysis using a subset of the data for which they can match vehicles to households). The NHTS data also provide the information needed for the IV approach, which is absent from other data sets. On the other hand, the NHTS sample, while quite large, is much smaller than the Smog Check sample. Furthermore, VMT in the NHTS is self-reported, as opposed to being measured from odometer readings. Below I show evidence that this limitation is unlikely to create substantial bias in practice, and that the results are fairly similar for California drivers and other U.S. drivers.

3.2 Summary Statistics

Before presenting the estimation results, I report summary statistics from the final data set. Table 1 and Figures 1 and 2 provide some information about the characteristics of households depending on the number of vehicles they have. As Panel A of Table 1 shows, one- and two-vehicle households account for about half of the population and 60 percent of VMT, which illustrates the importance of including in the analysis households that have more than two vehicles. Panel B of Table 1 shows that the characteristics of the households—except for the average gasoline price—vary considerably across the household types. Households with more than two vehicles tend to live in areas with lower population density, and their vehicles tend to have lower fuel economy.

Figures 1 and 2 show the distributions of two of the categorical variables, urban area type and income (Appendix Figures 1–8 show the remaining categorical variables). The demographic variables, including income, education, age of the household head, household size, number of adults, and number of drivers, vary considerably across household types. Households with more than two vehicles tend to live in less urbanized areas and have higher income.

Section 2 discussed the first approach to addressing the endogeneity of fuel economy in equation (2), which is to include model fixed effects. This approach rests on the assumption that within-model fuel economy variation is uncorrelated with omitted household and vehicle characteristics. Although this assumption cannot be tested directly, a common strategy to assess its validity is to estimate the correlations between fuel economy and observed household characteristics. Low correlations would suggest that fuel economy and unobserved household characteristics are also weakly correlated with one another.

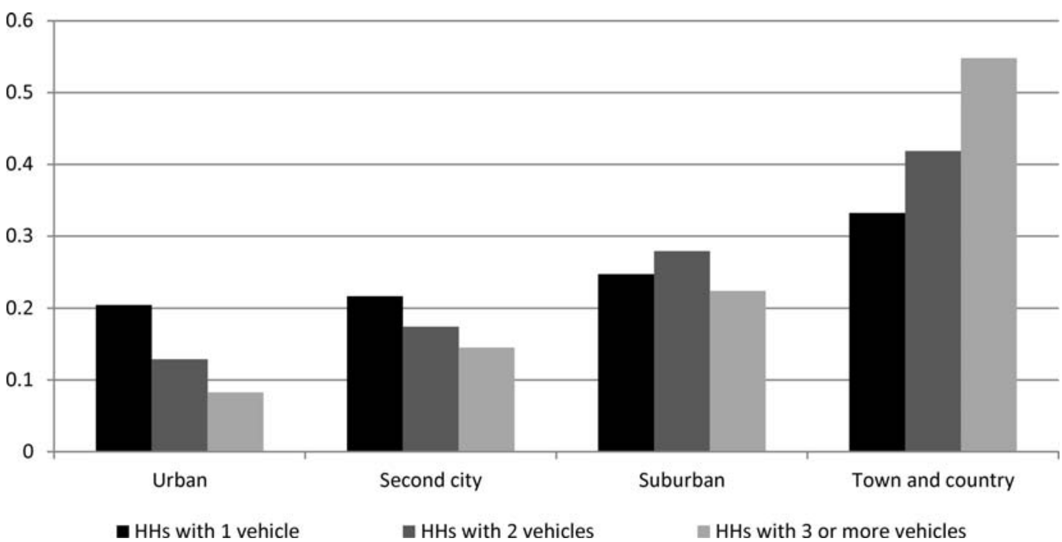
6. I prefer not to use the trip diary data for the main analysis because of the difficulty in generating annual VMT estimates from the daily data.

Table 1: Summary Statistics by Number of Household Vehicles

	Households with 1 vehicle	Households with 2 vehicles	Households with 3 vehicles	Households with 4 + vehicles
	Panel A: Shares of population, vehicles, and VMT			
Population share	0.11	0.42	0.26	0.20
Share of vehicles	0.18	0.42	0.23	0.17
VMT share	0.17	0.43	0.24	0.16
	Panel B: Means and standard deviations			
Thousand VMT	10.77	12.12	12.07	11.71
	(9.57)	(9.79)	(10.32)	(10.36)
Gasoline price	2.80	2.75	2.77	2.78
($/gallon)	(1.04)	(1.04)	(1.04)	(1.04)
Fuel economy (mpg)	23.80	22.53	22.00	21.44
	(5.26)	(5.69)	(5.79)	(5.68)
Thousand housing	5.71	4.03	3.09	2.51
units per sq mi	(6.97)	(5.25)	(4.42)	(3.77)
Thousand people per	2.90	1.73	1.26	0.96
sq mi	(4.71)	(2.75)	(2.16)	(1.54)

Notes: Each household is assigned a category based on the number of vehicles it has. For each category indicated in the column heading, Panel A reports the population share, share of vehicles, and share of VMT accounted for by households in the corresponding category. Shares are constructed using household weights. Panel B reports weighted means of the indicated variables by household category, with standard deviations in parentheses.

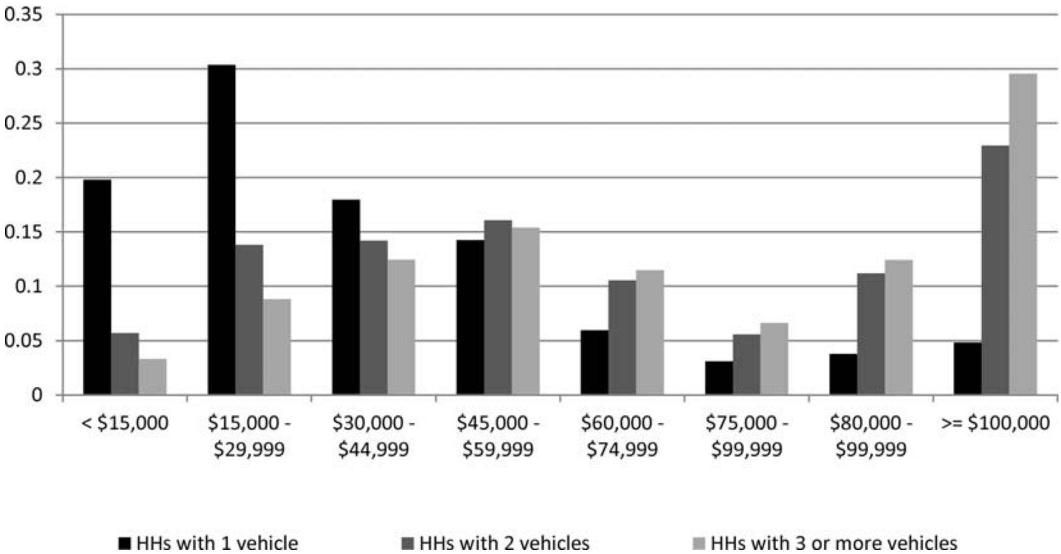
Figure 1: Urban Area Type by Number of Vehicles in Household



Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households in the indicated type of urban area. Observations are weighted by the final NHTS weights.

However, Table 2 provides evidence against the validity of the model fixed effects approach. Each column reports a separate regression with the dependent variable indicated at the top of the table. The sample includes all observations in the final data set, and the independent variables

Figure 2: Income by Number of Vehicles in Household



Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households in the indicated income range. Observations are weighted by the final NHTS weights.

Table 2: Joint Significance Tests of Categorical Variables for Gasoline Price and Fuel Economy Regressions

Dependent variable	(1) Vehicle fuel economy	(1) Fuel economy of other household vehicles	(2) Vehicle fuel economy	(2) Fuel economy of other household vehicles
Household income	0.00	0.00	0.11	0.00
Household size	0.00	0.04	0.43	0.17
Number of adults	0.00	0.00	0.00	0.22
Education	0.00	0.00	0.11	0.00
Age	0.00	0.00	0.15	0.01
Number of drivers	0.00	0.00	0.52	0.00
Urban size category	0.44	0.00	0.47	0.12
MSA size category	0.36	0.08	0.33	0.02
Urban area size category	0.63	0.02	0.83	0.24
Include model by vehicle number interactions?	No	No	Yes	Yes

Notes: Each column reports hypothesis tests based on a separate regression. The sample in each regression includes all households in the final sample, with 229,851 observations. The dependent variable is the vehicle's fuel economy in columns 1 and 3 and the log average fuel economy of the household's other vehicles in columns 2 and 4. Standard errors are clustered by CMSA and survey month, and observations are weighted by the household sample weight. Besides the reported variables, all regressions include vehicle age group fixed effects, an urban/rural indicator, log population density, log house density, and CMSA fixed effects. Columns 3 and 4 also include interactions of model fixed effects by fixed effects for the number of vehicles belonging to the household. Vehicle age uses the 5 age categories in Figure 1. Household income uses the 8 income categories in Figure 2. Household size uses the 7 categories in Figure 3. Number of adults uses the 5 categories in Figure 4. Education uses the 4 categories in Figure 5. Age uses the 5 age categories in Figure 6. Urban area type category uses the 4 categories in Figure 7. Number of drivers uses the 4 categories in Figure 8. The table reports the p-values from a series of F-tests on the joint significance of the indicated categorical variables in the corresponding regression.

include sets of dummy variables for the categorical variables indicated in the table, as well as CMSA fixed effects. Columns 3 and 4 also include interactions of model fixed effects with the number of vehicles belonging to the household. Observations are weighted using the NHTS survey weights, and standard errors are clustered by CMSA and survey month to account for geographic correlation of the error term (results are similar when clustering by CMSA). The table reports the p-values of F tests on the joint significance of the fixed effects for the categorical variables. Columns 1 and 2 show strong correlations between fuel economy and other variables. Column 3 shows that adding model by vehicle number interactions reduces the correlation between fuel economy and the other variables, but the fuel economy of other vehicles remains strongly correlated with many of the other variables (column 4). These correlations motivate the IV approach.

4. ESTIMATION RESULTS

4.1 Main Results

This section presents the main estimates of equation (2) and reports results from a variety of alternative specifications. In equation (2) the dependent variable is the log of the vehicle's VMT. Observations are weighted using the NHTS survey weights. Standard errors are clustered by CMSA and survey month. The regression includes interactions between model fixed effects and the number of household vehicles to try to account for the correlation between fuel economy and vehicle characteristics. Using OLS to estimate equation (2), Panel A of Table 2 reports the coefficients on the main variables of interest, and Appendix Table 1 reports the other coefficient estimates. While I do not focus on these estimates, they generally have the expected signs and plausible magnitudes. The estimates differ little between the OLS and IV models.

The IV estimates omit these interactions but instrument for the fuel economy variables based on the month in which the household obtained the vehicle. There are two endogenous variables—fuel economy and other vehicles' fuel economy—and two sets of instruments, the first based on the month in which the vehicle was obtained and the second based on the average price across the months the household's other vehicles were obtained. To allow for cross-household heterogeneity in the response of fuel economy to gasoline prices, those gasoline price instruments are interacted with fixed effects for vehicle age group, number of household vehicles, income, household size, number of adults, respondent age group, number of drivers, and respondent education. Appendix Table 2 reports the first stage coefficient estimates (columns 1 and 2 report coefficients for the fuel economy regression and columns 3 and 4 report coefficients for the other vehicles' fuel economy regression). The bottom of the table reports the F statistic on the test of the joint significance of the instruments in each of the two first stage equations. The instruments are jointly strong predictors of the endogenous variables, although the first stage for other vehicles' fuel economy is stronger. A Durbin-Wu-Hausman test for the endogeneity of the fuel economy variables rejects the hypothesis that they are endogenous at the 3 percent level for fuel economy and at less than the 1 percent level for other vehicles' fuel economy.

In column 1 of Table 3, which I refer to as the baseline specification, both the OLS and IV estimates show that VMT responds statistically significantly to fuel economy but not to gasoline prices. This statistically insignificant gasoline price coefficient reflects the limited price variation, and is consistent with Goldberg (1998) and Li et al. (forthcoming), who find a weak correlation between current gasoline prices and VMT using household data.[7]

7. Equation (2) includes CMSA fixed effects and time fixed effects, which appear to absorb most of the gasoline price variation. The results are similar using the NHTS gasoline prices, although using those prices the standard errors are even larger than in Table 3.

Table 3: Effects of Fuel Prices and Fuel Economy on VMT

	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS		
Specification	Baseline (model interacted with number of vehicles)	Model interacted with number of vehicles and vehicle age	Model interacted with number of vehicles and respondent age	Model interacted with numbers of vehicles and adults	Baseline, including only California
Log gas price	−0.093	−0.119	−0.107	−0.093	
	(0.093)	(0.090)	(0.087)	(0.090)	
Log fuel economy	0.245***	0.281***	0.232***	0.247***	0.261***
	(0.060)	(0.072)	(0.057)	(0.059)	(0.085)
Log other vehicles' fuel economy	−0.029***	−0.029***	−0.029***	−0.025***	−0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)
R2	0.17	0.23	0.25	0.22	0.19
Fuel economy rebound effect	0.222***	0.257***	0.208***	0.227***	0.237***
	(0.060)	(0.072)	(0.058)	(0.059)	(0.086)
			Panel B: IV		
Specification	Baseline (instruments include gas price interacted with household characteristics)	Instruments also include gas price interacted with income and number of vehicles	Instruments also include gas price interacted with income and age	Instruments include log GSP and income per capita	Baseline, including only California
Log gas price	−0.117	−0.114	−0.116	−0.117	
	(0.096)	(0.097)	(0.097)	(0.096)	
Log fuel economy	0.534**	0.430**	0.459**	0.657***	0.465**
	(0.239)	(0.207)	(0.216)	(0.233)	(0.224)
Log other vehicles' fuel economy	−0.116***	−0.119***	−0.107***	−0.119***	−0.074***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.028)
R2	0.09	0.09	0.10	0.08	0.09
Fuel economy rebound effect	0.438*	0.333	0.371*	0.560**	0.404*
	(0.240)	(0.205)	(0.216)	(0.234)	(0.230)

Notes: Each column in each panel reports a separate regression. Standard errors are reported in parentheses and are clustered by CMSA and survey month. The sample is the same as in Table 2, except for column 5, which include households in California (32,399 observations). The dependent variable is the log of VMT. The table reports coefficients on log fuel price, log fuel economy, and log of the average fuel economy of other vehicles. Appendix Table 1 reports other coefficient estimates for column 1. Panel A reports OLS estimates and Panel B reports IV estimates, using the instruments indicated at the top of the panel (see text for details). All regressions include the household and vehicle fixed effects used in the regressions in column 1 of Table 2. In Panel A, regressions also include interactions indicated at the top of the panel. Panel B does not include the interactions with model fixed effects. Panel B does not include model fixed effects. The fuel economy rebound effect is the effect on VMT of increasing all vehcles' fuel economy by 1 percent. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

Because the rebound effect is defined as the effect on VMT of increasing the fuel economy of all the household's vehicles, the rebound effect depends on the coefficient on the vehicle's fuel economy as well as the coefficient on the fuel economy of the household's other vehicles. In the baseline specification, the elasticity of VMT to the other vehicles' fuel economy is −0.03 using OLS and −0.12 using IV. These coefficients suggest that when the fuel economy of all vehicles increases—which would be the long-run effect of rising fuel economy standards, for example—two factors have opposing effects on the VMT of a particular vehicle. The coefficient on the vehicle's own fuel economy implies that VMT increases when that vehicle's fuel economy increases, but the increase in the fuel economy of the household's other vehicles causes the vehicle's own VMT to decrease (i.e., the vehicles are substitutes for one another).[8]

The bottom of each panel reports the elasticity of VMT to an increase in the fuel economy of all vehicles. The rebound effect is calculated by adding the coefficient on log fuel economy to the coefficient on the log of other vehicles' fuel economy, the latter of which is multiplied by the share of households in the sample with more than one vehicle (0.82; see Table 1). The rebound effect is 0.22 using OLS and 0.44 using IV. Both the OLS and IV estimates are substantially larger than many recent estimates of the rebound effect using aggregate data (e.g., Small and van Dender 2007), and the OLS estimate is similar to Knittel and Sandler (2013). The IV estimate is significant at about the 5 percent level, but the estimate is statistically indistinguishable from the OLS estimate. The fact that both the IV and OLS estimates are somewhat larger than some other recent estimates may be explained by the fact that these are longer-run estimates, although other explanations are possible. Because of the range of estimates, I continue to report both OLS and IV results throughout the paper.

In the IV case, the R-squared in the first stage for the vehicle's fuel economy is 0.1 (Appendix Table 2). The relatively low R-squared does not raise concerns about weak instruments bias, given the first stage F-statistic in Appendix Table 2. However, the low R-squared does imply that the predicted fuel economy has substantially less variation than actual fuel economy. Therefore, one might be concerned about the relevance of the IV estimate because only a portion of the overall fuel economy variation identifies the rebound effect. However, recall that tighter fuel economy standards motivate this analysis. Tighter fuel economy standards cause manufacturers to increase the relative price of vehicles with low fuel economy (Jacobsen 2013). These price changes induce consumer substitution from vehicles with low fuel economy to vehicles with high fuel economy. In theory, this effect is qualitatively similar to the effects of a gasoline price increase that raises the driving cost of vehicles with low fuel economy compared to vehicles with high fuel economy. Recent empirical evidence (e.g., Allcott and Wozny forthcoming and Busse et al. 2013) has demonstrated that, indeed, high gasoline prices induce substitution from vehicles with low fuel economy to vehicles with high fuel economy. Thus, the fuel economy variation used in the IV regressions is highly relevant to the motivating question. By comparison, the OLS regression coefficients are identified by substitution across versions of the same model that were sold in different years. In principle, I could add to the IV regressions the interactions of model fixed effects with fixed effects for the number of household vehicles, which would be analogous to the OLS regressions in Panel A of Table 3. In that case, the R-squared of the first stage fuel economy regression is 0.88 and the estimated fuel economy rebound effect is 0.38, which is very similar to the IV estimate reported in Table 3. However, I prefer the IV estimate that does not include these interactions because the rebound effect is identified by substitution across vehicles, which is more relevant to the question of how tighter fuel economy standards affect driving behavior.

4.2 Robustness of the Main Specification

I report the results of a variety of additional regressions that assess the overall robustness of the estimates in column 1 of Table 3. Table 2 shows that the vehicle's fuel economy is correlated

8. Knittel and Sandler (2013) also find some evidence of within-household substitution for vehicles in California, although the substitution does not have a large effect on their estimated elasticity of VMT to driving costs. Within-household substitution appears to be more substantial for the NHTS sample.

with some household characteristics. This correlation suggests that fuel economy is not exogenous and may therefore be correlated with omitted household characteristics. The IV approach in Panel B of Table 3 should address any resulting bias, but another approach is to add to the OLS regressions further interactions between the household characteristics and vehicle characteristics. This reduces the amount of variation available to identify the rebound effect, but it allows for greater household heterogeneity in (unobserved) preferences for driving.

Columns 2–4 in Panel A of Table 3 include triple interactions between model fixed effects, fixed effects for the number of household vehicles, and fixed effects for the household characteristic noted at the top of the panel. For example, column 2 controls for any unobserved household characteristic that varies by vehicle age group, model, and number of vehicles; this regression allows for the possibility that driving tendencies for the Toyota Camry, for example, differ between older and newer versions of the Camry. Looking across the specifications, the OLS coefficients are similar in magnitude and remain statistically significant in all cases.

The instruments in the baseline in Panel B allow for some heterogeneity across households in the response of fuel economy to the gasoline price at the time the vehicle was obtained. Columns 2 and 3 of Panel B consider the robustness of the IV estimates to alternative sets of instruments that allow for greater heterogeneity. Adding further interactions of gasoline prices and household characteristics has some effect on the point estimates, but yields qualitatively similar results.[9] Appendix Table 1 shows that some of the interaction terms are not highly statistically significant; omitting these variables from the set of instruments yields larger point estimates for the fuel economy coefficient, but the results are qualitatively similar (not reported).

I noted in Section 2 that one concern with the IV strategy is that gasoline prices may be correlated with business cycles, in which case the composition of households obtaining vehicles may vary with gasoline prices. To assess the validity of the IV approach I include as instruments gross state product and income per capita in the month and state in which the household obtained the vehicle. The results would differ from column 1 if business cycle fluctuations, rather than gasoline price variation, are driving the first stage. Column 4 suggests that this is not the case, as the estimated rebound effect is fairly similar to—less than one-third larger than—column 1.[10]

The Introduction noted that an advantage of the NHTS, relative to many other data sources, is that it contains a nationally representative sample. Gillingham (2013) and Knittel and Sandler (2013) have used the California Smog Check data to estimate the effect of fuel prices on VMT. To compare with their results, I restrict the NHTS sample to include California households. The estimates in column 5 of Table 3 are quite similar to those obtained for the full sample (note that I

9. The IV estimates reported in columns 2 and 3 allow for greater heterogeneity across households in their responses to gas prices as compared to the baseline estimates in column 1. A different concern about the baseline is that the household characteristics themselves may be correlated with unobserved household characteristics, invalidating their inclusion as exogenous variables or as interaction terms in the first-stage instruments. Omitting all of the variables related to income, education, and population density (MSA size, urban area category, etc.) yields an estimated rebound effect of 0.50 (standard error 0.24).

10. Controlling for state GDP addresses the possibility that aggregate wealth shocks are correlated with the price of gasoline at the time the vehicle was obtained. It is also possible that idiosyncratic wealth shocks are correlated over time. It is not possible to assess the persistence of wealth shocks using the available data, but if this were a significant concern it would likely be the case that the main estimates would differ when omitting observations for which the vehicle was obtained recently. Omitting observations for which the vehicle was obtained within the past two years yields similar results, which provides some support for the IV approach. However, it is assumed that idiosyncratic wealth shocks are not highly persistent.

Table 4: Alternative Measures of Other Vehicles' Fuel Economy

	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS		
Log gas price	−0.152	−0.150	−0.347	−0.094	−0.097
	(0.126)	(0.127)	(0.259)	(0.121)	(0.104)
Log fuel economy	0.326***	0.343***	0.254	0.257***	0.252***
	(0.072)	(0.071)	(0.171)	(0.063)	(0.059)
Log other vehicles' fuel economy				−0.023***	−0.027***
				(0.007)	(0.006)
Log fuel economy vehicle 1	−0.088***	−0.131***			
	(0.033)	(0.044)			
Log fuel economy vehicle 2	−0.031	−0.003			
	(0.030)	(0.047)			
Log fuel economy vehicle 3	−0.154***	−0.106			
	(0.051)	(0.079)			
R2	0.16	0.16	0.22	0.15	0.15
			Panel B: IV		
Log gas price	−0.202*	−0.201*	−0.587**	−0.142	−0.131
	(0.120)	(0.118)	(0.255)	(0.109)	(0.099)
Log fuel economy	0.520	0.528	0.145	0.469	0.414
	(0.321)	(0.326)	(0.597)	(0.287)	(0.259)
Log other vehicles' fuel economy				−0.080***	−0.097***
				(0.027)	(0.022)
Log fuel economy vehicle 1	−0.155	−0.133			
	(0.381)	(0.423)			
Log fuel economy vehicle 2	−0.103	0.024			
	(0.415)	(0.511)			
Log fuel economy vehicle 3	0.102	0.033			
	(0.333)	(0.446)			
R2	0.11	0.11	0.16	0.10	0.10
Specification	Rank other vehicles by VMT	Rank other vehicles by fuel economy	Include households with 1 vehicle	Include households with 1 or 2 vehicles	Include households with 1–3 vehicles

Notes: Each column in each panel reports a separate regression. Standard errors are reported in parentheses and are clustered by CMSA and survey month. Except as indicated, the specifications in Panel A are identical to the specification in column 1 of Panel A of Table 3 and the specifications in Panel B are identical to that in column 1 of Panel B of Table 3. Columns 1 and 2 replace the log of other vehicles' average fuel economy with the fuel economy of each of the other vehicles. The regressions include households with 1–3 vehicles. For column 1, vehicles are ranked in order of decreasing miles traveled, so that vehicle 1 has the highest miles traveled of vehicles owned by the household. Column 2 is similar, ranking vehicles by fuel economy rather than miles traveled. Columns 3–5 repeat the specification from Table 3 except that the sample includes households with 1, 2, or 3 vehicles. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

omit the current gasoline price from the California regressions because the other control variables absorb nearly all of the price variation).

Table 4 shows results using alternative measures of the fuel economy of other vehicles. As discussed above, it is straightforward to control for the fuel economy of the household's other vehicles for one- and two-vehicle households. In Table 3, for households with more than two vehicles, I use the average fuel economy of its other vehicles. An alternative to using average fuel economy is to order the household's other vehicles by some criterion and control separately for the fuel economy of those vehicles. Column 1 of Table 4 orders vehicles by VMT, and column 2 orders vehicles by fuel economy. The samples are restricted to households with 1–3 vehicles. For com-

Table 5: Fuel Economy Interacted with Number of Vehicles or Income

	(1)	(2)	(3)	(4)
Log gas price	−0.093	−0.093	−0.118	−0.110
	(0.101)	(0.101)	(0.098)	(0.096)
Log fuel economy	0.212**	0.244***	0.140	0.553**
	(0.095)	(0.054)	(0.343)	(0.242)
Log fuel economy X no. of vehicles	0.019		0.174	
	(0.042)		(0.113)	
Log fuel economy X log income		−0.010		−0.173
		(0.021)		(0.137)
Log other vehicles' fuel economy	−0.029***	−0.029***	−0.114***	−0.115***
	(0.006)	(0.006)	(0.022)	(0.022)
R2	0.17	0.17	0.10	0.08
Regression estimated by	OLS	OLS	IV	IV

Notes: Each column reports a separate regression. Standard errors are reported in parentheses and are clustered by CMSA and survey month. Except as indicated, the specifications are identical to the specification in column 1 of Table 3. Column 1 includes the interactions between the log fuel economy and the number of household vehicles, minus 1. Column 2 includes the log of fuel economy interacted with the log of household income, which is estimated as the midpoint of the corresponding income group. Columns 3 and 4 are identical to columns 1 and 2 except that they are estimated by IV rather than by OLS, using the same instruments as in column 1 of Table 3. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

parison with these results, columns 3–5 report estimates of equation (2) when restricting the sample based on the number of household vehicles. In these regressions, the rebound effect is estimated by multiplying each fuel economy coefficient by the probability that the corresponding variable is nonzero, and computing the sum. Unfortunately, the standard errors are very large in the regressions and the estimates do not provide strong evidence about how households allocate miles traveled across their vehicles.

Table 5 allows the rebound effect to vary across households by number of household vehicles or by income. Columns 1 and 3 report results allowing the fuel economy coefficient to vary with the number of household vehicles. The rebound effect is larger for vehicles belonging to multi-vehicle households; the estimates are not statistically significant, however. Columns 2 and 4 add to the baseline specification the interaction between the vehicle's fuel economy and the household's income, where income is computed as the midpoint of the corresponding income category. I find weak evidence that households with lower income are more responsive, which is consistent with West (2004), although the income–fuel economy interaction is not statistically significant.

4.3 Implications of Imposing the Three Assumptions

The Introduction discusses three assumptions maintained in the rebound literature. Columns 1–5 in Table 6 report versions of equation (2) that, starting from the baseline specification in Table 3, impose these assumptions one at a time.

The first assumption holds that vehicle fuel economy is uncorrelated with other vehicle characteristics. Column 1 imposes this assumption by replacing the model fixed effects with vehicle type fixed effects and by using OLS. The estimated rebound effect is much smaller than that reported in column 1 of Table 3.

The second assumption maintains that, for a multivehicle household, VMT is independent of the fuel economy of the household's other vehicles. Columns 2 and 3 impose this assumption

Table 6: Rebound Effects without Relaxing the Three Assumptions

	(1)	(2)	(3)	(4)	(5)	(6)
Log gas price	−0.115	−0.097	−0.138			
	(0.120)	(0.100)	(0.096)			
Log fuel economy	0.129***	0.247***	0.793**			
	(0.031)	(0.054)	(0.270)			
Log other vehicles' fuel economy	−0.031***					
	(0.006)					
Log fuel costs				−0.206***	−0.894***	−0.125***
				(0.049)	(0.199)	(0.030)
Log other vehicle fuel costs				0.040***	0.101***	
				(0.008)	(0.020)	
R2	0.12	0.17	0.08	0.17	0.06	0.12
Fuel economy rebound effect	0.103***	0.247***	0.793**	0.174***	0.811***	0.125***
	(0.034)	(0.054)	(0.270)	(0.050)	(0.198)	(0.030)
Specification	Omit model fixed effects	Omit other vehicle fuel economy	Omit other vehicle fuel economy	Replace fuel economy with fuel costs	Replace fuel economy with fuel costs	Omit model fixed effects and use fuel costs
Estimation by	OLS	OLS	IV	OLS	IV	OLS

Notes: Each column in each panel reports a separate regression. Standard errors are reported in parentheses and are clustered by CMSA and survey month. Regressions in columns 1, 2, 4, and 6 are estimated by OLS, and regressions in columns 3 and 5 are estimated by IV using the same instruments as in Table 3. The specifications are the same as in Table 3 except as indicated. Column 1 replaces model fixed effects with vehicle type fixed effects. Columns 2 and 3 omit the fuel economy of the household's other vehicles. Columns 4 and 5 omit the log fuel price and replaces fuel economy with fuel costs. In column 5 the instruments are constructed using the log of the ratio of the current gasoline price to the price of gasoline from the month the vehicle was obtained, rather than the log of the gasoline price from the month the vehicle was obtained. Column 6 is the same as column 1 except using fuel costs instead of fuel economy and the gas price and omitting other vehicle fuel economy. The fuel economy rebound effect is computed as in Table 3. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

by omitting the fuel economy of the household's other vehicles. For the IV estimates in column 3 the estimated fuel economy rebound effect is larger than in the baseline.

The third assumption holds that the response of VMT to gasoline prices is inversely proportional to the response to fuel economy. I impose this assumption by using fuel costs in place of fuel economy, where fuel costs are the ratio of the current gasoline price to fuel economy. Columns 4 and 5 implement this approach, and the specification is otherwise identical to the baseline. The rebound effect is similar to the baseline for OLS but larger for IV. Finally, column 6 imposes all three assumptions by repeating the specification in column 1, except replacing the gas price and fuel economy with fuel costs, and omitting other vehicle fuel costs. The estimated rebound effect is 0.13, which is statistically significantly smaller than the OLS and IV estimates that relax all three assumptions.

5. REBOUND EFFECT FOR HYPOTHETICAL FUEL ECONOMY INCREASES

I use the estimates from Section 4 to calculate the rebound effect from hypothetical fuel economy increases. This analysis has two main objectives. The first is to estimate the changes in VMT and gasoline consumption from the upcoming passenger vehicle fuel economy standards. This analysis does not include all of the behavioral responses to standards, such as changes in used vehicle markets and vehicle retirements, and instead focuses on the implications of the rebound

Table 7: Effect of Increasing Fuel Economy on VMT and Gasoline Consumption

	(1)	(2)	(3)	(4)	(5)
VMT (fractional change)	0.09	0.18	0.04	0.34	0.41
Gas consumption (fractional change)	−0.25	−0.19	−0.29	−0.07	−0.03
Specification used for simulations	Baseline, OLS (Table 3, column 1, Panel A)	Baseline, IV (Table 3, column 1, Panel B)	Omit model fixed effects (Table 6, column 1)	Omit other vehicle fuel economy (Table 6, column 3)	Fuel costs (Table 6, column 5)

Notes: Each column in each panel reports a separate simulation. The simulations include the assumption that each vehicle's fuel economy increases by the amount predicted by US EPA (2011). Assuming no rebound effect, both scenarios would reduce gasoline consumption by 31 percent. Each column uses the regression results from the specification indicated at the bottom of the table. The table reports the fractional change in VMT and gas consumption using the estimated coefficients and comparing the miles traveled and gasoline consumption in the 2009 NHTS with the counterfactual miles traveled and gasoline consumption under the fuel economy increases.

effect for estimates of future fuel savings. The second objective is to quantify the importance of relaxing the three assumptions, which is useful for researchers making modeling choices when estimating the welfare effects of fuel economy standards and other transportation policies.

To simulate the effects of increasing fuel economy on gasoline consumption I compare the change in gasoline consumption caused by a fuel economy increase for two cases: in the first, there is no rebound effect, and in the second the rebound effect is estimated in Section 4. I begin with the observed fuel economy and VMT of each household and vehicle in the estimation sample. I increase the fuel economy of each vehicle to equal the fuel economy predicted by the US EPA and National Highway Traffic Safety Administration analysis of the 2016 fuel economy standards. By raising the fuel economy of all vehicles in the data set, including vehicles obtained recently and those obtained many years prior to the survey, the scenario corresponds to the long run, after the entire vehicle stock has been replaced by vehicles meeting the new standards. If there were no rebound effect, the change in gasoline consumption is equal to the change in the fuel consumption rate, which is the reciprocal of fuel economy. Across the vehicles in the sample, average fuel economy increases by about 44 percent, which corresponds to about a 31 percent decrease in the average fuel consumption rate. This change would cause about a 31 percent decrease in gasoline consumption in the first case—i.e., if there were no rebound effect. In the second case, for each vehicle in the sample I compute the change in VMT using the fuel economy increase and the estimated elasticity of VMT to fuel economy. The first row in Table 7 reports the predicted fractional change in VMT. Each column uses the estimated elasticity of VMT to fuel economy from a separate regression from Section 4, which is indicated at the bottom of the table.

The baseline specifications are in columns 1 and 2, which use the coefficient estimates from column 1 of Table 3. In Table 7, column 1 reports the results based on the OLS coefficients, and column 2 reports the results based on the IV coefficients. In column 1, VMT increases by 9 percent, which is roughly equal to the fuel economy increase (44 percent, on average) multiplied by the elasticity of VMT to fuel economy (0.22, from Table 3). VMT increases by about twice as much using the IV estimates. The second row shows that gasoline consumption falls by 19 to 25 percent. Compared to the 31 percent decrease in the no-rebound case, the rebound effect erodes about 20 to 40 percent of the gasoline savings from the fuel economy increase.[11] This erosion is substantially larger than the 10 percent erosion assumed by US EPA (2011) in the agency's estimate of the benefits of upcoming fuel economy standards.

The remaining columns in Table 7 show the effects of imposing the three assumptions. Column 3 shows that the rebound effect is substantially smaller when omitting model fixed effects and estimating equation (2) by OLS rather than by IV. Omitting other vehicle fuel economy—that is, imposing the second assumption—results in a larger rebound effect, which can be seen by comparing columns 2 and 4. Finally, column 5 focuses on the assumption that gasoline prices and fuel economy have equal and opposite effects on VMT. Imposing this assumption does not affect the results (compare with column 2).

6. CONCLUSIONS

Rising passenger vehicle fuel economy standards in the United States and many other countries will dramatically reduce the cost of driving. The effectiveness of the standards at reducing fuel consumption and associated greenhouse gas emissions depends, in large part, on the extent to which consumers increase VMT because of the lower driving costs—that is, the magnitude of the rebound effect for passenger vehicles.

Although a substantial literature has attempted to estimate the rebound effect, the studies using micro data have made at least one of three assumptions: (a) fuel economy is uncorrelated with vehicle and household attributes that affect the utility of driving; (b) for multivehicle households, the fuel economy of one vehicle does not affect the VMT of another vehicle; and (c) the effect of gasoline prices on VMT is inversely proportional to the effect of fuel economy on VMT.

I quantify the implications of these assumptions for empirical estimates of the rebound effect. Relaxing these assumptions implies that a 1 percent increase in the fuel economy of all of a household's vehicles increases VMT by 0.2 to 0.4 percent. The rebound effect erodes about one-third of the fuel savings that would otherwise occur from rising fuel economy standards. The rebound effect is smaller when one imposes the assumption that fuel economy is uncorrelated with unobserved vehicle characteristics and larger when one assumes that the VMT of one vehicle does not affect the VMT of a household's other vehicles. Assuming that the effect of gasoline prices on VMT is equal in magnitude to the effect of fuel economy has ambiguous effects on the results. Note, however, that in many cases the point estimates are statistically indistinguishable when comparing the estimates that are obtained with and without imposing each assumption.

The results have three main implications for the rebound literature and for policy. First, there is strong evidence that fuel economy is endogenous and is correlated with vehicle and household characteristics. Second, imposing the three assumptions affects the estimated rebound effect, although the differences may not be statistically significant. Finally, the main estimates are substantially larger than in other recent studies, suggesting that fuel economy standards may be substantially more costly per gallon of gasoline saved than previously thought.

AKNOWLEDGMENTS

I thank Kevin Bolon, David Cooke, Ken Gillingham, Ken Small and anonymous referees for comments on earlier drafts. Shefali Khanna provided excellent research assistance.

11. The percent change in gasoline consumption reported in the table is approximately equal to the percent change in the fuel consumption rate (31 percent) plus the percent change in VMT.

REFERENCES

Allcott, H., and N. Wozny (Forthcoming). "Gasoline Prices, Fuel Economy, and the Energy Paradox." *Review of Economics and Statistics*. http://dx.doi.org/10.1162/REST_a_00419.

Anderson, S.T., R. Kellogg, and J.M. Sallee (2013). "What Do Consumers Believe about Future Gasoline Prices?" *Journal of Environmental Economics and Management* 66(2): 383–403. http://dx.doi.org/10.1016/j.jeem.2013.07.002.

Bento, A., L. Goulder, M. Jacobsen, and R. Von-Haefen. 2009. "Efficiency and Distributional Impacts of Increased US Gasoline Taxes." *American Economic Review* 99(3): 667–99. http://dx.doi.org/10.1257/aer.99.3.667.

Borenstein, S. (2015). "A Microeconomic Framework for Evaluating Energy Efficiency Rebound and Some Implications." *The Energy Journal* 36(1): 1–21. http://dx.doi.org/10.5547/01956574.36.1.1.

Busse, M., C. Knittel, and F. Zettlemeyer (2013). "Are Consumers Myopic? Evidence from New and Used Car Purchases" *American Economic Review* 103(1): 220–256. http://dx.doi.org/10.1257/aer.103.1.220.

Dubin, J.A., and D.L. McFadden (1984). "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption." *Econometrica* 52(2): 345–62. http://dx.doi.org/10.2307/1911493.

EPA (U.S. Environmental Protection Agency) and DOT (U.S. Department of Transportation) (2011). *Draft Joint Technical Support Document: Proposed Rulemaking for 2017–2025 Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards*. EPA-420-D-11-901. Washington, DC: EPA and DOT.

Feng, Y., D. Fullerton, and L. Gan (2013). "Vehicle Choices, Miles Driven, and Pollution Policies." *Journal of Regulatory Economics* 44(1): 4–29. http://dx.doi.org/10.1007/s11149-013-9221-z.

Frondel, M., N. Ritter, and C. Vance (2012). "Heterogeneity in the Rebound Effect: Further Evidence for Germany." *Energy Economics* 34(2): 461–67. http://dx.doi.org/10.1016/j.eneco.2011.10.016.

Gillingham, K. (2012). "Selection on Anticipated Driving and the Consumer Response to Changing Gasoline Prices." Working paper, School of Forestry and Environmental Studies, Yale University.

Gillingham, K. (2013). "Identifying the Elasticity of Driving: Evidence from a Gasoline Price Shock in California." Working paper, School of Forestry and Environmental Studies, Yale University.

Gillingham, K., M.J. Kotchen, D.S. Rapson, and G. Wagner (2013). "The Rebound Effect is Over-played." *Nature* 493: 475–76. http://dx.doi.org/10.1038/493475a.

Goldberg, P.K. (1998). "The Effects of the Corporate Average Fuel Economy Standards in the US." *Journal of Industrial Economics* 46: 1–33. http://dx.doi.org/10.1111/1467-6451.00059.

Greene, D.L. (2012). "Rebound 2007: Analysis of National Light-Duty Vehicle Travel Statistics." *Energy Policy* 41: 14–28. http://dx.doi.org/10.1016/j.enpol.2010.03.083.

Greene, D.L., J. Kahn, and R. Gibson (1999). "Fuel Economy Rebound Effect for U.S. Household Vehicles." *The Energy Journal* 20: 1–31. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol20-No3-1.

Hymel, K.M., and K.A. Small (2013). "The Rebound Effect for Automobile Travel: Asymmetric Response to Price Changes and Other Quirks of the 2000s." Unpublished manuscript.

Jacobsen, M. (2013). "Evaluating US Fuel Economy Standards in a Model with Producer and Household Heterogeneity." *American Economic Journal: Economic Policy* 5(2): 148–87. http://dx.doi.org/10.1257/pol.5.2.148.

Jacobsen, M.R., and A.A. van Benthem (2012). "Vehicle Scrappage and Gasoline Policy." Unpublished manuscript.

Klier, T., and J. Linn (2010). "The Price of Gasoline and the Demand for Fuel Efficiency: Evidence from Monthly New Vehicle Sales Data." *American Economic Journal: Economic Policy* 2(3): 134–53. http://dx.doi.org/10.1257/pol.2.3.134.

Klier, T., and J. Linn (2012). "New Vehicle Characteristics and the Cost of the Corporate Average Fuel Economy Standards." *RAND Journal of Economics* 43(1): 186–213. http://dx.doi.org/10.1111/j.1756-2171.2012.00162.x.

Knittel, C., and R. Sandler (2013). "The Welfare Impact of Indirect Pigouvian Taxation: Evidence from Transportation." Unpublished manuscript.

Li, S., C. Timmins, and R.H. von Haefen (2009). "How Do Gasoline Prices Affect Fleet Fuel Economy?" *American Economic Journal: Economic Policy* 1(2): 113–37. http://dx.doi.org/10.1257/pol.1.2.113.

Li, S., J. Linn, and E. Muehlegger (Forthcoming). "Gasoline Taxes and Consumer Behavior." *American Economic Journal: Economic Policy*. http://dx.doi.org/10.2139/ssrn.2010202.

Small, K., and K. van Dender (2007). "Fuel Efficiency in Motor Vehicle Travel: The Declining Rebound Effect." *The Energy Journal* 28(1): 25–51. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No1-2.

Spiller, E. (2012). "Household Vehicle Bundle Choice and Gasoline Demand: A Discrete-Continuous Choice." Unpublished manuscript.

UK Energy Research Centre (UKERC) (2007). "The Rebound Effect: An Assessment of the Evidence for Economy-Wide Energy Savings from Improved Energy Efficiency."

West, S. (2004). "Distributional Effects of Alternative Vehicle Pollution Control Policies." *Journal of Public Economics* 88: 735–57. http://dx.doi.org/10.1016/S0047-2727(02)00186-X.

Appendix Table 1: Additional Coefficient Estimates from Regressions Reported in Table 3, Column 1

	(1) Panel A (OLS)	(2) Panel B (IV)
	Urban/rural, population density and housing density	
Urban indicator	0.026	0.041*
	(0.019)	(0.021)
Log population density	−0.009	−0.010
	(0.008)	(0.009)
Log housing density	0.003	0.000
	(0.009)	(0.010)
	Vehicle age	
3–6 years	−0.051***	−0.040**
	(0.013)	(0.016)
6–9 years	−0.151***	−0.146***
	(0.015)	(0.018)
9–13 years	−0.248***	−0.240***
	(0.017)	(0.030)
>13 years	−0.449***	−0.473***
	(0.018)	(0.025)
	Income	
$15,000 to $30,000	0.102***	0.113***
	(0.027)	(0.030)
$30,000 to $45,000	0.124***	0.145***
	(0.028)	(0.032)
$45,000 to $60,000	0.180***	0.211***
	(0.026)	(0.031)
$60,000 to $75,000	0.228***	0.259***
	(0.028)	(0.033)
$75,000 to $80,000	0.234***	0.284***
	(0.032)	(0.038)
$80,000 to $100,000	0.239***	0.286***
	(0.027)	(0.035)
≥$100,000	0.233***	0.272***
	(0.027)	(0.035)
	Number of adults	
2	−0.103**	−0.097**
	(0.044)	(0.046)
3	−0.076	−0.071
	(0.048)	(0.052)
4	−0.062	−0.089
	(0.055)	(0.060)
>4	−0.102	−0.121
	(0.100)	(0.109)

(continued)

Appendix Table 1: Additional Coefficient Estimates from Regressions Reported in Table 3, Column 1 *(continued)*

	Household size	
2	0.125***	0.153***
	(0.045)	(0.046)
3	0.190***	0.229***
	(0.048)	(0.050)
4	0.221***	0.278***
	(0.048)	(0.051)
5	0.279***	0.345***
	(0.050)	(0.055)
6	0.291***	0.388***
	(0.057)	(0.062)
>6	0.238***	0.376***
	(0.072)	(0.078)
	Education	
High school	−0.033	−0.029
	(0.026)	(0.030)
Some college	−0.002	−0.004
	(0.026)	(0.029)
Bachelor's degree	−0.013	−0.026
	(0.027)	(0.032)
Graduate degree	0.041	0.018
	(0.029)	(0.037)
	Respondent age	
<39	−0.010	−0.001
	(0.015)	(0.018)
39 to 48	−0.041**	−0.037*
	(0.017)	(0.018)
48 to 55	−0.122***	−0.110***
	(0.019)	(0.021)
>55	−0.328***	−0.334***
	(0.019)	(0.021)
	Urbanization category	
Second city	−0.007	0.003
	(0.024)	(0.027)
Suburban	−0.000	0.010
	(0.022)	(0.024)
Town or country	0.052*	0.073**
	(0.027)	(0.030)
	Number of drivers	
1	−0.002	−0.059
	(0.295)	(0.311)
2	0.102	0.033
	(0.295)	(0.311)
3	0.135	0.064
	(0.297)	(0.312)
>3	0.179	0.121
	(0.297)	(0.313)

(continued)

Appendix Table 1: Additional Coefficient Estimates from Regressions Reported in Table 3, Column 1 *(continued)*

	MSA size	
MSA of 250,000–500,000	−0.005	−0.017
	(0.032)	(0.035)
MSA of 500,000–1 million	0.037	0.032
	(0.031)	(0.033)
MSA of 1–3 million	0.427***	0.400***
	(0.132)	(0.119)
MSA of 3 million or more	0.214	0.125
	(0.140)	(0.143)
Not in MSA	0.374	0.358**
	(0.157)	(0.157)
	Urban area size	
200,000–500,000	0.011	0.011
	(0.026)	(0.028)
500,000–1 million	−0.071**	−0.065**
	(0.030)	(0.033)
>1 million without rail	−0.028	−0.025
	(0.026)	(0.029)
>1 million with rail	−0.093***	−0.100***
	(0.027)	(0.030)
Not urbanized	0.008	−0.002
	(0.023)	(0.025)

Notes: The table reports coefficient estimates from the two regressions reported in column 1 of Table 3. Column 1 shows the OLS regression results from Panel A of Table 3 and column 2 shows the IV regression results from Panel B of Table 3. Both regressions also include state-CMSA fixed effects and column 1 includes interactions of model fixed effects with a set of fixed effects for the number of vehicles in the household. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

Appendix Table 2: First Stage Results for Regressions Reported in Table 3, Column 1, Panel B

	(1)	(2)	(3)	(4)
	Dep var is log fuel economy		Dep var is log other vehicle fuel economy	
	Panel A: Main effects of gasoline price variables			
Log gas price	0.021		0.075	
	(0.026)		(0.097)	
Log gas price in month vehicle obtained	0.208***		−0.258*	
	(0.055)		(0.152)	
Log gas price in month other vehicles obtained	−0.012		0.675***	
	(0.051)		(0.104)	
	Interaction with gas price in month obtained	Interaction with gas price in month other vehicles obtained	Interaction with gas price in month obtained	Interaction with gas price in month other vehicles obtained
	Panel B: Vehicle age			
3–6 years	−0.022	−0.003	−0.023	−0.032***
	(0.021)	(0.008)	(0.048)	(0.011)
6–9 years	−0.024	0.014	−0.047	−0.026**
	(0.020)	(0.009)	(0.047)	(0.013)
9–13 years	−0.026	0.010	−0.059	−0.023
	(0.020)	(0.009)	(0.046)	(0.014)
>13 years	0.004	−0.002	−0.082*	−0.030**
	(0.020)	(0.010)	(0.048)	(0.015)
	Panel C: Number of vehicles			
2	0.041***	0.046**	0.033	−1.159***
	(0.015)	(0.019)	(0.042)	(0.063)
3	0.067***	0.036*	−0.075**	−0.097
	(0.016)	(0.020)	(0.038)	(0.060)
4	0.076***	0.051***	−0.060	0.022
	(0.018)	(0.020)	(0.042)	(0.062)
5	0.097***	0.051**	−0.085*	0.063
	(0.025)	(0.022)	(0.045)	(0.068)
>5	0.094***	−0.138**		
	(0.028)	(0.057)		
	Panel D: Income			
$15,000 to $30,000	0.031*	−0.033**	−0.033	0.017
	(0.017)	(0.015)	(0.056)	(0.035)
$30,000 to $45,000	0.028	−0.029**	0.000	0.010
	(0.017)	(0.014)	(0.058)	(0.033)
$45,000 to $60,000	0.024	−0.036**	0.026	0.046
	(0.018)	(0.014)	(0.059)	(0.033)
$60,000 to $75,000	0.031	−0.006	−0.027	0.048
	(0.019)	(0.014)	(0.061)	(0.033)
$75,000 to $80,000	0.017	−0.021	−0.008	0.004
	(0.022)	(0.015)	(0.071)	(0.035)
$80,000 to $100,000	0.021	−0.016	−0.005	0.026
	(0.019)	(0.014)	(0.062)	(0.033)
≥$100,000	0.011	−0.022	−0.067	0.013
	(0.018)	(0.014)	(0.059)	(0.032)

(continued)

Appendix Table 2: First Stage Results for Regressions Reported in Table 3, Column 1, Panel B *(continued)*

	Panel E: Household size			
2	0.000	−0.017	−0.035	0.204***
	(0.027)	(0.032)	(0.073)	(0.062)
3	−0.007	−0.003	0.067	0.207***
	(0.029)	(0.031)	(0.074)	(0.063)
4	−0.003	0.012	0.119	0.215***
	(0.030)	(0.032)	(0.077)	(0.063)
5	0.038	0.024	0.001	0.241***
	(0.033)	(0.033)	(0.084)	(0.066)
6	0.015	0.004	0.001	0.199***
	(0.034)	(0.035)	(0.098)	(0.067)
>6	−0.019	0.008	−0.047	0.234***
	(0.055)	(0.044)	(0.105)	(0.081)
	Panel F: Number of adults			
2	0.027	−0.029	0.091	−0.144**
	(0.031)	(0.034)	(0.080)	(0.059)
3	−0.019	−0.042	0.033	−0.078
	(0.033)	(0.035)	(0.086)	(0.063)
4	−0.045	−0.033	0.006	−0.041
	(0.038)	(0.036)	(0.095)	(0.075)
>4	−0.073	−0.113**	−0.111	−0.166
	(0.055)	(0.050)	(0.166)	(0.113)
	Panel G: Respondent age			
<39	0.061***	−0.012	0.033	−0.004
	(0.013)	(0.008)	(0.036)	(0.015)
39 to 48	0.062***	0.006	0.064*	0.028*
	(0.013)	(0.008)	(0.037)	(0.016)
48 to 55	0.044***	0.010	0.042	0.008
	(0.013)	(0.009)	(0.036)	(0.016)
>55	0.057***	−0.002	0.027	−0.040**
	(0.013)	(0.009)	(0.039)	(0.019)
	Panel H: Number of drivers			
2	−0.271***	−0.027	0.204	0.080
	(0.047)	(0.041)	(0.128)	(0.074)
3	−0.327***	0.010	0.123	0.085*
	(0.044)	(0.018)	(0.122)	(0.043)
4	−0.270***	0.007	0.153	0.049
	(0.047)	(0.015)	(0.127)	(0.040)
>4	−0.233***		0.202	
	(0.051)		(0.134)	

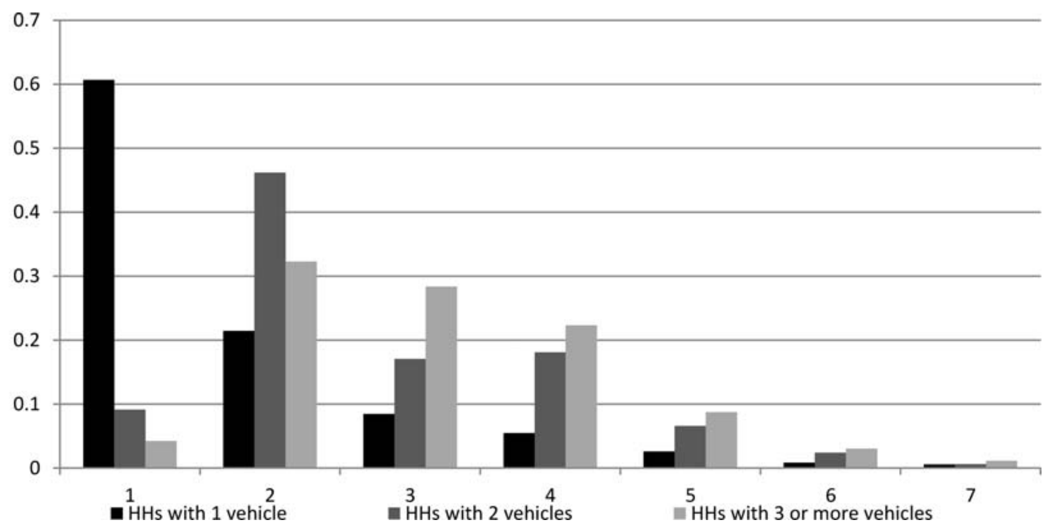
(continued)

Appendix Table 2: First Stage Results for Regressions Reported in Table 3, Column 1, Panel B *(continued)*

	Panel I: Education			
High school	0.018	0.018	0.063	−0.038
	(0.016)	(0.014)	(0.065)	(0.025)
Some college	0.020	0.019	0.086	−0.035
	(0.016)	(0.014)	(0.065)	(0.025)
Bachelor's degree	0.010	0.004	0.065	−0.052**
	(0.017)	(0.015)	(0.064)	(0.026)
Graduate degree	0.021	−0.007	0.090	−0.044*
	(0.018)	(0.015)	(0.067)	(0.026)
R2	0.10		0.80	
First stage F-statistic	5.17		94.22	

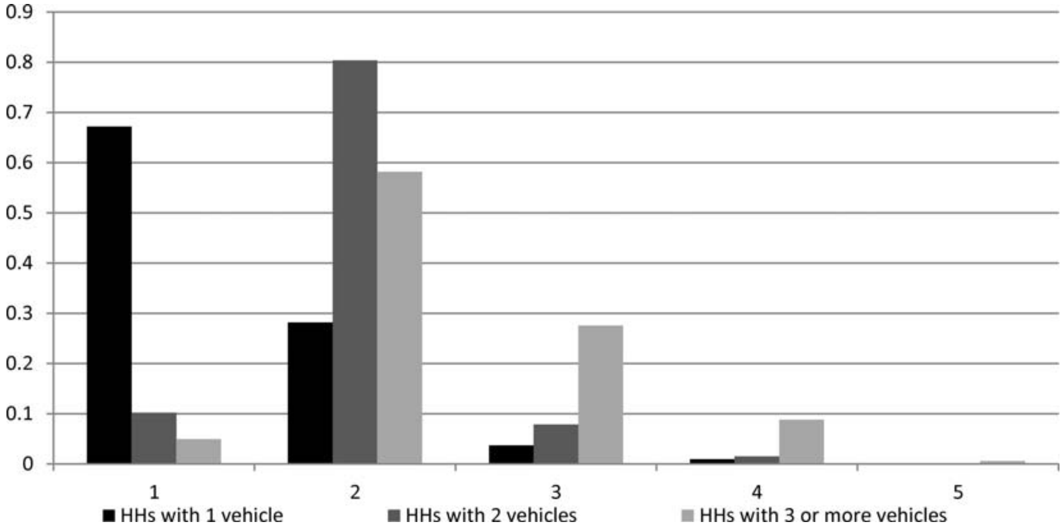
Notes: The table reports coefficient estimates from the first stage of the IV regression in column 1 of Table 3. Columns 1 and 2 show the first stage coefficients for the log fuel economy equation and columns 3 and 4 show the coefficients for the log other vehicle fuel economy equation. Columns 1 and 3 show coefficients, with standard errors in parentheses, of the interactions of gasoline price in the month the vehicle was obtained with the indicated fixed effects. Columns 2 and 4 show similar interactions, using the average gasoline price at the time the other vehicles were obtained. The bottom row reports the F-statistic from the joint test that the instruments equal zero. Asterisks denote 1 (***), 5 (**), and 10 (*) percent significance levels.

Appendix Figure 1: Household Size by Number of Vehicles in Household



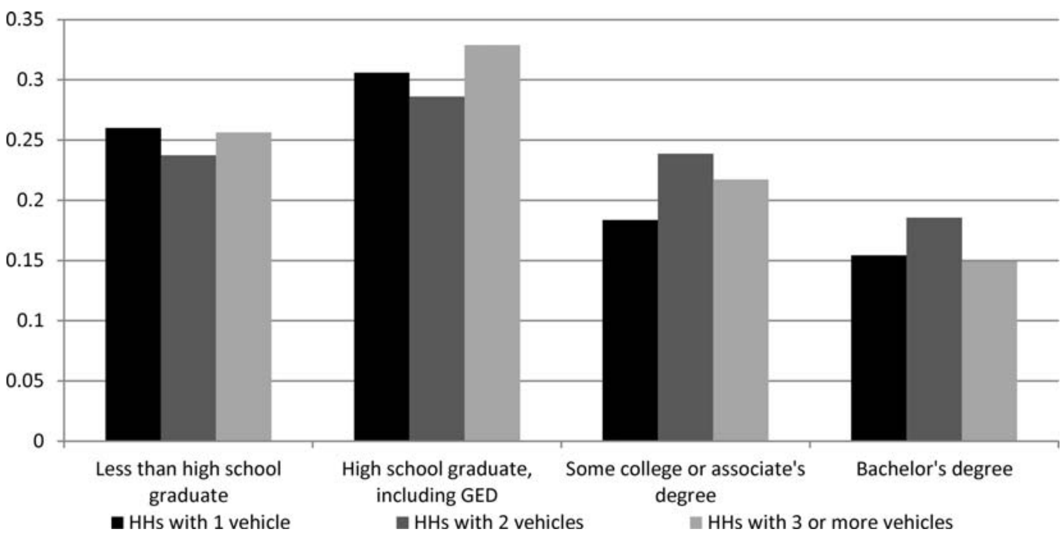
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated number of people. Observations are weighted by the final NHTS weights.

Appendix Figure 2: Number of Adults by Number of Vehicles in Household



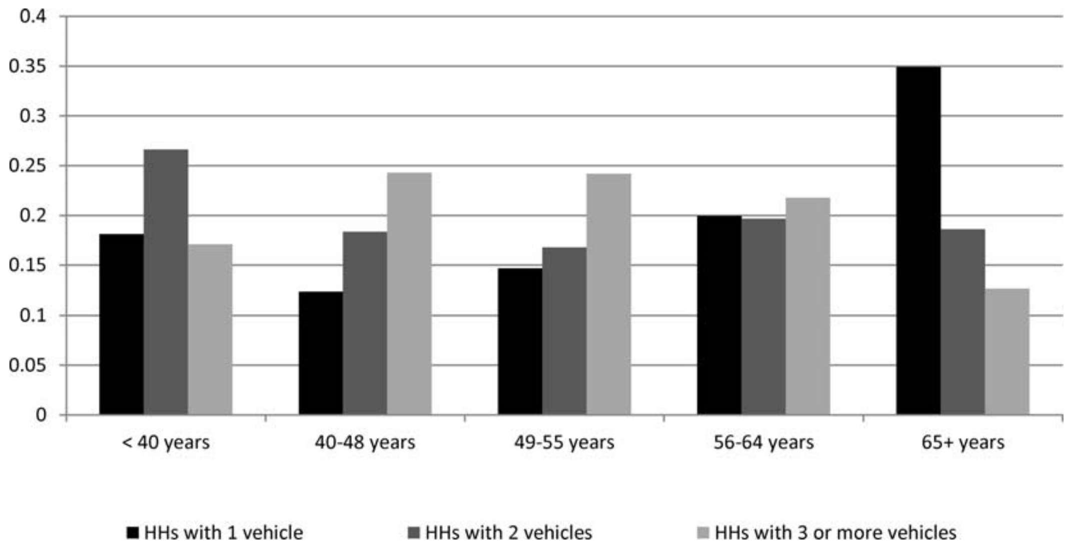
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated number of adults. Observations are weighted by the final NHTS weights.

Appendix Figure 3: Education Level by Number of Vehicles in Household



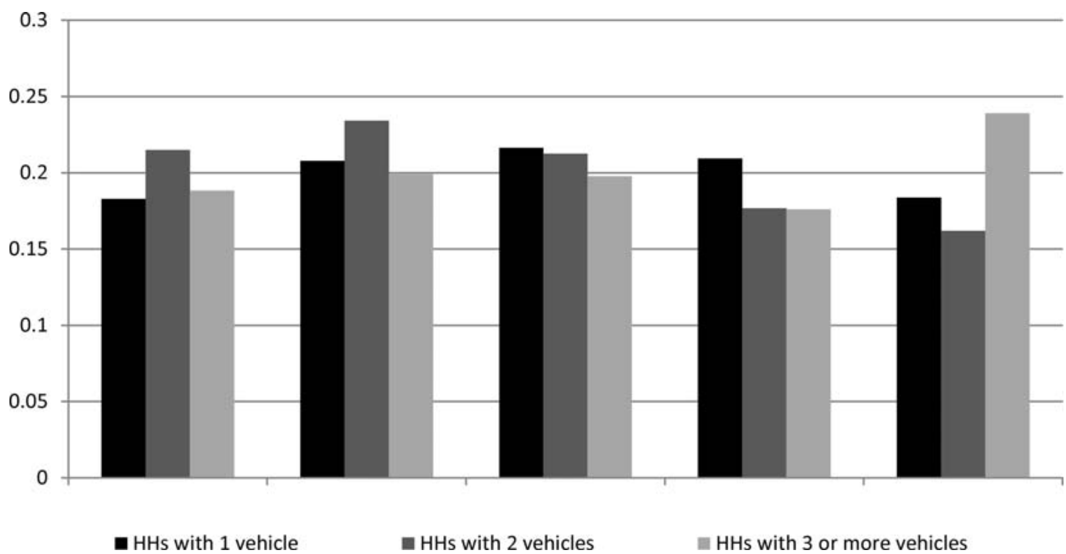
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with a household head achieving the indicated education level. Observations are weighted by the final NHTS weights.

Appendix Figure 4: Age of Household Head by Number of Vehicles in Household



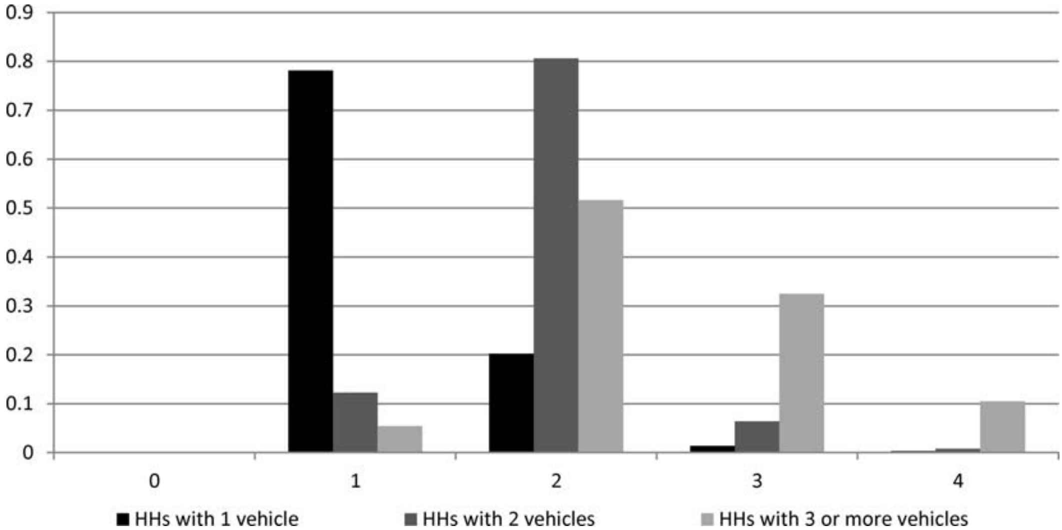
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with a household head in the indicated age range. Observations are weighted by the final NHTS weights.

Appendix Figure 5: Vehicle Age by Number of Vehicles in Household



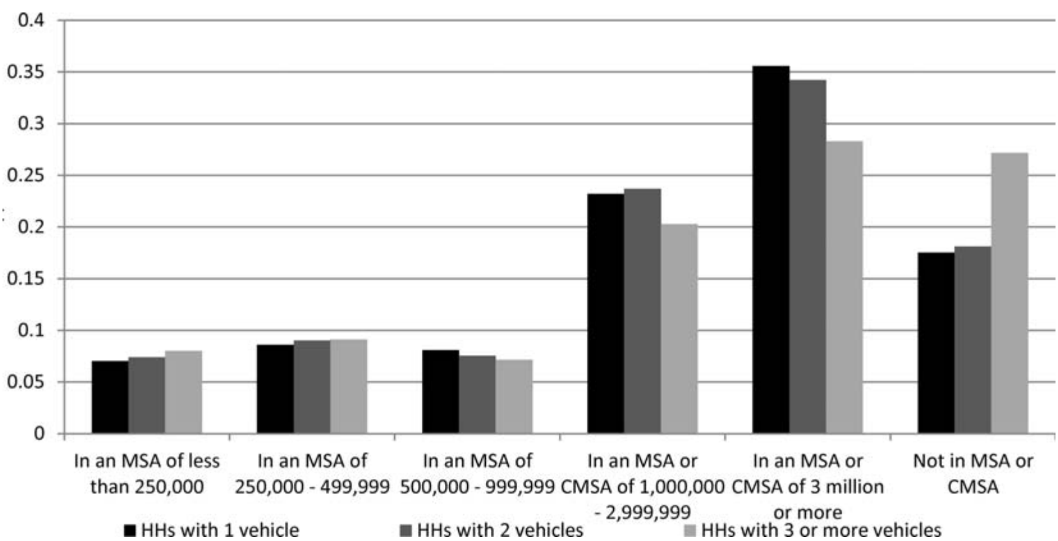
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of vehicles that are in the indicated age range. Observations are weighted by the final NHTS weights.

Appendix Figure 6: Number of Drivers by Number of Vehicles in Household



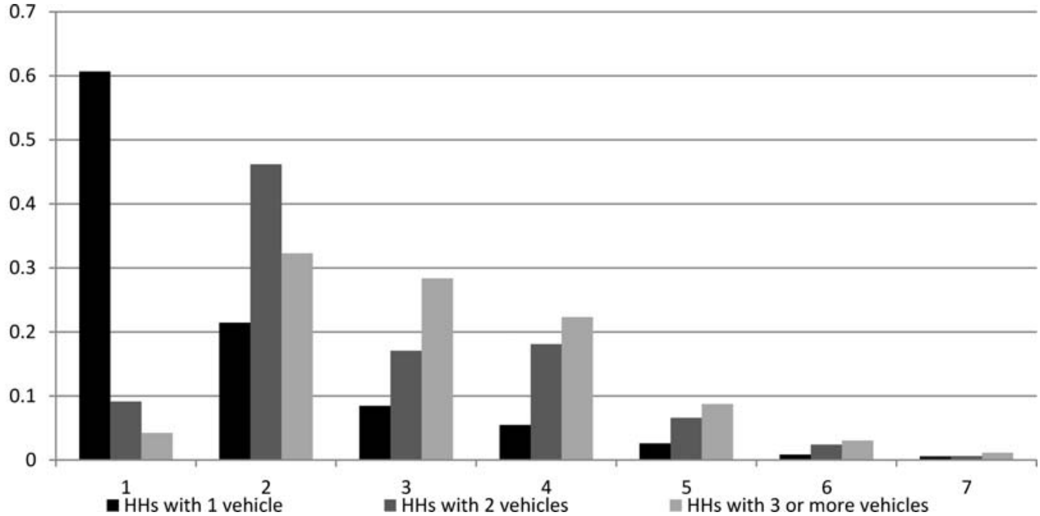
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated number of drivers. Observations are weighted by the final NHTS weights.

Appendix Figure 7: MSA Size by Number of Vehicles in Household



Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households in the indicated MSA size. Observations are weighted by the final NHTS weights.

Appendix Figure 8: Urban Area Size by Number of Vehicles in Household



Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated urban area size. Observations are weighted by the final NHTS weights.