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The Rebound Effect for Passenger Vehicles

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RESOURCES FOR THE FUTURE

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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 impose at least one of three behavioral assumptions: (a) fuel economy is uncorrelated with other vehicle attributes; (b) fuel economy is uncorrelated with attributes of other vehicles owned by the household; and (c) the effect of gasoline prices on vehicle miles traveled is inversely proportional to the effect of fuel economy. Relaxing these assumptions yields a large effect; a one percent fuel economy increase raises driving 0.2 to 0.4 percent.

Key Words: fuel economy standards, passenger vehicles, vehicle miles traveled, household driving demand

JEL Classification Numbers: Q52, R22, R41

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Joshua Linn*

1. Introduction

Motivated by a desire to reduce gasoline consumption and the associated external energy security and climate costs, the US fuel economy standards for new passenger vehicles will dramatically increase average new vehicle fuel economy. The current standards, which the US Environmental Protection Agency (US EPA) and the US 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. The recently finalized 2025 standards 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 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

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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 (US EPA 2011), and many recent estimates have fallen toward the lower end. Based on the results of several recent studies, the federal government used an elasticity of 0.1 for estimating the fuel savings of the upcoming fuel economy standards.

The literature has faced several major challenges to estimating the rebound effect, whether using aggregate or micro data. 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 has made at least one of three assumptions about consumer behavior. The paper's objective is to simultaneously relax these assumptions and obtain an unbiased estimate of the long-run rebound effect. The first assumption is that fuel economy is uncorrelated with other vehicle attributes that affect a consumer's utility from driving. Studies based on time series variation in aggregate average fuel economy (e.g., Small and van Dender 2007), or 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). Failing to control for these attributes would bias empirical estimates of the rebound effect.

[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).

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, 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 exception of Feng et al. (2005) and Spiller (2012), econometric analysis of the demand for VMT and gasoline treats each of a household's vehicles as an independent observation.

The third assumption is that VMT responds similarly to gasoline prices and fuel economy. Many recent studies have analyzed the effect of gasoline prices on VMT (e.g., Gillingham 2013). Such an analysis is appropriate for quantifying the effects of gasoline prices on gasoline consumption. However, most studies that have estimated a rebound effect for purposes of evaluating fuel economy standards have estimated the elasticity of VMT to *fuel prices* or to *fuel costs*. The implicit assumption is that fuel economy and fuel prices affect VMT by equal and opposite amounts. This assumption may not hold in practice. 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, Frondel et al. (2012) and Small and van Dender (2007) report no difference between the two effects, and Greene (2012) reports a difference in some specifications. However, the latter two studies use aggregate data and time series variation in fuel economy, making it difficult to identify the effect of fuel economy on VMT. Because fuel economy changes gradually over time, such changes may be correlated with other determinants of VMT that are difficult to measure, such as congestion.

This paper shows that simultaneously relaxing these assumptions significantly raises the estimated rebound effect. The first part of the paper demonstrates the empirical implications of maintaining the three assumptions held in the literature: (a) fuel economy is uncorrelated with other vehicle characteristics; (b) for multivehicle households, vehicles can be treated as independent observations; and (c) VMT responds similarly to fuel prices and to fuel economy. I show that all three assumptions introduce bias for previous estimates of the rebound effect, and the direction of the bias in each case is theoretically ambiguous.

The second part of the paper uses 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 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 (2012), rests on the strong correlation between fuel prices and new vehicle fuel economy documented by Klier and Linn (2010) and Busse et al. (2013), among others.

Turning to the other two assumptions on consumer behavior, based on the simple model in Section 2 and similar to Feng et al. (2005), I account for the effects of the household's other vehicles 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. I refer to the fuel economy rebound effect as 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 to 0.4. The effect of fuel economy on VMT is statistically significant in nearly all specifications.

I next show 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. However, there is mixed evidence as to the direction of bias from the third assumption. Overall, the assumptions prove to be empirically important.

Finally, I use the results to estimate the effect on VMT and gasoline consumption of future fuel economy increases caused by higher standards. I consider two scenarios to characterize the effects of the 2016 fuel economy standards on VMT. In the first scenario, fuel economy of all vehicles increases 44 percent, which is the average fuel economy increase predicted by US EPA (2011) for the 2011–2016 standards for the vehicles in my sample. Such an increase 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 second scenario uses 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). The results for this scenario similarly suggest that the rebound effect reduces the gasoline consumption savings by up to one-third.

Before proceeding, I note that 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.[2] The NHTS data also provide the information needed for the IV approach, which is absent from other data sets—because of which, Gillingham (2013) and Knittel and Sandler (2013) focus on the elasticities of VMT to gasoline prices and not to fuel economy. 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 US drivers. Consequently, this paper differs primarily by showing the importance of simultaneously relaxing all three assumptions and by introducing a straightforward IV strategy to estimate the fuel economy rebound effect. Therefore, this paper's results pertain directly to the effects of rising fuel economy, driven by fuel economy standards, on VMT and gasoline consumption.

2. Simple Model of Household Driving Decisions

Many empirical studies of consumer demand for VMT, and particularly those using household-level data, derive an estimating equation from an assumed utility function. I specify a

[2] Knittel and Sandler (2013) can perform this analysis using a subset of the data for which they can match vehicles to households.

simple utility function that is sufficient for demonstrating the potential bias from imposing each of the three assumptions discussed in the Introduction.

2.1 Miles Traveled for a Single-Vehicle Household (Assumption (a))

Consider a household endowed with a single vehicle and income, I . The vehicle provides services to the household so that the household's utility, U , depends on the VMT of the vehicle and on the consumption of good y , which represents all other goods in the economy.

The vehicle's fuel economy is m and the variable ξ represents the vehicle's "quality." The variable is known to the household but cannot be observed by the econometrician.

The household's utility is:

$$U = -(VMT * \xi)^{\alpha} + y \, , \tag{1}$$

where $\alpha < 0$. Utility is increasing in VMT and vehicle quality. The marginal utility of VMT decreases with VMT to reflect the fact that some driving purposes are more valuable than others. A vehicle with higher quality confers greater utility because driving the vehicle is more enjoyable.

The household's budget constraint is:

$$y + \frac{p * VMT}{m} = I \, ,$$

where p is the price of gasoline, and the price of y is normalized to 1. The vehicle's per-mile fuel cost is p/m.

The household chooses VMT and y to maximize utility, subject to the budget constraint. Rearranging the VMT first-order condition yields a log-linear relationship between VMT , per-mile fuel costs, and vehicle quality:

$$\ln(VMT) = \frac{1}{1-\alpha}\ln(-\alpha) - \frac{1}{1-\alpha}\ln(\frac{p}{m}) + \frac{\alpha}{1-\alpha}\ln(\xi) \tag{2}$$

where the first term is a constant. Because $\alpha < 0$, VMT decreases with per-mile fuel costs.

It is possible to use equation (2) as the basis for estimating the rebound effect. For example, equation (2) can be estimated by ordinary least squares (OLS) using household-level survey data on VMT and per-mile fuel costs and by assuming that the vehicle quality term is uncorrelated with per-mile fuel costs. The fuel cost coefficient can be interpreted as the estimate of the rebound effect, such that $1/_{1-\alpha}$ is the elasticity of VMT to per-mile fuel costs.

However, such an estimate of the rebound effect is unbiased only under assumption (a), that vehicle quality is uncorrelated with per-mile fuel costs. If the assumption does not hold, estimating equation (2) by OLS would yield biased estimates of the rebound effect. Whether (unobserved) quality is correlated with fuel economy is, of course, impossible to test directly. However, because consumer demand and production costs affect vehicle manufactures' choices of fuel economy and quality (Klier and Linn 2012), the correlation between fuel economy and quality is probably different from zero. It is not obvious whether the correlation is positive or negative; therefore, the direction of the resulting bias of estimating equation (2) by OLS is ambiguous.[3]

Despite the simplicity of the modeling environment and the utility function, this conclusion applies to much more sophisticated models and utility functions. For example, I assume that utility is the sum of two terms: the consumption of all other goods and a constant elasticity term involving VMT and vehicle quality. This functional form results in the log-linearity of equation (2). Relaxing the assumption that the utility from driving is separable from the utility from consuming good y would result in a more complicated expression than equation (2), and, in many cases, one that could not be estimated by OLS. However, the same conclusion would apply, namely that failing to account for the correlation between unobserved vehicle quality and fuel costs would result in a biased estimate of the rebound effect.

Another simplification in the preceding analysis is that the household is endowed with one vehicle. The previous literature has recognized that because a household chooses fuel economy and VMT, unobserved household characteristics could be correlated with fuel economy (Dubin and McFadden 1984). This introduces a second source of bias in a linear regression of VMT on fuel economy, besides the bias arising from unobserved vehicle characteristics. To address the bias caused by unobserved household characteristics, many papers analyzing the demand for VMT or for gasoline also model the household's vehicle choice, allowing households to have heterogeneous demand for VMT (e.g., West 2004; Bento et al. 2009). Jointly modeling these decisions makes it possible to account for the correlations between household characteristics and fuel economy. However, this approach does not account for the potential

[3] In equation (2) an increase in quality decreases VMT because of the functional form assumption for the utility function. As noted in the text, this functional form was chosen for analytical convenience, despite the fact that it imposes the assumption that quality and VMT are substitutes and that, in Section 2.2, the household's two vehicles are substitutes. Nevertheless, the utility function is sufficient for demonstrating the sources of bias in previous estimates of the rebound effect.

correlations between fuel economy and vehicle characteristics. In short, allowing for the correlations between *household characteristics* and fuel costs does not eliminate the bias caused by the correlations between *vehicle characteristics* and fuel costs. Unbiased estimates of the rebound effect would have to account for both sources of bias.

2.2 Multivehicle Households (Assumption (b))

The previous discussion imposes assumption (b): for multivehicle households, the fuel economy of other vehicles does not affect the fuel economy of the particular vehicle. To relax this assumption, I consider a household that owns two vehicles, $j = 1, 2$. The utility function is:
$U = -(VMT_1 * \xi_1)^{\alpha} (VMT_2 * \xi_2)^{\gamma} + y$,

where $\gamma < 0$. Rearranging the first-order conditions from the resulting optimization problem yields the two-vehicle analog of equation (2):

$$\ln(VMT_1) = \beta_0 + \beta_1 \ln(\frac{p}{m_1}) + \beta_2 \ln(\frac{p}{m_2}) + \varepsilon \qquad (3)$$

where

$$\beta_0 = \frac{1-\gamma}{1-\alpha-\gamma}\ln(-\alpha) + \frac{\gamma}{1-\alpha-\gamma}\ln(-\gamma),$$

$$\beta_1 = -\frac{1-\gamma}{1-\alpha-\gamma},$$

$$\beta_2 = -\frac{\gamma}{1-\alpha-\gamma}, \text{ and}$$

$$\varepsilon = \frac{\alpha}{1-\alpha-\gamma}\ln(\xi_1) + \frac{\gamma}{1-\alpha-\gamma}\ln(\xi_2).$$

Estimating equation (3) and omitting the other vehicle's fuel costs and quality may bias the estimated rebound effect (i.e., β_1) for two reasons. First, the vehicle's fuel economy (m_1) may be correlated with the other vehicle's fuel economy (m_2). Second, the vehicle's fuel economy may be correlated with the quality of the other vehicle (ξ_2).

2.3Persistence and the Long-Run Effects of Gasoline Prices and Fuel Economy (Assumption (c))

So far I have imposed assumption (c), that consumers respond in equal magnitude to the gasoline price and to fuel economy. I show that a simple extension of the basic model allows for the possibility that the effect of the gasoline price on VMT may differ from the effect of fuel economy on VMT.

Returning to the case where the household owns one vehicle, I introduce multiple time periods, $t = 1,2,3$. The household chooses VMT in each time period, but changing VMT between time periods has a fixed cost. The fixed costs represent adjustment costs, such as finding someone with whom to carpool or changing jobs. The fixed costs do not depend on the change in VMT (relaxing this assumption does not affect the conclusions).

Suppose that in period 1, the household expects that the price of gasoline equals p in all three time periods. In that case, the chosen VMT in each period is the same as in equation (2), which I refer to as $VMT*$.

Now, consider an unexpected and permanent increase in gasoline prices between periods 1 and 2, to p'. The household can either change its VMT at the beginning of period 2 or remain at $VMT*$. Because of the (fixed) adjustment costs, the household chooses to remain at $VMT*$ as long as p' is sufficiently close to p, with $\overline{p}$ defined as the price above which the household changes from VMT to VMT'. That is, $VMT = VMT*$ if $p < p' < \overline{p}$, and if $p' > \overline{p}$ the household reduces VMT to $VMT' < VMT*$.

Alternatively, suppose that the price increases unexpectedly to p' between periods 1 and 2, but the household expects the price increase to be temporary so that between periods 2 and 3 the price decreases back to p. As with the permanent price increase, the household changes VMT only if the price increase is sufficiently large. However, $\overline{p}$ is larger for a temporary price increase than for a permanent one. Consequently, the effect of a temporary price increase on VMT is smaller than the effect of a permanent price increase on VMT.

This conclusion implies that if households consider gasoline price changes to be less persistent than the vehicle’s fuel economy, households will change VMT less in response to a gasoline price increase than to a proportional fuel economy decrease. Presumably, consumers consider a vehicle’s fuel economy to be highly persistent over its lifetime. Therefore, the validity of the standard assumption that consumers respond equally to a gasoline price increase as to a fuel economy decrease (and vice versa) rests on whether consumers consider gasoline price shocks to be fully persistent. Anderson et al. (2011) conclude that households believe gasoline price shocks are fully persistent on average, but evidence from gasoline futures market suggests that price shocks are sometimes expected to be less than fully persistent (Allcott and Wozny 2012).

The model focused on the possibility that gasoline price shocks are less than fully persistent, but other factors could cause the effect of gasoline prices on VMT to differ from the effect of fuel economy on VMT. For example, consumers may pay more attention to variation in gasoline prices than to fuel economy. Because other factors may work in the opposite direction from the persistence argument, it is theoretically ambiguous whether consumers respond more to gasoline prices than to fuel economy.

3. 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 Section 2.

I begin with a version of equation (2) that specifies the VMT of vehicle i belonging to household h as a function of its fuel costs and household characteristics:

$$\ln(VMT_{hi}) = \delta_0 + \delta_1 \ln(p_h / m_{hi}) + X_h\beta + \varepsilon_{hi} \quad (4)$$

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.

Section 2 shows that estimating equation (4) 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 that are not included in equation (4). 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.

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) and may be correlated with fuel economy—in which case, fuel economy would still be correlated with the error term in equation (4) even after including model fixed effects. 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, which was discussed in Section 2.1. 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 (4) and including model fixed effects may still yield biased results.

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, 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 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) demonstrate a strong relationship between the fuel economy of new vehicle purchases, and Allcott and Wozny (2010) 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 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.

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, the correlation between the two gasoline price variables is close to zero after controlling for the other variables in equation (4).

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 (5) includes geographic controls, the first stage is identified by the substantial 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 after controlling for income, household composition, etc. A concern with this argument is that gasoline prices may be correlated with business cycles, in which case the composition of households purchasing a vehicle when gasoline prices are high may differ in important ways (e.g., income) from households purchasing 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.

Turning to the second assumption in equation (4), 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 (4), I simply allow for a separate coefficient on the contemporaneous gasoline price and the vehicle's fuel economy. These modifications yield the following equation:

$$\ln(VMT_{hi}) = \delta_0 + \delta_1 \ln(p_h) + \delta_2 \ln(m_{hi}) + \delta_3 \ln(\bar{m}_{h,-i}) + f(\eta_j, X_h) + \varepsilon_{hi} \qquad (5)$$

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 $f(\eta_j, Z_h)$ includes an extensive set of controls for household and vehicle characteristics. Specifically, the regressions contain controls for demographics including income, education, age, 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. As discussed in Section 4, many of these variables are categorical rather than continuous, and the regressions include fixed effects for each category. 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 and of the data collected by the NHTS.

Equation (5) is estimated either by OLS and including model fixed effects or by IV. The instruments include the interaction of household characteristics 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. Including the household interactions is motivated by recent papers showing substantial consumer heterogeneity in vehicle demand (e.g., Jacobsen 2013). I instrument for the vehicle's fuel economy, m_{hi}, and for the fuel economy of the household's other vehicles, $\bar{m}_{h,-i}$.[4]

Despite relaxing assumptions (a)–(c), some potential concerns remain for equation (5). First, although I instrument for the fuel economy of all vehicles in equation (5), I assume that the contemporaneous gasoline price, p_h, is exogenous. This is consistent with other recent papers using the NHTS (e.g., Li et al. 2011).

Second, equation (5) was derived from a very simple functional form for household utility in Section 2. I interpret the log-linear specification as an approximation of a more complicated functional relationship. Section 5.2 reports additional specifications of equation (5) that allow the elasticity to vary across households.

Because of the sources of variation used to identify the coefficients in equation (5), 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 time, and therefore reflects a short-run response to gasoline prices (as in, for example, Li et al. 2011). The fuel economy coefficients are identified by cross sectional variation, and therefore can be interpreted as long-run consumer responses. Because of these interpretations, I do not directly compare δ_1 with the other coefficients. Instead, I compare estimates of the rebound effect derived from δ_2 and δ_3 with long-run rebound estimates in the literature.

Before proceeding, I note that an alternative to equation (5) 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 assumptions [a]–[c]). 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. Second, by deriving the estimating equations from a household utility function, joint

[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.

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 (5) allows for potential correlations between fuel economy and unobserved household characteristics. An advantage of equation (5) over joint estimation is that it is much simpler to relax assumptions (a)–(c) 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 (5) is that welfare analysis of particular policies, such as a gasoline tax increase, is not possible. Nevertheless, equation (5) is suitable for the paper's primary objective, which is to estimate the rebound effect.

4. Data and Summary Statistics

4.1 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 (5) includes the current gasoline price. The NHTS provides gasoline prices, but regional variation is minimal. For this reason, 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 (5).

Li et al. (2011) 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 (5) if it is correlated with the independent variables, but I offer two arguments that such bias is unlikely to be large in magnitude. First, Li et al. (2011) 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]

4.2 Summary Statistics

Before presenting the estimation results, I report summary statistics from the final data set. Table 1 and Figures 1–10 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-

[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.

[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.

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 1–10 show the distributions of the 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 have higher income, more adults, and more drivers than households with fewer vehicles. Figures 7, 9, and 10 show that households with more vehicles also tend to be located in more rural areas.

Section 3 discussed the first approach to addressing the endogeneity of fuel economy in equation (5), 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 standard strategy to assess its validity is to estimate the correlations between fuel economy and observed household characteristics (e.g., Li et al. 2011). Low correlations would suggest that fuel economy and unobserved household characteristics are also weakly correlated with one another.

Table 2 shows evidence against the validity of the model fixed effects approach, however. 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 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. 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.

5. Estimation Results

This section presents the main estimates of equation (5) and reports results from a variety of alternative specifications. The baseline estimates suggest that a 1 percent increase in fuel economy increases VMT by 0.2 to 0.4 percent. The section concludes by showing that imposing the three assumptions described in Section 2 significantly affects the estimated rebound effect.

5.1 Main Results

Table 3 reports estimates of equation (5). The dependent variable is the log of the vehicle's VMT. Panel A reports OLS estimates and Panel B reports the IV estimates. Observations are weighted using the NHTS survey weights. Standard errors are clustered by CMSA and survey month. The OLS estimates include interactions between model fixed effects and the number of household vehicles. The IV estimates omit these interactions but instrument for the fuel economy variables based on the month in which the household obtained the vehicle. Besides the reported variables, the regressions include the same independent variables as in Table 2. The instruments include interactions of the gasoline price when the vehicle was obtained 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 1 reports the first stage coefficient estimates along with a test for weak instruments, which indicates a very strong first stage.

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 is consistent with Goldberg (1998) and Li et al. (2011), who find a weak correlation between current gasoline prices and VMT using household data.

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).

Because the coefficient on the vehicle's own fuel economy is larger in magnitude than the coefficient on the other vehicles' fuel economy, the net effect is that VMT increases.[7]

The bottom of each panel reports the elasticity of VMT to an increase in the fuel economy of all vehicles. 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. This suggests that the gasoline price instruments have just enough variation to jointly estimate the two fuel economy coefficients. 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 long-run estimates. Because of the range of estimates, I continue to report both OLS and IV results throughout the paper.

5.2 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 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 controls flexibly for other household characteristics that may be correlated with fuel economy.

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 bottom of the panel. For example, column 2 controls flexibly 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

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[7] 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.

specifications, the OLS coefficients are similar in magnitude and remain statistically significant in all cases.

Columns 2 and 3 of Panel B consider the robustness of the IV estimates to alternative sets of instruments. Adding further interactions of gasoline prices and household characteristics has some effect on the point estimates, but yields qualitatively similar results. 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 3 that one concern with the IV strategy is that gasoline prices may be correlated with business cycles, in which case the composition of households purchasing 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.

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 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 comparison with these results, columns 3–5 report estimates of equation (5) when restricting the sample based on the number of household vehicles. Overall, the rebound effect does not depend strongly on the measure of other vehicles' fuel economy.

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.

5.3 Implications of Imposing Assumptions (a)–(c)

Section 2 discusses three assumptions maintained in the rebound literature. Table 6 reports versions of equation (5) that, starting from the baseline specification in Table 3, impose these assumptions one at a time.

Assumption (a) 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 not instrumenting for fuel economy. The estimated rebound effect is much smaller than that reported in column 1 of Table 3.

Assumption (b) 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 by omitting the fuel economy of the household's other vehicles. For the IV estimates in column 3, and less so for the OLS estimates in column 2, the estimated fuel economy rebound effect is much larger than in the baseline.

Finally, assumption (c) holds that the response of VMT to gasoline prices is inversely proportional to the response to fuel economy. I impose this assumption by modifying equation (5) in two ways. First, column 4 omits the two fuel economy variables and omits the model fixed effects. The coefficient on gasoline prices represents the elasticity of VMT to gasoline prices, and the estimated coefficient is much smaller than the baseline estimates of the rebound effect.

The second approach to imposing assumption (c) is to use fuel costs in place of fuel economy, where fuel costs are the ratio of the current gasoline price to fuel economy. Column 4 implements this approach, and the specification is otherwise identical to the baseline. The rebound effect is similar to the baseline OLS estimate but is much larger than the baseline IV estimate.[8]

6. Rebound Effect for Hypothetical Fuel Economy Increases

I use the estimates from Section 5 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 effect for estimates of future fuel savings. The second objective is to quantify the importance of relaxing assumptions (a)–(c), which is useful for researchers making modeling choices when estimating the welfare effects of fuel economy standards and other transportation policies.

Table 7 reports the results. Panel A shows the change in VMT and gasoline consumption assuming that the fuel economy of all vehicles in the estimation sample increases by 44 percent, which is the increase expected for the 2016 standards (US EPA 2011). This scenario approximates the effects of fuel economy standards that raise the fuel economy of all vehicles proportionately. 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.

Each column shows the calculated fractional change in VMT and gasoline consumption using the coefficient estimates from the specification indicated at the bottom of the table. For reference, gasoline consumption would fall by 31 percent in the absence of a rebound effect.

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. VMT increases by

[8] Some studies define the rebound effect as the elasticity of gasoline consumption to fuel economy. An implication of the results in Table 6 is that estimating the rebound effect using this definition but using gasoline prices or fuel costs instead of fuel economy would mis-estimate the rebound effect.

about 9–18 percent, and the rebound effect erodes up to one-third of the gasoline savings from the fuel economy increase; this 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 assumptions (a)–(c). Column 3 shows that the rebound effect is substantially smaller when imposing assumption (a) by omitting model fixed effects and estimating equation (5) by OLS rather than by IV. Omitting other vehicle fuel economy—that is, imposing assumption (b)—results in a larger rebound effect, which can be seen by comparing columns 2 and 4. Finally, columns 5 and 6 focus on assumption (c), that gasoline prices and fuel economy have equal and opposite effects on VMT. Estimating equation (5) by OLS reduces the rebound effect (comparing columns 1 and 5) but estimating equation (5) by IV increases the rebound effect (comparing columns 2 and 6).

Panel B reports the same calculations but with the assumption that the vehicles achieve the fuel economy increases predicted by the US EPA and National Highway Traffic Safety Administration analysis of the 2016 fuel economy standards. This scenario may provide a more accurate sense of future fuel economy increases than those considered in the first scenario. The predicted fuel economy increases vary considerably across vehicle models, and this scenario allows for the possibility that the estimated level of the rebound effect is correlated (negatively or positively) with the predicted fuel economy increases. However, in practice, the estimated rebound effect is not strongly correlated with the predicted fuel economy increases, and the table shows that the results are nearly identical to those reported in Panel A.

7. 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 have made at least one of three assumptions: (a) fuel economy is uncorrelated with other vehicle 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 show that these assumptions have important implications 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 an ambiguous effect on the results.

The results have three main implications for the rebound literature and for policy. First, there is strong evidence supporting the use of IV when estimating the fuel economy rebound effect. Second, imposing the three assumptions dramatically affects the estimated rebound effect. 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.

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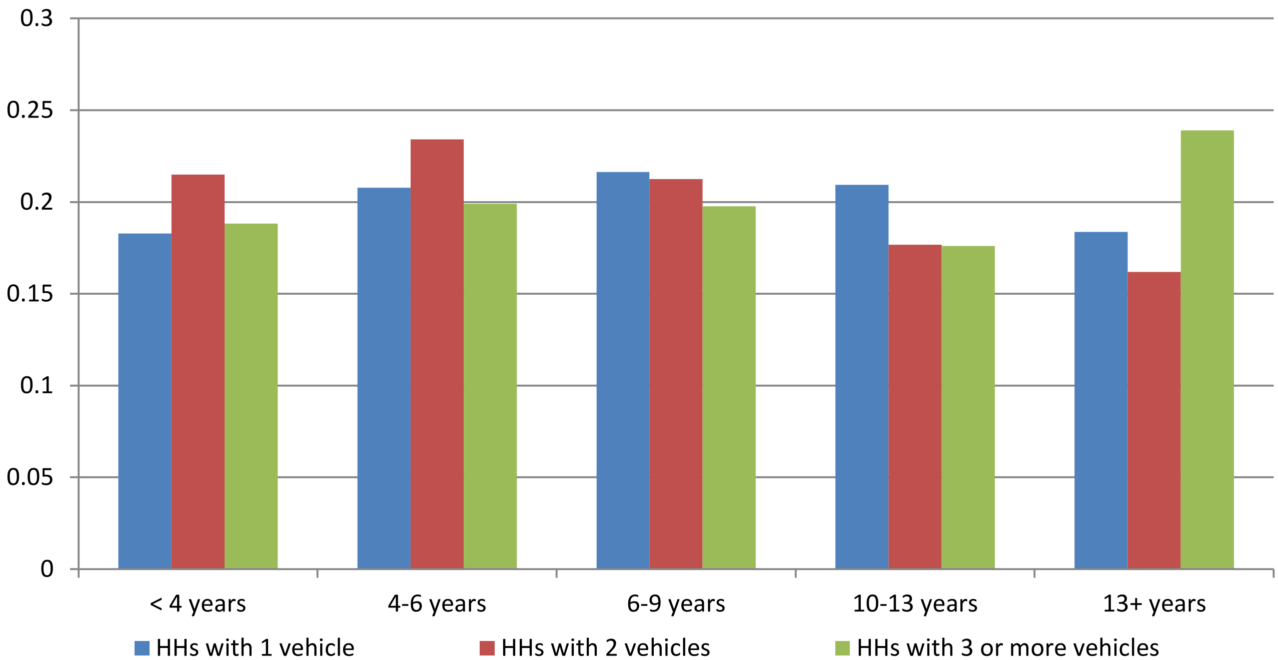
Figures and Tables

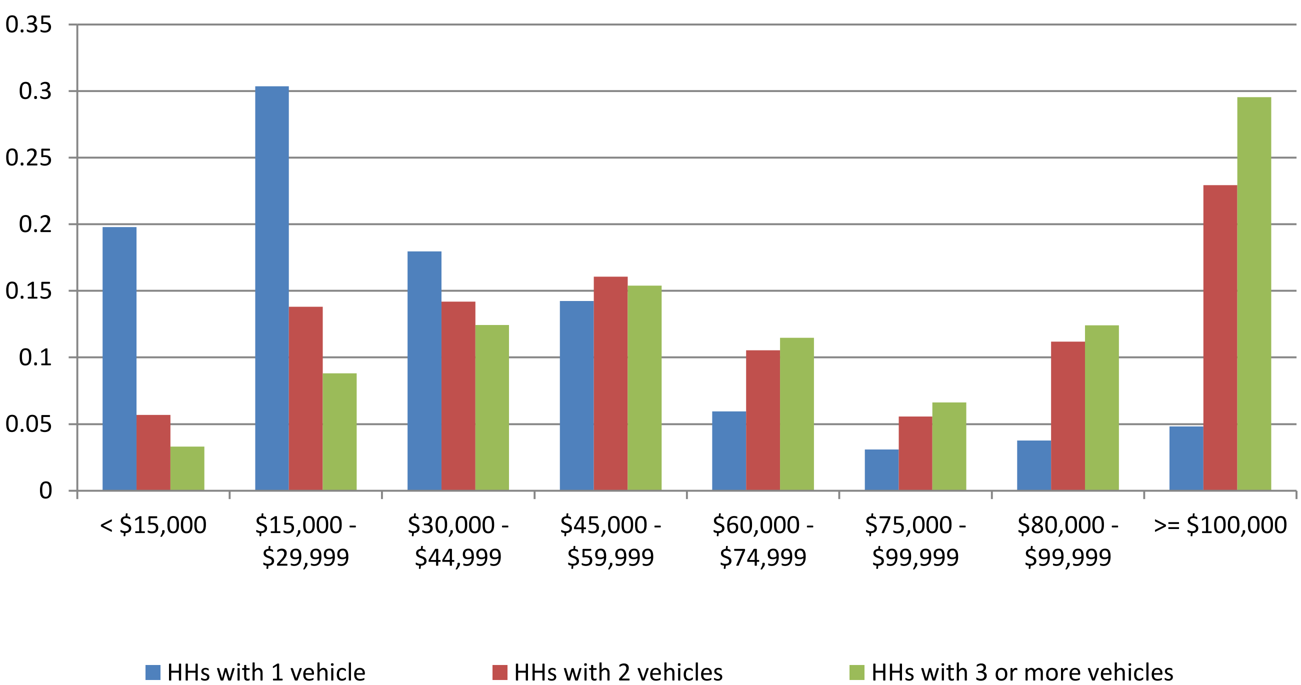
See following pages.

Figure 1. Vehicle Age by Number of Vehicles in Household



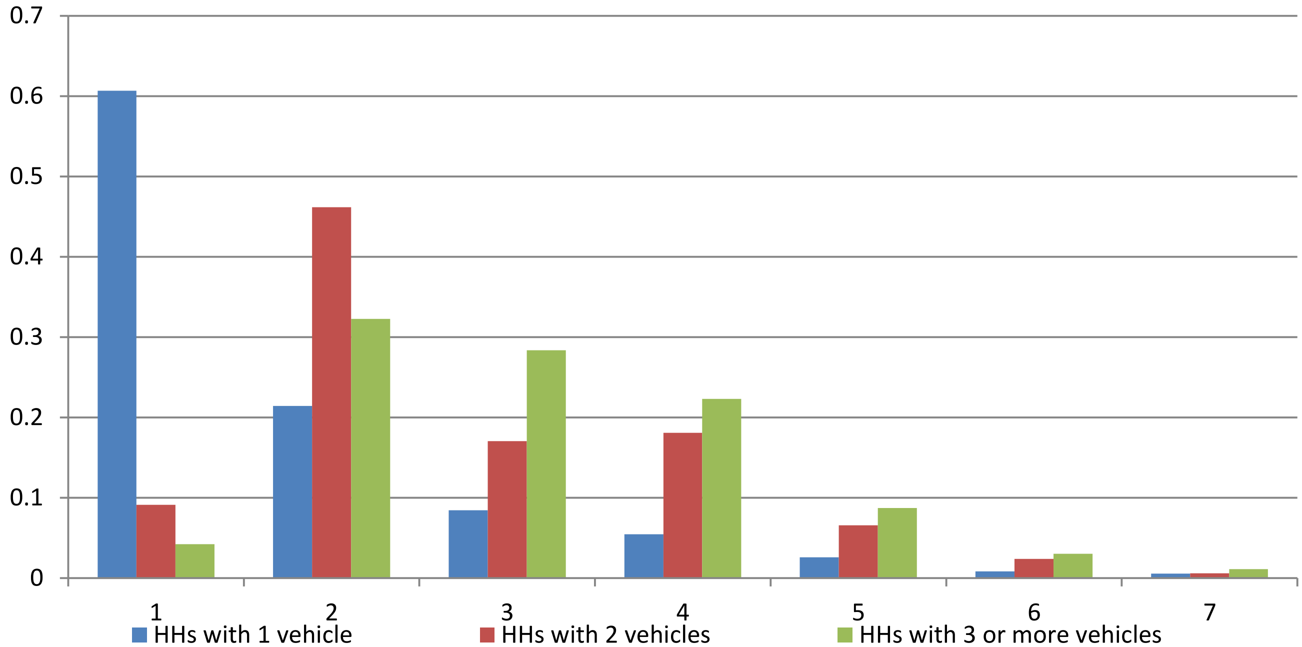
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of vehicles that are in the indicated age range. Observations are weighted by the final NHTS weights.

Figure 2. Income by Number of Vehicles in Household



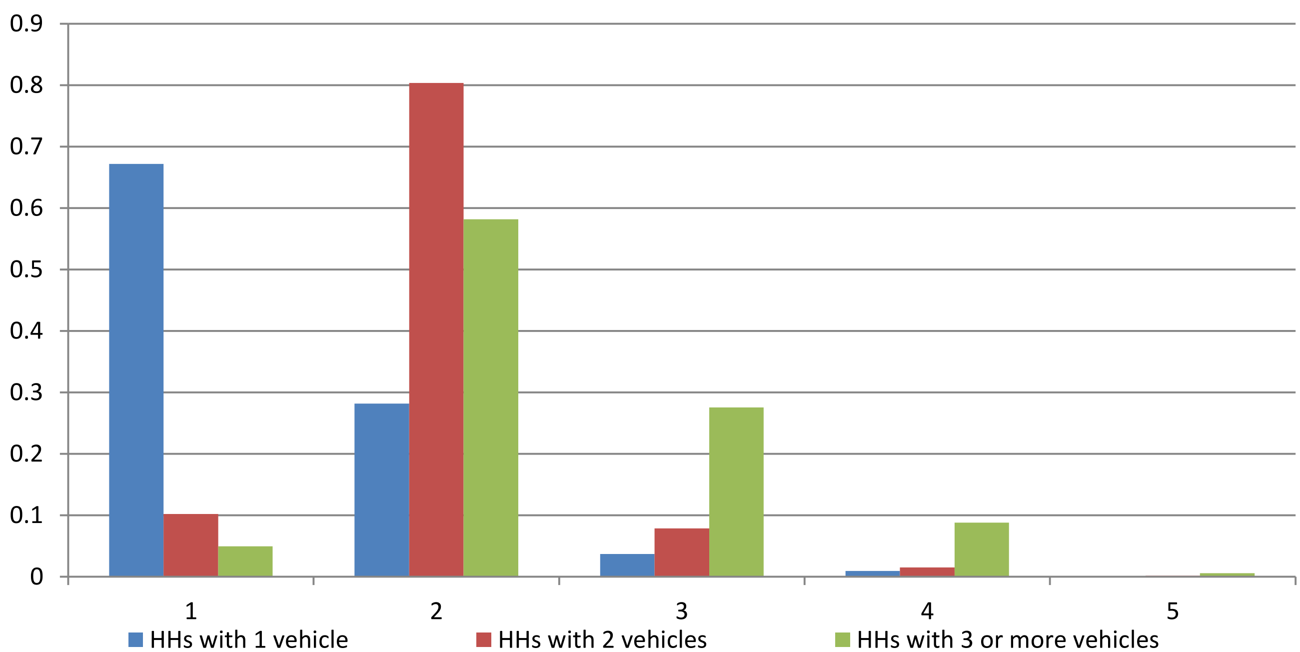
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households in the indicated income range. Observations are weighted by the final NHTS weights.

Figure 3. Household Size by Number of Vehicles in Household



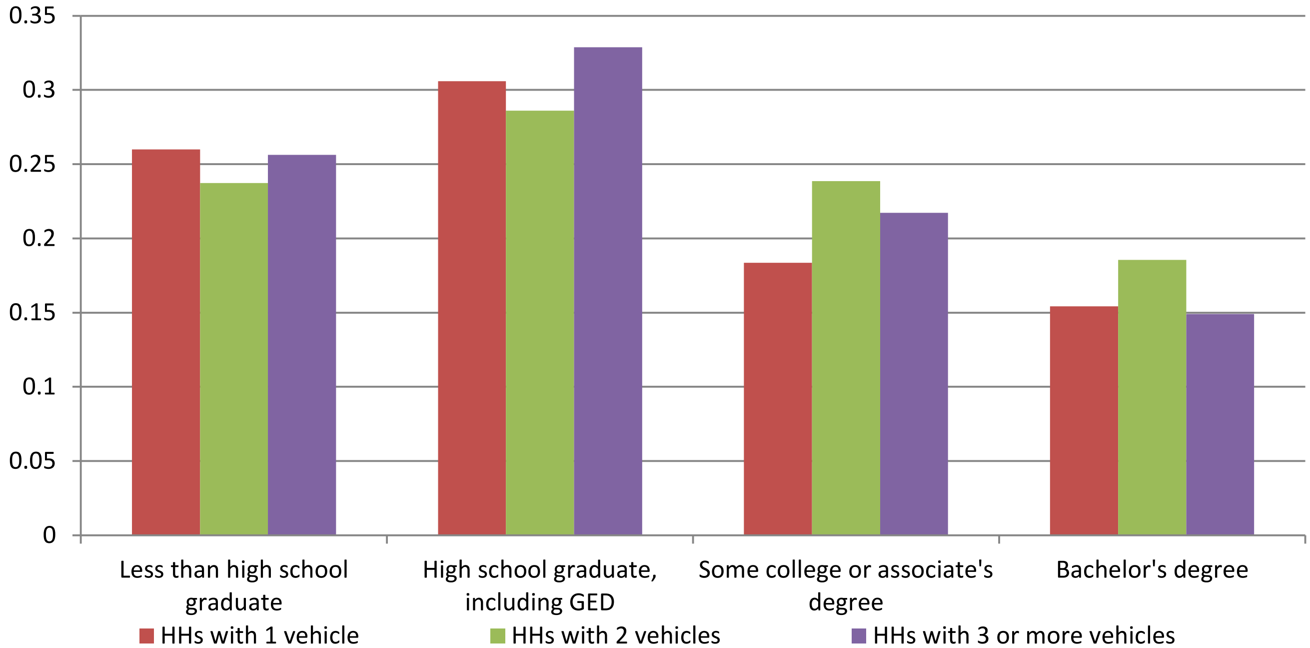
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated number of people. Observations are weighted by the final NHTS weights.

Figure 4. Number of Adults by Number of Vehicles in Household



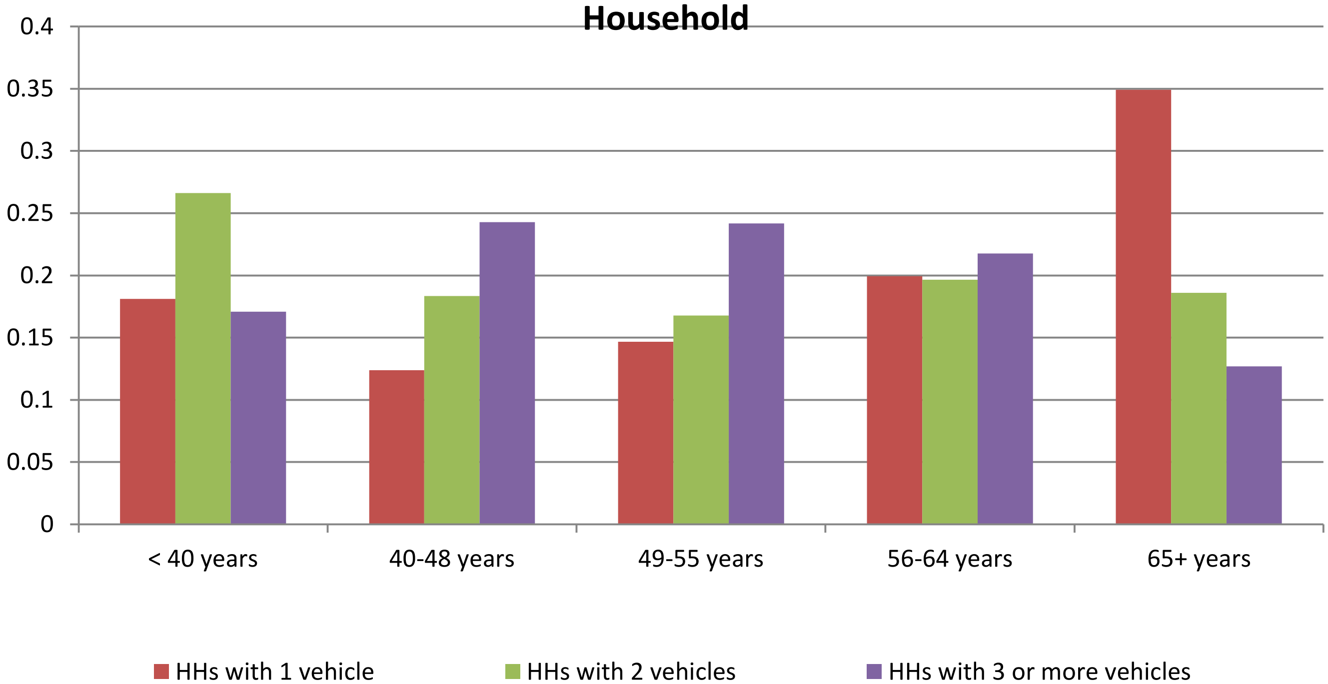
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated number of adults. Observations are weighted by the final NHTS weights.

Figure 5. Education Level by Number of Vehicles in Household



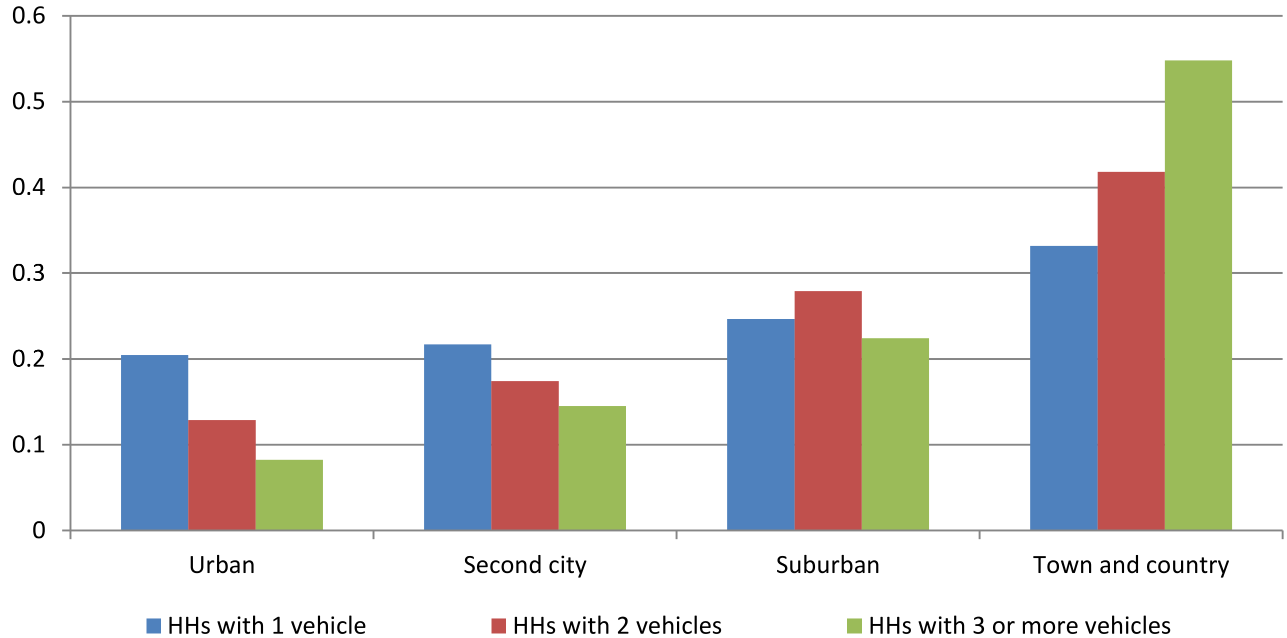
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with a household head achieving the indicated education level. Observations are weighted by the final NHTS weights.

Figure 6. Age of Household Head by Number of Vehicles in Household



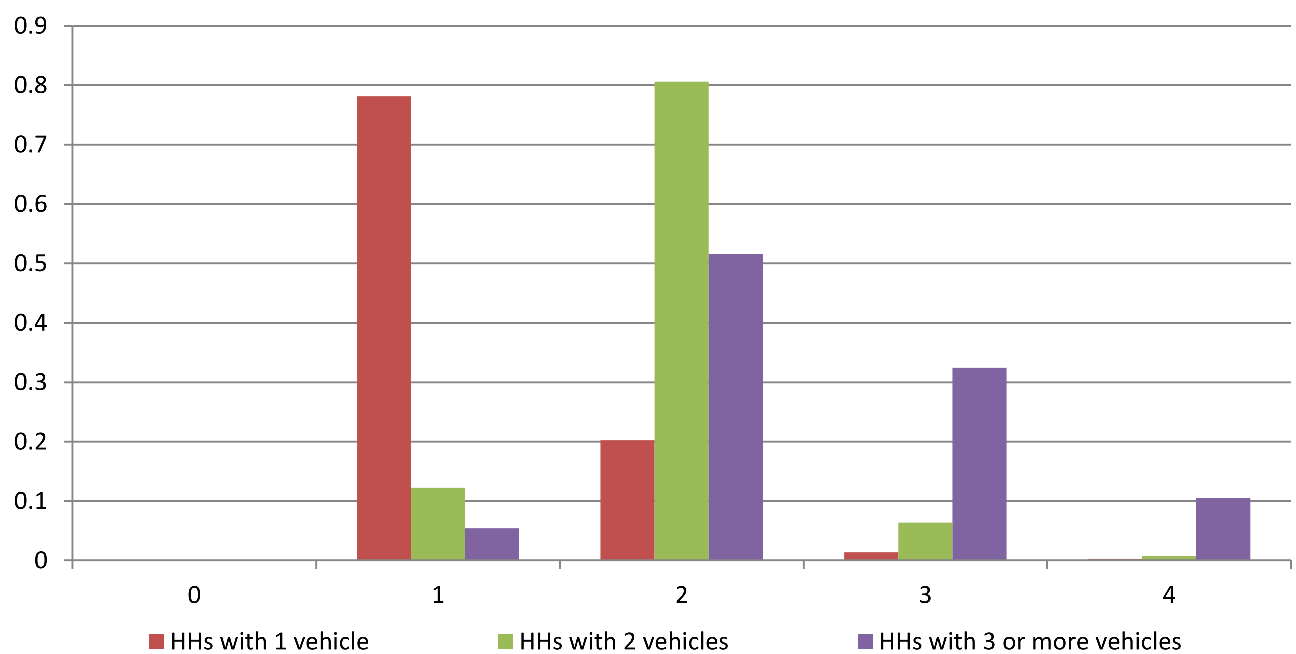
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with a household head in the indicated age range. Observations are weighted by the final NHTS weights.

Figure 7. Urban Area Type by Number of Vehicles in Household



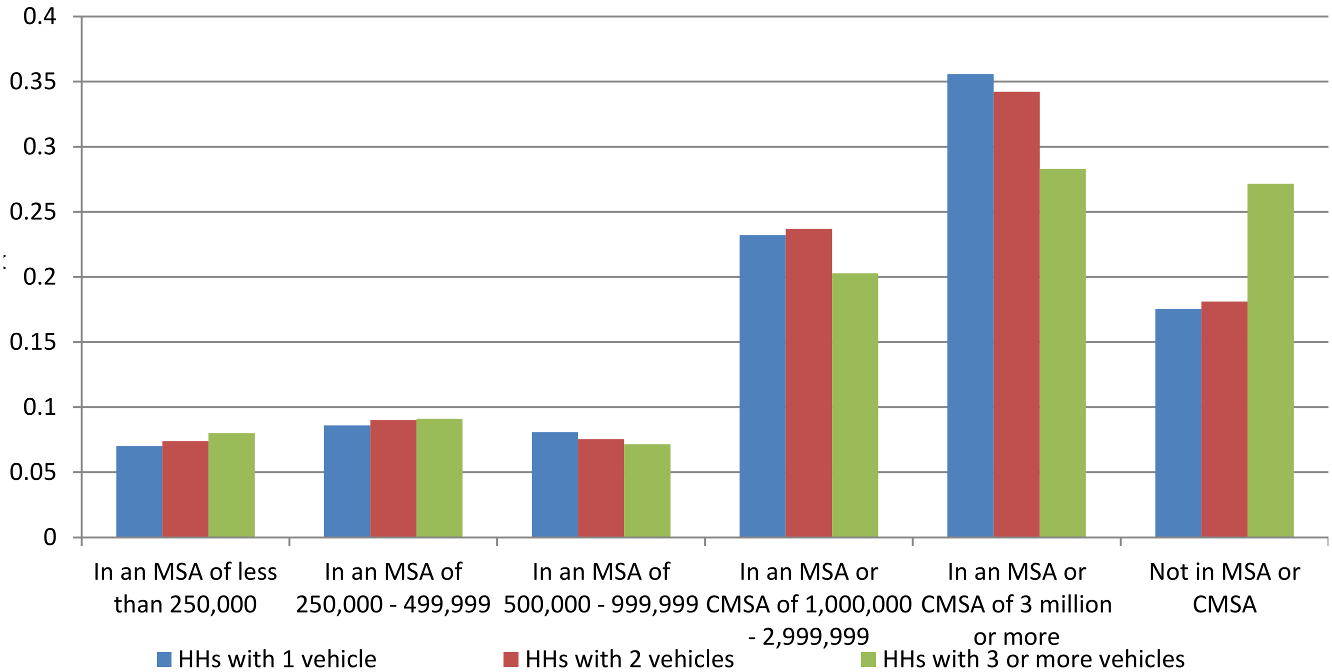
Notes: Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households in the indicated type of urban area. Observations are weighted by the final NHTS weights.

Figure 8. Number of Drivers by Number of Vehicles in Household



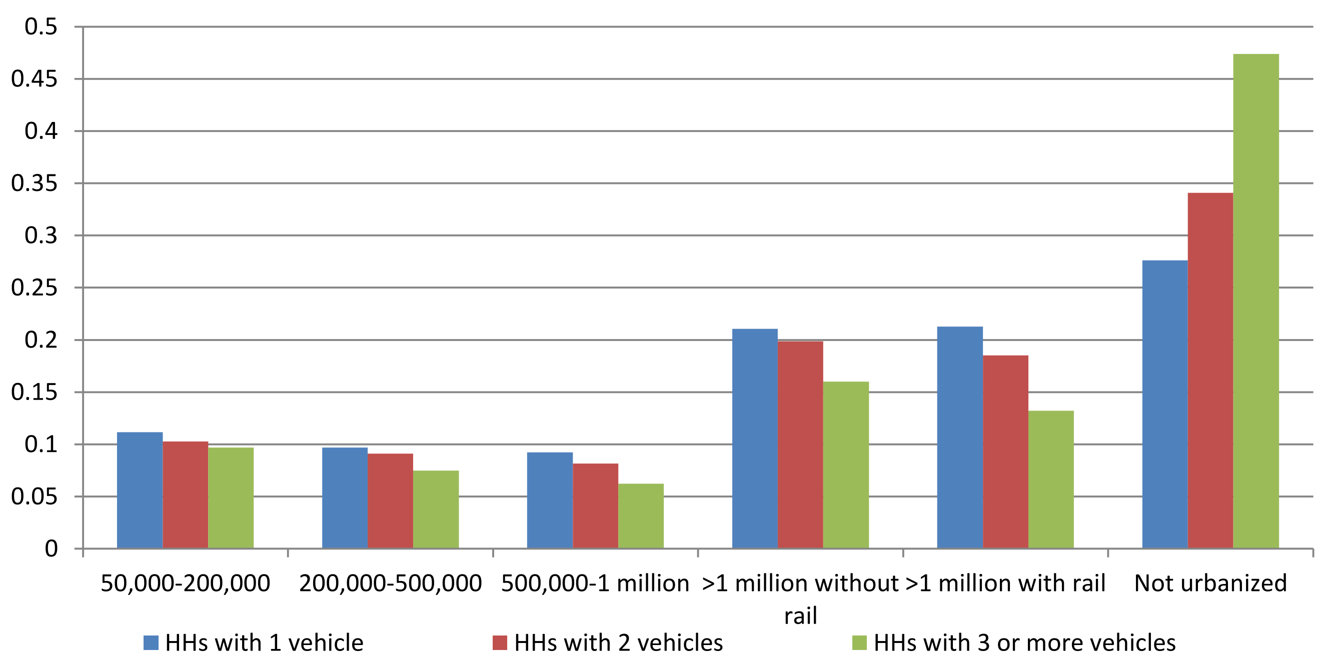
Notes : Households are assigned categories based on the number of vehicles. The chart shows, for each category, the share of households with the indicated number of drivers. Observations are weighted by the final NHTS weights.

Figure 9. 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.

Figure 10. 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.

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 (9.57)	12.12 (9.79)	12.07 (10.32)	11.71 (10.36)
Gasoline price ($/gallon)	2.80 (1.04)	2.75 (1.04)	2.77 (1.04)	2.78 (1.04)
Fuel economy (mpg)	23.80 (5.26)	22.53 (5.69)	22.00 (5.79)	21.44 (5.68)
Thousand housing units per sq mi	5.71 (6.97)	4.03 (5.25)	3.09 (4.42)	2.51 (3.77)
Thousand people per sq mi	2.90 (4.71)	1.73 (2.75)	1.26 (2.16)	0.96 (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.

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

	(1)	(1)	(2)	(2)
Dependent variable	Vehicle fuel economy	Fuel economy of other household vehicles	Vehicle fuel economy	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.

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

	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS		
Log gas price	-0.093 (0.093)	-0.119 (0.090)	-0.107 (0.087)	-0.093 (0.090)	
Log fuel economy	0.245 (0.060)	0.281 (0.072)	0.232 (0.057)	0.247 (0.059)	0.261 (0.085)
Log other vehicles' fuel	-0.029 (0.006)	-0.029 (0.006)	-0.029 (0.006)	-0.025 (0.006)	-0.028 (0.008)
R^2	0.17	0.23	0.25	0.22	0.19
Fuel economy rebound effect	0.222 (0.060)	0.257 (0.072)	0.208 (0.058)	0.227 (0.059)	0.237 (0.086)
Model fixed effects interacted with	No. of vehicles	No. of vehicles X vehicle age group	No. of vehicles X resp. age group	No. of vehicles X no. of adults	No. of vehicles
Sample includes	All households	All households	All households	All households	California households
			Panel B: IV		
Log gas price	-0.117 (0.096)	-0.114 (0.097)	-0.116 (0.097)	-0.117 (0.096)	
Log fuel economy	0.534 (0.239)	0.430 (0.207)	0.459 (0.216)	0.657 (0.233)	0.465 (0.224)
Log other vehicles' fuel	-0.116 (0.023)	-0.119 (0.022)	-0.107 (0.023)	-0.119 (0.023)	-0.074 (0.028)
R^2	0.09	0.09	0.10	0.08	0.09
Fuel economy rebound effect	0.438 (0.240)	0.333 (0.205)	0.371 (0.216)	0.560 (0.234)	0.404 (0.230)
Instruments include	Gas price interacted with hh. chars.	Add gas price X income X no. of vehicles	Add gas price X income X age	Add log state GSP and income per capita	Gas price interacted with hh. chars.
Sample includes	All households	All households	All households	All households	California

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. Panel A reports OLS estimates and Panel B reports IV estimates, using the instruments indicated at the bottom of the table based on the month in which the vehicle was obtained (see text for details). All regressions include the fixed effects used in the regressions in column 1 of Table 2. In Panel A, column 1 also includes interactions of model fixed effects by the household's number of vehicles. Columns 2-4 replace these interactions with the interactions indicated at the bottom of the panel. Panel B does not include the interactions with model fixed effects. The fuel economy rebound effect is the effect on VMT of increasing all vehcles' fuel economy by 1 percent.

Table 4. Alternative Measures of Other Vehicles' Fuel Economy

	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS		
Log gas price	-0.152	-0.154	-0.347	-0.094	-0.097
	(0.126)	(0.126)	(0.259)	(0.121)	(0.104)
Log fuel economy	0.326	0.339	0.254	0.257	0.252
	(0.072)	(0.072)	(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	-0.123			
	(0.033)	(0.044)			
Log fuel economy vehicle 2	-0.031	-0.009			
	(0.030)	(0.046)			
Log fuel economy vehicle 3	-0.154	-0.108			
	(0.051)	(0.080)			
R^2	0.16	0.16	0.22	0.15	0.15
			Panel B: IV		
Log gas price	-0.214	-0.214	-0.587	-0.142	-0.131
	(0.116)	(0.117)	(0.255)	(0.109)	(0.099)
Log fuel economy	0.417	0.405	0.145	0.469	0.414
	(0.294)	(0.297)	(0.597)	(0.287)	(0.259)
Log other vehicles' fuel economy				-0.080	-0.097
				(0.027)	(0.022)
Log fuel economy vehicle 1	-0.306	-0.364			
	(0.164)	(0.188)			
Log fuel economy vehicle 2	-0.163	-0.092			
	(0.129)	(0.108)			
Log fuel economy vehicle 3	-0.200	-0.046			
	(0.101)	(0.095)			
R^2	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.

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

	(1)	(2)	(3)	(4)
Log gas price	-0.093 (0.101)	-0.093 (0.101)	-0.118 (0.098)	-0.110 (0.096)
Log fuel economy	0.212 (0.095)	0.244 (0.054)	0.140 (0.343)	0.553 (0.242)
Log fuel economy X no. of vehicles	0.019 (0.042)		0.174 (0.113)	
Log fuel economy X log income		-0.010 (0.021)		-0.173 (0.137)
Log other vehicles' fuel economy	-0.029 (0.006)	-0.029 (0.006)	-0.114 (0.022)	-0.115 (0.022)
R^2	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.

Table 6. Rebound Effects without Relaxing Assumptions (a) - (c)

	(1)	(2)	(3)	(4)	(5)	(6)
Log gas price	-0.115	-0.097	-0.133	-0.120		
	(0.120)	(0.100)	(0.097)	(0.119)		
Log fuel economy	0.129	0.247	0.580			
	(0.031)	(0.054)	(0.241)			
Log other vehicles' fuel economy	-0.031					
	(0.006)					
Log fuel costs					-0.200	-0.525
					(0.049)	(0.240)
Log other vehicle fuel costs					0.007	-0.151
					(0.008)	(0.034)
R^2	0.12	0.17	0.09	0.11	0.17	0.09
Fuel economy rebound effect	0.103	0.247	0.580		0.194	0.649
	(0.034)	(0.054)	(0.241)		(0.049)	(0.241)
Specification	Omit model fixed effects	Omit other vehicle fuel economy	Omit other vehicle fuel economy	Omit fuel economy variables	Replace fuel economy with fuel costs	Replace fuel economy with fuel costs
Estimation by	OLS	OLS	IV	OLS	OLS	IV

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 5 are estimated by OLS, and regressions in columns 3 and 6 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. Column 4 omits fuel economy and other vehicle fuel economy. Columns 5 and 6 omit the log fuel price and replaces fuel economy with fuel costs. The fuel economy rebound effect is computed as in Table 3.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: 44% fuel economy increase					
VMT (fractional change)	0.09	0.18	0.04	0.24	0.05	0.27
Gas consumption (fractional change)	-0.25	-0.19	-0.28	-0.14	-0.28	-0.12
	Panel B: Predicted 2016 CAFE fuel economy increases					
VMT (fractional change)	0.09	0.18	0.04	0.24	0.05	0.27
Gas consumption (fractional change)	-0.25	-0.19	-0.29	-0.15	-0.28	-0.12
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)	Gas price coefficient (Table 6, column 4)	Fuel costs (Table 6, column 6)

Notes : Each column in each panel reports a separate simulation. Panel A simulates miles traveled and gasoline consumption assuming the fuel economy of every vehicle increases 44 percent. Panel B assumes 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.

Appendix Table 1. First Stage Results

	(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 (0.026)		0.075 (0.097)	
Log gas price in month vehicle obtained	0.208 (0.055)		-0.258 (0.152)	
Log gas price in month other vehicles obtained	-0.012 (0.051)		0.675 (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 (0.021)	-0.003 (0.008)	-0.023 (0.048)	-0.032 (0.011)
6-9 years	-0.024 (0.020)	0.014 (0.009)	-0.047 (0.047)	-0.026 (0.013)
9-13 years	-0.026 (0.020)	0.010 (0.009)	-0.059 (0.046)	-0.023 (0.014)
>13 years	0.004 (0.020)	-0.002 (0.010)	-0.082 (0.048)	-0.030 (0.015)
	Panel C: Number of vehicles			
2	0.041 (0.015)	0.046 (0.019)	0.033 (0.042)	-1.159 (0.063)
3	0.067 (0.016)	0.036 (0.020)	-0.075 (0.038)	-0.097 (0.060)
4	0.076 (0.018)	0.051 (0.020)	-0.060 (0.042)	0.022 (0.062)
5	0.097 (0.025)	0.051 (0.022)	-0.085 (0.045)	0.063 (0.068)
>5	0.094 (0.028)		-0.138 (0.057)	
	Panel D: Income			
$15,000 to $30,000	0.031 (0.017)	-0.033 (0.015)	-0.033 (0.056)	0.017 (0.035)
$30,000 to $45,000	0.028 (0.017)	-0.029 (0.014)	0.000 (0.058)	0.010 (0.033)
$45,000 to $60,000	0.024 (0.018)	-0.036 (0.014)	0.026 (0.059)	0.046 (0.033)

Appendix Table 1 (cont.)

$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)
		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: Respondant 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)

Appendix Table 1 (cont.)

	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)	
	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)
R^2	0.10		0.80	
Weak instruments F-statistic	30.50			

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 for the weak instruments test of the first stage.