

# The Effects of Market Size and Fuel Costs on Fuel-Saving Technology Adoption in Passenger Vehicles

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# The Effects of Market Size and Fuel Costs on Fuel-Saving Technology Adoption in Passenger Vehicles

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## Abstract

Although economic theory suggests that market size and fuel costs affect fuel-saving technology adoption by vehicle manufacturers, there is very little empirical evidence. We document a strong connection between market size, as measured by a vehicle's sales, and technology adoption. Using a demographics-driven demand shifter to instrument for market size, we find that a 10 percent increase in market size raises power train efficiency by 0.2 percent, compared with a mean improvement rate of 1.4 percent per year between 1997 and 2013. Higher fuel prices affect technology adoption directly by influencing willingness to pay for fuel cost savings, and indirectly by influencing market size. The results have two implications: policies promoting alternative-fuel vehicles will be less effective than previously thought; and fuel taxes have different effects on technology adoption than do fuel economy standards and feebates.

Key words: passenger vehicles, technological change, market incentives, innovation incentives

JEL classification numbers: L62, Q4, Q55, O31

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# 1 Introduction

Improving vehicle fuel economy is a central part of international efforts to reduce the risks of climate change. Passenger vehicles account for about 15 percent of US greenhouse gas emissions and half of transportation sector emissions (IPCC, 2014). To reduce fuel consumption and greenhouse gas emissions, many countries have introduced fuel economy or carbon dioxide emissions standards. For example, US regulations require new vehicle fuel economy to roughly double between 2005 and 2025. In addition to these standards, many countries have adopted complementary policies, such as subsidies for electric vehicles.

Meeting the near- and long-term emissions objectives requires substantial technology adoption (Knittel, 2012). This paper focuses on a manufacturer’s decision to adopt fuel-saving technology across its individual vehicle models. Previous studies suggest that variable costs and fuel savings of the technologies affect adoption (e.g., NRC (2015)). The literature also suggests that market size and fuel prices affect adoption. Market size could affect technology adoption through several channels, such as directed technical change (Acemoglu, 2002), fixed costs of technology adoption with variable markups (Berry et al., 1995), or learning by doing in vehicle production. These channels link a vehicle’s market size and a manufacturer’s technology adoption, but as we explain below theory does not predict the direction of this effect, and there is no empirical evidence on this effect. Moreover, Busse et al. (2013) and Allcott and Wozny (2014) demonstrate that high gasoline prices raise the market shares of vehicles with high fuel economy relative to vehicles with low fuel economy, and that consumers value the fuel cost savings offered by vehicles with high fuel economy. These findings suggest that an increase in fuel prices can affect technology adoption in two ways: first, by affecting market size; and second, by affecting consumers’ willingness to pay for fuel-saving technology that raises fuel economy, independently of changes in market size.

Whether market size and fuel costs affect technology adoption would have several implications for the overall effect of fuel consumption and carbon policies on technology adoption, emissions, and welfare depend. First, notwithstanding the media attention around electric vehicles and other alternative technologies, the internal combustion engine continues to dominate the passenger vehicles market, accounting for about 95 percent of new vehicles in the United States in 2015 (authors’ calculations). Given the market size advantage of gasoline-powered vehicles over plug-in electric vehicles and other alternatives, a strong market size effect on technology adoption would imply that manufacturers will continue directing fuel-saving technology improvements to gasoline-powered vehicles (Acemoglu et al., 2012). Such improvements would increase the challenge that alternative-fuel vehicles face in competing

with gasoline-powered vehicles, and reduce the effectiveness of subsidies, tax credits, and other policies promoting alternative-fuel vehicles. Most analysis of future market penetration of alternative-fuel vehicles does not consider potential improvements in the efficiency of gasoline-powered vehicles.

Second, [Goldberg \(1995\)](#), [Klier and Linn \(2012\)](#), [Jacobsen \(2013\)](#), [Roth \(2015\)](#), and other studies have compared the welfare effects of fuel taxes, carbon taxes, fuel economy standards, and feebates (which jointly tax and subsidize vehicles according to their fuel economy). The literature has emphasized the inefficiencies of standards and feebates relative to fuel taxes, but has not accounted for the differences across policies in their effects on technology adoption via the fuel cost and market size channels. As we show, increasing fuel taxes and imposing a carbon-based fuel tax affect technology adoption both directly via willingness to pay for fuel cost savings, and indirectly via market size. By contrast, in the short run (i.e., with each vehicle’s fuel economy fixed) fuel economy standards and feebates affect technology adoption via market size but not fuel costs. Therefore, the overall effects of these two types of policies on technology adoption depend importantly on the relative strength of these channels.

To date there exists very little evidence for the effects of either market size or fuel costs on technology adoption among energy-intensive durable goods such as passenger vehicles. Recent research provides evidence of the importance of path dependence on passenger vehicle engine patenting ([Acemoglu et al., 2016](#)), and of the role of market size in pharmaceutical innovation ([Acemoglu and Linn, 2004](#)). Other studies (e.g., [Newell et al. \(1999\)](#)) document the effects of consumer demand and energy prices on innovation and technology adoption in air conditioners and other industries. [Klier and Linn \(2016\)](#) show that the recent tightening of fuel economy and carbon dioxide standards accelerated the market-wide rate of adoption of fuel-saving technology in the United States and Europe.<sup>1</sup>

In this paper, we compare the effects of market size and fuel costs on fuel-saving technology adoption. Consistent with the empirical literature on directed technical change, we measure the market size of a vehicle by its sales ([Acemoglu and Linn, 2004](#)). We focus on fuel-saving technology for the internal combustion engine, including gasoline- and diesel-powered engines, and associated transmissions. Using a novel empirical strategy to account for the endogeneity of market size, and using unique data on consumer demographics, consumer preferences for new vehicles, and vehicle-level characteristics, we show that market size has a statistically significant effect on fuel-saving technology adoption for individual

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<sup>1</sup>The international trade literature focuses on the the link between market size and productivity ([Melitz and Ottaviano, 2008](#)) or product choice ([Mayer et al., 2014](#)), but firm-specific productivity and the technology of each product is exogenous in these models.

vehicles. We also show that fuel costs affect technology adoption independently of their effect on market size. Based on these results, we consider several counterfactual scenarios that illustrate the economic and policy implications for the relationships among market size, fuel costs, and technology adoption. The policy simulations illustrate the differing effects of fuel-based policies (e.g., fuel taxes) and vehicle-based policies (e.g., fuel economy standards) on technology adoption, which has not been discussed elsewhere in the literature.

Specifically, we begin by defining a vehicle power train’s efficiency, which is distinct from its fuel economy (miles per gallon, mpg). For a given level of power train efficiency, a manufacturer can trade off fuel economy, horsepower, and weight, analogously to movement along a production possibilities frontier. By definition, when a manufacturer adds fuel-saving technology, it shifts the frontier and can increase fuel economy without affecting other characteristics. We define the increase in efficiency that results from technology adoption as the increase in fuel economy that is feasible holding other vehicle characteristics constant. This definition accounts for the possibility that manufacturers adopt fuel-saving technology and use additional efficiency to boost horsepower or increase weight. We estimate the power train efficiency of each vehicle model by year from 1997 to 2013 similarly to [Klier and Linn \(2016\)](#).

The main empirical challenge is the endogeneity of a vehicle’s market size. The endogeneity problem, which is common to nearly all empirical analysis of market-driven technological change, arises from both potential reverse causality and omitted variable bias. Adopting fuel-saving technologies may increase demand for a vehicle, causing sales to increase and resulting in reverse causality. Furthermore, omitted demand or supply variables, such as a vehicle’s size, can be correlated with both market size and efficiency.

To address this challenge, we construct an instrumental variable (IV) that takes advantage of variation in consumer demographics over time, combined with variation in purchasing behavior across consumer groups. The IV is a demand shifter that captures changes in demand for a particular vehicle, relative to demand for other vehicles, which arise from changes in consumer demographics over time. For example, larger households tend to purchase more minivans than smaller households. The decrease in the share of large households in the United States over the sample period has reduced demand for minivans relative to other market segments. To construct the instrument, we use consumer preferences by demographic group that are measured at a specific point in time, combined with temporal variation in demographics. [Acemoglu and Linn \(2004\)](#) and [DellaVigna and Pollet \(2007\)](#) have similarly used demographic trends as exogenous determinants of market size in the pharmaceuticals and toys markets, using sales as a proxy for market size (other papers, such as [Blundell](#)

et al. (1999), have used pre-sample information to address endogeneity). The validity of the instrument rests on a) a positive correlation between the IV and actual market size; and b) the exclusion restriction, that the IV affects technology only via market size. We document a strong positive correlation between the IV and actual market size, and provide strong evidence supporting the exclusion restriction.

Market size positively affects efficiency. A one standard deviation increase in market size, which corresponds to about a 10 percent increase, raises a vehicle's efficiency by 0.2 percent. This estimate constitutes a substantial and statistically significant increase relative to the observed average annual efficiency increase of about 1.4 percent between 1997 and 2013. In addition to market size, we test whether a vehicle's efficiency responds to the efficiency of competing vehicles or to the manufacturer's stock of fuel-saving patents, finding some effects of competing vehicles. However, these effects are less precisely estimated than the primary effects of market size and fuel costs on efficiency. We also find that the main results are robust to alternative functional forms and constructions of the instrument.

We find that fuel costs affect technology adoption both directly and indirectly via market size. After controlling for market size, fuel costs have a positive and statistically significant effect on technology adoption. Moreover, fuel costs strongly affect market size, which is consistent with the literature and represents the indirect effect of fuel costs on adoption.

We illustrate the magnitudes of the market size and fuel cost effects using three sets of simulations. First, we compare the indirect and direct channels through which fuel costs affect efficiency, by focusing on the gasoline price increase that occurred between 2003 and 2007. The indirect effect works as follows. The 80 percent increase in real gasoline prices in that period raised the market size of vehicles with high fuel economy relative to vehicles with low fuel economy. In turn, the changes in market size caused efficiency of the lowest-fuel-economy vehicles to be lower than they would have been if fuel prices had remained at the low 2003 levels. Likewise, efficiency of the highest-fuel-economy vehicles was higher in 2007 than if fuel prices had remained at 2003 levels. We conduct a similar simulation that isolates the direct effect of the gasoline price increase on technology adoption, for comparison with the indirect effect that occurs via market size. The direct effect works in the opposite direction from the indirect effect. The increase in gasoline prices raised the willingness to pay for fuel cost savings more for low fuel economy vehicles than high fuel economy vehicles, and therefore raised the efficiency of vehicles with low fuel economy relative to others. The direct fuel cost effect was about twice as large as the indirect effect.

Second, demographics affected the efficiency distribution across models in different market segments. The overall shifts in demographics between 1980 and 2013 caused a shift in cumulative efficiency improvements away from light-duty trucks and toward cars. This effect occurred simultaneously with other demand- or supply-side effects on relative power train efficiencies of cars and light trucks, such as changes in gasoline prices that affected consumer demand for cars and light trucks and manufacturer technology adoption.

Third, changes in market size for crossovers and sport utility vehicles (SUVs) have affected technology adoption. Between 2001 and 2004, per model sales of crossovers increased sharply and per-model sales of SUVs decreased sharply. The increase in crossover market size raised crossover efficiency and the decrease in SUV market size reduced SUV efficiency, relative to a counterfactual in which market size remained unchanged.

The empirical results have two main implications for policies aiming to improve passenger vehicle fuel economy and reduce greenhouse gas emissions. First, the market size effect implies that manufacturers will continue to improve the efficiency of vehicles with internal combustion engines, which currently dominate the market. The efficiency improvements will increase the challenges faced by alternative-fuel vehicles to gain market share, and reduce the effectiveness of policies promoting those vehicles, compared with a counterfactual in which there is no market size effect.

Second, as noted above, the literature has compared the welfare effects of policies that affect fuel prices (such as raising gasoline taxes) and policies that affect new vehicle fuel economy (such as standards or feebates) in the short run. This comparison typically does not account for the effects of market size and fuel costs on technology adoption. Raising fuel prices differentially affects fuel costs of vehicles in the market and causes consumers to shift toward vehicles with higher fuel economy and away from vehicles with lower fuel economy. Therefore, the fuel price-based policies affect adoption via the fuel cost and market size effects, analogously to the 2003–2007 gasoline price increase. In contrast, starting from a particular market equilibrium, in the short run tightening fuel economy standards or introducing a feebate does not directly affect fuel costs but does affect market size.

Such policy-induced changes in market size and fuel costs in turn affect the cross-sectional efficiency distribution. In our data, efficiency is positively correlated with fuel economy. A feebate would strengthen this positive correlation by shifting sales to vehicles with high fuel economy and causing greater cumulative efficiency improvements for those vehicles than for vehicles with lower fuel economy. Raising fuel taxes or introducing a carbon tax creates opposing fuel cost and market size effects. Such policies do not strengthen the positive

correlation as much. Thus, the choice between fuel price or vehicle-based policies has implications for the evolution of technology adoption over time and for the competitiveness of plug-in electric vehicles and other alternatives. Relative to fuel price-based policies, standards and feebates have the perhaps unintended effects of making alternative-fuel vehicles less competitive with gasoline-powered vehicles and, in the absence of a fuel cost effect, decreasing the efficiency of vehicles with low fuel economy.

## 2 Data and Summary Statistics

### 2.1 Data

We assemble three data sets for the empirical analysis. The first includes vehicle characteristics and sales by model year and model version. This data set is constructed by merging vehicle characteristics by model year and model version with sales by model year, model, and power type. The characteristics are from *Ward's Automotive Annual Yearbooks* from 1997 through 2013 (a change in reporting in 1997 prevents us from extending the sample to earlier years). A model year begins in September of the previous calendar year and ends in August of the current calendar year. A model version refers to a unique model, trim, body type, and fuel type, such as the two-door gasoline-powered Honda Accord coupe. In addition to these identifying characteristics, other vehicle characteristics include fuel economy, horsepower, torque, weight, transmission type, engine displacement, number of cylinders, and market segment (market segment is aggregated from the *Ward's* vehicle classes, as in [Klier and Linn \(2016\)](#)). Our data exclude hybrid and electric vehicles, which account for 0.8 percent of sales between 1997 and 2013.<sup>2</sup>

The sales data are from *Ward's Automotive InfoBank*, which reports sales by month, model, and fuel type (gasoline, diesel fuel, and flex fuel, which refers to vehicles capable of using gasoline that contains a high percentage of ethanol). Because technology adoption depends on different factors for conventional internal combustion engines and hybrid electric

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<sup>2</sup>The recent Volkswagen scandal raises some concerns about the accuracy of laboratory testing of vehicle emissions because the results are used to assess compliance with fuel economy and emissions standards. Laboratory testing of US vehicle fuel economy typically overstates fuel economy by about 20 percent relative to the fuel economy values that appear on window stickers at new vehicle dealerships. In a few instances US laboratory tests have overstated fuel economy by a substantially greater amount, but these events have affected a smaller number of vehicles than the Volkswagen event. Testing inaccuracies likely affect emissions of other pollutants—such as nitrogen oxides—more than fuel economy or greenhouse gas emissions. The reason is that consumers can observe a vehicle's fuel economy (which is inversely proportional to its rate of greenhouse gas emissions) but they cannot directly observe emissions of other pollutants. This makes it easier to detect systematic cheating on fuel economy than on emissions of other pollutants and provides a disincentive for manufacturers to cheat on fuel economy ratings.

vehicles, our analysis includes only gasoline and diesel vehicles, as well as flex-fuel vehicles; these vehicles accounted for about 97 percent of the US market in 2013 and 99 percent between 1997 and 2013. We aggregate sales by model year, model, and fuel type and merge those data with the characteristics data. We collect the real average state-level gasoline and diesel fuel prices by model year from the US Energy Information Administration, and merge the fuel prices with the sales and characteristics data.

The second data set contains vehicle purchases by demographic group and year. We use the 1995 National Personal Travel Survey and the 2001 and 2009 National Household Travel Survey (NHTS). The Department of Transportation makes the survey data available to the public; the three waves had similar scope and sampling methodologies, but the samples are considerably larger in the later years. We refer to the three survey waves as the NHTS for convenience. For each household, the survey collects information on demographics (age, income, etc.), vehicle holdings, and vehicle use. We keep only vehicles that were purchased new in the survey year.

A demographic group is defined by a unique combination of age group, household income group, household size, education group, urbanization status, and geographic census division (see Appendix Table A.1 for definitions of the groups). The age and education groups are based on the attributes of the household head. Other groups are based on the attributes of the household. Using sample weights for each of the three survey waves, we compute the average number of new vehicles purchased per household by vehicle model name and demographic group. For example, we compute the average number of new Honda Civics purchased by the group defined by households headed by a 35- to 54-year-old with 12 or more years of schooling, with annual household income of \$75,000 to \$100,000, containing two people, and located in an urban area in New England.

The third data set is constructed from the Current Population Survey (CPS), which is available at the National Bureau of Economic Research, from 1980 through 2013. We compute the number of households for each demographic group using the sample weights. We use the same six-dimension demographic groups that we use for the NHTS.

## 2.2 Summary Statistics

In this subsection we present summary statistics of market trends, consumer purchasing patterns, the evolution of consumer demographics over time, and manufacturer adoption of fuel-saving technology. Figure 1 shows total sales by market segment for model years 1997 through 2013, separately for cars and light trucks. The figure illustrates considerable

variation in segment-level sales, such as the growth for crossovers that began in the late 1990s and the decline in sport utility vehicles (SUVs) that began shortly thereafter. This variation is useful in identifying the effect of market size on power train efficiency.

Table 1 shows average vehicle characteristics at various times in the sample. Average fuel economy was fairly flat through the mid-2000s and increased at the end of the sample. Horsepower and weight increased over the entire sample. Torque, which represents light truck towing ability, followed a similar pattern.

Figure 2 summarizes the variation in vehicle purchasing patterns across demographic groups. To construct the figure, we combine all three NHTS waves and weight observations using household survey weights. The figure indicates a substantial amount of variation in purchase behavior across groups. The variation is largely intuitive. For example, the age panel shows that younger households are more likely to buy small cars than older households, and wealthier households are more likely to buy crossovers and SUVs than lower-income households. Geographic variables are also correlated with purchase behavior: households in urban areas and the Northeast are much less likely to buy pickup trucks than are other households. The demographic variables are correlated with one another; for example, households with high incomes tend to be well educated.

Figure 3 shows changes in demographics over time from the CPS. Average age, education, and urbanization increased over time, whereas average household size decreased. As the next section explains, we combine this temporal variation with the variation in purchasing patterns across demographic groups illustrated in Figure 2 to construct the instrumental variable for market size. The raw data support this approach by indicating that the time series changes in demographics, combined with heterogeneous purchasing patterns across demographic groups, are consistent with changes in market size. For example, after the initial introduction of the crossover segment in the late 1990s, the market share of crossovers increased from the late 1990s through the 2000s. This is consistent with the facts that older households are more likely to purchase crossovers than younger households and that during the same time period the share of older households increased.

Finally, we present some background information about technology adoption in the US new vehicle market. Manufacturers continually redesign their vehicles, improving power train technology and other attributes that consumers value. Many vehicle models experience major redesigns at regular intervals, commonly every five to seven years. During a redesign, the manufacturer may make major changes to the power train, cabin, cargo space, or exterior. In between redesigns, manufacturers commonly make smaller changes to exterior design or

to the power train, offering new options such as paint color or increasing the number of transmission speeds.

These alterations yield a process of steady technology adoption over time. Figure 4 shows the share of vehicles in the market with the indicated fuel-saving engine or transmission technologies. The data cover 1986 through 2014 and are from the U.S. Environmental Protection Agency (EPA) Annual Fuel Economy Guides and Trend Reports. For many of these technologies, the figure suggests fairly typical patterns in the technology adoption literature, in which the penetration rate is very low initially, subsequently increases steeply, and then levels off—that is, an S-curve. Note that the penetration rate of multiport fuel injection decreases in the late 2000s because manufacturers began replacing this technology with more advanced fuel injection technologies.

### 3 Empirical Strategy

In this section we review the literature on technology adoption, which motivates estimating a reduced-form relationship among vehicle efficiency, market size, and fuel costs. Then, we estimate efficiency of each vehicle model in the sample, and finally we derive the estimating equation and explain how the IV strategy addresses the identification issues.

#### 3.1 Possible Channels of the Market Size and Fuel Cost Effects

There are several possible channels through which market size could affect technology adoption. First, manufacturers face fixed costs when adopting fuel-saving technology. Fixed costs may arise because of the need to redesign and test the vehicle before commencing full-scale production (Blonigen et al., 2013). These fixed costs are distinct from the additional production costs associated with adopting many technologies. Additional production costs can arise because of new components or because of greater complexity of the production process.<sup>3</sup> As a simple example of the role of fixed costs in the market size effect, consider a hypothetical manufacturer that sells two types of vehicles that are identical except that the first has a larger market size than the second. Adopting a fuel-saving technology would require the same increase in fixed and production costs for the two vehicles. Because the first vehicle has larger market size, the manufacturer can spread the fixed costs across a larger sales base, making it more likely that the manufacturer adopts the technology for that model.

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<sup>3</sup>For example, NRC (2015) estimates that adding cylinder deactivation, which effectively shuts off a subset of a vehicle’s cylinders when the vehicle is operating under a light load, increases production costs by \$118–\$133 per vehicle.

Learning by doing is a second possible channel linking market size and adoption. With learning by doing, the marginal costs of producing a vehicle decline with cumulative production. For example, [Levitt et al. \(2013\)](#) document large reductions in production costs and improvements in product quality following the introduction of a new vehicle at an automobile assembly plant. Learning by doing would imply greater cost reductions for vehicles with higher production volume and market size. Therefore, a manufacturer would be more likely to adopt technology for vehicles that are anticipated to have high market size. A third possible channel is directed technical change (e.g., [Acemoglu, 2002](#)), in which the profits accruing from innovation depend on a product's market size and price. Innovation and adoption of fuel-saving technology raise market size, which raises the returns to future innovation, and creating a positive feedback among market size, innovation, and technology adoption.

These arguments suggest a positive effect of market size on technology adoption. However, other considerations would imply a weaker or perhaps negative relationship between market size and technology adoption. For example, in the long run the learning-by-doing effect could create lock-in. Suppose a manufacturer produces a high-selling vehicle and learning by doing has reduced its cost and price. If adopting fuel-saving technology would require a new learning process, the initial cost of producing the more efficient vehicle could make it unprofitable to adopt the new technology. Moreover, competitive pressure could amplify or diminish each of these channels, depending on the distribution of consumer preferences and other factors.

In short, theory does not determine the relationship between market size and technology adoption; it could be either positive or negative. Fixed costs of adoption and directed technical change suggest a positive relationship, whereas learning by doing could imply either a positive or a negative relationship. This ambiguity, and the absence of empirical evidence on these channels, motivates our reduced form analysis that estimates the cumulative magnitude of these possible channels.

Fuel costs may affect technology adoption via two channels. First, an increase in gasoline prices raises the fuel costs for all vehicles but causes a larger fuel cost increase for vehicles with low fuel economy than for vehicles with high fuel economy. The increase in the relative fuel costs of vehicles with low fuel economy reduces their market size compared with the market size of vehicles with high fuel economy. The resulting change in market size affects adoption of fuel-saving technology, as discussed above; we refer to this channel as the *indirect effect of fuel costs via market size*.

The second effect is the *direct effect of fuel costs*—specifically, that an increase in gasoline prices raises consumers’ willingness to pay for fuel-saving technology (Busse et al., 2013). Because fuel costs are inversely related to fuel economy, a given increase in fuel prices has a larger effect on fuel costs for vehicles with low fuel economy than for vehicles with high fuel economy. A fuel-saving technology that raises the fuel economy of all vehicles’ proportionately would have a larger effect on the fuel costs of vehicles with low fuel economy than on vehicles with high fuel economy. Moreover, this differential in fuel cost savings from a hypothetical technology increases with fuel prices. Therefore, the fuel price increase raises willingness to pay for the fuel-saving technology more for vehicles with low fuel economy, and we expect fuel costs to positively affect technology adoption via the direct channel.

### 3.2 Estimating Power Train Efficiency

The empirical objective is to estimate the effects of market size and fuel costs on power train efficiency. In this subsection we describe the construction of the dependent variable, which is power train efficiency.

The data do not contain efficiency per se, but they do include fuel economy and a number of other observable variables that affect efficiency, such as the number of engine cylinders. We follow Knittel (2012) and Klier and Linn (2016) and estimate efficiency from the available data. Efficiency is the amount of useful work or energy that the power train produces per unit of fuel consumption. A vehicle’s fuel economy (miles per gallon) is distinct from its efficiency. Its fuel economy depends on the efficiency of its power train as well as characteristics such as horsepower, weight, and body type (which affects air resistance). As in Klier and Linn (2016), we conceive of an efficiency frontier defined in the fuel economy–horsepower–weight space. The frontier represents the maximum fuel economy that can be achieved given any particular level of horsepower and weight, and holding efficiency fixed along the frontier. That is, for a particular level of efficiency, as it moves along the frontier, the manufacturer can trade off fuel economy for weight and horsepower.

This framework yields a straightforward identification of efficiency improvements over time. Specifically, we estimate the shape of the frontier using within-model variation in horsepower, weight, and fuel economy. As a baseline we assume that the shape of the frontier does not change over time. In that case, if we control for the effects of weight, horsepower, and other attributes on fuel economy, an increase in fuel economy is equivalent to an increase in efficiency. To implement this approach, we estimate an equation similar to Klier and Linn (2016):

$$\ln e_{jt} = \lambda_h \ln h_{jt} + \lambda_w \ln w_{jt} + \tau_{mt} + X_{jt}\delta + \varepsilon_{jt}, \quad (1)$$

where  $e_{jt}$  is the fuel economy of vehicle  $j$  in model year  $t$ ,  $h_{jt}$  is horsepower for passenger cars (and torque for light-duty trucks),  $w_{jt}$  is weight,  $\tau_{mt}$  is a set of interactions of model by model year,  $X_{jt}$  includes a vector of vehicle attributes,  $\varepsilon_{jt}$  is an error term, and the  $\lambda$ s and  $\delta$  are coefficients to be estimated. The coefficients on weight and horsepower capture trade-offs between these characteristics and fuel economy. We expect both coefficients to be negative. The controls in  $X_{jt}$  include fixed effects for whether the vehicle uses diesel fuel, whether the vehicle is flex-fuel capable, and whether the vehicle has a manual transmission, as well as fixed effects for the number of doors and the number of cylinders. Together, these variables allow for the fact that versions of a particular model sold in the same model year have different efficiency depending on fuel type and body type (as approximated by the number of doors). We estimate the equation separately for cars and light trucks to allow the coefficients to vary across the two classes.

We interpret the interactions of model by model year,  $\tau_{mt}$ , as the average efficiency of vehicles belonging to the model and sold in model year  $t$ . The difference between  $\tau_{mt}$  and  $\tau_{m(t-1)}$  is the change in efficiency of model  $m$  between model years  $t - 1$  and  $t$ . Equation (1) thus allows us to identify changes in efficiency over time, where efficiency is measured in units of log fuel economy. We expect efficiency to increase over time as innovation reduces the cost of improving efficiency.

Before presenting the results from estimating equation (1), we briefly discuss identification and potential sources of bias. Equation (1) characterizes a technological relationship between vehicle characteristics and fuel economy. It does not include certain vehicle attributes that consumers care about, such as seating comfort. Such attributes could be correlated with variables that are included in equation (1), but in this context that would not bias the coefficients as long as the omitted variables affect fuel economy via horsepower, weight, or other included variables, and not independently of the included variables. In other words, identification rests on the ability to include the variables that directly determine a vehicle’s fuel economy. The high R-squared value reported below supports this estimation approach. See [Knittel \(2012\)](#) and [Klier and Linn \(2016\)](#) for additional discussion of identification of equation (1).

Table 2 reports the main coefficient estimates from equation (1). Because fuel economy, horsepower, torque, and weight enter equation (1) in logs, the horsepower, torque, and weight coefficients are elasticities. The coefficients on diesel fuel and flex fuel are the difference

between log fuel economy of a vehicle that uses diesel fuel or is flex-fuel capable and the log fuel economy of an otherwise comparable gasoline-powered vehicle. Diesel fuel vehicles achieve about 30 percent higher fuel economy, and flex-fuel light trucks achieve about 27 percent lower fuel economy than gasoline-powered vehicles. The negative coefficient on flex-fuel vehicles reflects the lower energy content of ethanol compared with gasoline (that is, the coefficient estimate reflects the fact that EPA reports the fuel economy of the flex-fuel version; the coefficient does not reflect a difference in efficiency of flex-fuel and conventional engines). Overall, the estimates in Table 2 have the expected signs and are statistically significant at the 1 percent level. The magnitudes are similar to those reported in Klier and Linn (2016) for both cars and light trucks. The magnitudes of many of the coefficients are fairly similar across the car and light truck classes, which reflects a substantial degree of shared technology across the classes.

Because of the large number of estimated model-by-model year interactions, we aggregate across observations before reporting those estimates. Figure 5 plots the change in power train efficiency, averaged across cars and light trucks. The figure shows steady efficiency improvements for both vehicle classes. Table 3 shows the average change in efficiency by five-year periods, separating models with sales above the median level of sales for the corresponding period and vehicles with sales below the median level of sales. Efficiency improvements are generally higher for the higher-selling models, which previews the main empirical finding that market size has a positive effect on efficiency-improving technology adoption.

### 3.3 Empirical Strategy for Estimating the Effects of Market Size and Fuel Costs on Efficiency

This subsection presents the strategy for estimating the effects of market size and fuel costs on efficiency. We assume a log-linear relationship between market size and efficiency that approximates nonlinear forms.

The estimating equation is

$$\hat{\tau}_{mt} = \gamma_1 \ln Q_{mt} + \gamma_2 C_{mt} + \phi_t + \phi_b + \phi_b \times t + \varepsilon_{mt} \quad (2)$$

where  $\hat{\tau}_{mt}$  is power train efficiency estimated from equation (1),  $Q_{mt}$  is sales,  $C_{mt}$  is fuel costs per mile (dollars-per-mile),  $\phi_t$  and  $\phi_b$  are sets of year and brand fixed effects,  $\phi_b \times t$  is the interaction of brand fixed effects with a linear time trend, and  $\varepsilon_{mt}$  is an error term. The two parameters of interest are  $\gamma_1$  and  $\gamma_2$ , which are the effects of log sales and fuel costs

on efficiency. As we discussed in section 3.1, theory implies that the coefficient on log sales could be positive or negative. The variable  $C_{mt}$  is the cost of driving the vehicle one mile. The coefficient on fuel costs is the direct effect of fuel costs on efficiency, holding market size fixed. We discuss the fuel cost variable construction and identification at the end of the subsection. The year fixed effects control for aggregate demand or supply shocks, and the brand (i.e., make) fixed effects control for brand-level supply or demand shocks, such as consumer perceptions of brand quality and brand-level productivity shocks. The brand fixed effects also control for brand-level economies of scope that may affect technology adoption, as well as brand-specific pass through of technology adoption costs to vehicle prices. The interactions of the brand fixed effects with a linear time trend allow these brand-specific factors to vary linearly over time. For example, the time trends control for changes in consumer preferences for brands as well as changes in brand quality.

Estimating equation (2) by ordinary least squares (OLS) is likely to yield biased estimates for two main reasons. First, there would be reverse causality if increasing a vehicle’s efficiency raises a vehicle’s demand and, therefore, equilibrium sales. Second, sales may be correlated with unobserved supply or demand determinants of fuel-saving technology. The brand fixed effects and time trends control for brand-level supply or demand shocks, but efficiency could be correlated with within-brand variation in vehicle characteristics. For example, there is anecdotal evidence that manufacturers test efficiency-improving technologies on luxury or performance vehicles before installing the technologies more broadly. This practice would cause sales and efficiency to be correlated with (omitted) characteristics such as seating quality or cabin space. Note that we could control flexibly for omitted model-level characteristics by including model fixed effects in equation (2). That approach would yield an undesirable interpretation of  $\gamma$ , however. The coefficient would be identified by within-model variation over time in sales and efficiency. In practice, manufacturers face choices not only about when to adopt technology for a particular model but also, given time and resource costs, about which of their models will receive improved technology at a particular time. Including model fixed effects would identify the former choice but not the latter and therefore might omit an important role of market size in technology adoption across vehicle models.

We instrument for sales and address both sources of bias. The IV is the vehicle’s potential market size, which is a demand shifter that depends on cross-sectional variation in consumer purchasing patterns and time series variation in demographics. Intuitively, the IV isolates changes in market size for an individual vehicle driven by changes in demographics. For example, compared with younger age groups, the older age groups tend to prefer large and

luxury cars, and an increase in the share of older age groups over time would increase demand for large and luxury cars relative to other vehicles. In standard models of imperfect competition, such as Bertrand with differentiated products, the increase in demand causes an increase in equilibrium sales. This creates a positive correlation between a vehicle’s endogenous sales and the IV.

More specifically, we define demographic group cell,  $g$ , by age, income, education, household size, urbanization, and census division (see Appendix Table A.1 for definitions of the groups). To measure purchasing behavior by group, we compute  $q_{mg;s}$  for each of the 2,628 cells as the number of vehicles of model  $m$  purchased per household by demographic group cell  $g$  in NHTS year  $s$  (recall that we use data from the NHTS years 1995, 2001, and 2009; each cell represents an average of about 28 households per year). The subscript  $s$  in potential market size reflects the fact that  $q_{mg;s}$  varies across NHTS waves. We define time periods  $s$  based on the NHTS waves: 1997–2000, 2001–2008, and 2009–2013. To measure time-series variation in demographics, we compute the number of households in demographic group cell  $g$  in year  $t$ ,  $w_{gt}$ , using CPS data. The potential market size,  $\tilde{Q}_{mt;s}$ , is the product of NHTS vehicle purchases per household and CPS number of households, summed across demographic group cells:

$$\tilde{Q}_{mt;s} = \sum_g (q_{mg;s} \times w_{gt}) \tag{3}$$

For each vehicle model, we subtract from  $\tilde{Q}_{mt;s}$  the average value for the corresponding model to obtain the instrument,  $\bar{Q}_{mt;s}$ . Subtracting the average value causes the variation of the IV to arise entirely from changes over time in potential market size caused by changes in demographics. Therefore, the IV does not include variation in cross-sectional purchasing patterns that may be correlated with unobserved vehicle attributes.

The IV is based on the assumption that changes in group-specific population weight  $w_{gt}$  after each survey round are uncorrelated with changes in demand- and supply-side factors that affect technology adoption. Temporal changes in educational attainment, labor participation, and the US income distribution are driven by broad technological developments (such as information technology), the decrease in unionization, and other factors that are largely unrelated to the new vehicles market (Black and Lynch, 2001; Bresnahan et al., 2002; Jorgenson, 2001; Johnson and Mieszkowski, 1970; Autor et al., 2008). Likewise, the overall increase in age depicted in Figure 3 arises from the aging of the baby boom generation. Household size, urbanization, and migration trends are similarly driven by changing preferences and other factors that are unrelated to unobserved demand and supply determinants of new vehicle technology. The assumed exogeneity of these demographics follows assumptions

made by [Acemoglu and Linn \(2004\)](#) and [DellaVigna and Pollet \(2007\)](#) for consumer demand in other industries.

The log potential market size,  $\ln \bar{Q}_{mt;s}$ , is the IV in the first stage for market size in equation (2)

$$\ln Q_{mt} = \beta_1 \ln \bar{Q}_{mt;s} + \beta_2 C_{mt} + \beta_3 I_{mt}^{imp} + \phi_t + \phi_b + \phi_b \times t + u_{mt} \quad (4)$$

where  $I_{mt}^{imp}$  is an indicator variable equal to one if the instrument is imputed using brand-segment-year means.<sup>4</sup> The instrument yields unbiased estimates of the sales coefficient in equation (2) if it is strongly correlated with sales and is uncorrelated with the error term in equation (2). As we show below, the instrument is a strong predictor of log sales, reducing concerns about weak instruments bias and satisfying the first condition for the validity of the IV.

The second condition is that the IV affects efficiency only via market size and not via other channels. If the IV were correlated with unobserved attributes of the vehicle, the estimates of equation (2) would be biased. Subtracting the average value of the sales reduces the likelihood that the IV is correlated with the error term in equation (2) because this step implies that the first stage is not identified by cross-sectional variation in vehicle sales, which may be correlated with unobserved vehicle attributes. After this step, the main remaining concern is that changes in population weight  $w_{gt}$  after each survey year may be correlated with demand- or supply-side shocks over time. For example, the population aged during the sample period, and the older age groups' preference for large and luxury cars may also have changed during the sample period. Another possibility is that temporal vehicle attribute changes were correlated with changes in potential market size. For example, innovation may have reduced the cost of improving efficiency for some segments and not others, leading to greater fuel-saving technology adoption in those segments. If these supply shocks are correlated with the IV, the estimates would be biased.

We can address this concern by comparing results if we use a different NHTS wave to construct the IV. The weights constructed from the NHTS,  $q_{mg;s}$ , reflect preferences and vehicle attributes in period  $s$ . If changes in demographics over time are correlated with changes in preferences or vehicle attributes across periods, we would observe a correlation between demographics and changes in  $q_{mg;s}$  across waves. In that case the estimates of

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<sup>4</sup>Some vehicle models appear in the sales and characteristics data but not in the NHTS data. Most of these are low-selling models, such as the Chevy Aveo. In these cases, we impute the instruments using brand-segment-year-level average NHTS weights.

equation (2) would depend on whether we use all three NHTS waves, or just one survey wave. In section 4 we show that the results are unchanged if we use either the 1995 or 2009 survey wave rather than all three survey waves. The stability of the estimates supports the underlying assumption of the IV strategy.

We interpret the coefficient on log sales in equation (2) as the effect on efficiency of a change in market size induced by a change in potential market size. In practice, changes in potential market size may affect equilibrium sales as well as vehicle prices. We do not control for vehicle prices in equation (2) because prices are likely to be correlated with unobserved demand or supply factors, and we lack suitable price instruments in the context in which technology and vehicle characteristics are endogenous (Klier and Linn, 2012). If the potential market size is a valid instrument, it is uncorrelated with unobserved supply or demand factors that affect vehicle price (and sales), and omitting the vehicle’s price would not cause spurious results. That is, omitting the price would affect only the interpretation of the log sales coefficient, as the effect of sales net of any potential market size or fuel cost-induced price changes.

A final consideration is that technology adoption is a dynamic decision that includes fixed and irreversible costs. Efficiency may therefore depend on current sales as well as expected future sales, or on past sales in the presence of learning by doing. Because of the high persistence of sales across years, we use current sales in equation (2) as a proxy for lagged or expected sales. This introduces measurement error that could bias the estimated sales coefficient. In the empirical analysis we report estimates of equation (2) that use other measures of market size and assess the importance of potential measurement error.

Next, we discuss the identification and interpretation of a vehicle’s fuel cost per mile. Recall that fuel costs can affect a vehicle’s efficiency via two channels. First, an increase in the fuel costs of a vehicle relative to the fuel costs of other vehicles would reduce the demand for that vehicle and its market size; that is, fuel costs can act as a demand shifter analogously to the IV. Second, higher fuel costs may raise consumers’ willingness to pay for technology that raises fuel economy, inducing technology adoption.

The first channel is captured in the first-stage equation (4). We aim to isolate the second channel in equation (2). The coefficient on fuel cost per mile is identified by fuel price and fuel economy variation across vehicles and over time. We use the contemporaneous fuel price under the assumption that price shocks are fully persistent (Busse et al., 2013). Previous research (Klier and Linn, 2010) has used the ratio of the national average fuel price to the vehicle’s fuel economy to approximate per mile fuel costs. Using this approach, fuel cost per

mile varies because of time-series variation in fuel prices and cross-model variation in fuel economy. We refine our previous approach and introduce additional variation by exploiting geographic variation in fuel prices and vehicle purchases. For example, fuel prices tend to be higher in the Northeast than in the Midwest. Households purchase more small cars relative to pickup trucks in the Northeast than in the Midwest, which causes the national average fuel price for households that purchase small cars to be higher than the national average fuel price for households that purchase pickup trucks. Formally, we compute a model-specific fuel price using NHTS data on vehicle purchases and U.S. Energy Information Administration (EIA) data on fuel prices by census division,  $d$ :

$$p_{mt;s} = \sum_g (p_{dt} \times q_{mg;s} \times w_{gt}) / \tilde{Q}_{mt;s}$$

We calculate the fuel cost per mile as the ratio of the model’s fuel price to its fuel economy  $e_{m0}$ , which is measured in the first year the model is observed in the sample:

$$\tilde{C}_{mt;s} = \frac{p_{mt;s}}{e_{m0}}$$

In the cross section,  $\tilde{C}_{mt;s}$  is correlated with the vehicle’s fuel economy (by construction) and may therefore be correlated with vehicle characteristics that are correlated with fuel economy, such as horsepower. Including  $\tilde{C}_{mt;s}$  in equations (2) and (4) as an independent variable would yield biased estimates because the variable would be correlated with the error term in those equations. To address this concern, we first construct  $\tilde{C}_{mt;s}$  using initial-year fuel economy  $e_{m0}$  to eliminate temporal variation that can be correlated with unobserved demand and supply factors. Second, similarly to the potential market size instrument, we subtract average fuel costs from the variable to obtain the independent variable  $\bar{C}_{mt;s}$ , which we include in equations (2) and (4). Subtracting average fuel costs eliminates cross-sectional variation arising from fuel economy or the NHTS weights, which could be correlated with unobserved demand or supply shocks.

The coefficient on fuel costs is the effect of fuel costs on efficiency after controlling for market size. Because the estimating equation includes year fixed effects, the coefficient on fuel costs is identified by within-year cross-sectional variation in fuel costs arising from fuel prices and fuel economy. We expect the coefficient to be positive because higher fuel costs raise the value of an efficiency improvement of a particular magnitude.

Because fuel costs shift vehicle demand, we interpret this coefficient as capturing the effect of consumers’ willingness to pay for fuel-saving technology that raises fuel economy.

The coefficient on log sales is identified by variation in the IV as well as all of the other independent variables, which include fuel costs. Therefore, fuel costs can affect efficiency via market size, as well as have a direct effect on efficiency.

## 4 Estimation Results

### 4.1 Main Results

Table 4 shows the main estimation results. Column 1 reports the OLS estimates of equation (2) for comparison with the preferred IV estimates in column 2. The dependent variable is the efficiency estimated in Table 2, and observations are by model and model year from 1997 through 2013. To control for aggregate demand or supply shocks as well as brand-specific shocks, the regression includes year fixed effects, brand fixed effects, and the interaction of a linear time trend with brand fixed effects. The table reports the estimated coefficient on log sales with the bootstrapped standard error in parentheses, clustered by brand to allow for arbitrary correlation of the error term within brands and over time, and for the fact that the dependent variable is estimated in equation (1). The estimated coefficient on log sales is 0.008, and the estimate is statistically significant at the 1 percent level. The coefficient on fuel costs is positive, but it is not statistically significant.

The OLS estimates in column 1 are likely to be biased because of reverse causality and omitted variable bias (see Section 3.3). To address these issues, we instrument for log sales using the log of demographics-driven potential market size,  $\ln \bar{Q}_{mt;s}$ . Column 2 in Panel B of Table 4 shows the results from the first stage. The instrument is a strong predictor of market size. The coefficient on the instrument has the expected positive sign and is statistically significant at the 1 percent level.

The magnitude of the IV estimate in Panel A is statistically and economically significant. Between 1997 and 2013, the average annual efficiency improvement is about 1.4 percent (see Figure 5). As shown in column 2, the estimated sales coefficient implies that a one standard deviation increase in log sales, or a 10 percent increase, raises efficiency by 0.2 percent. This estimate is substantially larger than the OLS estimate in column 1. Reverse causality would bias the OLS estimate away from zero, whereas omitted variables bias could bias the OLS estimate in either direction. The fact that the IV estimate is larger than the OLS estimate suggests that omitted variables bias is the dominant source of bias. In the following subsections we present a variety of additional estimation results, and we refer to column 2 in Table 4 as our baseline estimate.

The coefficient on fuel costs in the second stage is positive and statistically significant. A one standard deviation increase in fuel costs raises efficiency by 0.4 percent. In contrast, the coefficient on fuel costs is negative in the first stage, suggesting that the indirect effect via market size is opposite to the direct effect. Because fuel costs are an independent variable in the first stage, a potential concern is that the functional form in equation (2) may not properly distinguish between the two channels by which fuel costs affect efficiency. In fact, the baseline does appear to distinguish the two channels because the sales coefficient is similar in column 3 when we omit fuel costs from the first and second stages.

## 4.2 Possible Sources of Omitted Variables Bias

Recall that the IV strategy rests on the assumption that the IV affects efficiency only via market size. This assumption implies that changes in demographics over time are uncorrelated with preference changes over time. As we argue above, if this assumption does not hold, changes in purchasing patterns across survey waves would be correlated with changes in demographics, and the IV estimates would be sensitive to the choice of which NHTS waves to use in constructing the IV. Table 5 repeats the baseline in column 1 and shows the estimates for two alternative specifications: using only the 1995 or the 2009 NHTS. The point estimates on market size and fuel costs are barely changed, providing strong support for the validity of the IV strategy.

An alternative approach to assessing the validity of the IV is to test the sensitivity of the estimates to adding further controls to equation (2). If the IV is valid, it would be uncorrelated with the other control variables, and adding further controls would not affect the main estimates. Table 6 shows that the results are robust to adding further controls. The baseline includes controls for brand-level demand or supply shocks, but there may also be segment-level shocks. For example, the increase in market shares of crossovers in the late 1990s and early 2000s, along with the decrease in market share of SUVs during the same period, could reflect a shift in consumer preferences toward smaller, carlike light trucks. A correlation between preference changes and demographics would bias the IV estimate, but column 3 shows that the sales and fuel cost coefficients are similar if we add to the baseline the interactions of market segment fixed effects and a linear time trend.

Fuel economy standards varied over the data sample in stringency and form. The standards were roughly constant in the 1990s and early 2000s but began increasing for light trucks in 2005, and then for both cars and light trucks in 2011. Because of differences in fleet composition and market positioning, the standards impose varying degrees of pressure

across manufacturers to improve fuel economy over time, which has affected the adoption of energy efficiency technology (Klier and Linn, 2016).

Klier and Linn (2016) show that the stringency of the fuel economy standards was uncorrelated with fuel costs, addressing the concern that fuel economy standards bias the coefficient on fuel costs. However, this result leaves open the possibility that the stringency of the standards and market size may be correlated with each other. The interactions of brand fixed effects with a linear time trend control imperfectly for the standards because during the sample period the stringency of the standards varied nonlinearly over time and within brands.

We have tried several semi-parametric approaches to controlling for fuel economy standards. In particular, column 4 includes the interactions of brand fixed effects with a quadratic time trend. This controls for the nonlinear changes in the stringency of the standards over time and across manufacturers. Historically, the standards applied separately for cars and light trucks, but since 2011 manufacturers have been allowed to average across their entire fleet (Leard and McConnell, 2016). To account for the differing regulatory pressure across cars and light trucks, column 5 includes triple interactions of brand fixed effects, vehicle class fixed effects (i.e., passenger car or light-duty truck), and a linear time trend. This controls for changes in stringency of the standards over time and across vehicle classes. The results are similar to our baseline. Note that these specifications also address the potential bias caused by unobserved demand or supply shocks at the brand, market segment, or class level.

The results are also similar to the baseline if we control directly for the stringency of the standards as in Klier and Linn (2016). We define stringency as the difference between the level of the standard that a manufacturer faces at the end of the sample, and the average fuel economy of the manufacturer's vehicles at the beginning of the sample. We allow the effect of stringency on efficiency to vary over time, reflecting the fact that the standards were first tightened for light trucks in 2005 and for cars in 2011. Column 6 includes these controls, and the coefficient on log sales is similar to the baseline estimate. Finally, unobserved preference or cost shocks may be correlated with the shadow cost of the fuel economy standards and therefore with incentives the standards create for technology adoption. To allow for this possibility, in column 7 we add the interaction of the stringency variable with fuel costs (which depend on fuel economy and are therefore likely to be correlated with such shocks), yielding results that are similar to our baseline.

### 4.3 Alternative Measures of Efficiency and Market Size

In this subsection we show that the results are similar using alternative measures of efficiency or market size. In the baseline specification (repeated in column 1 of Table 7 for convenience), we estimate efficiency by model and model year using equation (1), implicitly assuming that efficiency is constant across versions of the same model and model year. This assumption is supported by the fact that versions of the same model, such as the Honda Accord, typically include engines produced on the same or a very similar production platform. However, because many technologies are installed at the engine platform rather than the model level and some models share an engine platform (Klier and Linn, 2012), platform-level market size could affect efficiency. To assess whether engine platform-level market size affects efficiency, columns 2 and 3 report estimates of equation (2) that are the same as the baseline, except for the estimation of the dependent variable. These specifications take advantage of highly detailed engine platform data, which allow us to identify the specific engine sold with each version. In column 2 we estimate efficiency in equation (1) by engine platform and model year rather than by model and model year, and we use the estimated efficiency as the dependent variable in equation (2). The estimated coefficient on log sales is similar to the baseline. In column 3 we estimate efficiency by model and platform generation (such that a redesign of the engine platform constitutes a new platform generation).<sup>5</sup> The log sales coefficient is similar to the baseline. Thus, we find similar elasticities of efficiency to market size across different levels of aggregation of the dependent variable.

As noted in Section 2.2, manufacturers typically make large changes to the power train or vehicle during major redesigns, and smaller changes between redesigns. The baseline estimates include efficiency improvements that occur both within and across redesigns, but the relationship between log sales and efficiency may be different across redesigns from the relationship within redesigns. To allow for this possibility, we define a change in model generation as occurring when the model experiences a major redesign (model redesigns do not always coincide with engine redesigns because many models share engine platforms). In column 4 we estimate efficiency and market size by model generation and year (we collect model generation information from Automotive News, as in Blonigen et al. (2013)). The estimated coefficient on log sales is similar to the baseline.

Next, we consider possible sources of measurement error (classical or nonclassical) in the market size variable. Because of regular production and redesign cycles in the vehicles market, efficiency may respond gradually to market size. Column 4 represents one approach

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<sup>5</sup>Different models in the same year sold under the same brand could share a platform, as could one model in different years. It is also possible for models sold under a different brand to share a platform.

to allowing for this possibility, by focusing on efficiency improvements across generations. Column 5 represents an alternative. In this case we use as the dependent variable the three-year moving average of efficiency. The estimate is close to the baseline.

Using the 2009 NHTS rather than the 1995 (or 2001) increases the average number of households per cell from 19 (or 27) to 38 (note that using the 2009 NHTS also increases the number of cells). We note that the specification using the 2009 NHTS addresses the possibility that the 1995 and 2001 NHTS waves have greater measurement error than the 2009 survey wave because of their smaller sample size. Second, analogously to the three-year moving average efficiency in column 5, we can use the three-year moving average of the model's sales to allow for the possibility that efficiency responds to the average market size over multi year periods; the results are similar to the baseline (not reported).

Column 6 reports result using lagged sales, an exercise motivated by a few considerations. First, learning by doing suggests that lagged sales may be correlated with fuel-saving technology adoption. Second, efficiency may lag behind sales because of the time required to redesign and test a vehicle before beginning production. The fact that shifts in demographics and potential market size can be forecast to some extent mitigates the lag between demographics-driven changes in market size and adoption, but there could nonetheless be a lag. We can consider this possibility empirically by replacing current log sales with the one-year lag of log sales and by replacing fuel costs with lagged fuel costs. Column 6 shows that the results are similar using the lag of sales rather than current sales (the high correlation between lagged and current sales prevents us from using a distributed lag model that includes both variables in the same regression).

Finally, the baseline allows market size to affect efficiency at the model level. We showed that market size has a similar effect at the model generation level as at the model level. Because of economies of scale or scope, market size defined at a higher level of aggregation, such as brand by segment, may affect market efficiency. Using brand by segment level efficiency and market size, we find results similar to the baseline (column 7).<sup>6</sup>

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<sup>6</sup>Another source of measurement error for market size is that some vehicle models are produced on global platforms, and technology could respond to global market size for these models. However, even in such cases manufacturers commonly select engines and transmissions that are specific to the market, in which case the US market size would be most relevant to the chosen engine and transmission technologies for the vehicles sold in the United States. In addition, the United States represents about 20 percent of global sales and therefore represents an important consideration in manufacturers' technology decisions for vehicles sold in the United States and other markets.

## 4.4 Additional Channels and Heterogeneous Technology Adoption

So far we have focused on the link between a vehicle’s market size and its efficiency. In this subsection we consider possible indirect effects on efficiency, such as competitors’ behavior, and possible heterogeneity across vehicles in the effect of sales on efficiency. We report these results in Table 8 repeating the baseline in column 1 for comparison. We do not find strong evidence of indirect effects or of heterogeneity, but this may reflect the limited variation in the variables we use to assess these possibilities.

Manufacturers may respond to the efficiency of competing models (Fischer, 2010). Because consumers have heterogeneous preferences for efficiency and other vehicle attributes, the efficiency of competing models could have a positive or negative effect on a particular model’s efficiency (see Section 3.1). In column 2 of Table 8 we add to the baseline specification the mean efficiency of other vehicles in the same market segment and technology group, where we assign each manufacturer to one of three technology groups (Japanese, US, and other). The efficiency variable may be endogenous because of reverse causality and perhaps other reasons, and we instrument for it using the mean potential market size of the corresponding vehicles. Column 2 provides some evidence that efficiency of competing models has a positive effect on technology adoption; in column 2 the coefficient on competing vehicle efficiency is positive, but the estimate is noisy.

Above we considered the possibility that the market size effect occurs at the brand rather than model level. A related possibility is that the efficiency of other models sold under the same brand affects a model’s efficiency. This could occur because of demand effects, rather than the supply-side effects that were considered earlier. We add to column 3 the mean power train efficiencies of other models sold under the same brand in the same market segment, and we use mean potential market size of the corresponding models as an instrument. Brand-level efficiency has a small and negative effect on efficiency, but the estimate is noisy.

Next, we consider the effect of the knowledge stock on technology adoption. To improve efficiency, manufacturers could adopt technologies that are already widely used in the market—either in their own vehicles or in those of competing manufacturers. Alternatively, they could innovate and adopt new technology. We construct a proxy for the effect of innovation and adoption of new technology by adding to equation (2) an estimate of a manufacturer’s knowledge stock based on its historical patents. The variable is the cumulative number of fuel-saving patents for which a parent company has applied. The variable, which is sometimes referred to as the knowledge stock, is the sum of the depreciated patent stock from the previous period and the flow of patents in the current period (see Zhou (2016) for details

on variable construction). Column 4 controls for knowledge stock between 1997 and 2010 and shows that knowledge stock has a positive effect on efficiency, but the estimate is not statistically significant.<sup>7</sup>

We have focused on the role of market size and fuel cost–driven willingness to pay for technology that raises fuel economy. Consumer demand for other vehicle attributes, such as horsepower, may also affect the adoption of fuel-saving technology. If the IV strategy is valid, such omitted factors would not yield biased or spurious estimates of the market size effect. To demonstrate this point and to consider the role of other factors driving technology adoption, we add to the main regression the vehicle’s price as a proxy for consumers’ overall willingness to pay for the vehicle. Column 5 shows that adding the vehicle price does not affect the estimate of log sales, supporting the validity of the IV strategy. The price coefficient is positive, which suggests that vehicle demand affects technology adoption, but this coefficient is likely to be biased because of correlation with unobserved vehicle attributes.

Finally, we consider the possibility of heterogeneous effects of market size. In section 4.3 we considered heterogeneous effects for new and continuing vehicle models and found that lag sales have a similar effect on efficiency as contemporaneous sales. In addition, we also consider possible heterogeneous effects across market segments or firms. In column 6, we interact market size with a dummy variable for light trucks, and we instrument for this variable with the interaction between the potential market size and the light truck dummy. The point estimate of the market size effect is barely affected although it is not precisely estimated, and we cannot reject the hypothesis that market size affects technology adoption by the same amount for cars and light trucks. Note that the light truck estimate suggests a weaker effect of sales on efficiency for cars than light trucks.

In column 7, we interact market size with a dummy variable equal to one for US-based manufacturers. As in the light truck exercise we do not find strong evidence of heterogeneous effects, although the limited variation of the market size variable prevents strong conclusions regarding heterogeneity.<sup>8</sup>

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<sup>7</sup>The patent stock variable ends at 2010. OECD Triadic Patent Family (TPF) data are available up to 2015. However, it is common practice to omit the last four to five years of TPF data because of reporting lags from the US Patent and Trademark Office.

<sup>8</sup>We have also allowed for heterogeneity across market segments or across other types of manufacturers, yielding similar conclusions.

## 5 Implications

This section discusses the economic and policy implications of the main estimates from Section 4. We quantify the economic implications by illustrating the effect of past variation in fuel prices on efficiency, the effect of changes in demographics on efficiency, and the effect of sales of crossovers and SUVs on efficiency. We discuss policy implications by comparing fuel price-based policies with vehicle-based policies, and the differing effects of these policies on fuel costs and market size. The analysis is based on counterfactuals derived from past changes in market conditions to ensure that the variation used in the simulations is consistent with the variation used to identify the sales and fuel cost coefficients.

### 5.1 Effects of Gasoline Prices on Efficiency

In Section 4 we quantified the economic significance of the sales and fuel cost coefficients by comparing the effect of a one standard deviation change in the independent variables. To further illustrate the economic importance of these estimates, we compare efficiency levels across scenarios of low and high gasoline prices.

Between 2003 and 2007 the real price of gasoline increased almost 80 percent. [Klier and Linn \(2010\)](#) show that this price change increased sales of vehicles with high fuel economy at the expense of sales of vehicles with low fuel economy. The shifts in market shares increased sales-weighted average fuel economy by about 1.1 mpg. Therefore, the gasoline price increase affected both fuel costs and market size.

We isolate these two channels, first considering market size. We assign each model in the data to one of five fuel economy quintiles, based on each model's fuel economy in the first year it appears in the data (for consistency with the empirical estimates). The first quintile consists of vehicles with the lowest-fuel-economy, and the fifth quintile consists of vehicles with the highest-fuel-economy. To maintain consistency with equation (2), which includes year fixed effects that control for the market-wide average efficiency increase, we hold fixed the market-wide average efficiency change across the scenarios. In the simulations, fuel prices affect the cross-sectional distribution of sales, which in turn affects the cross-sectional distribution of efficiency. We use equations (2) and (4) to generate the counterfactual efficiency each year from 2003 to 2007. Because gasoline prices are lower in the counterfactual scenario, we expect counterfactual efficiency to be higher than predicted efficiency for the first quintile, which consists of the lowest-fuel-economy vehicles. To isolate the market size effect, we adjust fuel prices for the first stage equation (4) but not the second stage equation (2).

In Panel A of Figure 6 the colored bars show the average predicted efficiency increase for each quintile using the actual fuel prices between 2003 and 2007 and the baseline estimates of equation (2). The clear bars show the average predicted efficiency increase assuming fuel prices had remained at 2003 levels. Comparing the predicted and counterfactual cumulative efficiency improvements across quintiles, we observe that if fuel prices had remained at 2003 levels, efficiency would have improved by 0.51 percent more for the lowest-fuel-economy quintile and by 0.47 percent less for the highest-fuel-economy quintile. These effects are consistent with expectation and they are large relative to the predicted cumulative 6.4 percent efficiency of improvement that actually occurred between 2003 and 2007. Thus, via the market size effect the increase in gasoline prices caused manufacturers to improve the efficiency of vehicles with high fuel economy.

In Panel B of Figure 6 we isolate the direct effect of fuel costs on efficiency. For this counterfactual we hold market size fixed. We use the fuel cost coefficient in the second stage and gasoline price change to predict the cumulative efficiency change for each model.

A gasoline price increase raises fuel costs for all vehicles, but by more for vehicles with low fuel economy. Considering a fuel-saving technology that raises efficiency proportionately for all vehicles in the market, the price increase raises the willingness to pay for the technology more for vehicles with low fuel economy than for other vehicles. Therefore, efficiency should increase more for vehicles with low fuel economy because of the fuel cost effect, and we expect the fuel cost effect to work in the opposite direction as the market size effect. Panel B shows this to be the case. Comparing the two simulations suggests that the fuel cost effect is larger in magnitude than the market size effect. Therefore, accounting for both effects implies that an increase in gasoline prices causes greater efficiency improvements for vehicles with low fuel economy.

## 5.2 Effects of Demographics on Efficiency

Next we analyze how demographics affect market size and the cross-sectional distribution of efficiency. As a counterfactual scenario, we suppose that all demographics remain unchanged at 1980 levels. The counterfactual reflects the changes in income, age, and other demographics over the 33 years between 1980 and 2013. In Figure 7, we compare predicted changes in efficiency using actual demographic changes in the colored bars with counterfactual efficiency changes that would have occurred if demographics had remained fixed at 1980 levels in the clear bars.

Similarly to the fuel price exercise, we use equations (2) and (4) to predict counterfactual efficiency improvements each year from 1997 through 2013, again assuming that annual market-wide average efficiency improvements are unchanged from their observed levels.<sup>9</sup> Panel A of Figure 7 compares the predicted and counterfactual cumulative efficiency improvements from 1997 through 2013. The figure shows that if demographics had remained constant at 1980 levels, small cars would have been 0.4 percent less efficient, medium cars would have been 0.3 percent less efficient, crossovers would have been 0.4 percent more efficient, and pickup trucks would have been 1.4 percent more efficient; other segments are less affected. For context, the overall change between 1997 and 2013 was 22.7 percent. Thus, demographics explain some of the cross-sectional variation in efficiency changes over the sample period via the market size channel.

The sample period includes substantial changes in age and income (see Figure 3). Panel B of Figure 7 isolates the effects of age and income on efficiency by comparing the predicted and counterfactual cumulative efficiency improvements, if only age and income had remained constant at 1980 levels. We construct counterfactual weight  $w_{g,t}^{age1980,inc1980}$  for each demographic cell holding age and income at 1980, and we construct counterfactual predicted sales using the counterfactual weight of these cells.<sup>10</sup> If age and income remained at 1980 levels, the most expensive vehicles would have been 0.69 percent more efficient, and the least expensive vehicles would have been 0.68 percent less efficient. The effects are noticeable relative to the overall efficiency improvements during the sample period but are small overall.

### 5.3 Effects of Crossover and SUV Market Size on Efficiency

Figure 1 shows the large shifts in sales for crossovers and SUVs that occurred in the early 2000s. Those shifts reflect segment-level sales changes, and underlying model-level sales changed in the same directions. Between 2001 and 2004, the average sales per crossover model increased by 44 percent and average sales per model of SUVs decreased by 25 percent (in contrast, the number of SUV models increased during this period). The empirical results suggest that these changes in market size increased efficiency for crossovers and decreased

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<sup>9</sup>We compute the weight of each demographic cell (i.e., six demographic groups) in 1980  $w_{g,1980}$ , and compute counterfactual predicted sales using equation (3).

<sup>10</sup>We assume that changes in the age and income distributions are independent of changes in other demographics. We compute weights by age and income in 1980,  $w_{(age, income), 1980}$ , and weights by age and income group each year,  $w_{(age, income), t}$ . We compute the weight for each demographic cell (i.e., six demographic groups),  $w_{g,t}$ . The counterfactual weight,  $w_{g,t}^{age1980,inc1980} = w_{g,t} \times \frac{w_{(age, income), 1980}}{w_{(age, income), t}}$ , represents the weight holding only income and age fixed but allowing other demographics to vary over time. We compute counterfactual predicted sales using equation (3).

efficiency for SUVs, relative to a counterfactual in which market size had remained at 2001 levels.

To quantify these effects, we estimate the cumulative efficiency changes between 2001 and 2004 that would have occurred if market size had not changed over this period.<sup>11</sup> On the left side of Figure 8 we compare the predicted and counterfactual efficiency of crossovers. The colored bar shows the predicted cumulative efficiency improvement over 2001–2004. The clear bar shows the counterfactual cumulative efficiency change holding market size of crossovers fixed at 2001 levels. In the counterfactual scenario, the lower market size of crossovers causes efficiency to be 0.09 percent lower.

As shown in the right panel of Figure 8, the counterfactual scenario causes efficiency of SUVs to be 0.17 percent higher than is predicted using the actual market size in 2004. This is substantial compared to the 2.9 percent cumulative change between 2001 and 2004 for SUVs. In short, comparing the simulations for fuel prices, demographics, crossovers, and SUVs, we observe that market size and fuel prices have had economically significant effects on the adoption of fuel-saving technology.

## 5.4 Effects of Taxes, Feebates, and Fuel Economy Standards on the Efficiency Distribution

Next, we turn to the policy implications of the estimated sales and fuel cost coefficients in equation (2). As noted in the introduction, the positive market size effect implies that manufacturers will continue to improve the efficiency of gasoline-powered vehicles, which currently dominate the market. The market size effect increases the challenge of alternative-fuel vehicles, such as plug-in electrics, to compete with gasoline-powered vehicles and reduces the effectiveness of policies that directly subsidize alternative-fuel vehicles, relative to a hypothetical in which there were no market size effect.

The second policy implication concerns the effects of fuel price and vehicle-based policies aiming to reduce passenger vehicle fuel consumption and greenhouse gas emissions. The discussion of fuel price-based policies includes fuel taxes or a carbon tax imposed on fuels, and the discussion of vehicle-based policies includes fuel economy standards, greenhouse gas emissions rate standards, and feebates.

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<sup>11</sup>Because we are interested in the effect of market size on crossover and SUV efficiency, our counterfactual represents a partial equilibrium outcome in which the market size of crossovers and SUVs does not affect total vehicle sales or total cumulative efficiency across the market. That is, total vehicle sales and average cumulative efficiency across all segments are identical in the predicted and counterfactual scenarios.

A feebate, fuel economy standard, or emissions standard can be designed to have identical effects on the new vehicles market, absent additional policies that interact with these policies (Roth, 2015). If the standard applies to the sales-weighted (harmonic) mean fuel economy of a manufacturer’s vehicles, as with the US standards and those in other regions, one compliance strategy available to manufacturers is to reduce the prices of vehicles with high fuel economy relative to vehicles with low fuel economy (Goldberg, 1995). The relative vehicle price change induces consumers to substitute from vehicles with low fuel economy to vehicles with high fuel economy. Consequently, standards cause the sales of low fuel economy vehicles to decrease relative to sales of high fuel economy vehicles. The sales shift raises the manufacturer’s sales-weighted average fuel economy, helping the manufacturer achieve the standard. The sales shift also creates a market size effect on technology adoption, which arises from the changes in vehicle prices.

A feebate refers to a combination of taxes and rebates: taxes on vehicles with low fuel economy and rebates on vehicles with high fuel economy. The taxes and rebates therefore mimic the pricing behavior of manufacturers facing fuel economy standards. A feebate affects market size via purchase prices and not fuel prices and therefore creates the same market size effect as an equivalent standard.

Fuel price-based policies differ from vehicle-based policies in their effects on technology adoption. The literature has focused on differences between these two classes of policies that arise because of differences in driving incentives (i.e., the rebound effect) and the fact that standards or an equivalent feebate cover only new and not existing vehicles, which introduces the inefficiencies associated with vintage differentiated regulation (Stavins (2006) and Jacobsen and van Benthem (2015)). In this paper we identify a further distinction between the two classes of policies. We compare the effects of the marginal effects of these policies on technology adoption holding each vehicle’s fuel economy fixed; this corresponds to a short-run analysis. In this setting, all policies induce the market size effect. Fuel taxes or a carbon tax differ from fuel economy standards or a feebate in that they also affect efficiency directly via fuel costs.

We conduct two simulations to illustrate this difference. In the following analysis we focus on a feebate and fuel tax as representative of vehicle- and fuel-based policies. Rather than consider the effects of feebates and fuel taxes on efficiency improvements for different fuel economy groups, as we did before, we further illustrate the implications of the market size and fuel cost effects by focusing on the policies’ effects on the variation of efficiency across vehicles in the market. In principle, these policies could widen or narrow the distribution of efficiencies of vehicles in the market. If, in the absence of any policy, fuel economy is

positively correlated with efficiency, the policies would widen the distribution because of the market size effect. This is because the market size of vehicles with high fuel economy would increase, raising their efficiency, and the market size of vehicles with low fuel economy would decrease, reducing their efficiency. Both changes would strengthen the positive correlation between fuel economy and efficiency. If, on the other hand, fuel economy is negatively correlated with efficiency, the policies would narrow the efficiency distribution. In practice, the correlation is positive, 0.29, in which case we expect the policies to increase the variance of efficiency across vehicles in the market due to the market size effect. The widening of the distribution would be greater for vehicle-based than fuel-based policies because the latter also include the fuel cost effect, which works in the opposite direction as the market size effect, as explained in section 5.1.

In the first simulation we implement the feebate as a price on fuel economy. A feebate is defined by a pivot, which is the fuel economy level above which vehicles receive a subsidy and below which vehicles are taxed. We set the pivot equal to the sales-weighted mean fuel economy in year  $t$ ,  $e_t$ . For comparability with the fuel price counterfactual in Figure 6, the rate of taxation is chosen such that the sales-weighted average fuel economy increases by 1.1 mpg, which is the same fuel economy change as that which occurred in the counterfactual scenario considered in Figure 6. We calibrate the feebate so that a model with fuel economy  $e_{jt}$  has a feebate of  $(1/e_{jt} - 1/e_t) \times 1.1$ . The counterfactual scenario includes a feebate for the years 2010–2013, and market conditions (e.g., fuel prices) are otherwise unchanged. We compute the predicted and counterfactual efficiency of each model in the sample for the years 2010 through 2013 and compute the cumulative predicted and counterfactual efficiencies for each model. The feebate is implemented over four years for comparability with the gasoline price scenario in section 5.1. Because of the feebate’s effect on market size, we expect the feebate to increase the variance of efficiency across vehicles in the market.

Panel A of Figure 9 presents a scatter plot of efficiency and fuel economy for each model in the sample. The solid dots represent the predicted cumulative efficiencies of models sold in 2013, and the black circles are counterfactual cumulative efficiencies. Because the feebate reduces the market size of vehicles with fuel economy below the pivot, the counterfactual efficiency lies below the predicted efficiency for models with fuel economy below the pivot. For these vehicles the cumulative efficiency from 2010 to 2013 would have been smaller had the feebate been in place. In contrast, the feebate increases the market size of vehicles with fuel economy above the pivot and causes counterfactual efficiency to lie above predicted efficiency for such vehicles. The lines in Panel A represent the fitted values of a linear regression of cumulative efficiency on fuel economy, which is estimated separately for the predicted and

counterfactual data points. The counterfactual line is steeper than the predicted line, which indicates that the feebate strengthens the positive relationship between efficiency and fuel economy. Figure A.2 provides an alternative view of the effect of the policy by showing this effect by illustrating the widening of the efficiency distribution caused by the feebate.

To compare with the feebate we consider a fuel tax of \$1.14 per gallon, which increases the sales-weighted average fuel economy by the same 1.1 miles per gallon. The fuel tax affects both fuel costs and market size. Panel B of Figure 9 shows that because these two effects oppose one another, the fuel tax does not strengthen the positive relationship between efficiency and fuel economy nearly as much as does the feebate.

Previous welfare analysis of these policies has not considered their effects on market size and technology adoption, which have several implications for both the cost-effectiveness of the policies and their distributional effects. First, the feebate introduces a shadow cost of fuel economy, inducing manufacturers to increase the fuel economy of all vehicles. Our analysis illustrates an unintended consequence of the feebate, which is that because of the feebate's effect on market size, the feebate causes manufacturers to lower the efficiency increase of their vehicles with fuel economy below the pivot. The market size effect lies behind this unintended effect, which could undermine the effectiveness of feebates at reducing fuel consumption.<sup>12</sup> This market size effect would also have the unintended consequence of exacerbating the challenge faced by alternative-fuel vehicles to compete with existing technologies. Panel B of Figure 9 shows that a fuel price-based policy, by contrast, causes less widening of the efficiency distribution because the fuel cost effect works in the opposite direction as the market size effect. Although estimating the welfare consequences of these efficiency improvements lies outside the scope of this paper, the scenario considered here illustrates the effects of these policies on the distribution of efficiency across vehicles in the market.

## 6 Conclusion

Current US fuel economy standards will dramatically increase the average fuel economy of new vehicles over at least the next decade. Despite the magnitude of this fuel economy change and the importance of technology adoption for meeting the standards, there is little empirical evidence on which factors determine a manufacturer's adoption of fuel-saving technology. This paper analyzes the effects of market size, as approximated by a vehicle's sales, and fuel costs on the adoption of efficiency-improving technology in the US new passenger vehicle

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<sup>12</sup>Although our analysis suggests that the market size effect undermines the effectiveness of fuel consumption policies, the market size effect does not necessarily undermine the economic efficiency of these policies. It may be economically efficient for the efficiency of the most efficient vehicles to improve the most.

market. We show that market size and fuel costs have substantial effects on technology adoption and discuss implications for fuel consumption policies.

The empirical analysis uses a unique data set that combines vehicle characteristics and sales with vehicle purchasing patterns by demographic group from 1997 to 2013. We address the endogeneity of market size by instrumenting for vehicle sales using potential market size as a demand shifter. Variation in potential market size arises from changes in demographics over time and cross-sectional heterogeneity in purchasing patterns across demographic groups. In the preferred specification a 10 percent increase in sales (corresponding to about one standard deviation) increases efficiency by 0.2 percent, compared with a mean annual efficiency improvement of about 1.4 percent in the sample. Fuel costs affect efficiency via market size and also independently of market size. [Acemoglu et al. \(2016\)](#) find that high fuel prices increase patents on alternative-fuel technologies, and our findings suggest that the adoption of fuel-saving technologies may respond directly to fuel costs or indirectly via market size.

We quantify the economic importance of the market size and fuel cost effects on efficiency. First, historical variation in fuel prices has had a substantial effect on the adoption of fuel-saving technology. Real fuel prices nearly doubled between 2003 and 2007, which affected the relative market size of vehicles according to their fuel economy. Had gasoline prices remained at 2003 levels, the efficiency of vehicles in the lowest-fuel-economy group would have increased 0.5 percent more between 2003 and 2007 than it did. Efficiency of the vehicles in the highest-fuel-economy group would have increased by 0.4 percent less than it did. The direct effect of fuel costs on technology adoption worked in the opposite direction, more than offsetting the market size effect.

Second, demographics have had a large effect on vehicle efficiency. Shifts in demographics increased efficiency of cars relative to light trucks. Third, shifts in market size of crossovers and SUVs have caused large changes in the efficiency of these vehicles. These three results imply that market size and fuel costs have had economically significant effects on technology adoption.

Finally, we discuss two policy implications of the empirical findings. First, the market size effect implies that manufacturers in the US market will continue to improve the efficiency of their best-selling gasoline-powered vehicles. This pattern of technology adoption decreases the competitiveness of alternative-fuel vehicles and decreases the effectiveness of policies promoting such vehicles, relative to an absence of a market size effect.

Second, we show that the policies commonly discussed for reducing vehicle fuel consumption and carbon dioxide emissions have differing effects on the efficiency distribution of vehicles in the market. Because of the market size effect, feebates, a fuel economy standard, or an emissions rate standard would widen the distribution, further harming the competitiveness of plug-in electric vehicles and other alternative-fuel vehicles. Fuel or carbon taxes do not have this effect because they induce a fuel cost effect that opposes the market size effect. The existing literature on the welfare effects of these policies has not considered this effect, and future research could incorporate it. Accounting for the effects of market size and fuel costs on technology adoption would affect the welfare and distributional consequences of these policies, as well as the demand for alternative-fuel vehicles.

The simulations in this paper hold fixed the set of vehicles in the market, but entry and exit of new vehicles may be an additional channel by which market size and fuel costs affect technology adoption. Future work could endogenize entry and exit decisions.

The empirical analysis does not identify the underlying reasons why market size affects efficiency. As we discuss in Section 3.1, a range of factors could explain a positive relationship between market size and technology adoption. Future work may distinguish among these possibilities, which would have implications for the welfare effects of fuel consumption policies.

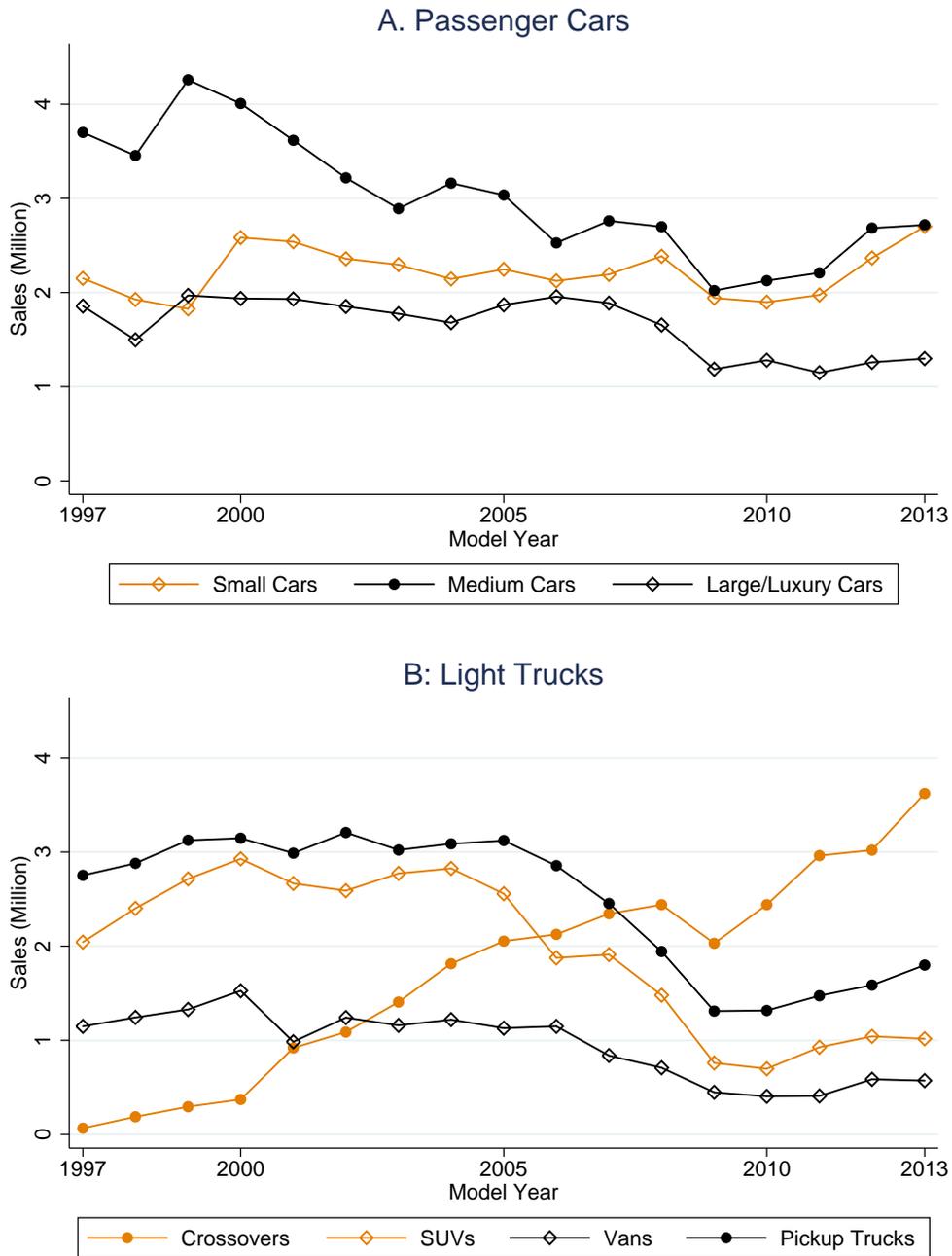
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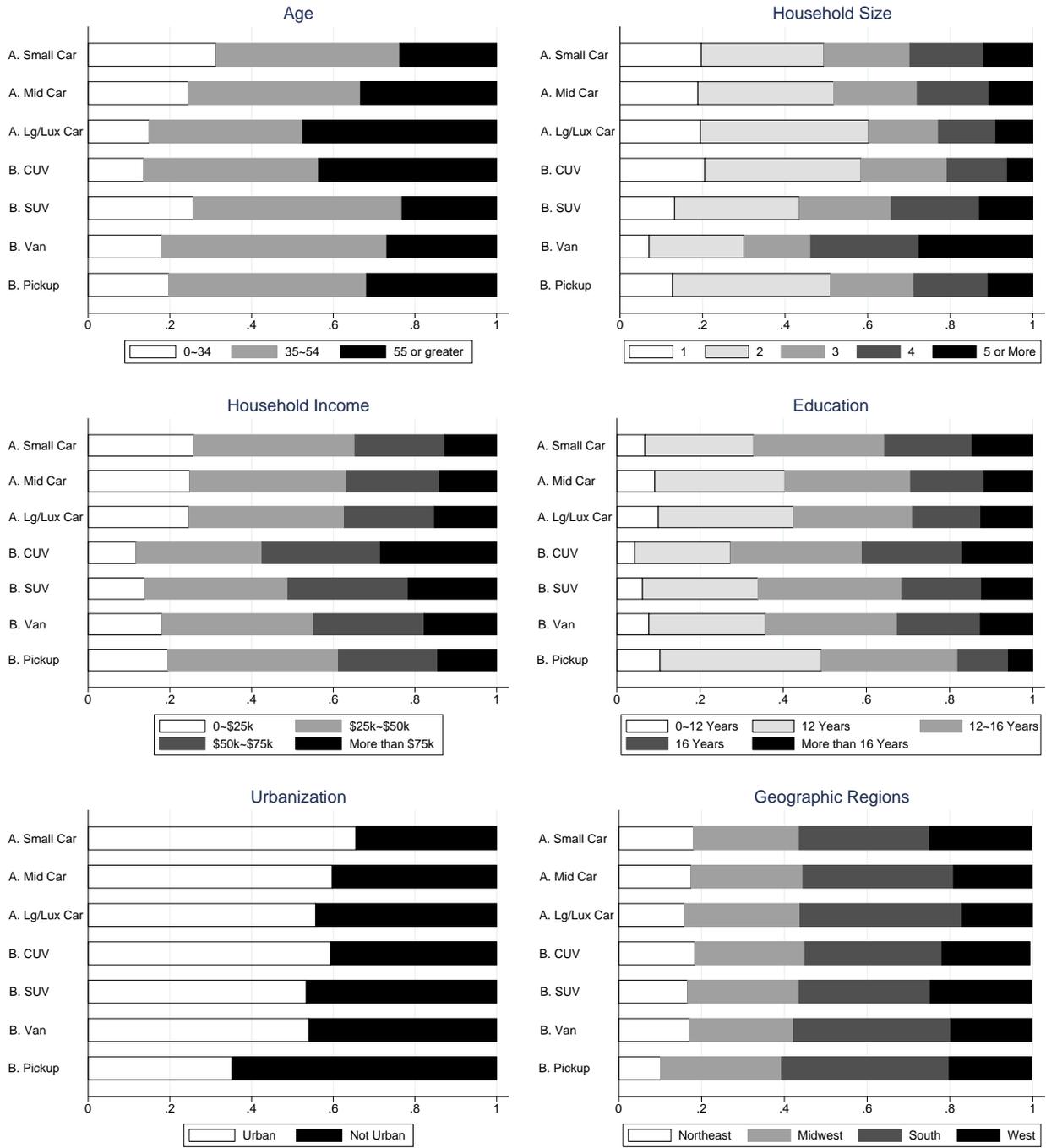
# Figures

Figure 1: Total Vehicle Sales by Segment, 1997–2013



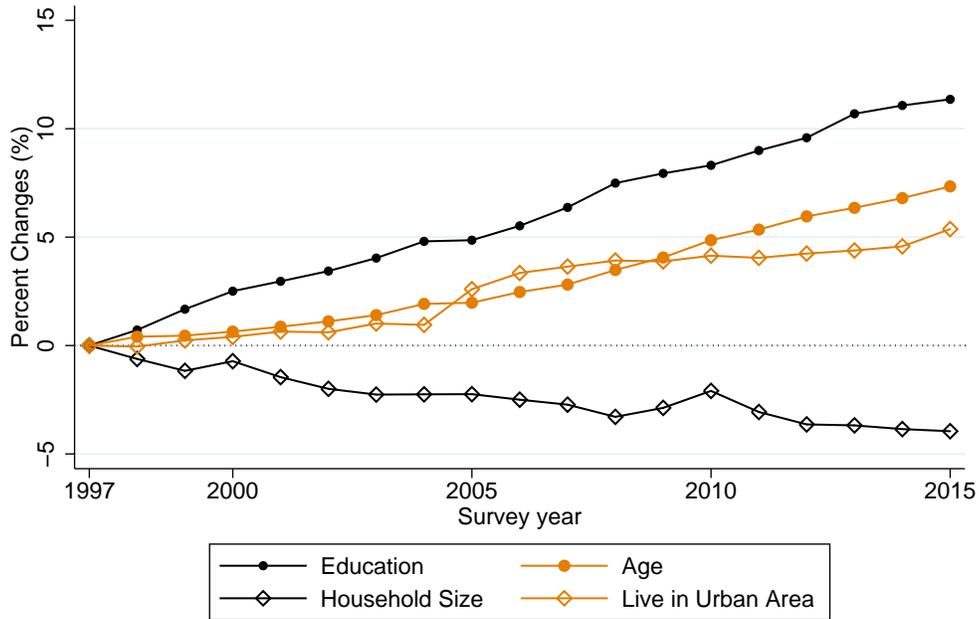
Notes: For each market segment, the figure plots the total model year sales.

Figure 2: Vehicle Purchase Patterns by Demographic Group



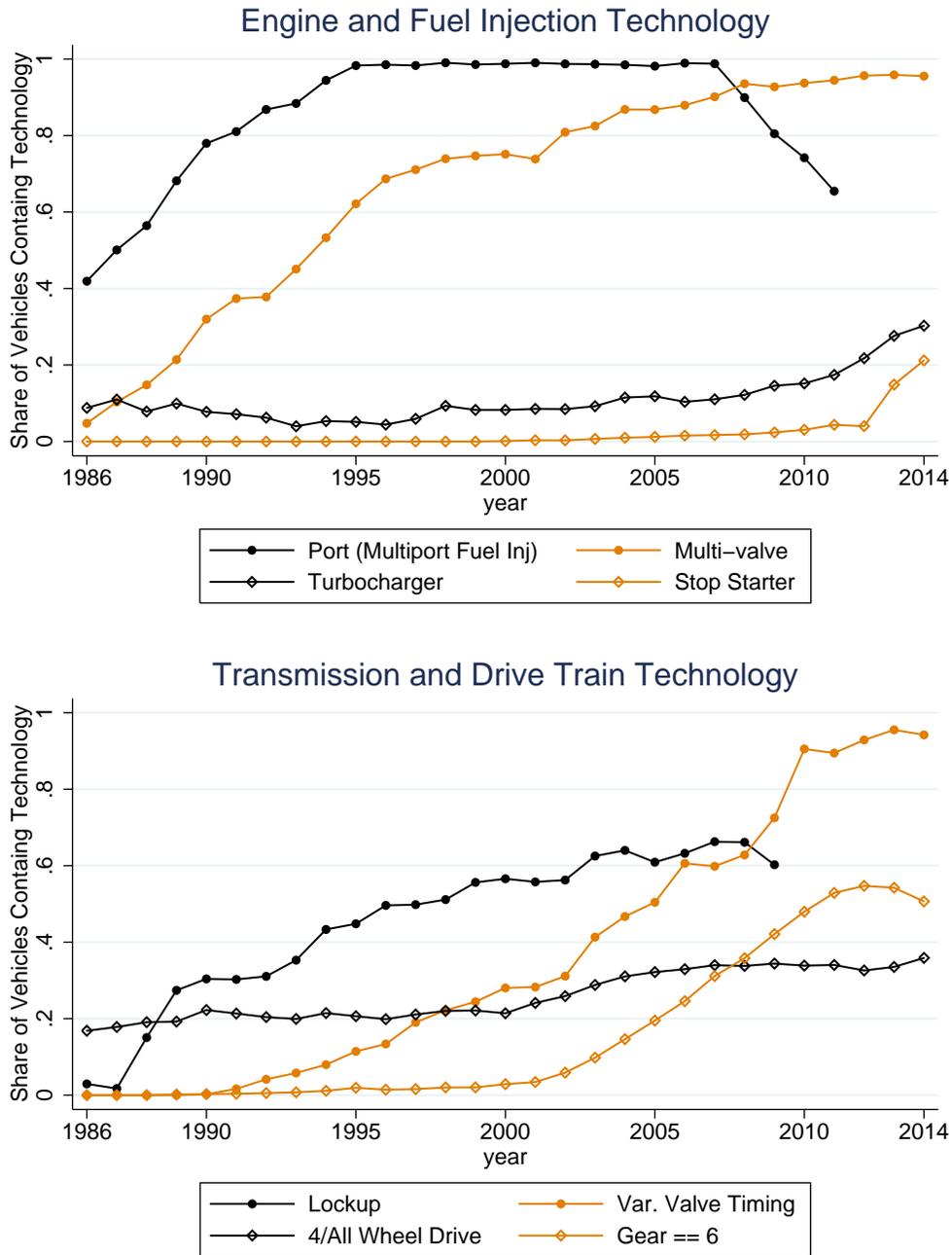
Notes: The figure is constructed using the NHTS data from the 1995, 2001, and 2009 survey waves. Each panel illustrates purchasing patterns for the indicated demographic variable. For households purchasing vehicles in a particular market segment, we compute the share of those households belonging to each category of the demographic variable, using the NHTS household survey weights. For example, among the households that purchase small cars, 64% of them live in urban areas.

Figure 3: Changes in Demographics, 1997–2015



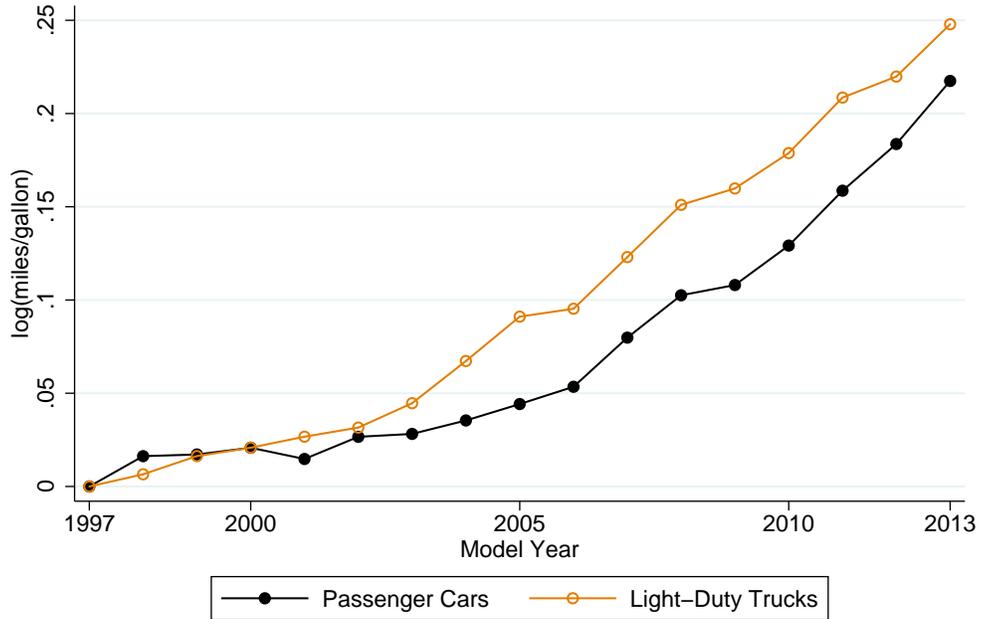
Notes: Using household survey weights from the CPS, we compute the weighted average of each demographic variable by year. The figure plots the percentage change since 1997 of each variable.

Figure 4: Market Penetration of Selected Fuel-Saving Technologies, 1986–2014



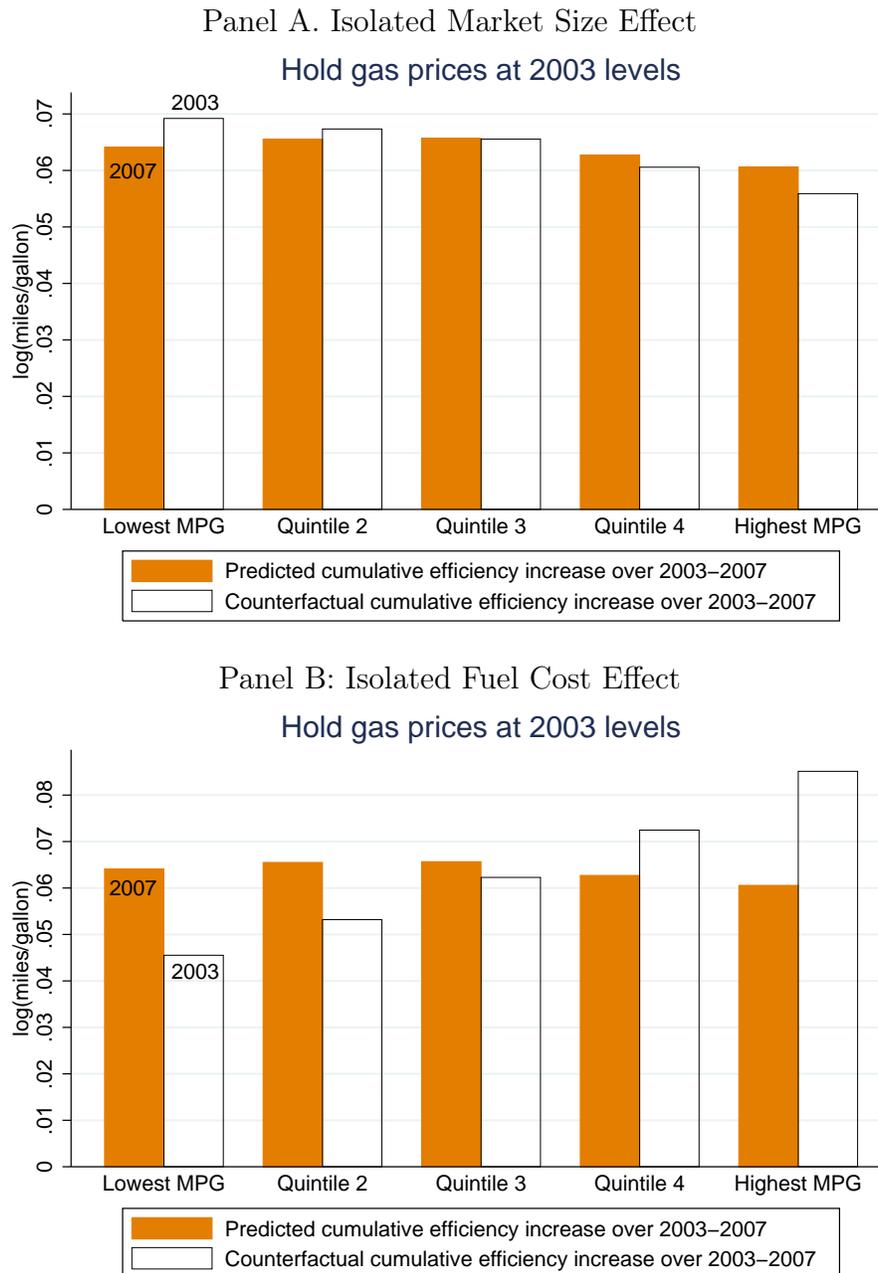
Notes: The figure is constructed from the EPA Fuel Economy Guide and EPA Fuel Economy Trends data. Technology penetration rates are the unweighted average across all vehicles in the corresponding model year.

Figure 5: Estimated Power Train Efficiency, 1997–2013



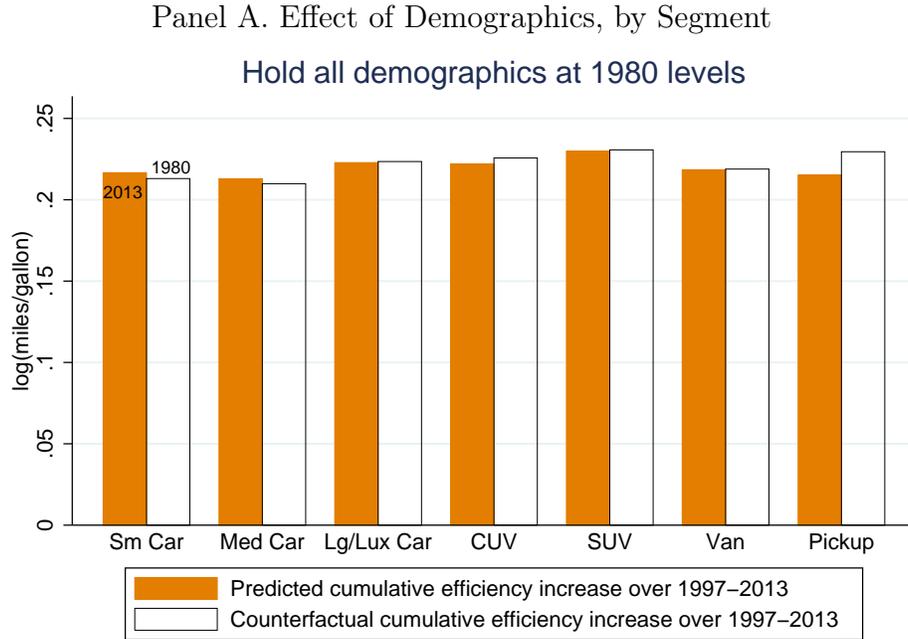
Notes: The figure plots the mean estimated efficiency across passenger cars and light trucks estimated from equation (1). To construct this figure, efficiency is normalized to zero for all observations in 1997.

Figure 6: Effect of 2003–2007 Gasoline Price Increase on Efficiency

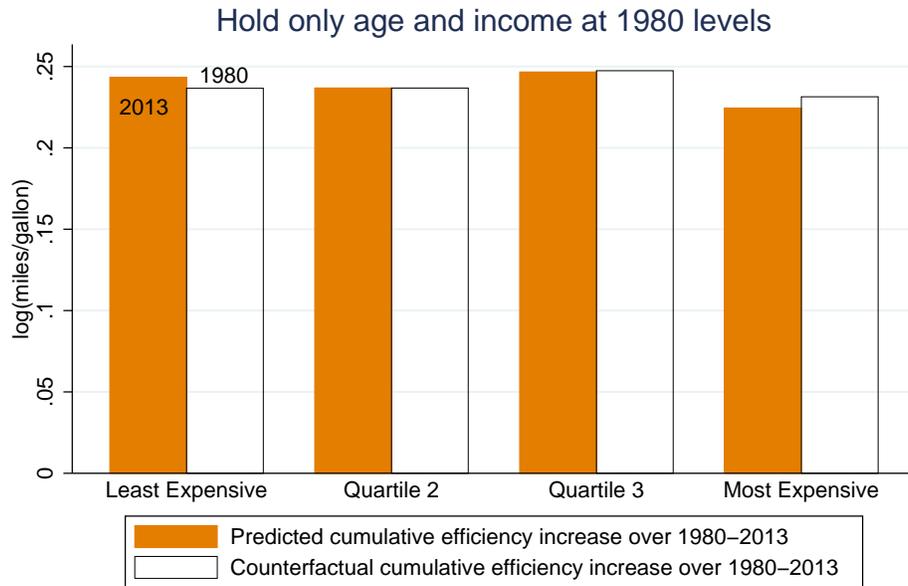


Notes: For each observation in equation (2), the frontier is predicted using the estimates reported in column 2 of Table 4. All observations are assigned to a fuel economy quintile based on the fuel economy distribution across observations between 2003 and 2007, using each vehicle model’s initial fuel economy when the model enters the market. The predicted frontier in each colored bar is the mean cumulative predicted efficiency change between 2003 and 2007 for each quintile. The clear bars show the cumulative counterfactual efficiency change by quintile. Counterfactual efficiency changes are computed by holding fixed fuel prices at 2003 levels and using equations (2) and (4) to predict the efficiency change for each observation between 2003 and 2007. Panel A simulates the isolated market size effect and Panel B simulates the isolated fuel cost effect.

Figure 7: Effect of Demographics on Efficiency, 1980–2013

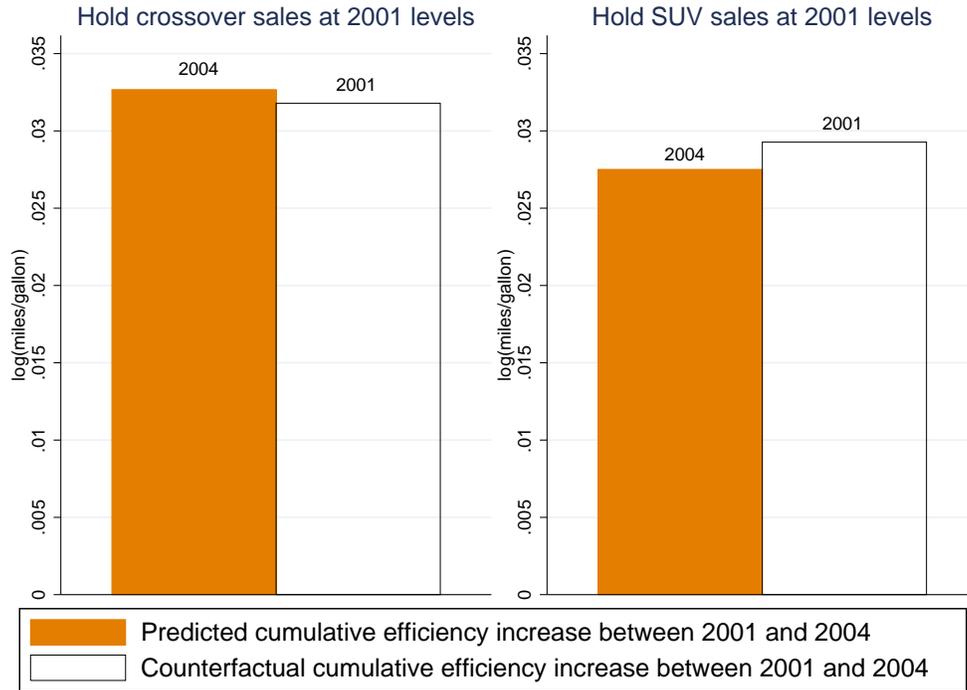


Panel B. Effect of Age and Income, by Vehicle Price Distribution



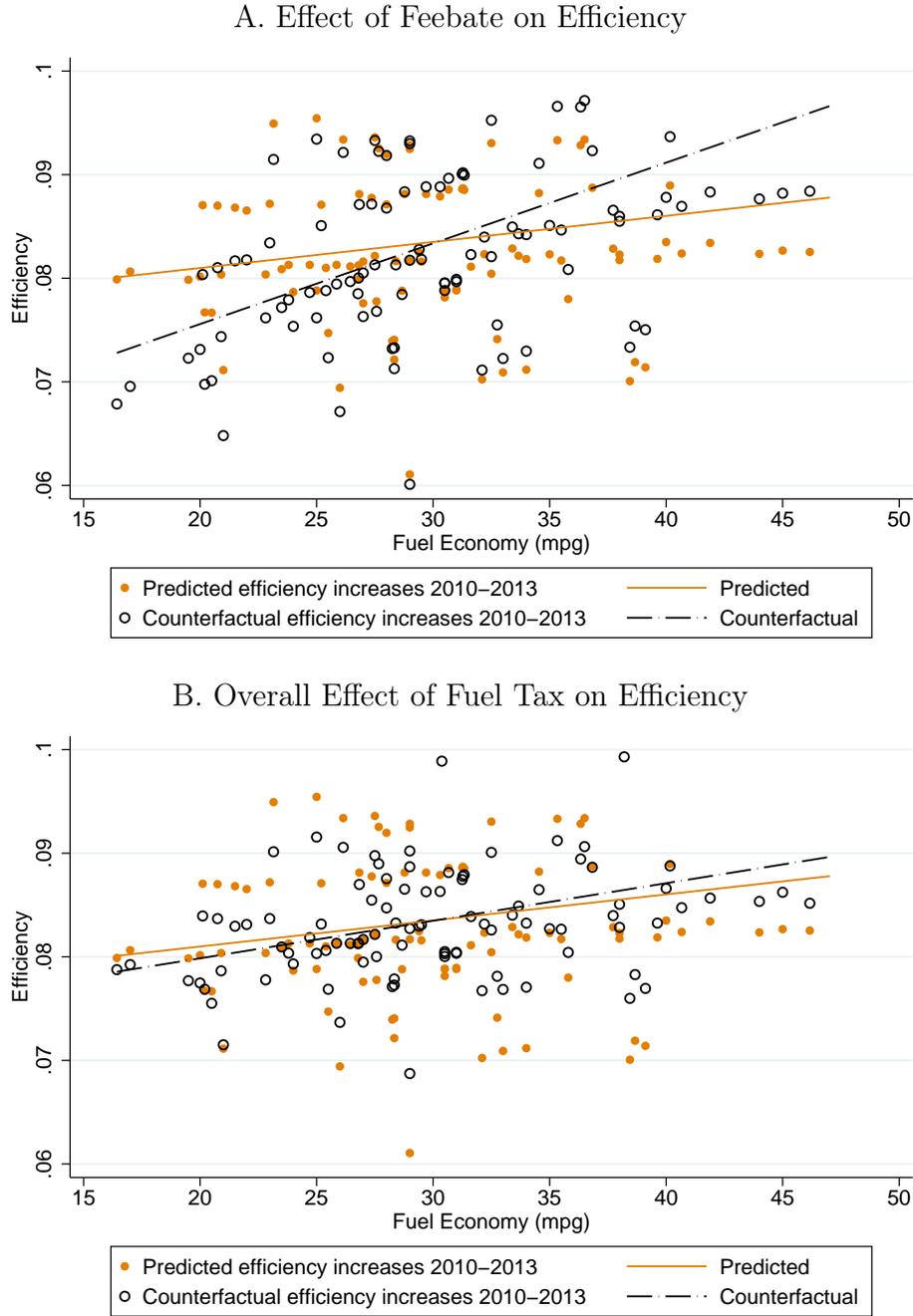
Notes: The colored bars show the mean cumulative predicted efficiency increase between 1997 and 2013, for each market segment. Predicted values are obtained from the estimation of equation (2) reported in column 2 of Table 4. The clear bars show the cumulative counterfactual efficiency change by market segment. In Panel A, the counterfactual holds fixed demographics at 1980 levels and uses equations (2) and (4) to predict the counterfactual efficiency change for each observation between 1997 and 2013. In Panel B, we construct predicted market size holding only age and income at 1980 levels.

Figure 8: **Effect of Sales on Efficiency, 2001–2004**



Notes: The colored bars show the mean cumulative predicted efficiency increase between 2001 and 2004 for crossovers (left panel) and SUVs (right panel). Predicted values are obtained from the estimation of equation (2) reported in column 2 of Table 4. The clear bars show the cumulative counterfactual efficiency changes for crossovers and SUVs. The counterfactual holds fixed crossover sales at 2001 levels and uses equation (2) to predict the counterfactual efficiency change for each crossover and SUV between 2001 and 2004.

Figure 9: Correlation of Fuel Economy and Efficiency



Notes: For each observation in equation (2), the frontier is predicted using the estimates reported in column 2 of Table 4. Panel A is a scatter plot of efficiency and fuel economy for each model in 2013. The solid dots represent cumulative predicted efficiency and the circles represent cumulative counterfactual efficiency. The two lines are the linear prediction of efficiency on fuel economy. The counterfactual efficiency of each vehicle is computed from the market size caused by introducing a feebate of  $(1/e_{jt} - 1/e_t) \times 1.1$  \$/gal, where  $e_{jt}$  is the fuel economy of model  $j$  in model year  $t$  and  $e_t$  is the harmonic mean of fuel economy in model year  $t$ . In Panel B, the counterfactual efficiency of each vehicle is computed from both its direct effect and its effect from the market size, caused by introducing a fuel tax at 1.14 \$/gal.

# Tables

Table 1: **Average Vehicle Characteristics, 1997–2013**

Model year	Fuel economy (miles per gallon)	Horsepower	Torque (newton-meters)	Weight (pounds)	Number of cylinders
1997	25.4	184	301	3607	6.0
2000	24.8	201	317	3746	6.2
2005	24.7	233	345	4035	6.3
2010	26.0	263	369	4223	6.2
2013	28.3	278	381	4234	6.1

Note: The table reports the sales-weighted average of fuel economy (in miles per gallon), horsepower, torque (maximum torque in newton-meters), weight (in pounds), and number of cylinders for the indicated years.

Table 2: **Estimated Trade-offs Between Fuel Economy and Other Characteristics**

Dependent variable: Log fuel economy	Passenger cars	Light-duty trucks
Log horsepower	-0.224*** (0.014)	- -
Log torque	- -	-0.157*** (0.016)
Log weight	-0.317*** (0.037)	-0.424*** (0.034)
Diesel	0.336*** (0.017)	0.260*** (0.015)
Manual transmission	0.008 (0.004)	-0.004 (0.004)
Flex fuel	- -	-0.272*** (0.012)
Observations	8676	15836
R-squared	0.95	0.93

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01.

Notes: The table reports coefficient estimates from equation (1), with standard errors in parentheses, clustered by model and model year. Observations are by model year and model version. The sample in column 1 includes passenger cars and the sample in column 2 includes light-duty trucks. In addition to the reported coefficients, the regressions include model by model year interactions, fixed effects for the number of cylinders, and fixed effects for the number of doors, similarly to [Klier and Linn \(2016\)](#).

Table 3: **Estimated Efficiency for High- and Low-Selling Vehicles**

Time period	High-Selling Vehicles			Low-Selling Vehicles		
	Efficiency in		Cumulative	Efficiency in		Cumulative
	starting year	ending year	change by period	starting year	ending year	change by period
1997–2000	0	0.017	0.017	0	0.012	0.012
2001–2005	0.019	0.070	0.051	0.006	0.057	0.051
2006–2009	0.068	0.140	0.072	0.078	0.135	0.057
2010–2013	0.156	0.239	0.083	0.161	0.234	0.074

Notes: Efficiency is estimated by model, market segment, and model year in equation (1), using the specification reported in Table 2. Models are assigned one of two categories depending on whether their sales are above the median sales in the initial year of the indicated time period. The table reports the mean estimated efficiency across the two groups and time periods in the first and last years of each period, as well as the cumulative change in mean efficiency over the time period.

Table 4: **Estimation Results: Effect of Market Size and Fuel Costs on Efficiency**

Estimated by	(1) OLS	(2) IV, Baseline	(3) IV
<b>Panel A.</b> Dependent variable: Efficiency			
Log sales	0.008*** (0.001)	0.021*** (0.004)	0.025*** (0.006)
Fuel costs	0.112 (0.101)	0.256*** (0.091)	
<b>Panel B.</b> First-stage estimate. Dependent variable: Log sales			
Potential market size (log)		0.138*** (0.029)	0.121*** (0.030)
Fuel costs		-20.543*** (1.776)	
If market size is imputed		-0.651*** (0.055)	-0.564*** (0.053)
Brand fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Brand fixed effects×linear time trend	Yes	Yes	Yes
Observations	2740	2740	2740
RMSE	0.06	0.06	0.06
F (1st stage excl. var.)	NA	83.69	46.69

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01.

Notes: The table reports coefficient estimates from equation (2), with bootstrapped standard errors in parentheses, clustered by brand (make). Observations are by model and model year. Column 1 is estimated by ordinary least squares (OLS). Columns 2 and 3 are estimated by instrumental variables, using potential market size and the imputation dummy as instruments according to equation (4). The bottom of the table reports the F statistics of a joint test of the significance of the excluded variables. All regressions include brand fixed effects, year fixed effects, and brand fixed effects interacted with a linear time trend.

Table 5: **Alternative NHTS Waves**

Estimated by	(1) Baseline, All NHTS	(2) 1995 NHTS	(3) 2009 NHTS
<b>Panel A.</b> Dependent variable: Efficiency			
Log sales	0.021*** (0.004)	0.020*** (0.004)	0.021*** (0.004)
Fuel costs	0.256*** (0.091)	0.269*** (0.086)	0.264** (0.127)
<b>Panel B.</b> First-stage estimate. Dependent variable: Log sales			
Potential market size (log)	0.138*** (0.029)	0.106*** (0.036)	0.072** (0.028)
Fuel costs	-20.543*** (1.776)	-18.445*** (1.787)	-18.422*** (1.716)
If market size is imputed	-0.651*** (0.055)	-0.749*** (0.057)	-0.552*** (0.054)
Brand fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Brand fixed effects×linear time trend	Yes	Yes	Yes
Observations	2740	2791	2736
RMSE	0.06	0.06	0.06
F (1st stage excl. var.)	83.69	84.27	61.77

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01.

Notes: The table reports coefficient estimates from equation (2), with bootstrapped standard errors in parentheses, clustered by brand. Column 1 repeats the baseline from Table 4, in which the potential market size is constructed using the 1995, 2001 and 2009 NHTS waves. In column 2, we construct the predicted market size using only the 1995 NHTS wave. In Column 3, we construct the potential market size using only the 2009 NHTS wave. The number of observations differs across the three columns because different models were purchased in each of the three NHTS waves.

Table 6: Potential Sources of Omitted Variable Bias

Dependent variable: Efficiency	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline						
Log sales	0.021*** (0.004)	0.021*** (0.004)	0.020*** (0.005)	0.019*** (0.004)	0.033*** (0.005)	0.021*** (0.004)	0.023*** (0.005)
Fuel costs	0.256*** (0.091)	0.314*** (0.100)	0.233** (0.105)	0.136 (0.103)	0.006 (0.121)	0.251*** (0.090)	0.479*** (0.127)
CAFE Stringency						0.027 (0.036)	0.074** (0.031)
Fuel costs×CAFE stringency							-2.878*** (0.796)
Brand fixed effects	Yes						
Year fixed effects	Yes						
Brand fixed effects×linear time trend	Yes						
Segment fixed effects		Yes	Yes				
Segment fixed effects×brand fixed effects		Yes					
Segment fixed effects×linear time trend			Yes				
Brand fixed effects×quadratic time trend				Yes			
Brand fixed effects×linear time trend×truck class					Yes		
Observations	2740	2740	2740	2740	2740	2740	2740
RMSE	0.06	0.05	0.06	0.06	0.06	0.06	0.06
F (1st stage excl. var.)	83.69	113.14	82.16	87.79	62.86	82.50	74.58

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01.

Notes: The table reports coefficient estimates from equation (2), with bootstrapped standard errors in parentheses, clustered by brand. Column 1 repeats the baseline from Table 4. Column 2 includes a set of segment fixed effects and their interaction with brand fixed effects. Column 3 includes a set of segment fixed effects interacted with a linear time trend. Column 4 includes brand fixed effects interacted with a quadratic time trend. Column 5 includes the triple interaction of brand fixed effects by light truck class by linear time trend. Column 6 includes the fuel economy stringency variable described in Klier and Linn (2016), and column 7 includes the interaction of this variable with fuel costs.

Table 7: **Alternative Methods for Estimating Efficiency and Market Size**

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Efficiency							
Efficiency estimated by:	Model by year (baseline)	Platform by year	Model by platform generation	Model by model generation	Model by year (3-yr moving average)	Lagged log sales	Brand by segment by year
Log sales	0.021*** (0.004)	0.023*** (0.005)	0.024** (0.009)	0.021*** (0.008)	0.025*** (0.005)	0.026*** (0.005)	0.019** (0.009)
Fuel costs	0.256*** (0.091)	0.567*** (0.166)	0.468** (0.221)	0.579** (0.244)	0.525*** (0.129)	0.352*** (0.123)	0.021 (0.100)
Brand fixed effects	Yes		Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand fixed effects ×linear time trend	Yes		Yes	Yes	Yes	Yes	Yes
Company fixed effects		Yes					
Company fixed effects ×linear time trend		Yes					
Observations	2740	1956	532	538	2096	2396	2600
RMSE	0.06	0.06	0.06	0.06	0.06	0.06	0.05
F (1st stage excl. var.)	83.69	65.90	16.49	20.73	50.10	65.97	22.57

\* p<0.10, \*\* p<0.05, \*\*\* p<0.01.

Notes: The table reports coefficient estimates with bootstrapped standard errors in parentheses, clustered by brand. Column 1 repeats the baseline from Table 4. In column 2 efficiency is estimated by platform and model year. In column 3 efficiency is estimated by model and platform generation. In column 4 efficiency is estimated by model generation and model year. In column 5 efficiency is estimated by model and model year, as in the baseline, but the dependent variable is the three-year moving average of efficiency. Column 6 includes the one-year lag of market size rather than contemporaneous market size, as well as lagged fuel cost, potential market size, and impute dummy. In all columns, the independent variables are aggregated to match the aggregation of the dependent variable. All regressions are estimated by instrumental variables using potential market size as an instrument, as in Table 4.

Table 8: **Additional Channels and Heterogeneity**

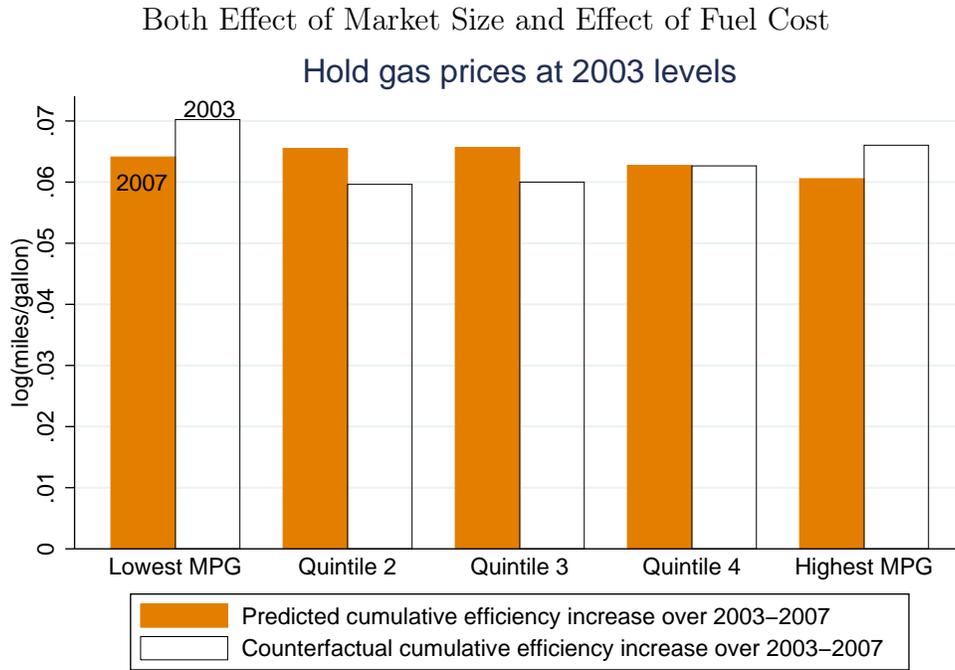
Dependent variable: Efficiency	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline					Truck	US firm
Log sales	0.021*** (0.004)	0.035** (0.014)	0.019** (0.007)	0.028** (0.011)	0.021*** (0.005)	0.030*** (0.007)	0.022** (0.009)
Fuel costs	0.256*** (0.091)	-0.105 (0.317)	0.204 (0.150)	-0.237 (0.150)	0.241** (0.102)	0.178 (0.138)	0.241* (0.128)
Efficiency of competing models		2.058 (1.654)					
Efficiency of models by the same brand and segment			-0.829 (1.734)				
Knowledge stock				0.003 (0.009)			
Log price					0.032*** (0.009)		
Log sales×truck						-0.038 (0.024)	
Log sales×US firm							-0.005 (0.028)
Brand fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand fixed effect× linear time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2740	2740	2740	2318	2740	2740	2740
RMSE	0.06	0.07	0.06	0.06	0.06	0.07	0.06
F (1st stg. excl. var.)	83.69	55.78	55.47	20.91	91.21	55.97	56.10

\* p<0.10 \*\* p<0.05 \*\*\* p<0.01.

Notes: The table reports coefficient estimates with bootstrapped standard errors in parentheses, clustered by brand. Column 1 repeats the baseline from Table 4. We assign each manufacturer to one of three technology groups: Japanese, US, and other. Column 2 includes the average efficiency by technology group as an independent variable. This variable is instrumented using the corresponding average potential market size of those models. Column 3 includes the average efficiency of other models sold under the same brand in the same market segment, using the average potential market size as an instrument. Column 4 includes the manufacturer’s knowledge stock, which is the cumulative number of fuel-saving patents that a parent company has applied for. Column 5 includes the log of the vehicle’s price as an independent variable. Columns 1–3 and 5–7 include observations from 1997 to 2013 and column 4 includes observations from 1997 to 2010. Column 6 includes a dummy for light truck, the interaction of market size with a dummy variable for light trucks, and the corresponding instrument. Column 7 includes a dummy for US-based manufacturers, the interaction of market size with a dummy for US-based manufacturers, and the corresponding instrument. All regressions are estimated by instrumental variables using potential market size as an instrument, as in Table 4.

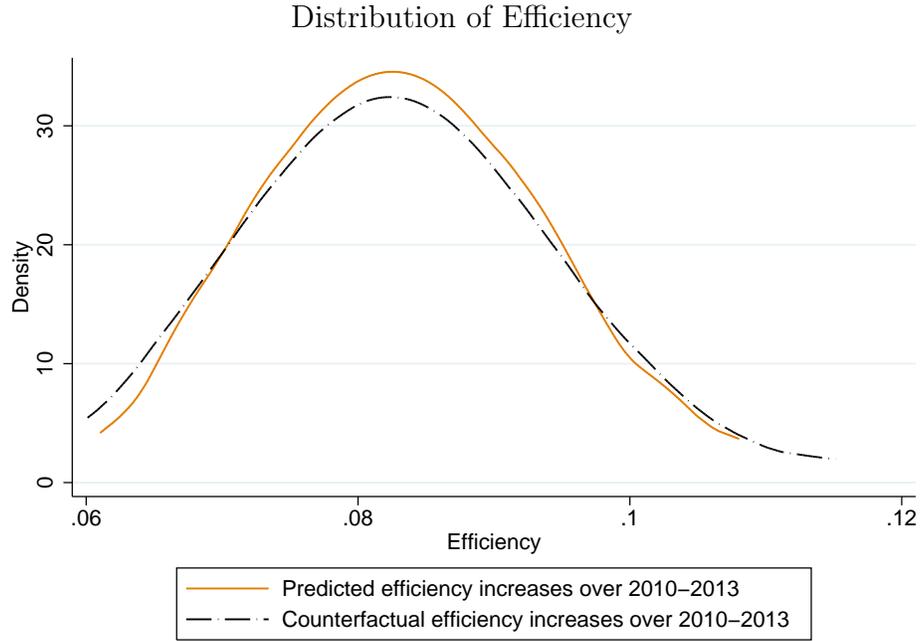
# Appendix

Figure A.1: **Effect of 2003–2007 Gasoline Price Increase on Efficiency**



Notes: For each observation in equation (2), the frontier is predicted using the estimates reported in column 3 of Table 4. All observations are assigned to a fuel economy quintile based on the fuel economy distribution across observations between 2003 and 2007, using each vehicle model’s initial fuel economy when the model enters the market. The predicted frontier in each colored bar is the mean cumulative predicted efficiency change between 2003 and 2007 for each quintile. The clear bars show the cumulative counterfactual efficiency change by quintile. Counterfactual efficiency changes are computed by holding fixed fuel prices at 2003 levels and using equations (2) and (4) to predict the efficiency change for each observation between 2003 and 2007.

Figure A.2: Effect of Feebate on Efficiency



Notes: For each observation in equation (2), the frontier is predicted using the estimates reported in column 2 of Table 4. The counterfactual efficiency of each vehicle is computed from the market size caused by introducing a feebate of  $(1/e_{jt} - 1/e_t) \times 1.53$ , where  $e_{jt}$  is the fuel economy of model  $j$  in model year  $t$  and  $e_t$  is the harmonic mean of fuel economy in model year  $t$ . The above figure shows the estimated density functions of cumulative predicted and counterfactual efficiencies over the period 2010 through 2013.

Table A.1: **Definitions of Demographic Groups**

Panel A: Group Definition

Group number	Age (years)	Household income (thousand nominal dollars)	Education (years)	Household Size	Urban	Census division
1	0–34	0–25	0–12	1	urban	New England
2	35–54	25–50	12+	2	not urban	Middle Atlantic
3	55+	50–75		3		East North Central
4		75–100		4		West North Central
5		100+		5+		South Atlantic
6						East South Central
7						West South Central
8						Mountain
9						Pacific
No. of Groups	3	9	2	5	2	9
Total number of groups						2,628

Panel B: Group Information

	All NHTS waves	NHTS 1995	NHTS 2001	NHTS 2009
Total number of groups	2,628	2,196	2,153	2,473
Number of households per cell	28	19	27	38