DISCUSSION PAPER

August 2009 ■ RFF DP 09-33

Lose Some, Save Some: Obesity, Automobile Demand, and Gasoline Consumption in the United States

Shanjun Li, Yanyan Liu, and Junjie Zhang

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES FOR THE FUTURE

Lose Some, Save Some: Obesity, Automobile Demand, and Gasoline Consumption in the U.S.

Shanjun Li, Yanyan Liu, and Junjie Zhang*

Abstract

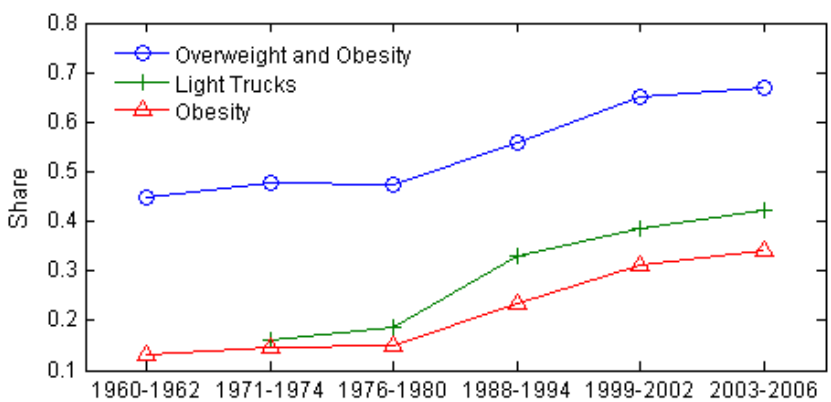
This paper examines the unexplored link between the prevalence of overweight and obesity and vehicle demand in the United States. Exploring annual sales data of new passenger vehicles at the model level in 48 U.S. counties from 1999 to 2005, we find that a 10 percentage point increase in the rate of overweight and obesity reduces the average MPG of new vehicles demanded by 2.5 percent: an effect that requires a 30 cent increase in gasoline prices to counteract. Our findings suggest that policies to reduce overweight and obesity can have additional benefits for energy security and the environment.

*We thank Arie Beresteanu, Avi Goldfarb, Hanan Jacoby, Martin Smith, Kenneth Train, and Chris Timmins for their helpful comments. Financial support from Micro-Incentives Research Center at Duke University is gratefully acknowledged. Affiliations: Shanjun Li, Resources for the Future, li@rff.org; Yanyan Liu, Postdoctoral Fellow, IFPRI, Washington DC, y.liu@cgiar.org; Junjie Zhang, Assistant Professor of Environmental Economics, University of California - San Diego, junjiezhang@ucsd.edu.

1 Introduction

Do people who are overweight or obese tend to buy larger and less fuel-efficient vehicles? If so, how significant is its implication on the fuel economy of vehicle fleet and gasoline consumption in the United States? We address these questions using a unique data set of annual sales of new passenger vehicles at the model level in 48 U.S. counties from 1999 to 2005. Our empirical analysis shows that the prevalence of overweight and obesity has a sizable effect on the fuel economy of new vehicles demanded. A 10 percentage point increase in the rate of overweight and obesity among the population reduces the average miles per gallon (MPG) of new vehicles demanded by 2.5 percent: an effect that requires a 30 cent increase in gasoline prices to counteract.[1]

Figure 1: Shares of Overweight, Obesity, and Light Trucks in the U.S. 1960-2006



Note: The overweight and obesity rates are for 20-74 years old adults. The middle line depicts the percentage of light trucks (including passenger vans, SUVs and pickup trucks) among all passenger vehicles in stock. The rates of overweight and obesity are from U.S. National Center for Health Statistics (2009) while data on vehicle stock are from U.S. Bureau of Transportation Statistics (2009).

[1] A 10 percentage point increase in the overweight and obesity rate could be realized in about 12 years should the recent U.S. trend continue. For example, the rate of overweight and obesity in the population increased from 52 to 62 percent from 1995 to 2006.

The increasing prevalence of overweight and obesity is one of the most serious health issues in the United States. As depicted in Figure 1, the obesity rate among adults 20-74 years of age reached 34 percent during 2003-2006 up from 13 percent during 1960-1962 while the rate of overweight and obesity increased from 45 to 67 percent over the same period. According to Wang and Beydoun (2007), the prevalence of overweight and obesity has been climbing at an alarming rate of 0.3-0.8 percentage point each year over the past three decades. If the rate continues to grow at the current pace, 75 percent of U.S. adults will be overweight or obese by 2015.

It is a well-established fact that overweight and obesity are associated with a number of medical conditions, most of which are costly to treat.[2] Sturm (2002) shows that obese individuals cost 36 percent more in inpatient and outpatient spending and 77 percent more in medications than individuals with normal weight and concludes that obesity outranks both smoking and drinking in its adverse health effects. The costs of overweight and obesity include both direct costs such as medical expenditures and indirect costs that are related to morbidity and mortality. Wolf and Colditz (1998) estimate that the total U.S. obesity costs, including both direct and indirect costs, amounted to $99 billion in 1995, with 52 percent being direct costs. A more recent study by Finkelstein et al. (2004) finds that the medical cost of overweight and obesity accounted for 9.1 percent of total U.S. medical expenditures in 1998 and reached $78.5 billion, half of which were through financially-distressed Medicare and Medicaid systems. Because of the significant health and economic consequences from overweight and obesity, many have called for making weight control a national priority.[3]

[2]These conditions include elevated cholesterol levels, depression, musculoskeletal disorders, gallbladder disease, nonalcoholic fatty liver disease, and several cancers (Kortt et al. (1998), Ogden et al. (2007)).

[3]For example, the Office of Surgeon General issued a report in 2001 titled "The Surgeon General's Call to Action to Prevent and Decrease Overweight and Obesity". In addition to detailing the economic and health consequences from overweight and obesity, the report provides many policy suggestions at both local and national levels.

During the same period, a seemingly unrelated but equally significant trend is the dramatic increase in the number of large passenger vehicles on American roads. As shown in Figure 1, the percentage of light trucks including passenger vans, SUVs, and pickup trucks among all passenger vehicles in stock increased from about 16 percent in early 1970's to more than 40 percent in recent years. Largely due to this trend, motor gasoline consumption in the United Stated increased by 38 percent from 6.6 million barrels a day in 1981 to more than 9 million barrels a day in 2007. In recent years, passenger vehicles have accounted for more than 40 percent of total U.S. oil consumption. As a result of increasing motor gasoline consumption, U.S. is more and more dependent on foreign oil: the proportion of imports in total petroleum products has reached 60 percent in recent years. The concerns for oil price volatility and energy security arise because a large portion of U.S. oil imports are from areas that are politically unstable. Moreover, the combustion of gasoline in automobiles imposes many environmental problems and contributes to global warming.[4] While producing an estimated 60 to 70 percent of total urban air pollution, motor gasoline combustion accounts for about 20 percent of the annual U.S. emissions of carbon dioxide, the predominant greenhouse gas that causes global warming.

Both the increasing prevalence of obesity and the growing energy consumption have become important public policy issues in the U.S. in recent years. Although these two have been almost always discussed as separate issues, several recent studies have demonstrated the link between the two based on the fact of physics that fuel consumption per unit of distance traveled increases with the weight of cargo/passengers in transportation. Based on this relationship between weight transported and fuel efficiency, Dannenberg et al. (2004) find that the weight gain among U.S. consumers during 1990s increased jet fuel consumption by 2.4 percent in 2000. Both Jacobson and McLay (2006)

[4]See Parry, Harrington, and Walls (2007) for a comprehensive review of externalities associated with vehicle usage and gasoline consumption as well as discussions on policy instruments.

and Jacobson and King (2009) quantify the effect of overweight and obesity on gasoline consumption due to the fact that heavier passengers reduce fuel efficiency of a vehicle. The latter finds that the weight gain among Americans from 1960s contributed to 0.8 percent of the gasoline consumption by passenger vehicles in 2005.

The aforementioned papers examine how fuel efficiency in travel is affected by passengers' weight after transportation choices being made (i.e., the ex-post effect). Our paper focuses on a different and as our findings suggest, a more significant channel whereby consumers choose different transportation tools in response to changes in their weights. In particular, we examine how the demand for passenger vehicles is affected by the increasing rate of overweight and obesity. Our findings suggest that consumers demand larger and less fuel-efficient vehicles, presumably to accommodate their heavier bodies. Moreover, obesity exhibits much stronger effects than overweight on vehicle demand. Our simulation results show that had the prevalence of overweight and obesity stayed at the level in 1981 (about 20 percentage points lower than that in 2005), the average MPG of new vehicles demanded in 2005 would have been about 4.6 percent higher, everything else being equal. The improved fuel efficiency implies total gasoline savings of about 138 million barrels and reduction in CO_2 emissions of 58 million tons over the lifetime of these vehicles.[5]

With volatile gasoline prices and growing concerns about climate change and local air quality, political support for curbing U.S. fuel consumption has increased dramatically in recent years. A suite of policy instruments such as more stringent Corporate Average Fuel Economy (CAFE) standards, consumer tax incentives for adopting alternative fuel vehicles, and government support for developing fuel-efficient technologies

[5]Assumptions about vehicle lifetime and vehicle miles traveled are presented in Section 4.3. In addition to environmental problems and climate change associated with increased gasoline consumption due to more and more large vehicles being used, recent empirical evidences have shown that a vehicle fleet with more large vehicles such as SUVs and pickup trucks can have more traffic fatalities and hence reduce overall traffic safety (White (2004) and Li (2008)).

have been adopted. Our findings suggest that the progress achieved through these policies could be reversed by the increasing prevalent of overweight and obesity. On the other hand, our findings also imply that overall benefits from local and national programs aimed to reduce overweight and obesity are larger than what has been previously thought once energy and environmental benefits are taken into account.

The remainder of this paper is organized as follows. Section 2 discusses the background of our study and describes our data. Section 3 discusses the empirical strategy. Section 4 present estimation results and caveats of our analysis. Section 5 conducts further robustness checks. Section 6 concludes.

2 Background and Data

We first briefly discuss the trends in the U.S. auto industry and then present data sets used in our study.

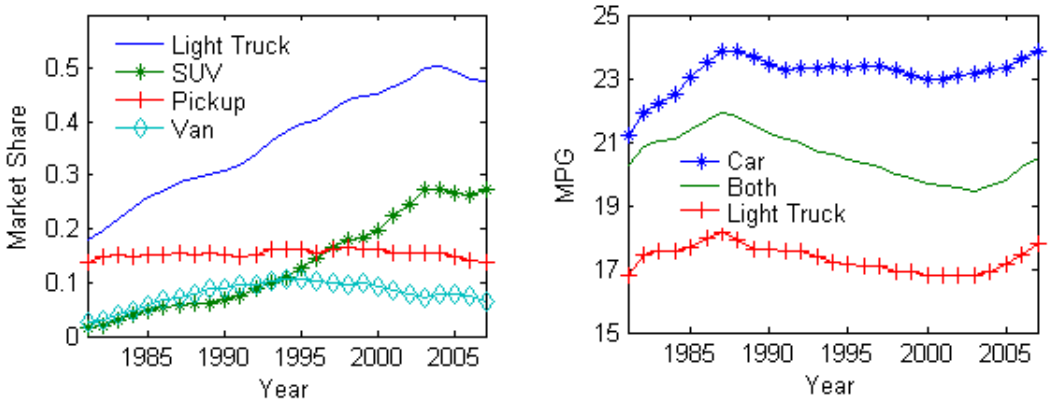
2.1 Background

The U.S. auto industry witnessed dramatic changes during the past three decades, one of which is the increasing popularity of large vehicles such as SUVs. As depicted by the left panel of Figure 2, the market share of new light trucks over total new light-duty vehicles grew from 17 percent to about 50 percent from 1981 to 2007.[6] The majority of the increase in light truck sales was accounted for by SUVs, whose share rose from 1.3 percent to almost 30 percent during the period. After two decades of constant growth, the market share of light trucks started to stabilize from 2002 largely due to the significant run-up in gasoline prices.

The right panel of Figure 2 plots the average MPG of new light-duty vehicles sold in each year from 1981 to 2007. The fuel economy of all new vehicles, shown by the line in the middle, increased to its peak in 1987 following two oil crisis and the enactment

[6]Light-duty vehicles are those vehicles that EPA classifies as cars or light trucks (SUVs, vans, and pickup trucks with less than 8500 pounds gross vehicle weight).

Figure 2: Market Shares by Vehicle Type and Fuel Economy 1981-2007



Note: To smooth the trend, the data points in the graph are three-year moving averages that are tabulated at the midpoint of each three consecutive years. Data source: Light-Duty Automotive Technology and Fuel Economy Trends: 1975 Through 2008 by EPA.

of CAFE standards in 1970's. It then continuously declined until the reversal of this long-term trend in 2005. Since light trucks are on average less fuel efficient than cars (by about 6 MPGs among those sold), the increase in the market share of light trucks is an important factor behind the decline in fuel economy of new vehicles. Moreover, even within the same segment (car or light truck), vehicles have become larger and less fuel efficient from late 1980's to early 2000's. For example, according to the EPA's classifications, the fraction of small cars in the car segment increased from 51 percent in 1981 to 65 percent in 1987 and then dropped to 44 percent in 2007 while the fraction of median-sized cars and that of large cars both show an opposite trend. The top and bottom lines in the right panel of Figure 2 present similar temporal patterns for the fuel economy of each of the two vehicle segments.

It is important to note that more advanced and fuel-efficient vehicle technologies have been constantly developed over time. These technologies include more efficient engines, better transmission designs, and better matching of the engine and transmission. That means that in the absence of these technologies, the average fuel economy of new vehicles would have been much lower and the effect of more and more large vehi-

cles on fuel economy would have been more pronounced. To understand the importance of these technologies on fuel economy, it is useful to look at an alternative fuel-efficiency measure, "Ton-MPG", which takes vehicle weight into consideration. This measure is defined as a vehicle's MPG multiplied by its inertia weight (i.e., vehicle weight with standard equipment plus 300 pounds) in tons.[7] From 1981 to 2007, the average Ton-MPG for new cars increased from 33.1 to 42.8 while that for new light trucks increased from 33.0 to 42.1. Typically, Ton-MPG for both vehicle types increased at a rate of about one to two percent a year over this period according to EPA.

2.2 Data

Several data sets are used in our study. The first data set, collected from the annual issues of Automotive News Market Data Book, containing characteristics and total sales of virtually all new vehicle models available in the U.S. from 1999 to 2005. Vehicle models with U.S. sales less than 10,000 units are excluded. These models account for less than 1 percent of total new vehicle sales. Table 1 reports summary statistics for the 1,287 models in this data set. Price is the manufacturer suggested retail prices (MSRP). Size, equal to the product of vehicle length and width, measures the "footprint" of a vehicle. Miles per gallon (MPG) is the weighted harmonic mean of city MPG and highway MPG based on the formula provided by the EPA to measure the fuel economy of the vehicle: $\text{MPG} = \frac{1}{0.55/\text{city MPG}+0.45/\text{highway MPG}}$.[8]

The second data set, purchased from R. L. Polk & Company, contains total annual registrations of each new vehicle model in each of the 48 U.S. counties from 1999 to

[7] Intuitively, an increase in vehicle's MPG at constant weight should be considered as an improvement in fuel-efficiency. Similarly, an increase in a vehicle's weight while holding MPG constant should also be considered as an improvement.

[8] Alternatively, the arithmetic mean can be used on Gallon per Mile (GPM, equals 1/MPG) to capture the gallon used per mile by a vehicle traveling on both highway and local roads: GPM = 0.55 city GPM + 0.45 highway GPM. The arithmetic mean directly applied to MPG, however, does not provide the correct measure of vehicle fuel efficiency.

Table 1: New Vehicle Characteristics 1999-2005

	Mean	Median	S. D.	Min	Max
Quantity ('000)	89.7	56.0	108.5	10.0	939.5
Price (in '000 $)	25.65	22.98	11.42	9.05	90.62
Size(in '0000 inch^2)	1.359	1.341	0.169	0.935	1.835
MPG	22.37	22.25	4.85	13.19	55.59

Note: Data are from various issues of Automotive News Market Data Book (1999-2005) and the EPA's fuel economy database. The number of observations is 1,287.

2005. These counties are within 20 MSAs that are studied in Li, Timmins, and von Haefen (2008).[9] These 20 MSAs are from all nine U.S. Census divisions and exhibit large variations in total population and average household demographics. They are well representative of national data in terms of vehicle fleet characteristics and household demographics. Although there are 160 counties in these MSAs, data on the rate of overweight and obesity are only available in large counties. Our study focuses on 48 counties that have at least 50,000 households. This implies that rural counties are under-represented in our data. Nonetheless, the correlation coefficient between vehicle sales in these counties and national sales is 0.914 (comparing to 0.94 between model sales in the 20 MSAs and national sales). In total, there are 61,776 (1287*48) observations of vehicle sales.

The fuel cost of driving is measured by dollars per mile (DPM = gasoline price/MPG). We collect annual gasoline prices for each MSA from 1999 to 2005 from the American Chamber of Commerce Research Association (ACCRA) data base. During this period, we observe large variations in gasoline prices both across years and MSAs. The average annual gasoline price is $1.66, with a minimum of $1.09 observed in Atlanta in 1998 and

[9]These 20 MSAs are: Albany-Schenectady-Troy, NY; Atlanta, GA; Cleveland-Akron, OH; Denver-Boulder-Greeley, CO; Des Moines, IA; Hartford, CT; Houston-Galveston-Brazoria, TX; Lancaster, PA; Las Vegas, NV-AZ; Madison, WI; Miami-Fort Lauderdale, FL; Milwaukee-Racine, WI; Nashville, TN; Phoenix-Mesa, AZ; St. Louis, MO-IL; San Antonio, TX; San Diego, CA; San Francisco-Oakland-San Jose, CA; Seattle-Tacoma-Bremerton, WA; Syracuse, NY.

a maximum of $2.62 in San Francisco in 2005. We assume that the gasoline price is the same in counties within an MSA. We collect median household income at the county level from Small Area Income and Poverty Estimates of U.S. Census Bureau. From 2000 Census and annual American Community Survey, we also collect several county-level demographic variables including total population, average household size, the proportion of households with children under 18 years old, and average driving time to work.

The overweight and obesity information are obtained from the National Health and Nutrition Examination Survey Data published by National Center for Health Statistics (NCHS) at Centers for Disease Control and Prevention (CDC). The survey is conducted at the individual level. The rates of overweight and obesity at the 48 counties under study are obtained based on individual observations. The range of overweight and obesity is determined by Body Mass Index (BMI) or Quetelet index. BMI is calculated based on a person's weight (W) and hight (H) following the formula: $BMI = W/H^2$. An adult is considered overweight if he/she has a BMI between 25 and 29.9, and considered obese if the BMI is 30 or higher. For children and teens, BMI ranges are age and gender-specific in order to account for normal differences in body fat between genders and across ages. Although BMI does not measure body fat directly, it has been shown to be a convenient and reliable indicator of obesity (Garrow and Webster (1985)). However, it is worth noting that BMI is not a perfect measure of weight partly because it ignores heterogeneity due to age, gender, and athleticity for adults.

Table 2 presents correlation coefficients among several variables of interest as well as their summary statistics based on data at the county level. There are in total 336 (48*7) county-level observations. The average MPG and size of new vehicles in each county are weighted by vehicles sales in the county. The market share of new vehicles is equal to total new vehicle sales over the number of households in the county. The correlation coefficients in columns 2 to 6 show some interesting patterns. The rate of overweight and obesity is negatively correlated with median household income and the average

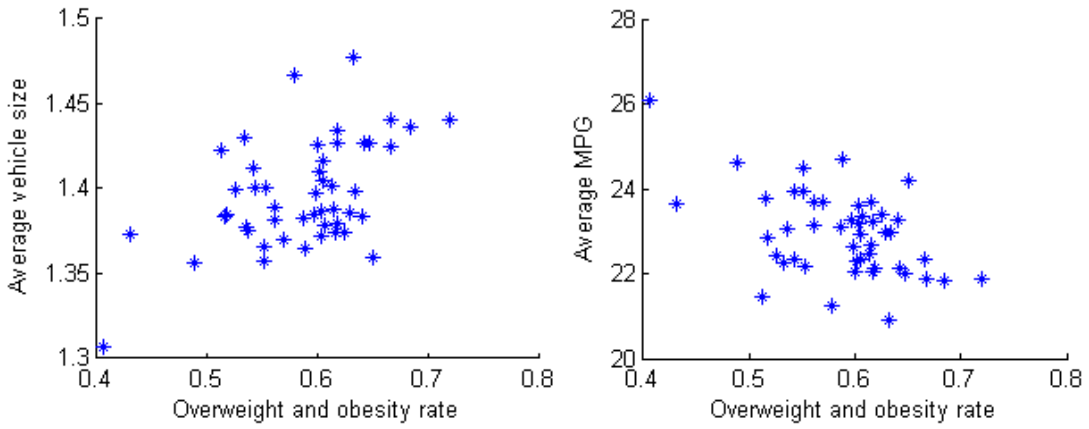
Table 2: Correlation Matrix and Summary Statistics

	(1)	(2)	(3)	(4)	(5)	Mean	S.D.
Rate of overweight and obesity (1)	1.000					0.553	0.066
Gasoline price (2)	0.103	1.000				1.764	0.320
Median household income (3)	-0.415	0.101	1.000			5.564	1.160
Average new vehicle MPG (4)	-0.156	0.459	0.068	1.000		22.473	0.877
Average new vehicle size (5)	0.411	-0.090	-0.239	-0.827	1.000	1.385	0.037
New vehicle market share (6)	-0.048	-0.272	0.227	-0.266	0.090	0.132	0.029

Note: Variables are at the county level. The number of observations is 336. Columns 2-6 show correlation coefficients and the last two columns are the means and standard deviations.

MPG of new vehicles in the county, and is positively correlated with the average size of new vehicles. The gasoline price is positively correlated with the average MPG of new vehicles and negatively correlated with the market share of new vehicles. There are larger variations in the rate of overweight and obesity in both temporal and geographic dimensions. For example, the average rate of overweight and obesity increased from 0.516 to 0.581 during the seven year period. In 2005, the lowest rate was 0.406 in San Francisco, CA while the highest was 0.72 in Galveston, TX.

Figure 3: Overweight and Obesity, Vehicle Size, and MPG in 48 Counties in 2005



The left panel of Figure 3 plots the average size of new vehicles against the rate of

overweight and obesity while the right panel plots the average MPG against the rate of overweight and obesity in the 48 counties in 2005. The plots clearly show a positive correlation between the average vehicle size and the prevalence of overweight and obesity and a negative correlation between the average MPG and the prevalence of overweight and obesity. The goal of our empirical model is to determine if a higher rate of overweight and obesity results in stronger demand for large and fuel-inefficient vehicles and to further quantify the relationship.

3 Estimation Strategy

Our empirical model is a linear model transformed from a multinomial logit model. To describe the empirical model, let m index markets (i.e., counties), and j index vehicle models. We assume that that consumers have total J vehicle models plus an outside good (indexed by 0) to choose from in a give year. With the time index suppressed, we estimate the following equation:

$$ln(s_{mj}/s_{m0}) = x_j\alpha + x_{mj}\beta + \xi_j + \nu_{mj}, \tag{1}$$

where s_{mj} and s_{m0} are the market shares of model j and the outside good, respectively. x_j is a vector of product attributes such as vehicle price (MSRPs) and vehicle size that do not vary across market. To save notation, x_{mj} includes market demographics (such as gasoline price and the rate of overweight and obesity) as well as the interaction terms between product attributes and market demographics (such as dollars per mile and the interaction term between the rate of overweight and obesity with vehicle size). ξ_j is the unobserved product attribute such as presentation/appearance, quality or prestige of a vehicle. It can also include promotions such as marketing campaign or consumption trend at the national level. ν_{mj} includes unobserved market-varying demographics that affect consumers' vehicle choices and are not controlled for.

This linear model is a transformation of a multinomial logit model as shown in Berry (1994) and exhibits the following two important features. First, the transformed model

is parsimonious: it only has product attributes (including price) of a single product j as explanatory variables. Nevertheless, the presence of s_{m0} in the equation allows attributes of other products to affect the market share of product j.[10] This contrasts with a linear demand model where the dependent variable is the quantity of a product and the regressors include prices of all competing products. Second, although the underlying multinomial model starts with individual utility maximization, the transformed model can be estimated based on market-level sales data in a linear framework.

We now discuss the implications of the unobserved product attribute ξ_j and local unobservables ν_{mj} on estimation. Controlling for the unobserved product attribute ξ_j is one of the focal points of previous studies on automobile demand based on aggregate sales data (Berry, Levinsohn, and Pakes (1995)). Since the unobserved product attribute may affect vehicle price, ignoring it could render vehicle price endogenous and cause price elasticities of demand to be under-estimated. The identification assumption commonly employed in the literature is that observed product attributes x_j are uncorrelated with the unobserved product attribute ξ_j. Therefore, attributes of the competing products can be used as instruments for vehicle price of a given product. However, the identification assumption could be violated if there are unobserved national promotions (could be treated as unobserved product attributes) that are correlated with product attributes. For example, there were strong marketing efforts for SUVs by automakers in late 1990's and early 2000's. These promotions unobserved to the researchers enter ξ_j and are also correlated with product attributes such as vehicle size and type. Taking advantage of the fact that we have sales data in multiple markets, we use product (i.e., model-year) fixed effects to control for unobserved product attributes (or national promotions). With

[10] Another way to see this point is to recognize that the market share of product j in a multinomial logit model is:

$$s_{mj} = \frac{x_j\alpha + x_{mj}\beta + \xi_j + \nu_{mj}}{1 + \sum_{h=1}^{J}(x_h\alpha + x_{mh}\beta + \xi_h + \nu_{mh})}. \tag{2}$$

product fixed effects, the above model can be written as:

$$ln(s_{mj}/s_{m0}) = \delta_j + x_{mj}\beta + \nu_{mj}, \tag{3}$$

where product dummy, δ_j, subsumes market-invariant product attributes x_j as well as the unobserved product attribute ξ_j.

The second challenge before taking equation (3) to the data lies in the market-level unobservable ν_{mj}, which may include local unobservables that affect consumer preferences. The possible correlation between local unobservables and observed market-level characteristics such as gasoline price or the rate of overweight and obesity would cause the observed variables to be endogenous. For example, in hilly areas or areas with snow, consumers may have stronger preference for four-wheel drive and hence SUVs and pickup trucks because four-wheel drive is more common among these vehicles than cars. If these unobserved conditions are also correlated with the rate of overweight and obesity, the interaction term between vehicle size and the rate of overweight and obesity will be endogenous. In order to control for the effect of local unobservables on vehicle preference, we include county dummies interacting with vehicle category dummies. That is, we allow consumer preferences for a certain vehicle category to be different across counties.

To understand the effect of ignoring unobservables on parameter estimates as well as if interaction terms between county dummies and vehicle category dummies are adequate controls for local unobservables, we carry out various robustness checks. Our robustness analyses suggest that local unobservables tend to attenuate the effect of overweight and obesity. Moreover, we find that the effect of overweight and obesity is quite robust to how both product unobservables and local unobservables are controlled for.

4 Estimation Results

Tables 3 and 4 present parameter estimates as well as the estimates for implied elasticities from six different model specifications. We first discuss the results for the first

specification which we believe, provides the most credible results. We then present the results from other specifications and discuss the significance of our findings as well as two caveats of our analysis.

4.1 Results from the Preferred Model

Specification 1 includes most control variables among the six specifications as shown in Table 3. In addition to the first six variables shown in the table, we include four demographic variables as well as their interactions with MPG and vehicle size. These four demographic variables are total population in logarithm, average household size, the proportion of households with children under 18 years old, and average driving time to work. The parameter estimates for these four variables as well as the eight interaction terms, available from authors, are not reported for the sake of brevity.[11] In the regression, product dummies are used to control for unobserved product attributes as well as national level trends or promotions. We include county dummies to control for county-level unobservables (such as the availability of public transportation) that could affect consumers' choice margin of whether to purchase a new vehicle. We also include interaction terms between county dummies and 11 vehicle segment dummies to control for county-level unobservables that affect consumer preference for different types of vehicles.

The overweight and obesity rate (OR) in the regressions is the percentage of people who are either overweight or obese in the population. The first two variables are used to capture the effect of overweight and obesity on vehicle demand. The parameter estimates imply that the partial effect of the rate of overweight and obesity on vehicle market share is: $\frac{\partial s_{mj}}{\partial \text{OR}} = (-8.601 + 6.317 * \text{vehicle size}) s_{mj}(1 - s_{mj})$. The partial effect is

[11] Because these variables are not available in all counties in 2000 to 2004 American Community Survey, we interpolate the values in between assuming geometric growth based on data from 2000 Census and 2005 American Community Survey. The results are virtually the same using the interpolation with arithmetic growth.

positive only for vehicles whose size is larger than 1.36 ('0000 inch^2), which is about 55 percentile in the vehicle size distribution among all 1,287 vehicles in the data. Moreover, the partial effect of overweight and obesity on vehicle demand is stronger for larger vehicles.

Based on the parameter estimates on the third and fourth variables, the partial effect of gasoline price on vehicle market share is: $\frac{\partial s_{mj}}{\partial \text{Gas price}} = (1.494 - 26.993/\text{MPG}) s_{mj}(1 - s_{mj})$. This implies that an increase in gasoline price would increase the demand for vehicles with MPG larger than 18.07 while reducing the demand for less fuel-efficient vehicles. Moreover, the more fuel-efficient a vehicle is, the larger the demand increase would be with an increase in gasoline price. The coefficient estimate on Log(price)/log(MHI) for specification 1 suggests that the own-price elasticity for product j is $\frac{-5.528}{\log(\text{MHI})}(1 - s_{mj})$. The price elasticity estimates for all 1,287 vehicle models range from -2.40 to -4.68 with the average being -3.39. The identification of the above partial effect relies not only on cross-sectional and temporal variations in vehicle demand due to differences in the demographic variables (i.e., the rate of overweight and obesity, gasoline price, and income) but also on cross-model variations arising from the fact that vehicle demand responds to changes in demographic variables differently across vehicles with different attributes (i.e., size, MPG, or price).

The parameter estimates suggest that as overweight and obesity become more prevalent, vehicles demanded will become larger and as a result, less fuel-efficient on average. The effects of an gasoline price increase on vehicle demand are opposite. In order to measure the magnitude of these effects, we simulate several elasticities and their standard errors, which are presented in panel 2 of Tables 3. The elasticity of MPG with respect to the rate of overweight and obesity being -0.139 in 2005 suggests that a one-percent increase in the rate of overweight and obesity would reduce the average MPG of new vehicles demanded in 2005 by 0.139 percent. The elasticity of MPG with respect to gasoline price is estimated at 0.191 in 2005. The elasticities of vehicle size to both

variables of interests are also presented.

Although we are not aware of any existing studies that we can compare to in terms of the effect of overweight and obesity on vehicle demand, there are several recent studies that provide the elasticity of average MPG to gasoline price. The elasticity estimate based on our preferred specification is 0.191 in 2005. Small and Van Dender (2007) obtain an estimate of 0.21 from 1997-2001 using U.S. state level panel data on vehicle fuel efficiency and gasoline prices. Li, Timmins, and von Haefen (2008) estimate the elasticity of the average MPG of new vehicles with respect to the gasoline price in 2005 to be 0.204 using a similar data set to ours but a different empirical framework.

4.2 Robustness Checks

In the first specification, we include interaction terms between county dummies and 11 vehicle segment dummies to control for local unobservables that may be correlated with observable demographics such as the rate of overweight and obesity or gasoline price. If local unobservables affect consumers' preferences on continuous vehicle characteristics such as vehicle size and MPG, we should include interaction terms between county dummies with these characteristics in the regression. However, doing so would eliminate crucial cross-county variations in the rate of overweight and obesity and especially gasoline price so that precise estimates on the effect of overweight and obesity as well as that of gasoline price cannot be obtained.[12]

To understand how local unobservables affects the parameter estimates, we conduct the following two estimations. In specification 2, we include interaction terms between county dummies with 3 vehicle type dummies (i.e., using a coarser categorization than vehicle segments) while in specification 3, no interaction terms between county dum-

[12]Due to the lack of gasoline price data at the county level, we use same gasoline price for counties within the same MSA. Because cross-MSA variations in gasoline prices, largely due to differences in state and local gasoline taxes and transportation costs, are fairly stable over time, county dummies would subsume most of the cross-sectional variations in gasoline price.

mies and vehicle category dummies are included. Comparing the results across the three specifications, we can see that all elasticity estimates (in absolute values) are similar across specifications with those from the first specification being slightly larger. This suggests that local unobservables that are controlled for by the interaction terms between vehicle category dummies and county dummies have little effect on our model estimates and if ignored, tends to bias the effect of the rate of overweight and obesity and that of gasoline price on vehicle demand toward zero. To the extent that local unobservables are not fully controlled for by interactions terms between county dummies and vehicle segment dummies (e.g., a even finer categorization is needed), we expect that the elasticity estimates from the first specification provide close lower bounds for the true effects.

It is worth pointing out that our empirical strategy controls for time-varying unobservables at the national level through product dummies. It also controls for time-invariant components of county-level unobservables through interaction terms of county dummies and vehicle category dummies. We cannot, however, rule out the possibility of time-varying components of local unobservables co-varying with the observed variables and affecting vehicle demand at the same time, although such variables are not easy to conceive. To investigate the potential effect of time-varying local unobservables on estimation results, we conduct three additional regressions where some of observed time-varying variables are omitted. The results of these three specifications are reported in Table 4. Specification 4 does not include median household income and its interaction with vehicle price in the regression. The elasticity estimates of overweight and obesity rate become only slightly smaller in magnitude while those of gasoline price decrease more visibly. As high-income households are more likely to buy large and less fuel-efficient vehicles and median household income is negatively correlated with the rate of overweight and obesity, the effects of overweight and obesity will be underestimated with income levels not being controlled for. Conversely, median household

income is positively correlated with gasoline price, therefore, the increased demand for fuel-efficient vehicles due to a higher gasoline price would be dampened by higher income. However, when income levels are not controlled for, the effect of gasoline price on vehicle fuel efficiency will be under-estimated. In specification 5, we also omit the addition 12 variables related to county demographics. Again, the elasticity estimates only change slightly compared to those from specification 1. Specification 6 excludes variables related to gasoline price in addition to those omitted in specification 5. The elasticity of MPG to overweight and obesity rate is estimated at -0.150 compared to -0.139. Our results from these three specifications show that the elasticity estimates with respect to overweight and obesity are very close to those from the first specification where more time-varying variables are included. This supports that time-varying components of local unobservables that are correlated with overweight and obesity and at the same time affect vehicle demand, if exist at all, may not significantly compromise key results on the effect of overweight and obesity.

Our previous analysis combines overweight and obesity together. It is interesting to see if they affect vehicle demand differently. Table 5 presents estimation results for three specifications where we separate overweight and obesity. These three specifications correspond to those in Table 3 where different categorizations of vehicle dummies are used. The first two parameters capture the effect of obesity on vehicle demand while the next two capture the effect of overweight. In all three specifications, the parameters suggest that obesity and overweight have qualitatively same effect on vehicle demand: an increase in either of them reduces the demand for small vehicles but increases the demand for large vehicles.

The results in all three specification also show that obesity exhibits larger effects on vehicle demand than overweight. This can be easily seen based on elasticity estimates presented in panel 2 of the table. Moreover, since the average overweight rate was 36.1 percent while the average obesity rate was 22.6 percent in 2005, this implies that even if

the MPG elasticity to obesity and that to overweight were the same, the effect of obesity on the fuel economy of vehicles demanded would be about 60 percent larger than that of overweight. Similar to findings from Table 3, the elasticity estimates are close across three specifications.

4.3 Discussion and Caveats

Our simulation results based on parameter estimates show that the average MPG of new vehicles demanded would have been 2.5 percent lower (22.42 instead of 22.99) in 2005 with a 10 percentage points increase in the rate of overweight and obesity from 0.587. This increase in overweight and obesity rate could be realized in about 12 years following the trend since 1995. In order to counteract this decrease in the average MPG, a 30 cents increase in gasoline price (e.g., through a higher gasoline tax) over the average price of $2.32 per gallon in 2005 is needed. Interestingly, obesity has a stronger effect on the fuel economy of vehicles demanded. A 10 percentage points increase in the obesity rate over that in 2005 (holding the overweight rate constant) would have increased the average MPG of new vehicles demanded by 3.4 percent, which needs a 41 cents increase in gasoline price to counteract. Meanwhile, the effect of a 10 percentage points increase in the overweight rate (holding the obesity rate constant) on the average MPG is about 1.6 percent in 2005. Many studies have shown that increasing the gasoline tax is a more effective way to reduce gasoline consumption than tightening CAFE standards.[13] Moreover, the average 41 cents gasoline tax in the U.S. is lower than the optimal level in relation to externalities associated with gasoline usage (Parry and Small (2005)). However, increasing gasoline taxes has been a politically difficult policy to pass.

Our simulation results suggest that if the rate of overweight and obesity in 2005 had stayed at the 1981 level (20 percentage points lower), the average MPG of new vehicles demanded would have been 24.04 instead of 22.99. This implies about 4.6 percent saving

[13]See for example, National Research Council (2002); Congressional Budget Office (2003); West and Williams (2005); and Bento, Goulder, Jacobsen, and von Haefen (2008).

in gasoline consumption over vehicles' lifetime holding vehicle usage constant. Assuming the annual average vehicle-miles-traveled to be 12,000 and annual new vehicle sales to be 17 millions, the total gasoline saving over 15 years for these vehicles is about 138 million barrels and the reduction in CO_2 emissions is about 58 million tons.[14] Our results show that the effect of overweight and obesity on gasoline consumption through vehicle choices is much larger than the ex-post effect (i.e, through the effect on fuel efficiency conditioning on vehicle choices) by Jacobson and McLay (2006) and Jacobson and King (2009) as discussed in the introduction. Taking these results together, we consider our empirical estimate on the effect of overweight and obesity on vehicle fuel economy and gasoline consumption to be quantitatively significant.

Two caveats regarding our analysis are worth mentioning. The first one is related to the undesirable feature of a logit model, independence of irrelevant alternatives (IIA). This property suggests unreasonable uniform substitution patterns across products. Both a nested logit model and to a larger extent, a random coefficient logit model allow for more reasonable cross-product substitutions than a logit model. As a logit model, a nested logit model can also be estimated in a linear framework following Berry (1994). We estimate a nested model with various nesting structures, all of which are rejected when product fixed effects are included. However, as we show in the next section, the usage of product fixed effects to control for unobserved product attributes is crucial to the identification of our empirical model.

Although a random coefficient logit model does not suffer from the IIA property, the estimation cannot be carried out in a linear framework and is very computationally intensive. The method to estimate a random coefficient model with aggregated sales data such as ours is a simulated Generalized Method of Moments (GMM) with a nested con-

[14] We find that although there is a small positive effect of overweight and obesity on the total number of new vehicles demanded, the effect is not statistically significant from zero. Improved fuel economy often increases vehicle usage, which is called rebound effect. A recent study by Small and Van Dender (2007) estimates that the short-run and long-run rebound effects are 2.2% and 10.7% during 1997-2001.

traction mapping developed by Berry et al. (1995). The contraction mapping recovers a vector with length being equal to the number of products that consumers can choose from (about 184 on average in our case). The larger the choice set is, the more computationally intensive the contraction mapping is. More importantly, it has to be done for each market in each year (48*7 times) for each parameter iteration. In addition, that fact that the objective function may have many local optima adds to computational burden. Although a full random coefficient model can provide significant gain in doing welfare analysis coupled with a supply side, it may not provide much benefit for our analysis where we are mainly interested in the average partial effects of explanatory variables. Beresteanu and Li (2008) estimate a random coefficient multinomial logit model based on an aggregate vehicle sales data in 22 MSAs from 1999 to 2006 augmented with a household survey data. It provides an estimate of 0.169 for the elasticity of average MPG to gasoline price in 2005, comparing to 0.191 from our preferred model. We take comfort from the fact that our estimate from a logit model is close to those from a random coefficient multinomial logit model as well as other models that do not suffer from the IIA property as discussed in Section 4.1.

The second caveat of our analysis is that we focus on the effect of overweight and obesity on vehicle demand rather than the equilibrium effect. Estimating the equilibrium effect necessitates the analysis of demand and supply sides simultaneously. Although the supply side is out of scope of our study, it is worth mentioning the following two important and counteracting factors in the supply side. First, given the positive correlation between overweight and the demand for large and less fuel-efficient vehicles, automakers are likely to increase the prices of those vehicles with an increase in the rate of overweight and obesity. The higher prices of large vehicles will in turn dampen the demand effect of overweight and obesity on fleet fuel economy in equilibrium. The changes in prices and their subsequent effects on vehicle demand depend on both across-firm competition and within-firm competition given the fact that all au-

tomarkers produce multiple products. The second factor in the supply side is the effect of overweight and obesity on automakers's product mix decisions which are inherently dynamic. Recognizing the demand effect of overweight and obesity, automakers are likely to introduce more large models into the market when overweight and obesity become more prevalent. This, opposite to the first factor, will exacerbate the static demand effect that we analyze. The decision of product choice should be more important than the first factor, especially in the long run. Nevertheless, it can be more challenging to model. In addition to the dynamic nature of product choice decisions, several facts about the auto industry should be considered: the industry consists of several big players that act strategically; each of them produces multiple products; and products are differentiated.

5 Further Robustness Analysis

To further check the robustness of our findings to model specifications, we estimate two additional specifications where we do not use product dummies to control for unobserved product attributes and national level promotions. In the first specification, we include brand dummies where a brand is defined by the model name. There are in total 330 brands in the data with the vast majority of the brands appearing in multiple periods. Vehicle models under the same name are sold in many year with minor changes (e.g., changes in small features and cosmetics) being done almost every year and major changes (e.g., changes on powertrain system and chassis) being done every 3-10 years in most cases. Although brand dummies can control for time-invariant unobserved product attributes, they cannot control for time-varying unobserved product attributes such as those associated with model changes. These time-varying components are likely to be correlated with vehicle prices and would cause vehicle price variable to be endogenous. We use instrumental variable method to deal with the price endogeneity problem by invoking the assumption that time-varying unobserved product attributes are not cor-

related with observed product attributes. Following the literature, we use the attributes of the competing products as instruments for vehicle price of a given product. Specifically, we use the averages of vehicle size, horsepower, and MPG of the other products produced by the same firm, and the average attributes of products of the same type produced by other firms. We also include the number of products of the same type produced by the same firm and that by all the other firms. The first stage regression shows that the instruments have good explanatory power for vehicle price.

Columns 2 to 5 in Table 6 present the results from both OLS and 2SLS with brand dummies in both regressions. We include interaction terms between county dummies and 11 segment dummies to control for local unobservables and interactions terms between year dummies and 11 segment dummies to control for time-varying unobservables at the national level such as promotions or trends. All the coefficient estimates have the expected signs in both regressions. With the instruments, the estimate of price coefficient changes from -3.473 to -4.553, comparing to the estimate of -5.528 in the preferred model where product dummies are used as shown in Table 3. The coefficient estimates on other variables only change slightly from OLS to 2SLS. Comparing the results from 2SLS to those from our preferred model shown in Table 3, the effects of overweight and obesity on the average MPG and size of vehicles demanded become smaller in magnitude while the effects of gasoline price on MPG and vehicle size become slightly larger in magnitude. This may arise from the possibility that time-varying unobserved product attributes (e.g., due to model changes over time) are correlated with vehicle size and fuel efficiency.

In the second specification, we do not include either brand dummies or product dummies. Therefore, both time-invariant and time-varying unobserved product attributes are not controlled for. To deal with the problem of price endogeneity, we use a commonly used assumption in the automobile demand literature following Berry et al. (1995)) that unobserved product attributes are not correlated with observed prod-

uct attributes. This assumption is likely to be stronger than the one used in the first specification that the time-varying component of unobserved product attributes are not correlated with observed product attributes. We use the same instrumental variables for the price variable as in the first specification. The coefficient estimate on the price variable changes from -2.289 in OLS to -1.618 in 2SLS, both of which are far from -5.528 in the preferred model. The coefficient estimate being -1.618 implies that the average price elasticity is only -0.99 among all products and that half of the products have inelastic demand, which are not consistent with profit-maximizing pricing decisions by firms with market power. These results suggest that the exogeneity assumption used to construct instruments could be violated. The elasticity estimates with respect to overweight and obesity are slightly larger in magnitude than those from the preferred model while the elasticity estimates with respected to gasoline price are much smaller than those from the preferred model.

These robustness analysis shows the importance of using product dummies to control for unobserved product attributes and in turn the benefit of having data from multiple markets. Consistent with the findings in previous analysis, the effects of overweight and obesity on the average MPG and size of vehicles demanded are quite robust to model specifications.

6 Conclusion

During the past several decades, the prevalence of overweight and obesity in the U.S. has been increasing at an alarming rate. Meanwhile, motor gasoline consumption and petroleum import have also been growing, partly due to the fact that American drivers have been buying larger and less fuel-efficient vehicles. This paper examines the unexplored link between these two trends and finds that new vehicles demanded by consumers are less fuel-efficient on average as the rate of overweight and obesity goes up. Our results show that if the prevalence of overweight and obesity has stayed at the 1981

level, the average fuel economy of new vehicles demanded would have been about 4.6 percent higher than that observed in 2005, *ceteris paribus*. We find that a 10 percentage point increase in the obesity rate from the 2005 level would decrease the average MPG of new vehicles demanded by 3.4 percent, more than twice as large as the effect of overweight.

The effect of overweight and obesity on vehicle fuel economy in the long run has potentially important implications for policies aiming to address U.S. energy security and environmental problems associated with gasoline consumption. Without taking into consideration the growth trend of overweight and obesity and its impact on vehicle demand, long-term government interventions are likely to miss the intended policy goals in reducing gasoline consumption and CO_2 emissions. Moreover, our findings imply that local and national policies that aim to prevent and decrease overweight and obesity could provide, in addition to the savings in health care costs, extra benefits in energy saving and environmental protection.

References

Bento, A., L. Goulder, M. Jacobsen, and R. von Haefen, "Distributional and efficiency impacts of increased U.S. gasoline taxes." American Economic Review, forthcoming.

Beresteanu, Arie and Shanjun Li, "Gasoline Price, Government Support, and the Demand for Hybrid Vehicles," 2008. Working Paper.

Berry, S., "Estimating Discrete Choice Models of Product Differentiation," *RAND Journal of Economics*, 1994, *25* (2), 242–262.

_ **, J. Levinsohn, and A. Pakes**, "Automobile Prices in Market Equilibrium," *Econometrica*, July 1995, *63*, 841–890.

Congressional Budget Office, *The Economic Costs of Fuel Economy Standards Versus a Gasoline Tax*, Washington, DC: Congress of the United States, 2003.

Dannenberg, A., D. Burton, and R. Jackson, "Economic and environmental costs of obesity, the impact on airlines," *American Journal of Preventive Medicine*, 2004, *27*, 264–264.

Finkelstein, E. A., I. C. Fiebelkorn, and G. Wang, "State-level estimates of annual medical expenditures attributable to obesity," *Obesity Research*, 2004, *12* (1), 18–24.

Garrow, J. S. and J. Webster, "Quetelet's index (W/H2) as a measure of fatness," *International Journal of Obesity*, 1985, *9* (2), 147–53.

Jacobson, S. and D. King, "Measuring the potential for automobile fuel savings in the US: the impact of obesity," *Transportation Research*, 2009, *14*, 6–13.

_ **and L. McLay**, "The Economic Impact of Obesity on Automobile Fuel Consumption," *The Engineering Economist*, 2006, *51* (4), 307–323.

Kortt, M. A., P. C. Langley, and E. R. Cox, "A review of cost-of-illness studies on obesity," *Clinical Therapeutics*, 1998, *20* (4), 772–9.

Li, S., C. Timmins, and R. von Haefen, "How Do Gasoline Prices Affect Fleet Fuel Economy," *American Economic Journal: Economic Policy*, 2009, *1* (2), 1–29.

Li, Shanjun, "Traffic Safety and Vehicle Choice: Quantifying the Arms Race on American Roads," 2008. Working Paper.

National Research Council, *Effectiveness and Impact of Corporate Average Fuel Economy (CAFE) Standards*, National Academy Press, 2002.

Ogden, C. L., S. Z. Yanovski, M. D. Carroll, and K. M. Flegal, "The epidemiology of obesity," *Gastroenterology*, 2007, *132* (6), 2087–102.

Parry, I., W. Harrington, and M. Walls, "Automobile Externalities and Policies," *Journal of Economic Literature*, 2007, pp. 374–400.

Parry, W. and K. Small, "Does Britain or the United States Have the Right Gasoline Tax?," *American Economic Review*, 2005, *95* (4), 1276–1289.

Small, K. and K. Van Dender, "Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect," *Energy Journal*, 2007, (1), 25–51.

Sturm, R., "The effects of obesity, smoking, and drinking on medical problems and costs," *Health Affairs*, 2002, *21* (2), 245–53.

U.S. Bureau of Transportation Statistics, *National Transportation Statistics*, U.S. Department of Transportation, 2009.

U.S. National Center for Health Statistics, *Health, United States, 2008*, Hyattsville, MD: Department of Health and Human Services Publication No. 2009-1232, 2009.

Wang, Y. and M. Beydoun, "The Obesity Epidemic In the United States– Gender, Age, Socioeconomic, Racial/Ethnic, and Geographic Characteristics: A Systematic Review and Meta-Regression Analysis," *Epidemiology Review*, 2007, *29*, 6–28.

West, S. and R. Williams, "The Cost of Reducing Gasoline Consumption," *American Economic Review*, 2005, (2), 294–299.

White, M., "The 'arms race' on American Roads: The Effect of SUV's and Pickup Trucks on Traffic Safety," *Journal of Law and Economics*, 2004, *XLVII* (2), 333–356.

Wolf, A. M. and G. A. Colditz, "Current estimates of the economic cost of obesity in the United States," *Obesity Research*, 1998, *6* (2), 97–106.

Table 3: Multinomial Logit Regression Results

Panel 1: Model Estimates	Specification 1		Specification 2		Specification 3	
	Para.	S.E.	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	-8.601	1.001	-6.839	0.866	-6.983	0.639
Overweight and obesity rate*vehicle size	6.317	0.747	5.010	0.654	5.122	0.485
Gas price	1.494	0.096	1.484	0.247	1.378	0.147
DPM (Gas price/MPG)	-26.993	1.128	-26.362	6.216	-24.710	3.670
Median household income (MHI)	-0.007	0.108	0.439	0.097	0.430	0.123
Log(price)/log(MHI)	-5.528	0.246	-4.247	0.212	-4.180	0.289
Additional demographic variables (12)	Yes		Yes		Yes	
Product dummy (1287)	Yes		Yes		Yes	
County dummy (47)	Yes		Yes		Yes	
County dummy * van dummy (47)	Yes		Yes		No	
County dummy * suv dummy (47)	Yes		Yes		No	
County dummy * pickup dummy (47)	Yes		No		No	
County dummy * medsize car dummy (47)	Yes		No		No	
County dummy * large car dummy (47)	Yes		No		No	
County dummy * luxury car dummy (47)	Yes		No		No	
County dummy * large van dummy (47)	Yes		No		No	
County dummy * medsize SUV dummy (47)	Yes		No		No	
County dummy * large SUV dummy (47)	Yes		No		No	
County dummy * luxury SUV dummy (47)	Yes		No		No	
County dummy * large pickup dummy (47)	Yes		No		No	
R^2	0.816		0.788		0.775	

Panel 2: Implied Elasticities in 2005	Elas.	S.E.	Elas.	S.E.	Elas.	S.E.
MPG elas to overweight and obesity rate	-0.139	0.008	-0.110	0.007	-0.113	0.006
Size elas to overweight and obesity rate	0.096	0.006	0.076	0.005	0.078	0.004
MPG elas to gas price	0.191	0.019	0.187	0.016	0.175	0.013
Size elas to gas price	-0.082	0.008	-0.081	0.007	-0.075	0.005

Note: The number of observations for all regressions is 61,766. The standard errors for parameter estimates are robust clustered at the county level. The 12 additional demographic variables include total population in logarithm, average household size, the proportion of households with children under 18 years old, and average driving time to work, as well as their interactions with MPG and vehicle size. Vehicles are divided into 4 categories (car, van, SUV, and pickup truck) and further classified into 12 segments (4 for cars, 2 for vans, 4 for SUVs, and 2 for pickup trucks) based on vehicle attributes and market orientations. The elasticities are calculated based on the observations in 2005. The standard errors for elasticity estimates are from bootstrapping.

Table 4: Multinomial Logit Regression Results - Continued

Panel 1: Model Estimates	Specification 4		Specification 5		Specification 6	
	Para.	S.E.	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	-7.435	0.907	-8.820	0.431	-9.061	0.417
Overweight and obesity rate*vehicle size	5.532	0.674	6.662	0.324	6.837	0.312
Gas price	1.116	0.089	1.006	0.047	No	
DPM (Gas price/MPG)	-18.901	1.127	-18.016	1.298	No	
Median household income (MHI)	No		No		No	
Log(price)/log(MHI)	No		No		No	
Additional demographic variables (12)	Yes		No		No	
Product dummy (1287)	Yes		Yes		Yes	
County dummy (47)	Yes		Yes		Yes	
County dummy * van dummy (47)	Yes		Yes		Yes	
County dummy * suv dummy (47)	Yes		Yes		Yes	
County dummy * pickup dummy (47)	Yes		Yes		Yes	
County dummy * medsize car dummy (47)	Yes		Yes		Yes	
County dummy * large car dummy (47)	Yes		Yes		Yes	
County dummy * luxury car dummy (47)	Yes		Yes		Yes	
County dummy * large van dummy (47)	Yes		Yes		Yes	
County dummy * medsize SUV dummy (47)	Yes		Yes		Yes	
County dummy * large SUV dummy (47)	Yes		Yes		Yes	
County dummy * luxury SUV dummy (47)	Yes		Yes		Yes	
County dummy * large pickup dummy (47)	Yes		Yes		Yes	
R^2	0.810		0.808		0.808	

Panel 2: Implied Elasticities in 2005	Elas.	S.E.	Elas.	S.E.	Elas.	S.E.
MPG elas to overweight and obesity rate	-0.122	0.008	-0.147	0.008	-0.150	0.008
Size elas to overweight and obesity rate	0.084	0.005	0.102	0.006	0.104	0.006
MPG elas to gas price	0.134	0.020	0.128	0.017	N/A	
Size elas to gas price	-0.058	0.009	-0.055	0.007	N/A	

Table 5: Multinomial Logit Regressions: Separating Obesity and Overweight

Panel 1: Model Estimates	Specification 1		Specification 2		Specification 3	
	Para.	S.E.	Para.	S.E.	Para.	S.E.
Obesity rate	-11.367	1.106	-8.924	0.888	-8.844	0.687
Obesity rate*vehicle size	8.396	0.822	6.589	0.659	6.519	0.506
Overweight rate	-5.492	0.100	-3.921	0.880	-4.168	0.691
Overweight rate*vehicle size	3.998	1.124	2.829	0.671	3.028	0.531
Gas price	1.463	0.106	1.473	0.242	1.367	0.147
DPM (Gas price/MPG)	-26.327	0.254	-26.095	6.038	-24.469	3.588
Median household income (MHI)	-0.033	0.829	0.414	0.094	0.413	0.120
Log(price)/log(MHI)	-5.649	0.623	-4.364	0.216	-4.264	0.295
Additional demographic variables (12)	Yes		Yes		Yes	
Product dummy (1287)	Yes		Yes		Yes	
County dummy (47)	Yes		Yes		Yes	
County dummy * van dummy (47)	Yes		Yes		No	
County dummy * suv dummy (47)	Yes		Yes		No	
County dummy * pickup dummy (47)	Yes		No		No	
County dummy * medsize car dummy (47)	Yes		No		No	
County dummy * large car dummy (47)	Yes		No		No	
County dummy * luxury car dummy (47)	Yes		No		No	
County dummy * large van dummy (47)	Yes		No		No	
County dummy * medsize SUV dummy (47)	Yes		No		No	
County dummy * large SUV dummy (47)	Yes		No		No	
County dummy * luxury SUV dummy (47)	Yes		No		No	
County dummy * large pickup dummy (47)	Yes		No		No	
R^2	0.812		0.783		0.770	

Panel 2: Implied Elasticities in 2005	Elas.	S.E.	Elas.	S.E.	Elas.	S.E.
MPG elas to obesity rate	-0.070	0.004	-0.055	0.003	-0.054	0.003
Size elas to obesity rate	0.049	0.003	0.038	0.002	0.038	0.002
MPG elas to overweight rate	-0.055	0.006	-0.039	0.005	-0.041	0.005
Size elas to overweight rate	0.038	0.004	0.027	0.004	0.029	0.004
MPG elas to gas price	0.187	0.019	0.185	0.005	0.173	0.014
Size elas to gas price	-0.080	0.008	-0.080	0.003	-0.075	0.006

Table 6: Multinomial Logit Regressions without Product Dummies

Panel 1: Model Estimates	With Brand Dummy				No Brand Dummy			
	OLS		2SLS		OLS		2SLS	
	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
OR	-6.551	1.045	-6.741	1.045	-10.264	0.541	-10.250	0.576
OR*vehicle size	4.803	0.779	4.967	0.777	7.535	0.417	7.465	0.445
Gas price	2.162	0.094	2.317	0.122	1.134	0.056	1.045	0.090
DPM (Gas price/MPG)	-41.205	0.565	-43.982	1.371	-23.009	1.170	-20.439	1.346
MHI	0.682	0.097	0.311	0.215	0.874	0.102	1.043	0.172
Log(price)/log(MHI)	-3.473	0.112	-4.553	0.513	-2.289	0.068	-1.618	0.262
Vehicle size	9.134	1.115	8.762	1.125	-1.650	0.540	-0.974	0.471
Horsepower	0.356	0.006	0.420	0.031	0.511	0.018	0.357	0.028
Demographic variables (12)	Yes		Yes		Yes		Yes	
Brand dummy (330)	Yes		Yes		No		No	
R^2	0.746		0.746		0.263		0.256	

Panel 2: Implied Elasticities	Elas.	S.E.	Elas.	S.E.	Elas.	S.E.	Elas.	S.E.
MPG elas to OR	-0.092	0.007	-0.095	0.008	-0.144	0.010	-0.143	0.012
Size elas to OR	0.072	0.006	0.075	0.006	0.114	0.008	0.113	0.010
MPG elas to gas price	0.189	0.011	0.202	0.012	0.105	0.032	0.094	0.034
Size elas to gas price	-0.090	0.005	-0.096	0.006	-0.051	0.015	-0.045	0.016

Note: A brand is defined according to the name of a vehicle model (e.g., Ford Taurus) while a product is a brand-year observation (e.g., a 1999 Ford Taurus). In all regressions, there are county dummies (47) interacting with segment dummies (11) as well as year dummies (6) interacting with segment dummies (11). We control for the endogeneity of vehicle price due to unobserved product attributes using the observed attributes of other competing products in 2SLS.