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Lose some, save some: Obesity, automobile demand, and gasoline consumption

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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 new vehicles demanded by consumers are less fuel-efficient on average as a larger share of people become overweight or obese. The OLS results show that a 10 percentage point increase in obesity and overweight reduces the average MPG of new vehicles demanded by 1.4 percent, an effect requiring a 12 cent increase in gasoline prices to counteract. The 2SLS results after controlling for possible endogeneity in overweight and obesity prevalence put those two numbers at 5 percent and 54 cent, respectively. These findings, robust to a variety of specifications, suggest that policies to reduce overweight and obesity can have additional benefits for energy security and the environment.

1. Introduction

The increasing prevalence of overweight and obesity is a pressing health issue in the United States.[3] According to the recent survey by [27], the obesity rate among adults 20–74 years old increased from 15 to 34 percent during the past three decades while the rate of overweight and obesity increased from 47 to 67 percent. The medical literature has clearly demonstrated that overweight and obesity are associated with a number of medical conditions that are costly to treat [15,20].

In addition to significant medical costs, recent research points out that the impact of overweight and obesity on energy consumption is not negligible. Weight gain among U.S. consumers during 1990s increased jet fuel consumption by 2.4 percent in 2000 [8]. Overweight and obesity also affect gasoline consumption, due to the fact that heavier passengers reduce fuel efficiency of a vehicle [13,14]. Weight gain among Americans since the 1960s contributed to 0.8 percent of the gasoline consumption by passenger vehicles in 2005 [13].

These three studies examine the extent to which 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 their vehicle size based on their weight. In particular, we quantify the effect of the increasing rate of overweight and obesity on the demand for passenger vehicles and investigate its implications

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3 Following the health literature, we use overweight as both a noun and an adjective in the paper.

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on energy consumption and CO_2 emissions. To our knowledge, this is the first paper to analyze the link between the prevalence of overweight and obesity and vehicle demand.

Our benchmark empirical model is a multinomial logit model of vehicle demand. Due to the lack of household level data containing information on both weight status of the members and characteristics of vehicles owned, we estimate the model using data aggregated to the county level [2]. Our unique data set combines market sales data and obesity surveys in 48 U.S. counties from 1999 to 2005. In the demand model, we control for unobserved product attributes using fixed effects at the vehicle model level. We include a rich set of consumer demographic variables and control for (time-invariant) unobserved preference heterogeneity for different types of vehicles using fixed effects. To deal with possible endogeneity in the rate of overweight and obesity in the demand model due to (time-varying) unobservables, we employ two instruments: the ratio of the average price of fast food over the average food price at home, and the participation rate in the food stamp program. Both instruments are found to be relevant in the first stage estimation and the exogeneity assumption could not be rejected in the second stage.

The empirical analysis shows that as the rate of overweight and obesity increases, consumers have a stronger demand for larger and less fuel-efficient vehicles. Moreover, obesity exhibits much stronger effects than overweight on vehicle demand. We perform a variety of robustness checks and find that these results are invariant to the use of instruments and fixed effects. The benchmark multinomial logit model exhibits the undesired property of independence of irrelevant alternatives (IIA). To check the sensitivity of our findings to this framework, we estimate a linear demand model and similar results are obtained.

The OLS estimates in the benchmark model suggest that a 10 percentage point increase in the rate of overweight and obesity reduces the average miles per gallon (MPG) of new vehicles demanded by 1.4 percent, an effect that would require a 12 cent increase in gasoline prices to counteract. However, after controlling for the endogeneity in overweight and obesity prevalence using instruments, the estimation suggest that the effect on MPG would be 5 percent, an effect that would require a 54 cent increase in gasoline prices to counteract. 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 24.96 instead of 22.99, everything else being equal. The improved fuel efficiency implies total gasoline savings of about 251 million barrels and reduction in CO_2 emissions of 105 million tons over the lifetime of these vehicles.

With volatile gasoline prices and growing concerns about climate change and local air quality, a suite of policy instruments to reduce gasoline consumption 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 have been proposed. Our findings suggest that the effectiveness of these policies could be (partially) offset by the increasing prevalence of overweight and obesity. Our findings also imply that the overall benefits from local and national programs that aimed to reduce overweight and obesity are larger than what has been previously thought once energy and environmental benefits are taken into account.

The rate of overweight and obesity has been increasing not only in developed nations but also in many developing countries. For example, the rate of overweight and obesity among adults in Brazil increased from 20 percent to almost 50 percent from 1975 to 2003 while that in China increased from 13 to 27 percent from 1991 to 2004. Vehicle ownership is also growing dramatically in these countries, with China becoming the largest auto market by annual sales in the world in 2009. Taken together, our findings show that overweight and obesity are relevant for global efforts to deal with climate change.

2. Background and data

We first briefly discuss the trend of overweight and obesity in the U.S. and some important changes in the auto industry. We then present data sets used in our study.

2.1. Background

The overweight and obesity prevalence has been increasing at an alarming rate in the U.S. in the past 30 years as shown in Fig. 1. If the rate of overweight and obesity continues to grow at the current pace of 0.3–0.8 percentage point each year, 75 percent of U.S. adults will be overweight or obese by 2015 [28]. There are many medical conditions associated with overweight and obesity, most of which are costly to treat. Medical costs of overweight and obesity reached $78.5 billion in 1998 and accounted for 9.1 percent of total U.S. medical expenditures [10], half of which were through financially distressed medicare and medicaid systems. In light of significant health and economic consequences from overweight and obesity, many have called for making weight control a national priority.[4]

During the same period, an equally significant trend is the dramatic increase in the number of large passenger vehicles as shown in Fig. 1. The share of light trucks including passenger vans, SUVs, and pickup trucks among all passenger vehicles in stock grew from about 17 percent in late the 1970s to more than 40 percent in recent years. This trend can be largely

[4] For example, the Office of the 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 the economic and health consequences from overweight and obesity, the report provides many policy suggestions at both local and national levels.

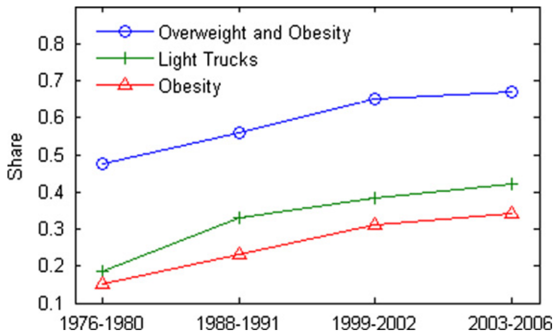

Fig. 1. Shares of overweight, obesity, and light trucks in the U.S. 1960–2006. Note: The overweight and obesity rates are for 20–74 years old adults. The middle line depicts the percentage of light trucks (including passenger vans, SUVs and pickup trucks) among all passenger vehicles in stock. The rates of overweight and obesity are from [27] while data on vehicle stock are from [26].

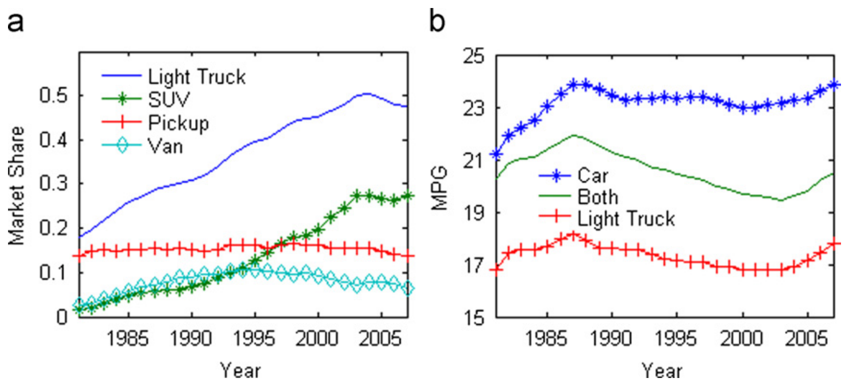

Fig. 2. New vehicle market shares by type and fuel economy 1981–2007. Note: The data points in the graph are three-year moving averages that are tabulated at the midpoint of each three consecutive years to smooth the trend. Data source: Light-duty automotive technology and fuel economy trends: 1975–2008 by EPA.

attributed to the introduction of the minivan in the early 1980s and the increased popularity of SUVs since the 1990s. The left panel of Fig. 2 plots the market share of new light trucks over total new light-duty vehicles, which grew from 17 percent to about 50 percent from 1981 to 2007.[5] Since 2002, after two decades of constant growth, the market share of light trucks began to stabilize.

The right panel of Fig. 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 crises and the enactment of CAFE standards in 1970s. 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 like segments (cars or light trucks), vehicles became larger and less fuel efficient from the late 1980s to the early 2000s. For example, according to 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 medium-sized cars and that of large cars both show an opposite trend. The top and bottom lines in the right panel of Fig. 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 developed over time. These technologies include more efficient engines, better transmission designs, and better engine and transmission matching. 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 vehicles 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.[6] From 1981 to 2007, the average Ton-MPG for

[5] 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).

[6] 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.

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
Front seat volume (in cu. ft.)	54.94	54.54	4.38	44.95	68.55
Vehicle size (in '0000 in^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), www.cars.com, and EPA's fuel economy database. The number of observations is 1287.

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 1–2 percent a year over this period, according to the EPA.

2.2. Data

We use several data sets. The first data set, collected from issues of Automotive News Market Data Book as well as online sources (www.cars.com), contains 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, which account for less than 1 percent of total new vehicle sales, are excluded). Table 1 reports summary statistics for the 1287 models in this data set. Price is the manufacturer suggested retail prices (MSRP). Front seat volume (in cubic feet) measures the roominess of the front row and is used to capture the comfort that a vehicle provides to overweight and obese people. Used to classify vehicle type for regulatory purposes (e.g., by the Department of Transportation), front seat volume is defined as the product of: front head room, front leg room, and the average of front shoulder room and front hip room, if shoulder room is more than 5 in. larger than hip room, and front shoulder room otherwise. Vehicle size is equal to the product of vehicle length and width and measures the "footprint" of a vehicle. The correlation coefficient between front seat volume and vehicle size is 0.827. Miles per gallon (MPG) is the weighted harmonic mean of city and highway MPGs based on the formula provided by the EPA to measure vehicle fuel economy: MPG=1/(0.55/city MPG+ 0.45/highway MPG). The correlation coefficients of MPG with front seat volume and vehicle size are -0.631 and -0.653, respectively.

The second data set, purchased from R. L. Polk & Company, contains total annual registrations of each new vehicle model in each of 48 U.S. counties from 1999 to 2005. These counties are within the 20 MSAs that are studied in [16].[7] 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 for the years during 1999–2005. 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 (compared 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 divided by MPG). We collected annual gasoline prices for each MSA from 1999 to 2005 from the American Chamber of Commerce Research Association (ACCRA) database. 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 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 collected median household income at the county level from small area income and poverty estimates from the U.S. Census Bureau. From the 2000 Census and the annual American Community Survey, we also collected several county-level demographic variables including median household income, total population, average household size, the proportion of households with children under 18 years old, house tenure status, and age. These variables are considered to be important in vehicle purchase decisions in current literature [1,22,25,29].

The overweight and obesity information are obtained from the National Health and Nutrition Examination Survey Data published by the National Center for Health Statistics (NCHS) at the Centers for Disease Control and Prevention (CDC). The survey is conducted at the individual level. The rates of overweight and obesity in the 48 counties under study are obtained based on individual observations. The range of overweight and obesity is determined by the body mass index, BMI=W/H^2, where W is the person's weight in kilograms and H is height in meters. An adult is considered overweight if their BMI is between 25 and 29.9, and obese if the BMI is 30 or higher. For children and teens, BMI ranges are age and gender-specific in

[7] 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.

Table 2
Correlation matrix and summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	Mean	S.D.
Overweight and obesity rate (1)	1						0.553	0.066
Gasoline price (2)	0.103	1					1.764	0.320
Median household income (3)	−0.415	0.101	1				5.564	1.160
Average new vehicle MPG (4)	−0.156	0.458	0.068	1			22.473	0.877
Average front seat volume (5)	0.441	0.140	−0.198	−0.676	1		55.913	0.939
Average vehicle size (6)	0.411	−0.090	−0.239	−0.827	0.942	1	1.385	0.037
New vehicle market share (7)	−0.048	−0.272	0.227	−0.266	−0.003	0.090	0.132	0.029

Note: Variables are at the county level. The number of observations is 336. Columns (1)–(6) show correlation coefficients and the last two columns are the mean and standard deviation.

order to account for normal differences in body fat between genders and across ages. Although the BMI does not measure body fat directly, it has been shown to be a convenient and reliable indicator of obesity [11].

It is worth noting that the BMI is not a perfect measure of weight partly because it ignores heterogeneity due to age, gender, and athleticism for adults. Other physical characteristics such as waist circumference (girth) may also be a good indicator of a person's desire for some vehicle characteristics such as seat weight. We use BMI in this paper to construct our variable of interest (overweight and obesity rate) for three reasons. First, BMI is arguably the most popular measurement of overweight and obesity. Second, waist circumference is not commonly recorded in physical examinations and health surveys. And while this measure is available in the National Health and Nutrition Examination Survey (NHANES), the survey is conducted only every two years, less frequent than annual obesity rates and other data used in our analysis. Finally, BMI is a good proxy for waist circumference: based on the data from four NHANES surveys (1999–2006) with 39,352 individual observations, the correlation coefficient between waist circumference and BMI is 0.93.

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 vehicle 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 (1)–(6) show some interesting patterns. The rate of overweight and obesity is negatively correlated with median household income and the average MPG of new vehicles in the county, and is positively correlated with the average front seat volume and 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.

The first panel of Fig. 3 plots the average front seat volume of new vehicles against the rate of overweight and obesity in the 48 counties in 2005. The second panel shows the average size of new vehicles against the rate of overweight and obesity, while the third panel plots the average MPG against the rate of overweight and obesity. The top plot clearly depicts a positive correlation between the average front seat volume and the prevalence of overweight and obesity. The second plot shows a similar relationship between vehicle size and the rate of overweight and obesity. The third plot presents a negative correlation between the average MPG and the prevalence of overweight and obesity. Recognizing the correlation shown in the graph could be spurious (e.g., both are caused by other common factors), we aim to determine in the regression analysis if and how much a higher rate of overweight and obesity results in stronger demand for large and fuel-inefficient vehicles.

3. Estimation strategy

We first present our empirical model and then discuss the challenge in identifying the causal effect of overweight and obesity on vehicle demand.

3.1. Empirical model

The empirical model comes from a random utility framework where a consumer chooses among multiple vehicle models as well as the option of no purchase in order to maximize her utility. Ref. [2] shows that a (non-linear) multinomial logit model from this framework can be transformed into a linear model and be estimated using only aggregate data. In the next section, we estimate an alternative linear demand model to check the robustness of our findings with respect to model specifications.

To describe the key empirical model, let m index markets (i.e., counties), and j index vehicle models. We assume that consumers have a total of J vehicle models plus an outside good indexed by 0 (i.e., not purchasing a new vehicle) to choose from a give year. With the time index suppressed, we estimate the following equation from the linear transformation of the

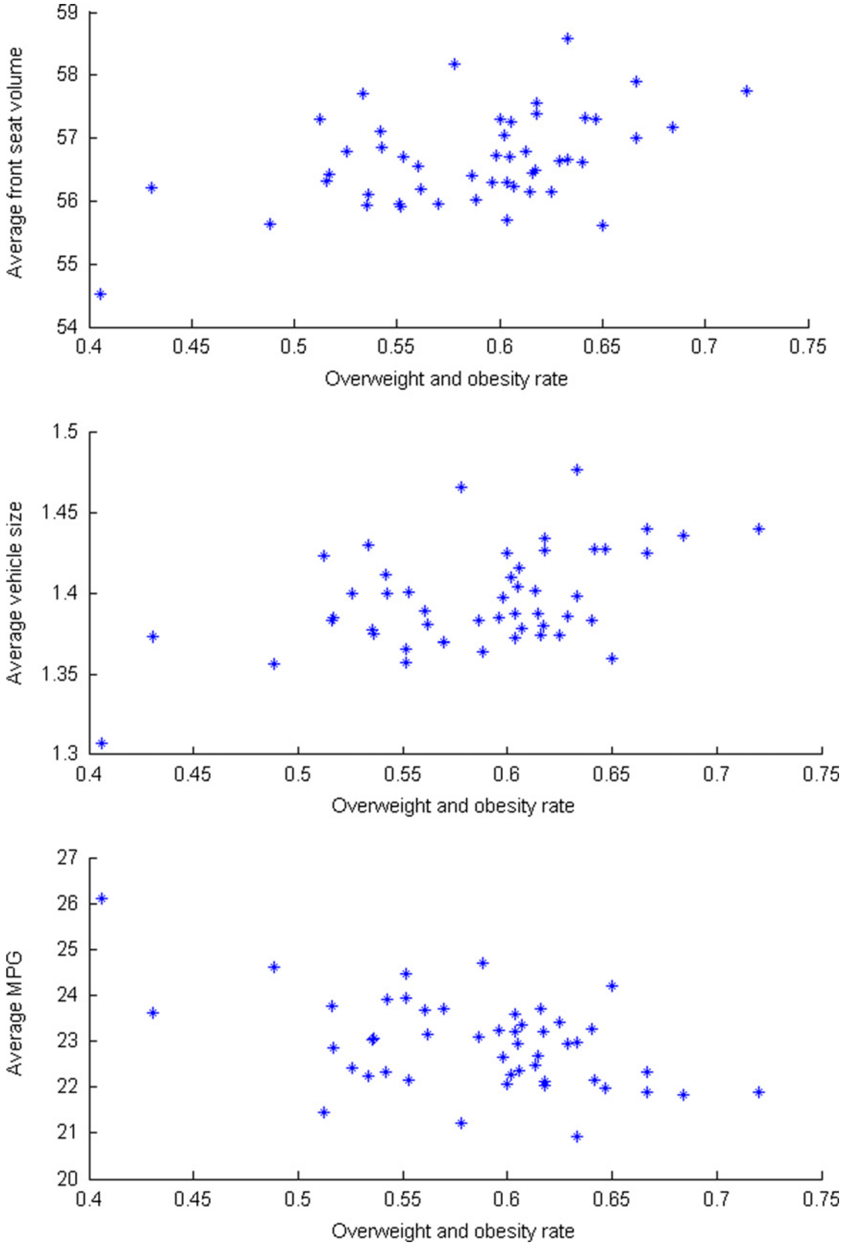

Fig. 3. Overweight and obesity and vehicle characteristics in 48 counties in 2005.

multinomial logit model:

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

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 front seat volume that do not vary across markets. α is a vector of corresponding consumer preference parameters. To save notation, x_{mj} includes market demographics (such as the rate of overweight and obesity) as well as the interaction terms between product attributes and market demographics (such as the interaction term between the rate of overweight and obesity with front seat volume). These variables capture heterogeneity in consumer preferences on vehicle attributes as well as on the choice margin of buying or not buying a new vehicle. 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 campaigns or consumption trends at the national level. v_{mj} includes unobserved market-varying demographics that affect consumers' vehicle choices, which are not controlled for.

This linear model exhibits 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 including prices to affect the market share of product j.[8] 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.

One of the focal points of previous studies on automobile demand is to control for the unobserved product attribute ξ_j [3]. Since the unobserved product attribute may affect vehicle price, ignoring it could render vehicle price endogenous and cause price elasticities of demand to be underestimated. 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 product fixed effects, the above model can be written as

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

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

3.2. Identification

To facilitate the discussion of the challenge, we now spell out the key variables of interest in x_{mj}:

$$\begin{aligned}\ln(s_{mj}/s_{m0}) = {} & \beta_1 \mathrm{OBS}_m + \beta_2 \mathrm{OBS}_m * \mathrm{FSVOL}_j + \beta_3 \mathrm{GasP}_m + \beta_4 \mathrm{GasP}_m/\mathrm{MPG}_j \\ & + \beta_5 \mathrm{Log}(\mathrm{Income}_m) + \beta_6 \mathrm{Log}(\mathrm{Price}_j)/\mathrm{Log}(\mathrm{Income}_m) + \delta_j + \text{ Others Variables } + v_{mj},\end{aligned} \tag{4}$$

where OBS_m is the rate of overweight and obesity in market m. The first two variables are used to capture the effect of overweight and obesity on vehicle demand including the effect on the choice margin of whether to purchase a new vehicle and the selection among the set of new vehicle models. The interaction term between OBS_m and front seat volume (*FSVOL*) captures consumer preference heterogeneity on front seat roominess: a positive β_2 implies that consumers in areas with a higher rate of overweight and obesity on average have a stronger preference for large vehicles. The next two variables capture the effect of gasoline price on vehicle demand where $\mathrm{GasP}_m/\mathrm{MPG}_j$ is the fuel cost of per mile traveled for vehicle model j in market m. The fifth and sixth variables allow consumer preferences on vehicles to depend on household income. A negative β_6 implies that consumers dislike vehicle price and more importantly that consumers with high household income are less sensitive to vehicle price.

The model also includes five demographic variables at the county level as well as their interactions with MPG and vehicle size, total population, average household size, the proportion of households with children under 18 years old, the percentage of households in rented houses, and the median resident age. The model includes county dummies to control for time-invariant unobservables at the county level (such as the availability of public transportation or sidewalks) that could affect consumers' choice margin of whether to purchase a new vehicle as well as the rate of overweight and obesity. In addition, the model also includes interaction terms between county dummies and vehicle type dummies to control for county-level unobservables that affect consumer preference for different types of vehicles. 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.

In the above model, product fixed effects δ_j control for unobserved product attributes as well as the county-invariant time trend in vehicle preferences. County fixed effects and their interactions with vehicle type dummies control for time-invariant county specific preferences on vehicle types. However, the model does not control for additional unobservables such as time-varying *and* county specific unobservables that could be correlated with both consumer preference on vehicle size and the rate of overweight and obesity. These unobservables subsumed in v_{mj} could cause the rate of overweight and obesity to be endogenous, and hence prevent a causal interpretation of coefficients β_1 and β_2.

We use the instrumental variable method to deal with the endogeneity problem. To this end, we require variables that are correlated with the prevalence of overweight and obesity but do not affect vehicle demand, conditioning on variables controlled in the model. Based on the extensive literature on the cause of rising obesity in the U.S., we choose two instruments. The first one is the ratio of the average price of fast food over the average food price at home. The second one is the participation rate in the food stamp program. In estimation, we use the lagged values of these two variables as instruments to minimize potential contemporaneous correlation with the error term in the vehicle demand equation. In addition, we expect that the effect of these variables on overweight and obesity takes time to realize.

Previous studies have shown that among many factors, declining food prices and advances in food preparation technology have played a role in the rapidly increasing prevalence rate. Prices at fast food restaurants, prices at full-service restaurants,

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

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

and food prices at home all have negative effects on individual body mass index [4], suggesting that lower food prices may increase food consumption and caloric intake. In addition, the per capita number of restaurants has a positive effect on weight outcomes. Similarly, proximity to fast food restaurants is positively correlated with weight outcomes for both school children and mothers [7]. These results are consistent with the findings that due to larger portions and higher calorie density, meals from restaurants on average contain more calories those prepared at home [9,23].

To construct the first instrument, we collect prices of food items from the American Chamber of Commerce Researchers Association Cost of Living Index (ACCRA COLI) for the 48 counties under study. Because ACCRA only provides price data at the MSA level, we assume that food prices are the same across counties within an MSA. Similar to [4,6], we construct the average food price at home based on the prices of 12 food items in COLI as well as the corresponding weights used by ACCRA to construct COLI's grocery price index.[9] The average fast food price is the average price of the following three items: a QUARTER-POUNDER with cheese from McDonald's, half of a 12-in. thin crust cheese pizza at Pizza Hut or Pizza Inn, and a thigh and drum-stick of fried chicken from Kentucky Fried Chicken or Church's. Because the level of these average prices could affect consumer vehicle demand through budget constraints, we use the ratio of the average fast food price over the average price for food at home as the instrument for the rate of overweight and obesity. A lower ratio implies that fast food is relatively cheaper than food prepared at home. This could lead to dining out at fast food restaurants more often and in turn a higher rate of overweight and obesity.

The second instrument is the participation rate in the food stamp program at the county level. Data on the number of food stamp program participants and population size at the county level are from the Small Area Estimates Branch of U.S. Census Bureau. Several studies based on either aggregate or individual data have documented the positive association between the participation of the food stamp programs and the incidence of overweight and obesity, especially among women [12,18,31]. Although the causality remains a point of contention, several conjectures about the possible mechanisms have been put forth.

The first suggests that limiting program participation benefits to food purchases may only result in more food consumption compared to non-participants. The second explanation argues that program participation may induce more spending on high calorie food and lead to overconsumption of calories. The third mechanism has to do with the practice of distributing food stamps only once a month, which could result in periods of under- and over-consumption. This "food stamp cycle" could cause weight gain. Although the participation rate of the food stamp program could affect the prevalence of overweight and obesity through any of the channels, we argue that it is otherwise uncorrelated with consumer preference on new vehicles (i.e., other than through the indirect correlation with other controlled variables).

Both these instruments exhibit significant variations both across counties and over time. The average food stamp participation rate in the 48 counties in 1998 was 0.0438 with a standard deviation of 0.028. The lowest was 0.0015 in Douglas County, Colorado while the highest was 0.1080 in Fulton County, Georgia. In 2004, the average food stamp participation rate increased to 0.0621 with a standard deviation of 0.0336. The lowest of 0.0128 was in San Mateo County, California while the highest of 0.1554 was in Milwaukee County, Wisconsin. The average price ratio (fast food over food at home) is 8.01 with a standard deviation of 0.76 across the MSAs from 1998 to 2004. The lowest ratio was 6.23 in counties within San Francisco MSA in 2005. The highest was 10.71 in Houston MSA in 2004.

4. Estimation results

4.1. Results from OLS

The second and third columns in Table 3 present parameter estimates and implied elasticities from OLS. The standard errors for parameter estimates are robust clustered at the county level. The standard errors for implied elasticities are from bootstrapping with 100 replications.

The overweight and obesity rate (OR) in the regressions is the percentage of people who are either overweight or obese in the population. As discussed in the previous section, the first two variables 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

$$\frac{\partial s_{mj}}{\partial \mathrm{OR}} = (-8.561+0.156 * \text{ front seat volume})s_{mj}(1-s_{mj}). \tag{5}$$

The partial effect is positive only for vehicles whose front seat volume is larger than 54.88 cubic feet, which is about the 53th percentile in the distribution of front seat volume among all 1287 vehicles in the data. In addition, the effect of overweight and obesity on vehicle demand is stronger for larger vehicles among those in the upper 47 percentiles of the size distribution. That is, a rise in the rate of overweight and obesity would lead to an increased demand for large vehicles and the increase in 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 demand is

$$\frac{\partial s_{mj}}{\partial \text{ Gas price}} = (1.989-37.853/\mathrm{MPG})s_{mj}(1-s_{mj}). \tag{6}$$

[9] These 13 food items are: steak, ground beef, chicken, tuna, whole milk, eggs, margarine, cheese, tomatoes, bananas, lettuce, and bread.

Table 3
OLS and 2SLS results.

Panel 1: model estimates	OLS		2SLS	
	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	−8.561	0.802	−29.609	2.483
OR*front seat volume	0.156	0.015	0.560	0.041
Gas price	1.989	0.225	1.668	0.255
DPM (gas price/MPG)	−37.853	5.393	−31.064	6.384
Median household income (MHI)	0.182	0.103	−0.173	0.171
Log(price)/log(MHI)	−4.017	0.183	−4.486	0.202
Additional demographic variables (15)	Yes		Yes	
Product dummy (1287)	Yes		Yes	
County dummy (47)	Yes		Yes	
County dummy * van dummy (47)	Yes		Yes	
County dummy * suv dummy (47)	Yes		Yes	
County dummy * pickup dummy (47)	Yes		Yes	
R^2	0.777		0.771	
Overidentification test stat. (*P*-value)			0.513 (0.774)	
Panel 2: implied elasticities in 2005	Elas.	S.E.	Elas.	S.E.
MPG elas to overweight and obesity rate	−0.080	0.005	−0.287	0.016
Front seat volume elas to OR	0.040	0.003	0.145	0.008
MPG elas to gas price	0.268	0.015	0.220	0.015
Front seat volume elas to gas price	−0.067	0.004	−0.055	0.004

Note: The dependent variable is $\ln(s_{mj}/s_{m0})$ where s_{mj} is the market share of model *j* in county *m*. The number of observations in both regressions is 61,766. The standard errors for parameter estimates are robust clustered at the county level. The 15 additional demographic variables include total population in logarithm, average household size, the proportion of households with children under 18 years old, the percentage of renters, median age as well as their interactions with MPG and front seat volume. Vehicles are divided into four categories (cars, vans, SUVs, and 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 with 100 bootstrap samples.

This implies that an increase in gasoline price would increase the demand for vehicles with an MPG larger than 19.03 while reducing the demand for less fuel-efficient vehicles. Moreover, the more fuel-efficient a vehicle is, the larger the demand increase would be given an increase in gasoline prices. The negative coefficient estimate on Log(price)/log(MHI) from OLS suggests that consumers in areas with higher median household income are less price sensitive. Based on the coefficient estimate, the own-price elasticity for product *j* is $(-4.017/\log(\text{MHI}))(1-s_{mj})$. The price elasticity estimates for all 1287 vehicle models range from −1.70 to −3.32 with the average being −2.40.

We note in passing that the identification of the above partial effects relies not only on cross-county and temporal variations in vehicle demand due to differences in market demographics (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., front seat volume, MPG, or price). A study using only aggregate vehicle fleet information at the county level (such as average front seat volume or MPG of new vehicles sold) would not have cross-county and temporal variations at the *vehicle model* level. In addition, it would lose the second source of variation.

The parameter estimates from OLS suggest that as overweight and obesity become more prevalent, vehicles demanded will have a large front seat volume and as a result, less fuel efficiency on average. The effects of a gasoline price increase on vehicle demand are opposite. In order to measure the magnitude of these effects, we simulate elasticities with respect to these two variables. The estimates and their standard errors are presented in panel 2 of Table 3. The elasticity of MPG with respect to the rate of overweight and obesity being −0.08 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 0.08 percent. The elasticity of MPG with respect to gasoline price is estimated at 0.268 in 2005. The elasticities of front seat volume to both variables of interests are also intuitively signed and statistically significant.

4.2. Results from 2SLS

To deal with the potential endogeneity of the rate of overweight and obesity in the demand model, we employ the following two instruments: the lagged ratio of the average price of fast food over the average price of food at home, and the lagged participation rate of the food stamp program. We interact these two variables with front seat volume to serve as instruments for the interaction term between the rate of overweight and obesity with front seat volume. The last two columns in Table 3 report the results from 2SLS. With four (excluded) instruments and two endogenous variables, we can test whether overidentifying restrictions are valid. The overidentification test statistic is 0.513 with a *p*-value of 0.774, failing to reject the exogeneity of the instruments at any conventional significance level.

Table 4
First stage regression results.

	The rate of overweight and obesity		Overweight and obesity and front seat volume	
Food stamp participation rate	0.639	0.126	−14.366	5.466
Fast food price/home food price	−0.006	0.002	−0.987	0.182
Food stamp rate * front seat volume	1.8E−04	0.001	0.910	0.095
Fast food/home food price *front seat volume	1.9E−05	1.8E−05	0.013	0.003
Gas price	−0.011	0.016	−0.624	0.402
DPM (gas price/MPG)	−0.007	0.027	0.176	7.825
Median household income (MHI)	0.145	0.046	8.226	0.361
Log(price)/log(MHI)	−1.3E−04	0.002	0.302	0.346
Additional demographic variables (15)	Yes		Yes	
Product dummy (1287)	Yes		Yes	
County dummy (47)	Yes		Yes	
County dummy * van dummy (47)	Yes		Yes	
County dummy * suv dummy (47)	Yes		Yes	
County dummy * pickup dummy (47)	Yes		Yes	
R^2	0.642		0.641	

Note: The number of observations in both regressions is 61,766. The standard errors for parameter estimates are robust clustered at the county level.

Based on the parameter estimates, all the findings from OLS discussed above still hold qualitatively. However, significant differences exist in the magnitude of the coefficient estimates between OLS and 2SLS, especially for the first two variables. The coefficient estimates from 2SLS are much larger in magnitude than those from OLS. The implied elasticity of the average MPG with respect to overweight and obesity is −0.287 from 2SLS, compared to −0.08 from OLS. This suggests that without controlling for the endogeneity problem, the effect of overweight and obesity on the average MPG would be largely underestimated. The comparison highlights possible unobservables in the demand equation that are negatively correlated with overweight and obesity prevalence yet positively correlated with consumer preference for front seat volume.

We offer two examples here. First, these unobservables could capture changes in preference toward risks (health risk as well as vehicle safety). Increased awareness of both vehicle safety and health risks associated with obesity could lead to reduced rate of overweight and obesity and increased demand for larger vehicles.[10] On the other hand, reduced risk aversion could increase the rate of overweight and obesity and reduce the demand for large vehicles. The second example of unobservables is about changes toward more active lifestyles (such as participating more outdoor activities). Those changes could reduce the rate of overweight and obesity while increasing the demand for larger vehicles such as SUVs (for example for their off-road driving capacity or added space for outdoor gear). Turned around, changes toward less active lifestyles would cause people to be overweight and obese while reducing the demand for large vehicles.

The elasticity of average MPG with respect to gasoline price is estimated at 0.22 from OLS, compared to 0.26 from OLS. 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. Ref. [24] obtain an estimate of 0.21 from 1997 to 2001 using U.S. state-level panel data on vehicle fuel efficiency and gasoline prices. Ref. [16] 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. Therefore, our estimates from both OLS and 2SLS are similar to those from recent studies.

To check the relevance of the instruments, Table 4 reports the regression results from the first stage. The dependent variables in the two regressions are the two endogenous variables in the vehicle demand model: the rate of overweight and obesity, and its interaction with front seat volume. The first four variables reported in the table are the instruments. The corresponding instruments (the first two in the first equation, the second two in the second equations) are statistically significant even in the presence of county and model-year fixed effects, suggesting the instruments are relevant. In the equation for the rate of overweight and obesity, the coefficient estimate on the participation rate in the food stamp program is positive and statistically significant. As discussed above, the positive link between the use of food stamps and weight gain has been documented in several studies. The coefficient estimate on the ratio of the average fast food price over the average food price at home is negative and significant. This implies that an increase in the fast food price relative to the price of food prepared at home would decrease the rate of overweight and obesity. This is consistent with the finding in the literature that meals at fast food restaurants contain higher calories on average than meals prepared at home.

The coefficient estimate on the gasoline price is negative but not significant, consistent with [6]. The coefficient estimate on median household income is positive and significant. Although obesity has been viewed as a problem mostly of the low income households, the disparity in the obesity rate among the rich and poor is diminishing rapidly in recent years. While the obesity rate among households with annual income less than $25,000 (in 2000 dollars) was 22.5 percent, compared to only

[10] Large vehicles tend to be safer due to their larger mass and better absorption of crash energies from larger interior or crumple zones. Moreover, many SUVs and pickups are taller than passenger cars and in collisions with cars, their passenger compartments could absorb less crash energy and subject their occupants less harm.

Table 5
Robustness checks.

Panel 1: model estimates	Model 1		Model 2		Model 3	
	Para.	S.E.	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	−19.573	2.324	−20.766	2.332	−17.303	2.666
OR*front set volume	0.371	0.036	0.375	0.036	0.338	0.048
Gas price	1.124	0.187	0.125	0.174	0.418	0.114
DPM (gas price/MPG)	−19.714	4.792	−18.810	4.669	−18.151	4.081
Median household income (MHI)	−0.036	0.140	−0.787	0.240	−0.667	0.109
Log(price)/log(MHI)	−4.033	0.286	−3.872	0.368	−4.086	0.296
Additional demographic variables (15)	Yes		Yes		No	
Product dummy (1287)	Yes		Yes		Yes	
County dummy (47)	Yes		No		No	
County dummy * van dummy (47)	No		No		No	
County dummy * suv dummy (47)	No		No		No	
County dummy * pickup dummy (47)	No		No		No	
R^2	0.759		0.720		0.704	
Overidentification: *J*-stat and *P*-value	0.112 (0.945)		2.383 (0.304)		38.547 (0.000)	
Panel 2: Implied Elasticities in 2005	Elas.	S.E.	Elas.	S.E.	Elas.	S.E.
MPG elas to OR	−0.190	0.012	−0.192	0.012	−0.173	0.012
Front seat volume elas to OR	0.096	0.006	0.097	0.006	0.088	0.006
MPG elas to gas price	0.140	0.012	0.129	0.013	0.126	0.012
Front seat volume elas to gas price	−0.035	0.003	−0.032	0.003	−0.031	0.003

9.7 percent for household with annual income more than \$60,000 during 1971–1974; by contrasts, these obesity rates were 32.5 percent and 26.8 percent during 2001–2002 [17]. Because county dummies eliminate most of the cross-county variations in income, the positive coefficient could reflect the fact that the prevalence of obesity is growing three times faster among households with income more than \$60,000 than it is among the low income group in recent years.

Table 5 reports the results for three alternative regressions where different sets of variables are used. The first regression does not include interactions terms between county dummies and three vehicle type dummies. Although it allows consumers in different counties to have different preferences for the outside good, there is no heterogeneity across counties in terms of preferences for different types of vehicles. The second regression excludes county dummies as well, while the third regression excludes additional 15 demographics variables. Most of the coefficient estimates from all three regressions have the same directions as those from the full model. The estimates of elasticities become smaller in magnitude while retaining the same signs.

4.3. Separating overweight and obesity

In the previous analysis, overweight and obesity are combined together. It is interesting to examine if the two affect vehicle demand differently. To the extent that the overweight and obese tend to purchase large vehicles to accommodate their bigger waistlines, we expect that the obesity rate would have a stronger demand effect than the overweight rate. Table 6 presents estimation results from OLS and 2SLS where we separate overweight and obesity. The first two parameters capture the effect of obesity on vehicle demand while the next two capture the effect of overweight. In both regressions, the parameters suggest that obesity and overweight have qualitatively the 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 from both OLS and 2SLS show that obesity exhibits larger effects on vehicle demand than overweight. The elasticity of average MPG to the obesity rate is −0.11 while that of average MPG to the overweight rate is −0.12. The elasticity of average MPG to overweight from 2SLS is not statistically significant at the 10 percent confidence level. This could be a result of the relatively low explanatory power of the instruments on the overweight rate in the first stage. The average overweight rate was 36.1 percent while the average obesity rate was 22.6 percent in 2005. This implies that the effect of 1 percentage point increase in obesity on the fuel economy of vehicles demanded would be approximately 60 percent larger than that of overweight.

5. Alternative specification and discussion

5.1. Linear demand model

The multinomial logit model estimated above is subject to the undesired property of independence of irrelevant alternatives (IIA), manifested by the fact that the ratio of choice probabilities (or market shares) between two models is independent of other choices available on the market. To check the robustness of our findings to the multinomial logit

Table 6
Regressions results: separating obesity and overweight.

Panel 1: model estimates	OLS		2SLS	
	Para.	S.E.	Para.	S.E.
Obesity rate	−11.200	0.902	−29.900	2.572
Obesity rate*front seat volume	0.205	0.017	0.558	0.032
Overweight rate	−5.055	0.650	−20.061	21.546
Overweight rate*front seat volume	0.091	0.012	0.365	0.412
Gas price	1.967	0.221	1.711	0.274
DPM (gas price/MPG)	−37.353	5.274	−31.734	6.557
Median household income (MHI)	0.176	0.100	0.017	0.559
Log(price)/log(MHI)	−4.069	0.188	−4.484	0.197
Additional demographic variables (15)	Yes		Yes	
Product dummy (1287)	Yes		Yes	
County dummy (47)	Yes		Yes	
County dummy * van dummy (47)	Yes		Yes	
County dummy * suv dummy (47)	Yes		Yes	
County dummy * pickup dummy (47)	Yes		Yes	
R^2	0.777		0.773	
Panel 2: implied elasticities in 2005	Elas.	S.E.	Elas.	S.E.
MPG elas to obesity rate	−0.040	0.003	−0.108	0.006
Front seat volume elas to obesity rate	0.020	0.001	0.055	0.003
MPG elas to overweight rate	−0.029	0.004	−0.116	0.087
Front seat volume elas to overweight rate	0.015	0.002	0.059	0.044
MPG elas to gas price	0.264	0.015	0.225	0.016
Front seat volume elas to gas price	−0.066	0.004	−0.056	0.004

framework used above, we estimate a linear demand model where the dependent variable is the quantity of vehicles sold for each model (normalized by population size). The demand equation is specified as follows:

$$\begin{aligned}\ln(q_{mj}/\text{nhouse}_m) = {} & \beta_1 \text{OBS}_m + \beta_2 \text{OBS}_m * \text{FSVOL}_j + \beta_3 \text{GasP}_m + \beta_4 \text{GasP}_m/\text{MPG}_j \\ & + \beta_5 \text{Log(Income}_m) + \beta_6 \text{Log(Price}_j)/\text{Log(Income}_m) \\ & + \sum_{k \neq j} \gamma_{jk} \text{Log(Price}_k) + x_j \alpha + \xi_j + \text{Others Variables} + v_{mj},\end{aligned} \tag{7}$$

where q_{mj} is the quantity sold of vehicle j in county m and nhouse_m is the number of households in county m. Different from this specification, the dependent variable in the multinomial logit specification is $\log(s_{mj}/s_{m0})$, the logarithmic market share ratio of model j and the outside good. Another difference between the two models is the presence of prices of all the other products defined by $\gamma_{jk}\text{Log(Price}_k)$ in the linear demand model, where γ_{jk} defines the cross-price elasticity between models j and k. Due to the presence of the prices for all products in the right side of the equation, the linear demand model does not exhibit the IIA property given that the ratio of market shares between two products will depend on other vehicle models in the choice set.

After introducing product fixed effects δ_j, the model can be rewritten as:

$$\begin{aligned}\ln(q_{mj}/\text{nhouse}_m) = {} & \beta_1 \text{OBS}_m + \beta_2 \text{OBS}_m * \text{FSVOL}_j + \beta_3 \text{GasP}_m + \beta_4 \text{GasP}_m/\text{MPG}_j \\ & + \beta_5 \text{Log(Income}_m) + \beta_6 \text{Log(Price}_j)/\text{Log(Income}_m) \\ & + \delta_j + \text{ Others Variables } + v_{mj},\end{aligned} \tag{8}$$

where δ_j subsumes $\sum_{k \neq j} \gamma_{jk} \text{Log(Price}_k) + x_j \alpha + \xi_j$. Although δ_j subsumes different variables in the multinomial logit model defined by Eq. (4), the only practical difference in estimation between the two model specifications is the dependent variable.

Table 7 reports the estimation results from both OLS and 2SLS. We use the same instrumental variables in the 2SLS estimation as in the previous section. The coefficient estimates from both OLS and 2SLS are very similar to their counterparts in the multinomial logit model reported in Table 3. The overidentification test cannot reject the exogeneity assumption of the instruments in this linear demand model either. Panel 2 of the table presents elasticity estimates. They are also very close to those from the multinomial logit model: a 1 percent increase in the rate of overweight and obesity results in a 0.29 percent decrease in the average MPG of new vehicles purchased and a 0.15 percent decrease in the average front seat volume of new vehicles purchased. The comparison suggests that our findings are robust to the demand model specification, both qualitatively and quantitatively.

Table 7
Results for linear demand model.

Panel 1: model estimates	OLS		2SLS	
	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	−8.564	0.802	−29.735	2.458
OR*front seat volume	0.156	0.015	0.561	0.041
Gas price	1.970	0.226	1.647	0.257
DPM (gas price/MPG)	−37.811	5.389	−31.012	6.376
Median household income (MHI)	−0.015	0.090	−0.362	0.153
Log(price)/log(MHI)	−4.016	0.184	−4.486	0.202
Additional demographic variables (15)	Yes		Yes	
Product dummy (1287)	Yes		Yes	
County dummy (47)	Yes		Yes	
County dummy * van dummy (47)	Yes		Yes	
County dummy * suv dummy (20)	Yes		Yes	
County dummy * pickup dummy (20)	Yes		Yes	
R^2	0.774		0.769	
Overidentification: *J*-stat and *P*-value			0.664 (0.717)	
Panel 2: implied elasticities in 2005	Elas.	S.E.	Elas.	S.E.
MPG elas to overweight and obesity rate	−0.080	0.005	−0.289	0.016
Front seat volume elas to OR	0.040	0.003	0.146	0.008
MPG elas to gas price	0.268	0.015	0.220	0.015
Front seat volume elas to gas price	−0.067	0.004	−0.055	0.004

Note: The dependent variable is $\ln(q_{mj}/\text{nhouse}_m)$ where q_{mj} is the quantity sold of model j in county m and nhouse_m is the number of household size in county m. The number of observations in both regressions is 61,766. The standard errors for parameter estimates are robust clustered at the county level. The standard errors for elasticity estimates are from bootstrapping with 100 bootstrap samples.

5.2. Discussion

Based on 2SLS estimates from the benchmark multinomial logit model, our simulation results show that the average MPG of new vehicles demanded would have been 5 percent lower (21.83 instead of 22.99) in 2005 with a 10 percentage point increase in the rate of overweight and obesity (i.e., from 0.587 to 0.687). An increase of this size in the overweight and obesity rate could be realized in about 12 years, following the recent trend since 1995. In order to counteract the decrease in the average MPG, a 54 cent increase in gasoline prices (e.g., through a higher gasoline tax) over the average price of $2.32 per gallon in 2005 is needed. Moreover, obesity has a stronger effect on the fuel economy of vehicles demanded. A 10 percentage point increase in the obesity rate over that in 2005 (holding the overweight rate constant) would have decreased the average MPG of new vehicles demanded by 5.3 percent, compared to 3.3 percent given an increase in the overweight rate of the same magnitude.

These findings suggest that the effect of overweight and obesity on fleet fuel economy is dramatic, especially in the context of the gasoline price increases or other policies required to counteract them. Many have argued that the average gasoline tax of 41 cents in the U.S. is much lower than the optimal level in relation to externalities associated with gasoline usage [21]. However, raising the gasoline tax has been a politically difficult policy to pass. In addition, recent studies have shown that raising the gasoline tax is a more effective way to reduce gasoline consumption than tightening the CAFE standards [1,5,19,30].

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 24.96 instead of 22.99. This implies about 8.6 percent savings in gasoline consumption over those 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 million, the total gasoline savings over 15 years for these vehicles is about 251 million barrels, and the reduction in CO_2 emissions is about 105 million tons.[11] The effect of overweight and obesity on gasoline consumption through vehicle choices is almost 10 times as large as the ex-post effect (through the effect on fuel-efficiency conditioning on vehicle choices) described by [13,14]. All these points considered, the estimated effects of overweight and obesity on vehicle fuel economy and gasoline consumption are economically significant.

Our analysis focuses on the effect of overweight and obesity on vehicle demand rather than the equilibrium effect. Estimating the equilibrium effect would necessitate simultaneous analysis of demand and supply sides. Analyzing the supply side is complicated by two factors: First, given the positive correlation between consumer weight status and the demand for

[11] We find that there is a small positive effect of overweight and obesity on the total number of new vehicles demanded. Because the fuel consumption from the outside good is unknown, the above analysis essentially assumes that the fuel consumption from the outside good is the same with new vehicles demand. In addition, improved fuel economy often increases vehicle usage, which is called the rebound effect [24].

large and less fuel-efficient vehicles, automakers are likely to increase the prices of those vehicles given 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 automakers produce multiple products. Second, the effect of overweight and obesity on automakers' product mix decisions is 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. In contrast to the first factor, this will exacerbate the static demand effect.

6. Conclusion

This paper finds that new vehicles demanded by consumers are less fuel-efficient on average as the rate of overweight and obesity goes up. Our results from 2SLS (OLS) show that if the prevalence of overweight and obesity has remained at the 1981 level, the average fuel economy of new vehicles demanded would have been about 8.6 (2.5) percent higher than that observed in 2005, *ceteris paribus*. For a change in the opposite direction, we find that a 10 percentage point increase in the rate of overweight and obesity from the 2005 level would decrease the average MPG of new vehicles demanded by 5 (1.4) percent.

Passenger vehicles as a whole account for more than 40 percent of total oil consumption and over 17 percent of total greenhouse gas emissions in the U.S. in recent years. Therefore, the passenger transportation sector plays an important role in policies aiming to address climate change, energy security, and environmental problems associated with gasoline consumption. Our study suggests that the effect of overweight and obesity on vehicle demand could have potentially important implications for these policies. Without taking into consideration the growth trend of overweight and obesity and its impact on vehicle demand, long-term government interventions could miss the intended policy goals and face added obstacles in reducing gasoline consumption and greenhouse gas emissions. On the other hand, our findings imply that in addition to the savings in health care costs, national and local policies that aim to prevent and decrease overweight and obesity could provide extra benefits in energy saving and environmental protection.

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