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

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Preliminary: Comments Welcome

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 in 48 U.S. counties from 1999 to 2005, we find that the rate of overweight and obesity exhibits a large effect on the fuel economy of new vehicles demanded. A 10 percentage points increase in the rate of overweight and obesity reduces the average MPG of new vehicles demanded by 6 percent: an effect requires a 49 cents increase in gasoline price to counteract. Our findings suggest that health polices aiming to reduce overweight and obesity can have potentially important benefits on energy security and the environment.

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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 passenger vehicles in 48 U.S. counties from 1999 to 2005. Our empirical analysis shows that the prevalence of overweight and obesity has an economically significant effect on the fuel economy of new vehicles demanded. A 10 percentage points increase in the rate of overweight and obesity among the population reduces the average miles per gallon (MPG) of new vehicles demanded by 6 percent: an effect requires a 49 cents increase in gasoline prices to counteract.¹

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



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

¹A 10 percentage points 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 66 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 obesity and overweight 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 medical conditions, most of which are costly to treat (Kortt et al. (1998), Ogden et al. (2007)).² Sturm (n.d.) shows that obese individuals cost 36 percent more in inpatient and outpatient spending and 77 percent more in medications than non-obese individuals and concludes that obesity outranks both smoking and drinking in its adverse health effects. The cost of overweight and obesity include both direct costs such as medical expenditures and indirect costs that are relate 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) find that the medical cost of overweight and obesity accounted for 9.1 percent of total U.S. medical expenditures in 1998 and may have reached \$78.5 billion, half of which are 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

²These conditions include elevated cholesterol levels, depression, musculoskeletal disorders, gallbladder disease, nonalcoholic fatty liver disease, and several cancers.

³For 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 economics and health consequence from overweight and obesity, the report provides many policy suggestions at both national and local 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. For example, the percentage of light trucks including passenger vans, SUVs, and pickup trucks among all passenger vehicles in stock increased from about 15 percent in early 1970's to almost 40 percent in recent years as shown in Figure 1. Largely due to this trend, motor gasoline consumption in the United Stated increase 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 account 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 separated 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 relation of weight 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) and Jacobson and

⁴See 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.

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.

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. That is, we study the ex-ante effect of overweight and obesity on energy consumption instead of the ex-post effect (i.e., relative to transportation choices). 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. Based on the parameter estimates of the empirical model, 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 10 percent higher, everything else being equal. The improved fuel efficiency implies sizable savings in gasoline consumption over vehicles' life-time. Therefore, our results point to the increase in the prevalence of overweight and obesity as one important contributing factor behind the growing gasoline consumption and oil dependence in the United States.⁵

With volatile gasoline prices and growing concern 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

⁵In 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)).

vehicles, and government support for developing fuel-efficient technologies 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 considered.

2 Background and Data

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

2.1 Background

The U.S. auto industry witnessed some 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 only 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 of CAFE standards in 1970's. It then continuously declined until the reversal of this

⁶Light-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.

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 left panel of Figure 2 present parallel temporal pattern 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 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.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: $MPG = \frac{1}{0.55/\text{city MPG}+0.45/\text{highway MPG}}$.⁸

The second data set, purchased from R. L. Polk & Company, contains total annual

⁸Alternatively, 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.

⁷Intuitively, 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.

	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

Table 1: New Vehicle Characteristics 1999-2005

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.

registrations of each new vehicle model in each of the 48 U.S. counties from 1999 to 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,

⁹These 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.

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 counties within the same MSA have same gasoline prices. We collect median household income for each counties from 2000 Census and annual American Community Survey.

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 genderspecific. They are defined to take into account normal differences in body fat between genders and differences in body fat at various ages. Although BMI does not measure body fat directly, it has been shown that this proxy is 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 for adults, it ignores heterogeneity of age, sex, and athleticity.

Table 2 presents correlation coefficients among several variables of interests 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

	(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

Table 2: Correlation Matrix and Summary Statistics

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.





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 confirm if the relationships are causal and if so, to what extent they are by utilizing cross-sectional as well as temporal variations while controlling for other confounding factors.

3 Empirical Model and Results

Our baseline model is a multinomial logit model estimated using detailed vehicle sales data for each model in 48 U.S. counties. In the next session, we present results from linear models based on aggregated data at the county level as a robustness check.

3.1 Empirical Model

To describe the multinomial logit model, let m index a market (i.e., county), i index a consumer, and j a vehicle model. In a given year, a consumer has total J models plus an outside good (indexed by 0) to choose from. The utility of consumer i in market m from product j is

$$u_{mij} = x_j \alpha + x_{mj} \beta + \xi_j + \nu_{mj} + \epsilon_{ij}, \tag{1}$$

where x_j is a vector of product attributes that do not vary across market while x_{mj} includes the interaction terms between product attributes and market demographics, such as dollars per mile (gasoline price/DPM) or the interaction term between the rate of overweight and obesity with vehicle size. ξ_j is the unobserved product attribute or national promotions. ν_{mj} represents local promotions or price variations given that we use MSRPs for vehicle price. It can also include other market level unobservables.

Assuming that the random taste shock, ϵ_{mij} , has a type I extreme value distribution and normalizing the utility from the outside good to be zero, the market share of product j in market m can be written as

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

Following Berry (1994), the above utility function specification can be transformed into the following linear model:

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

where s_{mj} and s_{m0} are the market shares of model j and the outside good, respectively. This model has two important features to note. First, the transformed model is parsimonious: it only has product attributes (including price) of the single product as explanatory variables while allowing attributes of other products to affect the market share of a given product as shown in equation (2). This contrasts with a linear demand model where the explanatory variable is the quantity of a product and regressors include prices of all competing products. Second, although our model specification starts from individual utility maximization, the transformed model can be estimated based on market-level sales data.

One of the focal points of previous studies on automobile demand based on aggregate sales data from a single market is to control for the unobserved product attribute ξ_j , which could render vehicle price (either in x_j or in x_{mj}) endogenous and cause demand elasticities to price to be under-estimated (e.g., Berry, Levinsohn, and Pakes (1995)). The identification assumption employed in those studies is that observed product attributes x_j are uncorrelated with the unobserved product attribute. Therefore, attributes of the competing products can be used as instruments for vehicle price. However, the identification assumption could be violated if there are unobserved promotions at the national level (could be treated as unobserved product attributes) that are correlated with product attributes (i.e., strong marketing campaign for SUVs by producers in late 1990's and early 2000's). Taking advantage of the fact that we have sales data in multiple markets, we use product fixed effects to control for unobserved product attributes (and national level promotions). The above model could be written as:

$$ln(s_{mj}/s_{m0}) = \delta_j + x_{mj}\beta + \nu_{mj},\tag{4}$$

where δ_j subsumes market-invariant product attributes x_j and ξ_j .

Nevertheless, with multiple-market data, we have to control for local unobservables such as local marketing efforts or local price variations that could cause variables in x_{mi} to be endogenous. For example, retailers in areas with a high rate of overweight and obesity (or high gasoline prices) may offer deeper discounts for smaller vehicles (or fuelinefficient vehicles) than those in areas with a low rate of overweight and obesity (or low gasoline prices). Without controlling for unobserved factors, the effect of an increase in the prevalence of overweight and obesity (or gasoline price) on vehicle size (or fuel economy) would be under-estimated. To address the possible endogeneity of variables in x_{mj} , we take advantage of the multi-market feature of our data set and use the average of the corresponding variable in distant counties as the instrument. For example, for the fuel cost variable in county m, we use the average fuel cost of the same vehicle in all the counties in different Census divisions as instruments.¹⁰ The identification assumption is that after unobservables at the national level such as promotions being controlled for by product fixed effects, local unobservables are not correlated with demographics or gasoline prices in counties that are geographically distant. The validity of our instruments hinges on the assumption that local unobservables are not correlated across counties in different Census divisions, which is plausible given that the geographic areas under study are counties and that counties in different Census divisions are very far

¹⁰We use the number of households in each county as weight in obtaining the averages. The nine U.S. Census divisions are: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.The 48 counties studied are from all nine Census divisions.

from each other. Similar ideas for instruments have been explored in Hausman (1996) and Nevo (2001) to deal with price endogeneity due to local unobservables in studies using multi-market data.

It is worth noting that with data from a single market, not only could the endogeneity of variables in x_j or x_{mj} (such as the fuel cost variable or the rate of overweight and obesity) still exist, but the instruments proposed here would not be available anymore. Moreover, the exogeneity assumption used in the literature (e.g., Berry et al. (1995)) to deal with the price endogeneity problem that observed product attributes are uncorrelated with unobserved product attributes would not be applicable when there are unobservables such as promotions (can be viewed as unobserved product attributes) that are correlated with product attributes and are not controlled for.

3.2 Estimation Results

Tables 3 and 4 present parameter estimates as well as the estimates for implied elasticities from six different model specification. Specification 1 is the preferred one where most control variables are included. The estimation results from both OLS and 2SLS are presented for all specifications. In 2SLS, we control for the potential endogeneity of the first six explanatory variables which may be correlated with local unobservables such local promotions or local price variations. In all these model specifications, the use of instruments generates substantial differences in parameter estimates. For example, the coefficient estimate on Log(price)/MHI from OLS for specification 1 suggests that the own-price elasticity for product j is $\frac{-9.188}{MHI}(1 - s_{mj})$ while the price elasticity based on 2SLS estimates is $\frac{-11.305}{MHI}(1 - s_{mj})$. Based on OLS, the price elasticity estimates range from -0.94 to -2.84 with the average being -1.72. Among all the 1,287 products in the data, 539 of them have inelastic demands, which are not consistent with profit-maximizing pricing decisions by firms with market power. Based on parameter estimates from 2SLS, the estimates of price elasticity range from -1.15 to -3.49 with the average being -2.11. In this case, there is no inelastic demand. The fact that the results from 2SLS are more reasonable than those from OLS points to the possibility that even after we control for the unobserved product attribute using product fixed effects, price endogeneity could still exist likely due to local unobservables such as local promotions and price variations as we alluded to above.

The overweight and obesity rate (OR) in the regressions is the percentage of people who are either overweight or obese in the population.¹¹ The first two variables are used to capture the effect of overweight and obesity on vehicle demand. The estimates from 2SLS in the first specification imply that the partial effect of the rate of overweight and obesity on vehicle market share is: $\frac{\partial s_{mj}}{\partial OR} = (-18.951 + 15.235 * vehicle size)s_{mj}(1 - s_{mj})$. The partial effect is positive only for vehicles whose size is larger than 1.244 ('0000 inch²), which is about 36 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. Notice that in the absence of the first variable as in the fourth specification shown in Table 4, a positive coefficient estimate on the interaction term between vehicle size and the rate of overweight and obesity, OR * vehicle size, would suggest a counter-intuitive result that overweight and obesity would have a positive effect on the demand for vehicles of all sizes.

The identification of the above partial effect relies not only on cross-sectional and temporal variations in vehicle demand due to differences in the rate of overweight and obesity but also on cross-model variations arising from the fact that vehicle demand responds to changes in overweight and obesity differently across vehicles with different size. Similarly, the partial effect of gasoline price on vehicle market share based on 2SLS results for the first specification is: $\frac{\partial s_{mj}}{\partial \text{Gas price}} = (1.705 - 39.924/\text{MPG})s_{mj}(1 - s_{mj})$.

¹¹We also estimated models where we allow the rate of overweight and the rate of obesity to have different coefficients. We cannot reject that they have the same effects. Those results are available from authors upon request.

This implies that an increase in gasoline price would increase the demand for vehicles with MPG larger than 23.42 (63 percentile of the MPG distribution) while reducing the demand for other vehicles. Moreover, the more fuel-efficient a vehicle is, the large the demand increase would be with an increase in gasoline price.

Based on the parameter estimates, we simulate several elasticity measures which are presented in panel 2 of Tables 3 and 4. The elasticities based on 2SLS results in specification 1 have expected signs: a higher rate of overweight and obesity increases the demand for fuel-inefficient and large vehicles while a higher gasoline price results in the opposite. All the elasticity estimates have the same signs from OLS and 2SLS with the exception of the demand elasticity to gasoline prices. The estimate from OLS suggests that a higher gasoline price increases the demand for new vehicles with while the estimate from 2SLS implies otherwise. In addition, results from 2SLS suggest that the average MPG and size of new vehicles are more sensitive to the rate of overweight and obesity as well as to the gasoline price than what results from OLS suggest. For example, the elasticity of MPG with respect to the rate of overweight and obesity is -0.122 from OLS and -0.290 from 2SLS. Similarly, the elasticity of MPG with respect to the gasoline price is 0.112 from OLS, comparing to 0.181 from 2SLS. These findings are consistent with our conjecture on the source and the direction of the endogeneity. In areas with stronger demand for fuel-inefficient or large vehicles due to underlying demand factors such as a higher rate of overweight and obesity or lower gasoline prices, dealers may offer deeper discount over MSRPs for fuel-efficient or smaller vehicles. Without controlling for these local promotions, demand sensitivity to those variables of interests would be under-estimated.

To check the sensitivity of our results to model specifications, we also estimate the logit model with different set of control variables. In specification 2, we drop county dummies which control for county level unobservables such as the availability of public transportation system that could affect consumers' choice margin of whether to pur-

chase a new vehicle. Similar to the results from specification 1, the elasticities of the fuel economy of new vehicles demanded to both the gasoline price and the rate of overweight and obesity are under-estimated in OLS compare to the estimates from 2SLS. Moreover, the elasticity estimates from 2SLS are close to those obtained from specification 1 with the exception of the demand elasticity with respect to gasoline price. In specification 3, we drop median household income variable as well as Log(P)/MHI. Although the estimates of the elasticities with respect to the rate of overweight and obesity are very close to those obtained from the first specification, the elasticities of MPG and size with respect to gasoline prices become much smaller in magnitude, pointing to the importance of allowing interaction between income and vehicle price in the demand model. Specification 4 does not include three stand-alone variables: the rate of overweight and obesity, median household income, and gasoline price in the regression. Different from specification 1, this specification does not allow opposite effects from overweight and obesity or gasoline prices on vehicles with different size or MPG. For example, a positive coefficient estimate on the interaction term between vehicle size and the rate of overweight and obesity, OR*vehcle size, suggests that an increase in the rate of overweight and obesity would increase the demand for new vehicles of all sizes. Compared to the results from specification 1, the demand elasticities with respect to both gasoline prices and the overweight rate become much larger in magnitude while the MPG and size elasticity estimates become smaller in magnitude. In specification 5, we only keep the first two variables together with dummy variables. The elasticity estimates with respect to the overweight and obesity rate are very close to those from the first specification. Specification 6 does not use product fixed effects. Since the instruments that we use are not valid any more in the presence of national level promotions, the MPG and size elasticities with respect to the gasoline price do not have the right sign. Moreover, the coefficient estimate on Log(P)/MHI suggests that most products have inelastic demand.

Table 5 reports the estimation results for the first stage regressions where the dependent variable is one of the six endogenous explanatory variables in the logit model. For each of the endogenous variables, we construct as an instrument the average of the same variable in all counties in other Census divisions weighted by the number of households in the county. In all the six regressions, the coefficient estimate on the corresponding instrument is highly significant, suggesting that the instruments have good explanatory power for the endogenous variables.

3.3 Discussion

Our simulation results based on parameter estimates show that the average MPG of new vehicles demanded would decrease by 6 percent (from 22.99 to 21.62) in 2005 with a 10 percentage point increase in the rate of overweight and obesity (from 0.586), which could be realized in about 12 years following the trend since 1995. In order to counteract this decrease in the average MPG, a 49 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. Many studies have shown that increasing the gasoline tax is an effective way to reduce gasoline consumption, e.g, compared to tightening CAFE standards.¹² Moreover, the average 41 cents gasoline tax in the U.S. is lower than the optimal level regarding externalities associated with gasoline usage (Parry and Small (2005)). However, increasing gasoline taxes has been a politically difficult policy to pass.

Our simulation results also suggest that if the rate of overweight and obesity in 2005 had stayed at the 1981 level (20 percentage points lower), the market share of light trucks would have been 42 percent instead of 54 percent in the 48 counties in 2005. The average MPG of new vehicles demanded would have been 25.32 instead of 22.19, implying more than 10 percent saving in gasoline consumption over vehicles's life-time holding

¹²See for example, National Research Council (2002); Congressional Budget Office (2003); West and Williams (2005); and Bento, Goulder, Jacobsen, and von Haefen (2008).

vehicle usage constant.¹³ Our results show that the ex-ante effect of overweight and obesity (i.e., through vehicle purchase) is much larger than the ex-post effect (i.e, through fuel-efficiency during vehicle usage) by Jacobson and McLay (2006) and Jacobson and King (2009) as discussed in the introduction. Taking these estimates together with their comparison to the effect of gasoline prices, we consider our empirical estimate of the effect of overweight and obesity on fuel economy demanded and gasoline consumption to be quantitatively significant.

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 prices. The elasticity estimate from our preferred specification is 0.181 from 1999 to 2005. Small and Van Dender (2007) obtain an estimate of 0.21 from 1997-2001 using U.S. level time-series 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 to be 0.204 using a similar data set and a different empirical model. Beresteanu and Li (2008) estimate a random coefficient multinomial logit model based on a similar data set to ours augmented with a household survey data and provide an estimate of 0.169 for the elasticity. 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 in a logit model. Further robustness checks are provided in the next section.

Our study focuses on the effect of overweight and obesity on vehicle demand rather than the equilibrium effect, which necessitates the analysis of the demand and supply sides simultaneously. Although the supply side is out of scope of our study, it is worth

¹³Improved 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.

mentioning the following two important and counteracting factors in the supply side. First, given the positive relation between overweight and the demand for 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 effects on vehicle demand depend on both across-firm competition and within-firm competition given the fact that all automarkers 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 that the demand effect of overweight and obesity, automakers are likely to introduce more large models into the market with an increase in overweight and obesity. This, different from 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. However, it is likely to 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.

4 Further Robustness Analysis

An undesirable feature of the logit model is the IIA property which suggests unreasonable substitution patterns across products. As discussed above, our estimate of the MPG elasticity to gasoline price is close to the result from a computationally intensive random coefficient model which does not exhibit the IIA property in Beresteanu and Li (2008). To further check the robustness of our findings, we estimate three linear equations simultaneously based on aggregate data at the county level. The dependent variables in these three equations are the average MPG of new vehicles, the average size of new vehicles, and the market share of new vehicles (the total number of new vehicles divided by the total number of households) in each county in each year. The key explanatory variables are the rate of overweight and obesity, annual gasoline price, and the median household income at the county level. We control for unobserved effects across years (such as vehicle offering) and across counties (such as traffic and road conditions). Nevertheless, the three key explanatory variables could still be endogenous due to time-varying unobservables such as local promotions and advertisements, which could be correlated with demand factors such as those captured by the three key explanatory variables. Similar to IVs employed in the previous section, we use the averages of the corresponding variable in all the counties in different Census divisions as instruments.

Table 6 presents parameter estimates as well as implied elasticities. Columns (1) to (6) are the results from 3SLS where the first three explanatory variables are instrumented while columns (7) to (12) are results from seemingly unrelated regressions (SUR). The parameter estimates for the MPG equation from 3SLS suggest that a county with a higher rate of overweight and obesity or a lower gasoline price has a lower average MPG among new vehicles. The coefficient estimates on the rate of overweight and obesity and the gasoline price are not statistically significant (p-values are 0.11 and 0.12 respectively) at the 10% significant level. However, this is most likely due to the fact that there are only 336 observations. The implied MPG elasticities with respect to the rate of overweight and obesity and the gasoline price are -0.287 and 0.215, compare to -0.290 and 0.181 from the preferred logit regression in Table 3. The implied vehicle size elasticities with respect to the overweight rate and the gasoline price are 0.057 and -0.065. Both of them have intuitive signs and their p-values are 0.23 and 0.07, respectively. All the coefficients estimates in the new vehicle market share equation have intuitive signs but are insignificant.

The coefficient estimates from SUR are quite different from those from 3SLS. For ex-

ample, in the MPG equation, the parameter estimates for the rate of overweight and obesity and the gasoline price are both highly insignificant. However, the parameter estimate for median household income is positive and significant, compared to the negative and insignificant estimate from 3SLS. Table 7 presents the regression results from the first stage. The R² is high in all three regressions and the t-values for the coefficient estimates on the third instrumental variables are large, suggesting that they have good explanatory powers for the three endogenous variables.

Note that the three equations estimated here do not impose any restrictions on the substitution patterns among different vehicle models. The identification of the parameters are based on variations in the characteristics of new vehicle fleet due to time-varying changes in the key explanatory variables at the county level. Compared to the results from logit models, the regressions based on aggregate level data provide similar estimates for the effects of the rate of overweight and obesity as well as the gasoline price on the fuel economy of new vehicles demanded.

5 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. 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 10 percent higher than that observed in 2005, *ceteris paribus*.

The significant effect of overweight and obesity on vehicle fuel economy has po-

tentially 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, 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, significant benefits in energy saving and environmental protection.

Panel 1: Model Estimates		Specific	cation 1			Specific	ation 2			Specific	ation 3	
	10	່ນ	2SI	Ŋ	OL	່ທ່	2SI	Ş	OL	່ນ	2SL	Ň
	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	-8.500	0.325	-18.951	1.908	-7.741	0.473	-19.207	1.884	-5.763	0.567	-18.561	2.605
OR*vehicle size	6.401	0.252	15.235	1.449	6.050	0.271	15.004	1.422	4.399	0.418	14.565	1.931
Gas price	1.325	0.113	1.705	0.197	0.523	0.098	0.983	0.196	0.778	0.145	0.680	0.245
DPM(Gas price/MPG)	-24.266	2.814	-39.924	3.774	-22.420	3.117	-39.649	3.800	-13.442	4.026	-17.754	5.450
Median household income(MHI)	-0.101	0.023	-0.471	0.049	-0.114	0.009	-0.265	0.064	No		No	
Log(P)/MHI	-9.188	0.480	-11.305	1.473	-7.717	0.545	-11.148	1.492	No		No	
County dummies (47)	Yes		Yes		No		No		Yes		Yes	
Product dummies (1287)	Yes		Yes		Yes		Yes		Yes		Yes	
\mathbb{R}^2	0.770		0.763		0.733		0.720		0.762		0.755	
Panel 2: Implied Elasticities												
MPG elas. to OR	-0.122	0.006	-0.290	0.015	-0.115	0.006	-0.286	0.016	-0.084	0.005	-0.277	0.017
Size elas. to OR	0.096	0.005	0.229	0.012	0.091	0.005	0.226	0.013	0.066	0.004	0.219	0.013
Demand elas. to OR	0.167	0.041	1.015	0.190	0.296	0.032	0.740	0.085	0.152	0.038	0.758	0.155
MPG elas. to gas price	0.112	0.008	0.181	0.011	0.099	0.007	0.176	0.014	0.062	0.008	0.080	0.010
Size elas. to gas price	-0.054	0.004	-0.088	0.005	-0.049	0.004	-0.087	0.007	-0.030	0.004	-0.039	0.005
Demand elas. to gas price	0.295	0.085	-0.244	0.132	-0.803	0.030	-1.327	0.065	0.231	060.0	-0.229	0.158
Note: The overweight and obesity 1	ate (OR) i	s the per	centage c	of people	who are e	either ov	erweight	or obese	. The nur	nber of o	bservatio	ns for
all regressions is 61,766. The stands	ard errors	for para	meter est	imates ai	re robust	clustere	d at the co	ounty lev	el. The e	lasticitie	s are calcı	ulated
based on all the observations. The	standard 6	errors fo	r elasticity	y estimat	es are fro	m boots	trapping.					

Table 3: Multinomial Logit Regression Results

Panel 1: Model Estimates		Specific	cation 4			Specifi	cation 5			Specifi	cation 6	
	IO	່ທ່	2SI	Ņ	IO	်လု	2SI	Ş	Ю	່ທ່	2SI	Ş
	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
Overweight and obesity rate (OR)	No		No		-6.263	0.492	-23.415	2.532	-5.312	0.123	-10.342	0.439
OR*vehicle size	0.363	0.045	3.657	0.348	4.767	0.356	17.992	1.862	2.646	0.098	2.416	0.102
Gas price	No		No		No		No		-1.007	0.031	-0.475	0.049
DPM (Gas price/MPG)	-6.869	1.679	-20.871	1.501	No		No		8.802	0.656	9.546	0.715
Median household income (MHI)	No		No		No		No		-0.835	0.031	-0.500	0.033
Log(P)/MHI	-7.891	0.450	-6.087	1.080	No		No		-7.628	0.206	-7.362	0.204
County dummies (47)	Yes		Yes		Yes		Yes		Yes		Yes	
Product dummies (1287)	Yes		Yes		Yes		Yes		No		No	
R ²	0.767		0.751		0.761		0.752		0.147		0.122	
Panel 2: Implied Elasticities												
MPG elas. to OR	-0.007	0.001	-0.070	0.005	-0.090	0.006	-0.343	0.015	-0.050	0.002	-0.045	0.002
Size elas. to OR	0.006	0.001	0.057	0.004	0.071	0.005	0.271	0.012	0.039	0.001	0.033	0.001
Demand elas. to OR	0.239	0.044	2.428	0.187	0.155	0.041	0.707	0.160	-0.784	090.0	-3.282	0.139
MPG elas. to gas price	0.030	0.003	060.0	0.006	N/A		N/A		-0.043	0.002	-0.044	0.003
Size elas. to gas price	-0.015	0.002	-0.045	0.003	N/A		N/A		0.020	0.001	0.021	0.001
Demand elas. to gas price	-0.492	0.057	-1.489	0.093	N/A		N/A		-0.911	0.036	-0.044	0.060
Note: The number of observations	for all re	gression	s is 61,76	6. The s	tandard	errors f	or parame	eter esti	mates ar	e robust	clustered	l at the
county level. The elasticities are cald	culated b	ased on	all the ob	servatio	ns. The	standard	l errors fc	or elastic	ity estim	iates are	from boc	tstrap-
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Dependent Variable			OR*vel	n. size	Gas 1	orice	DB	M	M		Log(P),	IHW/
-	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
OR in other divisions	0.993	0.039	-0.002	0.051	0.080	0.053	0.002	0.003	0.076	0.247	0.002	0.007
OR*veh size in other divisions	0.001	0.001	0.996	0.006	0.000	0.001	0.001	0.000	-0.005	0.001	-0.002	0.000
Gas price in other divisions	0.005	0.004	0.006	0.006	0.971	0.013	-0.001	0.001	-0.030	0.020	-0.001	0.001
DPM in other regions	-0.005	0.002	0.008	0.003	0.003	0.003	0.982	0.005	-0.026	0.004	0.032	0.003
MHI in other divisions	-0.002	0.003	-0.003	0.004	-0.003	0.003	0.000	0.000	0.912	0.019	0.003	0.001
Log(P)/MHI in other divisions	0.001	0.001	0.000	0.001	-0.001	0.000	0.001	0.000	0.018	0.002	0.995	0.010
County dummies (47)	Yes		Yes		Yes		Yes		Yes		Yes	
Product dummies (1287)	Yes		Yes		Yes		Yes		Yes		Yes	
R ²	0.659		0.836		0.968		0.978		0.986		0.962	
Note: These are results from OLS	regressi	ons whe	re the de	penden	t variabl	e is one	of 6 end	ogenous	explana	tory var	iables in	Tables
3 and 4. The first 6 explanatory ve	ariables a	ire the ir	strumer	its. They	r are the	average	of the co	orrespon	iding var	iable in	all the co	ounties
in different census divisions weig	ghted by	the nun	hber of h	ousehol	ds in ea	ch of the	se coun	ties. The	e numbei	r of obse	rvations	for all
regressions is 61,766. The standar	d errors	for para	meter est	imates a	are robu	st cluster	red at the	e county	level.			

Table 5: First Stage Results

Panel 1: Model Estimates			3SI	Ś					SL	R		
Dependent Variable	MF	Ŋ	Si	ze	Sha	are	IM	Ð	Siz	ze	Sha	re
1	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.	Para.	S.E.
	(1)	(2)	(3)	(4)	(2)	(9)	6	(8)	(6)	(10)	(11)	(12)
Overweight and obesity rate (OR)	-11.730	7.424	0.144	0.120	0.031	0.176	-0.208	0.316	0.001	0.008	-0.011	0.018
Gas price	2.712	1.746	-0.050	0.028	-0.022	0.041	-0.034	0.201	-0.010	0.005	0.012	0.011
Median household income (MHI)	0.758	1.242	0.024	0.020	0.040	0.030	-0.697	0.075	0.007	0.002	0.026	0.004
\mathbb{R}^2	0.702		0.955		0.848		0.951		0.980		0.859	
Panel 2: Implied Elasticities	MF	Q	Si	ze	Shê	are	IW	D.	Si	ze	Sha	re
Elas. to OR	-0.287	0.182	0.057	0.048	0.123	0.696	-0.005	0.008	0.000	0.003	-0.041	0.071
Elas. to gas price	0.215	0.138	-0.065	0.036	-0.277	0.528	-0.003	0.016	-0.013	0.007	0.159	0.146
Note: The number of observation is	336 in all	regressi	ions. 7 y	ear dum	mies and	d 47 cou	inty dum	nmies ar	e include	ed. The	total nur	nber of
vehicles sold in each county is used	as weight	. In 3SL	S, the fir	st three	explanat	ory vari	ables are	e instrun	nented u	sing the	ir averag	e in all

Table 6: Results from Aggregate Data

5 4 other counties in different census divisions.

Table 7: First Stage Regressions

Dependent Variable	ō	2	Gas F	rice	MI	
	Para.	S.E.	Para.	S.E.	Para.	S.E.
Overweight and obesity rate in other divisions	-5.090	1.548	-3.188	2.218	-14.530	6.378
Gas price in other divisions	-0.765	0.536	-6.276	0.769	-0.220	2.210
MHI in other divisions	-0.459	0.297	0.610	0.425	-5.714	1.223
R2	0.713		0.984		0.988	
Note: 7 year dummies and 47 county du	ummies a	ure inclu	ded in th	ne regres	sions.	

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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," *Obes Res*, 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.
- Hausman, J., "Valuation of New Goods under Perfect and Imperfect Competition," inT. Bresnahan and R. Gordon, eds., *The Economics of New Goods*, University of Chicago Press, 1996.
- 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?," 2009. American Economic Journal: Economic Policy, forthcoming.
- 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.
- **Nevo, A.**, "Mergers with Differentiated Products: the Case of the Ready-to-eat Cereals Industry," *Econometrica*, 2001, (2), 307–342.
- 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*.

- **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.