A SILVER LINING? THE CONNECTION BETWEEN GASOLINE PRICES AND OBESITY

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Abstract:
I find evidence of a negative association between gasoline prices and body weight using a fixed effects model with several robustness checks. I also show that increases in gas prices are associated with additional walking and a reduction in the frequency with which people eat at restaurants, explaining their effect on weight. My estimates imply that 8% of the rise in obesity between 1979 and 2004 can be attributed to the concurrent drop in real gas prices, and that a permanent $1 increase in gasoline prices would reduce overweight and obesity in the United States by 7% and 10%.

JEL Classification: I10

Abbreviations Used: BMI: Body Mass Index
BRFSS: Behavioral Risk Factor Surveillance System DDB: Doyle Dayne Bernbach
EIA: Energy Information Administration
MSA: Metropolitan Statistical Area
NHANES: National Health and Nutrition Examination Surveys
NLSY: National Longitudinal Survey of Youth OLS = Ordinary Least Squares
OPEC: Organization of the Petroleum Exporting Countries

Article:

I. INTRODUCTION

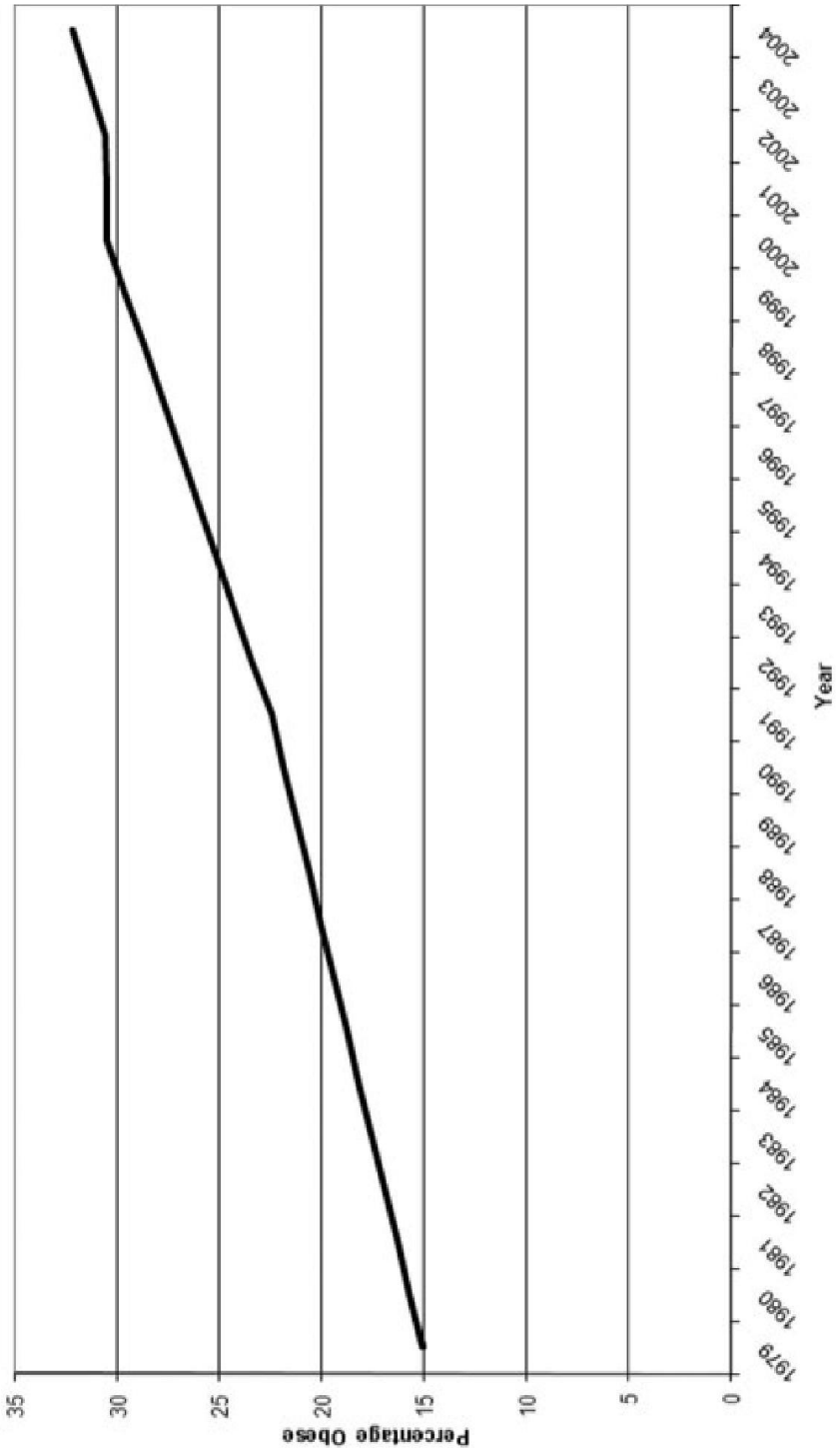
America's rising obesity rate has become a prominent public health concern in recent decades. Studies have linked being obese (the condition of weighing substantially more than the medical optimum)[1] to high blood pressure, diabetes, heart disease, stroke, and a number of other adverse health conditions (Strum 2002). The percentage of adults in the United States who are classified as obese has more than doubled since 1979, increasing from 15.1% to 32.2% (Figure 1), and two-thirds are now overweight (Flegal et al. 2005, Hedley et al. 2004). Obesity imposes substantial costs on society both in terms of early mortality and medical expenses, with recent estimates of these costs being 112,000 deaths and $117 billion per year (Flegal et al. 2005, U.S. Department of Health and Human Services 2001).

Another prominent issue in recent decades has been gasoline prices. They first entered the public spotlight in the 1970s, when supply restrictions by the petroleum cartel OPEC (Organization of the Petroleum Exporting Countries) caused the price of oil to jump from $2 per barrel in 1970 to $38 per barrel in 1980 (Reid 2004). Although real gas prices actually declined throughout much of the 1980s and 1990s (Figure 2), they have again risen sharply in recent years, from $1.60 per gallon at the start of 2004 to $3.22 in May of 2007 (Figure 3). How to reduce the U.S. dependence on foreign oil is a subject of frequent policy debate, with suggestions including increasing fuel taxes to encourage the development of alternatives (Staff Editorial 2005).

A rise in gasoline prices has the potential to affect body weight in three ways. First, individuals may substitute from driving to more physically demanding modes of transportation, such as walking, bicycling, or taking public transportation. Second, substitution and income effects may lead people to eat out at restaurants less and

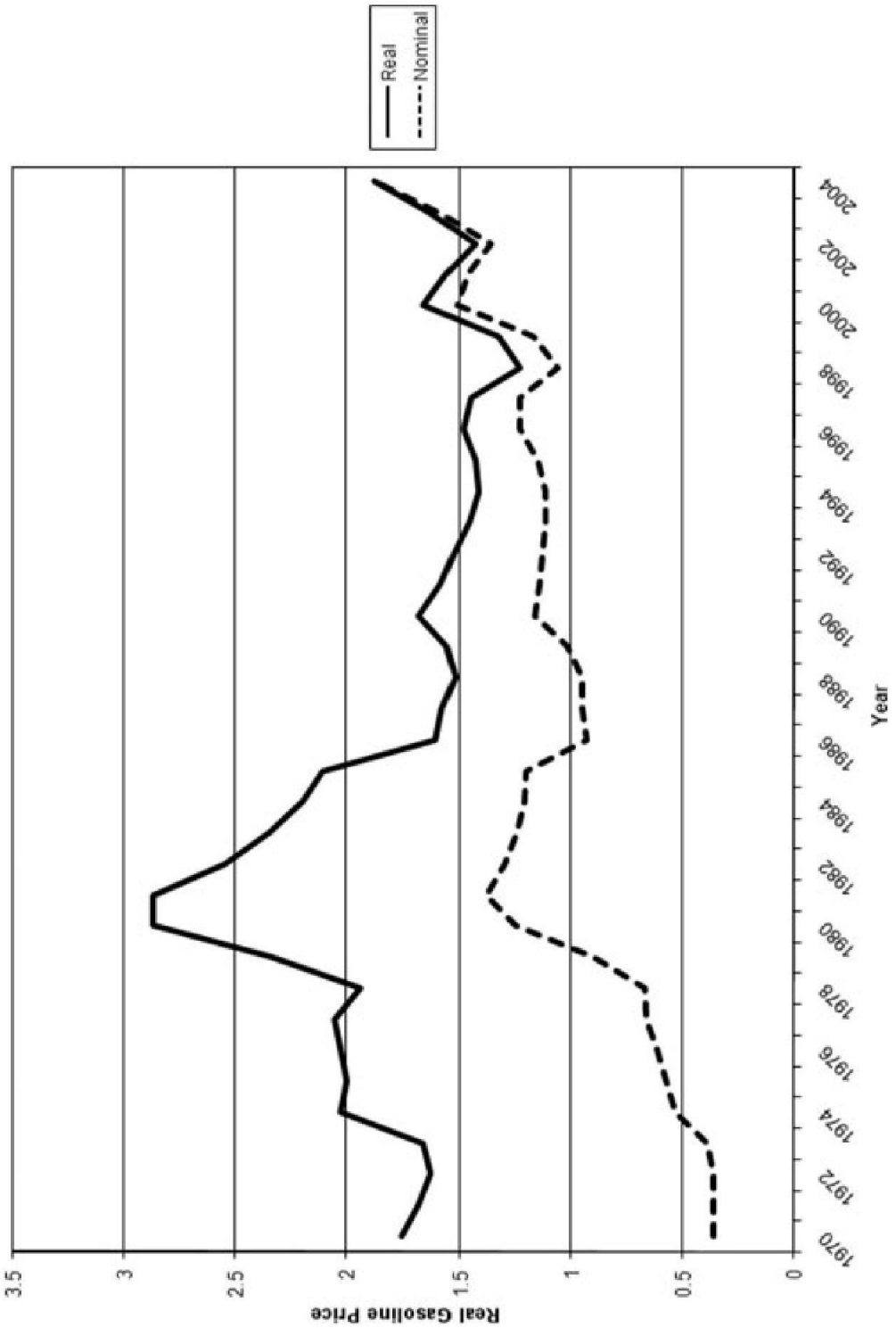
instead prepare their own meals at home, which tend to be healthier. Third, higher gas prices may impact eating habits more generally, either through income effects or increases in food prices.

FIGURE 1
Growth in Obesity: 1979–2004



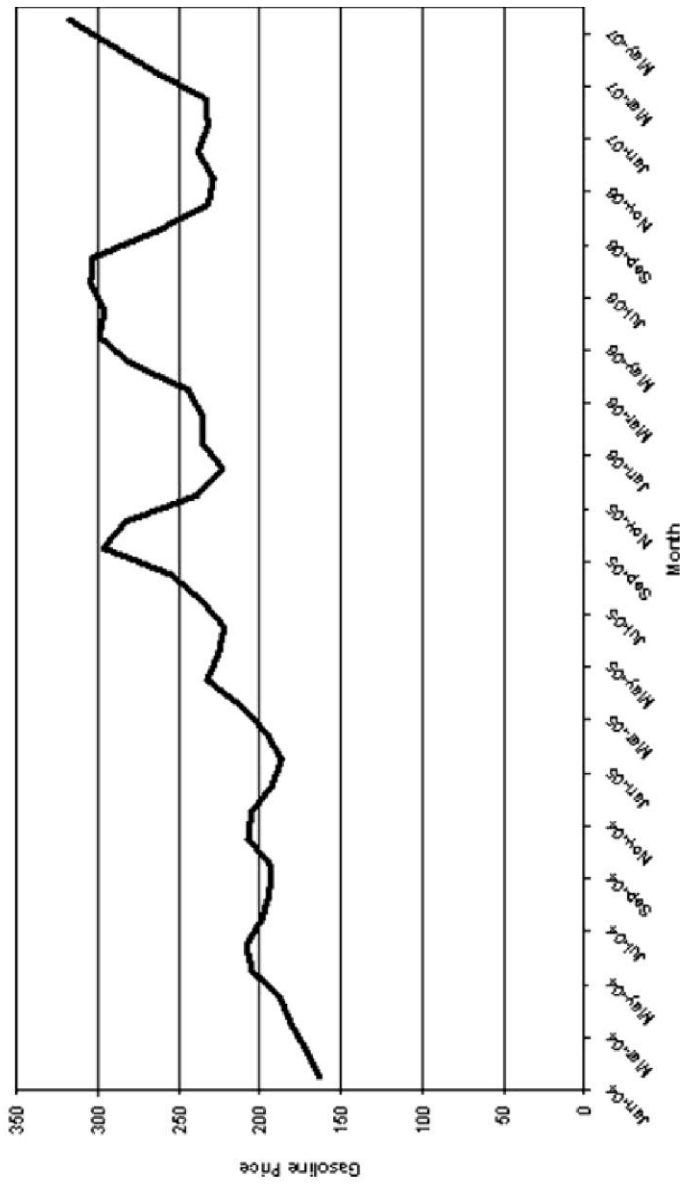
Using pooled cross-sectional individual-level data from the 1984–2004 waves of the Behavioral Risk Factor Surveillance System (BRFSS) matched with state-level gasoline prices, I estimate a negative relationship between state gasoline prices and BMI, probability of being overweight, and probability of being obese using state fixed effects models with demographic controls. Results are robust to the inclusion of year fixed effects; a quadratic time trend; controls for state food prices, population density, and unemployment rate; state-specific quadratic time trends; region-year interactions; and the use of gasoline tax rate as an instrument for prices. I also add lags of gas price to the models and find evidence that the effect is gradual. I estimate that 8% of the recent rise in obesity from 1979 to 2004 can be attributed to the decline in real gasoline prices during the period.

FIGURE 2
Changes in Gas Prices: 1970–2004



Although we should use caution when assuming that the effect is symmetric, my results imply that a permanent $1 rise in the price of gasoline would reduce overweight and obesity by 7% and 10% in the United States. The reduction in obesity would save approximately 11,000 lives and $11 billion per year, savings that would offset 10% of the increased expenditures on gasoline. I also provide evidence that a rise in gas prices is associated with an increase in walking and a decrease in the frequency of eating at restaurants, explaining the effect on weight, but no other clear changes in eating habits. These results suggest that the recent spike in gas prices may have the “silver lining” of reducing obesity in the coming years.

FIGURE 3
Changes in Gas Prices: 2004–2007



Source for figures 2 and 3: Energy Information Administration. Prices are for all grades.

II. BACKGROUND AND THEORY

Numerous efforts have been made to deter-mine the price elasticity of gasoline, most finding demand to be responsive to price changes but inelastic. Espey (1998) surveys this literature, determining that the median out of 300 short-run elasticity estimates in the United States and other developed countries is —0.23. The long-run elasticity, however, appears to be closer to the —0.7 to —0.8 range (Wheaton 1982, Espey 1998). Changing gas prices may affect modes of transportation, frequency of optional trips such as going to restaurants, and over-all eating habits. All of these could influence either calories consumed or expended, leading to changes in body weight.

A rise in gas prices may cause people to, when possible, substitute walking, bicycling, or taking public transportation for driving. Walking and bicycling are forms of exercise, which increases calories expended. If a person uses public transportation, such as subways, buses, trolleys, or rail services, the need to move to and from the mass transit stops is likely to result in additional walking, again increasing calories expended. Several studies link driving instead of taking alternative forms of transportation to higher body weight. For example,

Wen et al. (2006) conducted a study in Australia, concluding that people who drove to work were more likely to be obese than others. Studies such as these suffer from potential reverse causality as people who are obese may drive more frequently than those who are not, simply because walking is more physically challenging for them due to carrying the extra weight. Nonetheless, the existence of such research provides reason to suspect that a rise in gasoline prices might lower weight by increasing functional exercise, at least for people for whom walking, bicycling, or public transportation are viable options.

Next, an increase in the price of gas may lead to less eating at restaurants through both substitution and income effects. Because eating out involves using gas while eating at home does not, the relative price of the former increases, possibly inducing substitution toward the latter. Income effects, especially for the poor, may also lead people to eat out less in an effort to save money to pay for the increased cost of gas. Fewer restaurant meals may reduce obesity because they are generally assumed to be less healthy than meals prepared at home. A variety of research finds a positive association between frequency of eating fast food and calories, fat, and saturated fat consumed (e.g., see Satia et al. 2004). Full-service restaurants have also come under attack in both the popular press and scholarly research, mainly for serving increasingly large portions (Young and Nestle 2002) and adding hidden high-calorie flavor-enhancers such as butter and oil ("Deadly Secrets .. ." 2007). In contrast to the exercise mechanism, the restaurant mechanism has the potential to affect all people.[2]

Finally, rising gas prices may impact food choices even for food consumed at home. Higher energy costs mean higher food production and distribution costs, likely leading to higher food prices. Several papers argue that falling real food prices have contributed to the rise in obesity, so an increase in food prices should reduce obesity.[3] However, relative prices of different types of food also matter (Gelbach et al. 2007), and how an increase in gas prices would affect the relative price of healthy versus unhealthy food is unclear ex ante. Presumably, relative price changes should be driven largely by differences in "food miles," or the distance food travels between where it is grown or raised and where it is purchased. However, comparing the miles traveled by healthy and unhealthy foods is difficult because few food miles calculations exist for unhealthy processed foods, as they often involve combining foods grown in several different places (Pirog and Benjamin 2005). The price of healthy food relative to unhealthy food may rise as fruits and vegetables are often grown far from the point of consumption because of regional comparative advantages in production. Alternatively, the relative price of unhealthy food may rise as a result of the aforementioned combination of foods from various locations. The effects likely differ by state. For example, the price of corn-syrup-based processed foods may be less affected by gas prices in Iowa than in Florida, while the reverse is likely true for oranges; also, transportation costs may be larger in larger states. Additionally, if a rise in gas prices increases demand for ethanol, the price of corn syrup may rise, increasing the relative price of unhealthy processed foods (Dubner 2007). Finally, rising gas prices could affect food consumed at home through an income effect. At first glance, the drop in real incomes should lead people to consume less food. However, research has generally found that a drop in income is actually associated with an increase in weight for most of the income distribution in developed countries (e.g., see Lakdawalla and Philipson 2002). This may be because healthy foods, such as fruits, vegetables, and lean meats, tend to be more expensive than unhealthy processed foods, and additional income makes these healthier foods more affordable.

To summarize, economic theory predicts that an increase in gas prices should increase exercise, decrease eating out, and have an indeterminate effect on general eating habits. The net effect on body weight is therefore ambiguous but would be negative unless the effect on general eating habits leads to an increase in calorie consumption that is large enough to outweigh the other effects. While no research to date estimates the effect of gasoline prices on weight, a recent paper by Rashad, Chou, and Grossman (2005) studied, among other topics, the relationship between state gasoline taxes and weight. Using pooled micro-level data from the National Health and Nutrition Examination Surveys (NHANES), they found that the marginal effect of gas taxes on weight was actually slightly positive at the sample mean.

I contribute to the literature primarily by becoming the first to directly estimate the effect of gasoline prices on weight and obesity. I use state gasoline prices inclusive of state and federal taxes, which should provide a more

precise estimate than only using state taxes as gas taxes are a poor proxy for gas prices. In the data used in this paper (see Section III), real estate taxes account for an average of only 15% of the total real price of gasoline. Additionally, variation in tax between states and over time is small, as its standard error is less than 1/3 of the mean and the maximum tax is only 42 cents per gallon. According to the Energy Information Administration, taxes are only one of many sources of variation in gas prices between states. Others include proximity to supply, efficiency of distribution, number of gas stations, environmental programs requiring the use of special types of gasoline, and operating costs.[4] The use of prices instead of taxes, however, raises questions about the consistency of my estimates, as demand-side characteristics may also affect prices. I address these concerns through the use of state fixed effects, individual- and state-level controls, time-location interactions, and instrumental variables.

Another contribution is that I study the impact of gasoline prices in the preceding 6 yr, instead of merely the current year, on weight. Differentiating between short- and long-run responses is useful because weight tends to respond gradually to shocks. Body weight is typically modeled in the economics literature as a capital stock, the growth of which in each period is the difference between calories consumed and expended in that period. If an external factor causes eating or exercise habits to change, daily caloric consumption and expenditure patterns may change immediately, but body weight will slowly change over time until a new steady-state equilibrium is reached, possibly years into the future.[5] In the case of gasoline prices, longer-run estimation techniques may be especially useful as gasoline is more elastic in the long run than in the short run. Additionally, as people become accustomed to additional walking, physical activity becomes more pleasant for them, and they may increase other types of exercise. A longer-range perspective is necessary to fully capture this effect. Finally, the use of lags also allows time for people to move, in response to rising gas prices, to areas where alternative methods of transportation to driving are more feasible (i.e., from suburbs to cities), or for cities to improve their mass transit systems.

A third contribution is that I show that gas prices have the expected effect on walking and frequency of eating at restaurants, but no effect on the frequency of consumption of various types of food. This provides insight into the mechanisms by which gas prices affect obesity while lending credibility to the reduced-form results.

III. DATA

My main data source is the BRFSS, a telephone survey of health conditions and risky behaviors conducted by state health departments and the Center for Disease Control.[6] The BRFSS consists of repeated cross sections of randomly selected individuals from 1984 to 2006. In 1984, only 15 states and 12,258 individuals participated, but the number of states steadily grew, to 40 in 1989 and all 50 by 1996. The number of respondents also rapidly increased, reaching 355,710 in 2006. I utilize BRFSS questions on height, weight, exercise, food consumption, household income, age, marital status, gender, race, and education.

I calculate BMI using respondents' self-reported weight and height, which may be problematic as people tend to underreport their weight and, to a lesser extent, exaggerate their height. Some economists in the obesity literature have employed a correction for self-reported BMI developed by Cawley (1999). They use the National Health and Nutrition Examination Survey, which includes both actual and self-reported weight and height, to estimate actual BMI as a function of self-reported BMI and a variety of demographic characteristics. Researchers have generally found that the correlation between actual and self-reported BMI is very high, and that correcting for measurement error does not substantially alter the coefficient estimates in regressions (Cawley 1999, Lakdawalla and Philipson 2002). Therefore, I elect not to employ the correction in this paper.

I construct the variable for exercise frequency as follows. The 1984–2000 surveys ask the respondents to identify the two types of physical activity they obtain most frequently, and to estimate the frequency with which they perform each. People were allowed to choose from a list of activities, including walking, jogging, running, bicycling, and a variety of sports. Using these answers, I calculate the number of times an individual walks, bicycles (excluding stationary bikes), and obtains other types of exercise per week. Although these variables should be correlated with actual measures, they are flawed in two ways. First, they underestimate the amount of

exercise for people who regularly engage in more than two types of activities. Second, they are self-reported and therefore subject to measurement error, both from limited memory and exaggeration in an effort to impress the interviewer.

I also utilize the weekly frequencies with which the respondents consume sweets, fried potatoes, hamburgers or similar items, bacon or sausage, green salad, carrots, vegetables (excluding salad, carrots, and potatoes), and fruits. Data on consumption of the healthy foods green salad, carrots, other vegetables, and fruits exist for all waves from 1990 to 2003, while data on the other foods only exist from 1990 to 1994. These variables also likely suffer from measurement error, but should still provide a general sense of the healthiness of the respondents' eating habits.

I match the BRFSS data with annual state-level gasoline prices from the Energy Information Administration (EIA), available from 1983 to 2004. My matched sample therefore includes the 1984–2004 waves. The EIA data is missing for 152 state-year cells, so they are omitted from my analysis. The EIA prices do not include taxes, so I add them using federal gasoline tax rates from the Congressional Research Service Tax Foundation and state tax rates from the Federal Highway Administration and the American Petroleum Institute.[7] I convert the prices to 2004 dollars using consumer price index (CPI) data from the Bureau of Labor Statistics.

In some regressions, I include annual prices of food at home and food away from home as additional controls using data from the *American Chamber of Commerce Researchers Association Cost of Living Index* (*ACCRA COLI*). For the price of food at home, I use the *ACCRA COLI*'s grocery price index, constructed based on the prices of 27 grocery items, 24 of which are foods or drinks. For the price of food away from home, I use the inflation-adjusted average of the prices of the three reported restaurant items: a Quarter-Pounder with cheese from McDonald's, a thin-crusted cheese pizza from Pizza Hut or Pizza Inn, and a thigh and drumstick of fried chicken from Kentucky Fried Chicken or Church's. The A*CCRA COLI* prices are city level, with the number of cities increasing from 230 in 1984 to 324 in 2004. Following Chou, Grossman, and Saffer (2004), I construct state-level prices by weighting each city by its population, as given by the U.S. Census Bureau.[8] While such an approach suffers from measurement error, these measures should be highly correlated with actual state food prices.

I also add population density and unemployment rate as additional state-level controls in some regressions. I calculate the number of thousands of people per square mile using data on land area from the online almanac www.infoplease.com, and state population from the U.S. Census Bureau. I obtain annual state unemployment rates from the Bureau of Labor Statistics.

After eliminating observations with missing values, my final matched sample consists of 1,807,266 individuals spanning 793 state-year combinations. The column labeled "BRFSS" in Table 1 reports the summary statistics, including descriptions of the variables used. The average BMI is 26.1, while 35% of respondents are overweight (but not obese) and 18% are obese. Respondents report walking an average of 1.5 times per week, biking 0.1 times, and obtaining other forms of exercise 1.6 times. The mean real gas price in the sample is $1.52 per gallon. The variable "real gasoline tax" represents the portion of the price that consists of the federal and state excise taxes; its mean is $0.42 per gallon.

TABLE 1
Summary Statistics

Variable	Description	Mean and Standard Deviation	
		BRFSS	DDB
BMI	Body mass index = weight in kilograms divided by height in meters squared	26.123 (5.123)	—
Overweight	Binary variable that equals 1 if 25≤BMI<30	0.349 (0.477)	—
Obese	Binary variable that equals 1 if BMI≥30 and 0 otherwise	0.184 (0.388)	—
Real gasoline price	Real gasoline price (in 2004 dollars) in the respondent's state of residence	1.522 (0.187)	1.502 (0.181)
Real gasoline tax	Sum of real federal and state gasoline tax rates in the respondent's state of residence	0.416 (0.061)	—
Food at home price	Price index for grocery items	104.914 (9.858)	100.088 (6.872)
Food away price	Average price of the three *ACCRA COLI* restaurant items	5.215 (0.392)	5.105 (0.376)
Population density	Thousands of people per square mile in the respondent's state of residence	0.162 (0.216)	0.205 (0.202)
Unemployment rate	Annual unemployment rate in the respondent's state of residence	4.989 (1.407)	4.971 (1.018)
Income	Real household income (in 2004 dollars) in units of $10,000	4.327 (2.932)	5.246 (2.590)
Race: Black	Binary variable that equals 1 if the respondent's race is black and 0 otherwise	0.086 (0.280)	0.062 (0.241)
Race: Other	Binary variable that equals 1 if race is neither white nor black	0.088 (0.283)	0.049 (0.217)
Married	Binary variable that equals 1 if the respondent is married	0.550 (0.497)	0.723 (0.447)
Some high school	Binary variable that equals 1 if the respondent's highest grade completed is 9–11	0.081 (0.273)	0.356 (0.479)
High school graduate	Binary variable that equals 1 if highest grade completed is 12	0.324 (0.468)	0.288 (0.453)
Some college	Binary variable that equals 1 if highest grade completed is 13–15	0.276 (0.447)	0.130 (0.337)
College graduate	Binary variable that equals 1 if highest grade completed is at least 16	0.275 (0.446)	0.126 (0.332)

continued

TABLE 1
Continued

Variable	Description	Mean and Standard Deviation	
		BRFSS	DDB
Age	Respondent's age	46.488 (17.173)	46.484 (15.971)
Female	Binary variable that equals 1 if the respondent is female and 0 otherwise	0.581 (0.493)	0.556 (0.497)
Walking	Number of times the respondent walks (for an extended period of time) per week	1.508 (2.350)	—
Bicycling	Number of times the respondent bicycles (for an extended period of time) per week	0.148 (0.823)	—
Other exercise	Number of times the respondent obtains other types of exercise per week	1.742 (2.640)	—
Sweets	Number of times per week the respondent eats doughnuts, cookies, cake, pastries, or pies	2.421 (3.643)	—
French fries	Number of times per week the respondent eats french fries or fried potatoes	1.152 (2.105)	—
Hamburgers	Number of times per week the respondent eats hamburgers, cheeseburgers, or meatloaf	1.475 (1.912)	—
Bacon	Number of times per week the respondent eats bacon or sausage	1.000 (2.431)	—
Salad	Number of times per week the respondent eats green salad	3.459 (3.378)	—
Carrots	Number of times per week the respondent eats carrots	1.892 (2.787)	—
Vegetables	Number of times per week the respondent eats vegetables	8.950 (6.550)	—
Fruits	Number of times per week the respondent eats fruit, not counting fruit juice	5.610 (5.711)	—
Breakfast	Number of times in the preceding year the respondent went out to breakfast at a restaurant	—	10.170 (12.308)
Lunch	Number of times in the preceding year the respondent went out to lunch at a restaurant	—	17.184 (15.658)
Dinner	Number of times in the preceding year the respondent went out to dinner at a restaurant	—	19.117 (15.818)

Because the BRFSS does not include data on frequency of visiting restaurants, I utilize a second source of individual data to estimate the effect of gas prices on eating out, the Doyle Dayne Bernbach (DDB) Needham Lifestyle Surveys. This is one of the data sources used by Robert Putnam in Bowling Alone, and I obtained it from his website. Respondents were asked a total of 389 questions relating mostly to participation in certain activities and beliefs/values. Three of these variables are the self-reported annual frequencies with which

respondents "went out to eat" breakfast, lunch, and dinner "at a restaurant." The survey questions group responses into the following categories: none, 1–4 times, 5–8 times, 9–11 times, 12–24 times, 25–51 times, and 52+ times. I construct continuous variables by assigning them the midpoint of the chosen category, or 52 if "52+ times" is chosen. The DDB data consists of repeated cross sections for every year from 1975 to 1998, but I utilize only the 1988–1998 waves, which contain all of the restaurant and control variables.

The column labeled "DDB" in Table 1 contains the summary statistics for the DDB data. The average individual eats breakfast at a restaurant 10 times per year, lunch 17 times, and dinner 19 times. These frequencies seem low, possibly from measurement error from flawed memory. Given the wording of the question, it is also possible that respondents only count trips made specifically to eat, and not, for example, times stopping at a fast-food restaurant on the way from one place to another. The sample size is 32,783 for regressions with breakfast as the dependent variable, 43,411 for lunch, and 41,813 for dinner.

IV. REDUCED-FORM ESTIMATION

As discussed in the introduction, gasoline prices may affect body weight by influencing exercise, frequency of eating at restaurants, and food choices at home. The fact that my restaurant variables come from a different data set, plus my lack of additional instruments for exercise, eating out, and food consumed at home, prevents me from estimating a structural model. Instead, my empirical approach consists of first estimating a reduced-form model using the BRFSS data, and then examining the relationships between gas prices and exercise, eating out, and consumption of different types of foods to examine the mechanisms.

I begin by estimating a reduced-form model. Following convention in the literature, I use BMI as the measure of weight. My regression equation is

$$(1) \qquad BMI_{ist} = \alpha_0 + \alpha_1 PGAS_{st} + \alpha_2 X_{ist} + \tau_t + \lambda_s + \varepsilon_{ist}$$

where *PGAS* is the real state-level price of gas, *X* is a vector of the aforementioned individual characteristics, and τ and λ are year and state fixed effects.[9] A potential problem with using BMI as the dependent variable is that an increase in BMI does not represent a reduction in health at the lower end of the distribution. If a rise in gasoline prices reduces weight, health would only improve if the weight reduction leads to lower levels of overweight and obesity. I therefore also estimate an ordered probit model where the dependent variable, *CATEGORY*, is 0 if the individual is not overweight or obese, 1 if she/he is overweight but not obese, and 2 if she/he is obese:

$$(2) \qquad P(CATEGORY_{ist} = i) = \Phi(\psi_i - (\alpha_1 PGAS_{st} + \alpha_2 X_{ist} + \tau_t + \lambda_s + \varepsilon_{ist}))$$

where ψ_i is the cutoff point for category *i*.10 I do not include separate categories for underweight or morbid obesity, as both categories contain less than 3% of my sample.

A potential problem with this analysis is that the standard error of $\hat{\alpha}_1$ is likely inflated because of multicollinearity caused by the inclusion of both state and year fixed effects, which explain almost all of the variation in gas prices between 1984 and 2004. Specifically, in a regression of gas prices on only state and year fixed effects, the R^2 is 0.94. Consequently, I also estimate a variation of Equations (1) and (2), replacing the year fixed effects with a quadratic time trend. Chou, Grossman, and Saffer (2002, 2004) employed a similar solution to the problem of multicollinearity in regressions with state-level prices as explanatory variables. The regression equations become

$$(3) \qquad BMI_{ist} = \beta_0 + \beta_1 PGAS_{st} + \beta_2 X_{ist} + \beta_3 t + \beta_4 t^2 + \sigma_s + \epsilon_{ist}$$

$$(4) \qquad P(CATEGORY_{ist} = i) = \Phi(\psi_i - (\beta_1 PGAS_{st} + \beta_2 X_{ist} + \beta_3 t + \beta_4 t^2 + \sigma_s + \epsilon_{ist}))$$

where *t* is year and σ is the state fixed effect. My estimates of β_1 should be more precise than my estimates of α_1 as the state effects and quadratic trend explain only 55% of the variation in gas prices, but consistency becomes a concern. However, note that the growth in obesity during the sample period was smooth (Figure 1), suggesting that a continuous time trend may be appropriate.

Models (1)–(4) include state fixed effects. Because gas prices are state level, the state effects should remove sources of omitted variable bias that are constant over time. While gas prices are largely driven by the supply-side characteristics discussed in Section II, the potential still exists for bias from omitted variables which vary over time or reverse causality. I therefore perform a variety of robustness checks to assess the consistency of the baseline estimators.

First, I include four additional state-level variables as controls: the price of food at home, the price of food away from home, population density, and unemployment rate. I add food prices out of concern that my baseline results capture a general "price effect" instead of a gas price effect, as the prices of different goods are likely positively correlated. If increases in food prices coincide with increases in gas prices, then my estimators for the gas price effect could be biased downward, as an increase in food prices should reduce weight. However, controlling for food prices could lead to an over-controlling problem if the price of food is one of the mechanisms through which gas prices influence weight. Including population density addresses the concern that trends in population may be driving both changes in gas prices and changes in weight. As states become more heavily populated, mass transit systems may become more developed, reducing the demand for driving and therefore the price of gas. At the same time, the number of supermarkets and restaurants may rise, granting people easier access to food and increasing weight. Therefore, omitting population density may result in either a spurious negative or positive relationship between gas prices and weight. I control for unemployment rate as gas prices may simply act as a proxy for general economic conditions. Again, however, general economic conditions may be one of the mechanisms through which gas prices affect weight, so controlling for unemployment rate could either correct for possible endogeneity or lead to an over-controlling problem.

Next, I interact time with location to address possible bias from changes over time in unobservable state characteristics or reverse causality. For example, states with increasing health-consciousness may experience a reduction in both weight and gas price, because people interested in their health may walk more and therefore demand less gas than others. Additionally, weight may determine gas price, as a recent study by Jacobson and McLay (2006) showed that obesity causes more gas to be used simply by adding more weight to the car, reducing its fuel economy. This could increase demand and therefore price in heavier areas.[11] For the quadratic trend regressions, I interact the quadratic trend with the state fixed effects to form quadratic state-specific time trends. For the year fixed effects regressions, interacting the year dummies with the state dummies would result in perfect collinearity. I therefore interact the year dummies with region dummies, using region classifications from the U.S. Census Bureau.

Finally, I estimate two-stage least squares models, instrumenting for gasoline price using the sum of the federal and state taxes on a gallon of gasoline (adjusted for inflation). As noted by Gruber and Frakes (2006), tax rates are often more plausibly exogenous than prices as they are not directly affected by demand-side characteristics. In Section II, I argued that gasoline tax rates are a poor proxy for state gasoline prices; indeed, federal and state tax rates make up only one-quarter of the variation in gas prices, so my instrument is fairly weak.

Table 2 reports the gas price coefficient estimates in the regressions with BMI as the dependent variable. Table 3 reports the gas price coefficient estimates from the ordered probit regressions, as well as the marginal effects on the probability of being overweight (but not obese) and the probability of being obese.[12] (Results for the controls are generally consistent with other estimates in the literature and available upon request). In all regressions, standard errors are heteroskedasticity-robust and clustered by state. The left half of each table uses year fixed effects, while the right half uses the quadratic trend. In each half, the first column contains the base-line results, the second column includes the four state-level control variables, the third column also includes the time-location interactions, and the fourth column uses gas tax as an instrumental variable for gas price.

TABLE 2
Effect of Gasoline Price on BMI

	Year Fixed Effects				Quadratic Trend			
	Baseline	State Controls	Time-Location	IV	Baseline	State Controls	Time-Location	IV
Real gasoline price	−0.345 (0.166)***	−0.294 (0.170)*	−0.264 (0.249)	−0.360 (0.338)	−0.350 (0.050)***	−0.342 (0.048)***	−0.328 (0.048)***	−0.506 (0.335)
R^2	0.087	0.087	0.087	0.087	0.087	0.087	0.087	0.087

Notes: Standard errors in parentheses. ***indicates statistically significant at the 1% level; **5% level; *1% level. All standard errors are heteroskedasticity-robust and clustered by state. State fixed effects and the individual-level controls are included in all regressions.

TABLE 3
Effect of Gasoline Price on Overweight and Obesity Status

	Year Fixed Effects				Quadratic Trend			
	Baseline	State Controls	Time-Location	IV	Baseline	State Controls	Time-Location	IV
Ordered probit coefficient estimate	−0.068 (0.037)*	−0.057 (0.038)	−0.083 (0.052)	−0.073 (0.063)	−0.045 (0.009)***	−0.037 (0.009)***	−0.038 (0.009)***	−0.015 (0.014)
Marginal effect on *P* (overweight but not obese)	−0.010 (0.005)*	−0.008 (0.005)	−0.012 (0.008)	−0.011 (0.009)	−0.007 (0.001)***	−0.005 (0.001)***	−0.005 (0.001)***	−0.002 (0.002)
Marginal effect on *P*(obese)	−0.017 (0.009)*	−0.015 (0.010)	−0.021 (0.013)	−0.018 (0.016)	−0.011 (0.002)***	−0.009 (0.002)***	−0.009 (0.002)***	−0.004 (0.004)
R^2	0.043	0.043	0.043	0.043	0.043	0.043	0.043	0.043

See notes for Table 2.

As shown in Table 2, a $1 increase in the price of a gallon of gas reduces BMI by 0.345 units in the baseline regression with year effects and 0.35 units in the baseline regression with the quadratic time trend. At the sample mean height, these magnitudes correspond to 2.24 and 2.28 pounds.[13] As expected, the estimate using the quadratic trend is more precise: it is significant at the 1% level, while the estimate using year dummies is only significant at the 5% level. The standard error is more than three times larger with year effects. The coefficient estimates remain similar after adding the additional controls and time-location interaction terms. The instrumental variable estimates are imprecise because of the instrument's weakness, but the gas price effect remains negative in both regressions and similar in magnitude. The similarity of the coefficient estimate for gas price across specifications suggests that omitted time-varying state-level variables are not biasing the baseline results. Also, the fact that the results are similar using either year effects or the quadratic trend suggests that nation-wide shocks are not driving the quadratic trend estimates.

In the baseline ordered probit regressions reported in Table 3, the estimated marginal effect of gas prices on *P*(overweight) is —1.0 percentage points with year fixed effects and —0.7 with the quadratic trend, while the marginal effect on *P* (obese) is − 1.7 percentage points with year fixed effects and − 1. 1 with the quadratic

trend. The quadratic trend estimates are again more precise. While gas price is highly significant using the quadratic trend, the standard error is more than four times larger using year dummies, making gas price significant at only the 10% level. The coefficient estimates and marginal effects are not sensitive to the addition of the extra control variables or the time-location interactions. Instrumenting for gas price does not affect the year fixed effect results, while with the quadratic trend the magnitude shrinks but remains negative.

A. Stratification by Gender, Income, and Race

I next split the sample according to gender, income, and race in an effort to assess the heterogeneity of the gas price effect. For gender, I estimate separate regressions for men and women. For income, I divide the sample into individuals below and above the median of $35,666. For race, I classify individuals as either non-white (about 17% of the sample) or white. I present the results in Table 4. I only report results for the year fixed effects models with BMI as the dependent variable, although the conclusions reached are similar using the other specifications. Women appear to respond some-what more strongly than men, and people with incomes below the median respond somewhat more strongly than those with incomes above the median. The gas price effect is considerably larger for minorities than whites. One possible explanation for these results is that minorities and the poor tend to live disproportionately in cities and therefore have better access to public transportation than people who live in suburbs. Additionally, people with low incomes may be the most willing to change behavior to save money when prices rise.

B. Lagged Prices

As discussed in Section II, there is ample reason to suspect that the short- and long-run responses of weight to changes in gas price are different. If the response is gradual, simply regressing BMI/overweight and obesity status on contemporaneous gas prices may not capture the full effect. I therefore estimate Equations (1)–(4) including 6 yr of lags for gas prices. This reduces the sample size to 1,598,509 because the EIA gas price data began in 1983. Estimates of the total gas price effect are similar if I add more lags, so I include only six in an effort to eliminate as little of the sample as possible.

This approach leads to measurement error in the gas price lags because individuals who have recently moved to a new state should not respond to their new state's prices or taxes before the period in which they moved. Under the assumption that the measurement error is classical, it will lead to attenuation bias and the estimators will be biased toward zero (Wooldridge 2006, p. 318–322). An additional concern is that, owing to the fact that the BRFSS does not track the same individuals over time, I am unable to include lags of the control variables. As pointed out by Ruhm (2004), this omission may bias my estimates of the coefficients of the gas price lags. However, the results from the preceding sections are very similar if I remove some or all of the time-variant control variables, so I do not expect that omitting the lags of the controls in this section significantly alters my results. [14]

Table 5 reports the results. After 7 yr, a $1 increase in the price of gasoline reduces average BMI by 0.73 –0.76 units, *P* (overweight) by 1.6–2.2 percentage points, and *P*(obese) by 3.1–4.4 percentage points. All estimates of the total effect using year dummies are significant at the 5% level, while those using the quadratic trend are significant at the 1% level. The magnitudes are substantially larger than those estimated using only contemporaneous prices.

While the magnitude of the total effect is similar across specifications, the timing is less clear. In all regressions, there is evidence of a gradual effect, as at least one of the lags is statistically significant and the majority of the effect does not occur immediately. In the regressions with year dummies, the positive effect of the second lag and the large negative effect of the sixth lag seem implausible. This odd pattern may be the result of imprecise estimation owing to multicollinearity. The variance inflation factors for each of the seven gas price variables is around 50 in the regressions with year dummies, well above the commonly used level of 10 at which we conclude that severe multicollinearity is present (Wooldridge, 2006, p. 99). In the regressions with the quadratic trend, most of the effect occurs within the first 3 yr. The variance inflation factors for the gas price variables are

between 5 and 6, indicating that multicollinearity is a much less serious problem. Therefore, while I am unable to reach a definitive conclusion regarding timing, the pattern revealed by the quadratic trend regressions is likely more credible.

TABLE 4

Effect of Gasoline Prices on BMI; Stratification by Gender, Income, and Race

	Gender		Income		Race	
	Female	Male	Below Median	Above Median	Non-White	White
Real gasoline price	−0.410 (0.207)*	−0.247 (0.150)	−0.350 (0.189)*	−0.220 (0.173)	−0.799 (0.325)**	−0.234 (0.176)
R^2	0.101	0.067	0.084	0.102	0.090	0.083

See notes for Table 2. Also, all regressions include year dummies.

TABLE 5

Effect of Contemporaneous and Lagged Gasoline Prices on BMI, P(Overweight but Not Obese), and P(Obese)

	BMI		P(Overweight)		P(Obese)	
	(1)	(2)	(1)	(2)	(1)	(2)
Real gasoline price	−0.212 (0.138)	−0.268 (0.064)***	−0.007 (0.004)*	−0.008 (0.002)***	−0.013 (0.008)*	−0.016 (0.003)***
Real gasoline price in year $t-1$	0.020 (0.142)	−0.098 (0.061)	0.002 (0.005)	−0.001 (0.002)	0.004 (0.009)	−0.002 (0.004)
Real gasoline price in year $t-2$	0.303 (0.174)*	−0.293 (0.071)***	0.009 (0.006)	−0.008 (0.002)***	0.017 (0.011)	−0.016 (0.004)
Real gasoline price in year $t-3$	−0.305 (0.220)	−0.010 (0.077)	−0.008 (0.007)	−0.000 (0.002)	−0.015 (0.013)	−0.000 (0.004)
Real gasoline price in year $t-4$	0.135 (0.167)	−0.078 (0.057)	0.003 (0.005)	−0.003 (0.002)	0.005 (0.010)	−0.006 (0.003)
Real gasoline price in year $t-5$	−0.021 (0.168)	0.049 (0.049)	−0.003 (0.005)	0.001 (0.002)	−0.005 (0.010)	0.002 (0.003)
Real gasoline price in year $t-6$	−0.654 (0.196)***	−0.063 (0.056)	−0.012 (0.006)*	−0.003 (0.002)**	−0.024 (0.012)*	−0.006 (0.003)**
R^2	0.081	0.081	0.040	0.040	0.040	0.040
Sum of All Years	−0.733 (0.269)***	−0.760 (0.230)***	−0.016 (0.008)**	−0.022 (0.004)***	−0.031 (0.016)**	−0.044 (0.008)***

Notes: (1) Includes year dummies; (2) includes a quadratic time trend. See other notes for Table 2.

I next attempt to assess the economic significance of these results by estimating the percent-age of the rise in obesity from 1979 to 2004 that can be explained by the decline in real gas prices during the period. The estimated percent-age point change in obesity because of changes in gas prices is

$$(5)\ \widehat{OBESE}_{2004} - \widehat{OBESE}_{1979} = \sum_{j=0}^{6}(\hat{\beta}_{1,\,t-j}\mathrm{PGAS}_{2004-j} - \hat{\beta}_{1,\,t-j}\mathrm{PGAS}_{1979-j}.$$

According to the EIA, the average real retail prices of a gallon of gasoline in the years 1973–1979 were \$1.66, \$2.03, \$2.00, \$2.03, \$2.06, \$1.94, and \$2.34, respectively.[15] In the years 1998–2004, the average annual gas prices were \$1.23, \$1.33, \$1.66, \$1.56, \$1.43, \$1.63, and \$1.88. Substituting these numbers and the coefficient estimates from the next to last column of Table 7 into Equation (5), I calculate that the drop in real gas prices increased the obesity rate by 1.4 percentage points. As the obesity rate rose by a total of 17.1 percentage points between 1979 and 2004, this analysis suggests that changes in gas prices accounted for 7.9% of the increase in obesity during the period.[16]

The results from this section can also be used to provide rough estimates of the changes in the prevalence of overweight and obesity that would result from a permanent \$1 increase in gasoline prices (assuming that the full effect is reached within 7 yr). As obese people are also classified as overweight, the reduction in the percentage of adults who are overweight is the sum of the effects on P(overweight) and P(obese) divided by the proportion of U.S. adults who are overweight, which was 0.657 in 2002 (Hedley et al. 2004). Using the smaller of the P(overweight) and P(obese) estimates, a \$1 increase in gas prices would therefore reduce the overweight by approximately 7.2%. The percentage decline in obesity is simply 0.031 (the smaller of the two P(obese)

estimates) divided by the 2004 obesity rate of 0.322 (Ogden et al. 2006). Therefore, after 7 years a $1 increase in gas prices would reduce the prevalence of obesity in the United States by approximately 9.6%. I form a rough estimate of the number of lives and dollars saved from the reduced obesity by multiplying 9.6% by the annual costs of obesity discussed in the introduction: 112,000 lives and $117 billion. These calculations suggest that the rise in gas prices would save 10,752 lives and $11.2 billion dollars in medical expenditures per year. As a caveat to this analysis, note that a $1 rise in the price of gas represents a 66% increase, relative to my sample mean of $1.51. It is possible that the effect of a $1 increase would be more modest when gas prices are $3 per gallon or higher. Also, we should use caution when using estimates obtained with data from a period when real gas prices were generally falling to predict changes in obesity when gas prices rise. It is not clear that the effect of gas prices on obesity is symmetric.

Although the $11.2 billion decline in medical expenditures is substantial, it must be weighed against the additional spending on gasoline to determine the net effect on consumers. The United States consumes approximately 146 billion gallons of gasoline each year ("How Much Gasoline ..." 2007). Starting at the May, 2007 price of $3.18 per gallon, and assuming a price elasticity of demand for gasoline of −0.2, the $1 increase in price would reduce consumption by 9.2 billion gallons. Old expenditures on gasoline were $3.18*146 billion, while new expenditures are $4.18*136.8 billion. Therefore, an additional $107.5 billion would be spent on gasoline after the price change. The drop in medical expenditures would offset 10% of this additional spending. It is important to mention that this analysis ignores new spending on alternative methods of transportation, such as mass transit, and therefore overstates the percent of additional expenses that are offset. Nonetheless, it appears that the savings on medical expenditures, expressed as a fraction of the extra spending on gasoline, are nontrivial.

V. EXPLAINING THE GAS PRICE EFFECT

In this section, I attempt to determine the mechanisms through which gas prices affect BMI and obesity. I discussed three possible mechanisms in Section II: increased exercise, reduced eating out at restaurants, and different eating patterns at home.

A. Exercise

I begin by estimating the effect of gas prices on the frequency of walking, bicycling, and obtaining other types of exercise. Presumably, walking and bicycling are the most likely types of exercise to be affected by gas prices. I estimate Tobit models (left-censored at 0) with the individual- and state-level controls and state and year fixed effects[17]:

$$(6)\ EXERCISE^{*}_{ist} = \alpha_0 + \alpha_1 PGAS_{st} + \alpha_2 X_{ist} + \alpha_3 Z_{st} + \tau_t + \lambda_s + \varepsilon_{ist}$$
$$EXERCISE_{ist} = \max(EXERCISE^{*}ist, 0)$$

where *EXERCISE* is either number of times walking, bicycling, or obtaining other types of exercise per week, and Z is the set of state-level controls. Because *EXERCISE* only exists up to 2000, my sample size is reduced to 807,920.

Even though I expect gas prices to only affect walking and bicycling, I estimate the model for other types of exercise as well for two reasons. First, using other exercise serves as a falsification test for the results for walking/bicycling. If omitted variables such as a state's level of health-consciousness are driving my results, I should expect to observe a correlation between gas prices and all types of exercise. Second, gas prices could conceivably affect recreational exercise as well as functional exercise. For example, if people begin to walk more after gas prices rise, physical activity may become more tolerable, leading to an increase in other types of exercise. Alternatively, people who begin to walk as a mode of transportation may consider this walking a substitute for recreational exercise and, for example, work out at the gym less.

TABLE 6
Effect of Gasoline Price on Number of Times Walking, Bicycling, and Obtaining Other Types of Exercise Per Week

	Walking	Bicycling	Other Exercise	Walking Urban	Walking Rural
Coefficient on real gasoline price	1.304 (0.421)***	−0.340 (1.120)	−0.149 (0.616)	1.882 (0.504)***	0.467 (0.915)
Marginal effect	0.513 (0.166)***	−0.016 (0.053)	−0.072 (0.297)	0.753 (0.202)***	0.192 (0.377)
R^2	0.002	0.011	0.006	0.002	0.003

See notes for Table 2. Also, all regressions include year dummies and the state-level controls.

Table 6 displays the results. A rise in gasoline prices is associated with a statistically significant increase in walking. The coefficient on gas price in the regression for walking is 1.3, translating to an unconditional marginal effect of 0.5. The average person therefore walks an average of 0.5 times more per week if the price of gas rises by $1. This estimate is statistically significant at the 1% level, despite the severe multicollinearity caused by including both state and year fixed effects. I do not estimate a statistically significant relationship between gas prices and bicycling. However, only 5% of my sample reports ever bicycling, so it is possible that the lack of a significant result is only because the estimation is too imprecise for estimates of a reasonable magnitude to be statistically significant. Finally, the effect of gas prices on types of exercise besides walking and bicycling is practically zero and highly statistically insignificant.

Next, for frequency of walking, I divide the sample into individuals who live in an urban area and those who do not, using county identifiers from the BRFSS matched with county classifications from the U.S. Census Bureau.[18] Walking and taking public transportation are more viable transportation options in urban areas than in rural areas, so the effect of gas prices on exercise should be stronger in urban areas. County identifiers are missing for many observations, so my urban and rural subsamples consist only of 198,453 and 55,921 individuals, respectively. I report the results in the last two columns of Table 6. The association between gas prices and walking is strong and statistically significant in urban areas, as the unconditional marginal effect of gas prices on walks per week is 0.75. In rural areas, however, the effect is still positive but small and statistically insignificant.

I next attempt to approximate the portion of the effect of gas price on weight that occurs through changes in walking using a simple back-of-the-envelope calculation. The regressions including lagged gasoline prices and the quadratic time trend imply that most of the gas price effect occurs within 3 yr; the estimated effect of a $1 increase in gas price after 3 yr is —0.66 units BMI. At the sample mean height, this estimate corresponds to 4.3 pounds. Suppose that each additional walk caused by a rise in gas prices lasts for 20 min at 3 miles per hour. Such a walk would burn 112 calories for a person of the sample mean weight (Health Status Internet Assessments 2007a). If people walk an average of 0.51 times more per week after gas prices rise by $1, then each person burns 0.51*112*52=2,970 extra calories per year. After 2 yr, people burn 8,910 extra calories as a result of the additional exercise. As one pound equals 3,500 calories (Health Status Internet Assessments 2007b), the extra walking would cause an average weight loss of 2.5 pounds. Therefore, my calculations suggest that the effect on exercise explains about 59% of the reduction in weight that occurs after gas prices rise. This calculation is admittedly crude, and relies on strong assumptions about the timing of the effect, length of the additional walks, and biological process behind weight changes. Nonetheless, it appears safe to conclude that a substantial portion of the effect of gas prices on obesity occurs through walking frequency.

B. Restaurants

I next attempt to determine if gas prices impact the frequency with which people eat out at restaurants. In this section, I use the DDB data instead of the BRFSS. In regressions with both state and year fixed effects, the standard errors are too large for the estimates to provide useful inference, likely because the DDB data contain only 2% the number of observations of the BRFSS. I therefore use an approach common in papers estimating price elasticities (Decker and Schwartz 2000), and include year and region fixed effects. I also estimate models with state effects and a quadratic time trend. My regression equations are:

$$(7) \quad RESTAURANT_{isrt} = \alpha_0 + \alpha_1 PGAS_{srt} + \alpha_2 X_{isrt} + \alpha_3 Z_{st} + \tau_t + \rho_r + \varepsilon_{ist}$$

$$(8) \quad RESTAURANT_{ist} = \beta_0 + \beta_1 PGAS_{st} + \beta_3 X_{ist} + \beta_3 Z_{st} + \beta_4 t + \beta_5 t^2 + \sigma_s + \epsilon_{ist}$$

where *RESTAURANT* is one of four variables—the number of times the respondent ate breakfast, lunch, or dinner at a restaurant in the previous year, or the sum of the three meals—while *r* denotes region and ρ is the region effect. Although breakfast, lunch, and dinner are left-censored at 0 and right-censored at 52, few respondents report never eating out for any of the meals, or eating out more than 52 times per year for any of them. I therefore estimate ordinary least squares (OLS) instead of Tobit models.

Another concern is that, as mentioned in Section III, the average reported frequencies of eating out seem too low to be accurate. Measurement error in the dependent variable would bias the estimators for α_1 and β_1 if the measurement error is correlated with gas price, but it is not clear that this is the case. Although systematic underreporting means that the measurement error does not have a zero mean, this alone would only bias the intercept. This measurement error will, however, inflate the standard errors (Wooldridge 2006, p. 316).

Table 7 reports the results. In the regression with year dummies, a rise in gas price corresponds to a strong and statistically significant decline in eating out for dinner. The effects on breakfast and lunch are negative but insignificant. Using the sum of the three meals, a $1 rise in the price of gas is associated with a reduction in eating out of 7.2 times per year. Despite the large magnitude, gas price is statistically insignificant, likely because of the multicollinearity from including the year dummies. In the regressions with the quadratic time trend, a $1 increase in gas price leads to a very similar—and, in this case, statistically significant—decrease in the frequency of eating out for any meal of 7.3 times per year. However, the strongest effect is on breakfast, while the weakest effect is on dinner.

I next attempt to estimate the effect of this reduction in eating out on weight using a similar calculation to that for exercise. Zoumas-Morse et al. (2001) find that children consume an average of 350 more calories when they eat a meal at a restaurant instead of at home. Assuming the same discrepancy for adults, eating 7.2 fewer meals per year at restaurants corresponds to 7,560 fewer calories consumed per person over a 3 yr period. 7,560 calories equals 2.16 pounds, or about 50% of the estimated long-run effect of gas prices on weight. While this calculation is again crude, it appears likely that the effect of gas prices on eating at restaurants explains a substantial portion of their effect on obesity.

As discussed previously, gas prices could affect the amount people eat out in two ways: through a substitution effect by increasing the price of eating at restaurants relative to eating at home, and through an income effect. The contribution of each of these explanations is important for policy considerations. If the effect of gas prices on obesity occurs primarily through an income effect, then revenue-neutral policies, such as increasing the gasoline tax while lowering other taxes in such a way that real incomes are unchanged, would not be effective in lowering obesity.

The regression output in Table 7 can help to approximate the portion of the impact of gas price on eating out that is due to an income effect. Using the gas consumption data from Section IV, a $1 rise in the price of gas would cost consumers $146 billion if gas consumption remains constant. Assuming that there are 109.3 million households in the United States,[19] each household would spend an additional $1,336 per year on gasoline. I can estimate the portion of the effect of the price increase on eating out that occurs through a drop in real income by determining how eating out would change if household income dropped by $1,336. At the sample mean income, such a drop would decrease the number of times eating at restaurants per year by 0.6 in both regressions. The income effect, then, appears responsible for only a small portion of the overall effect of gas prices on eating at restaurants. There are two caveats to this analysis, however. First, it is unclear if the estimated effect of income on eating out reflects causality or merely correlation. Second, as expenses due to rising gas prices can be sudden and unpredictable, a change in income caused by gas prices may affect people's restaurant decisions differently than other, more predictable income changes.

C. Food Consumption

I next explore the third possible explanation offered in Section II for why rising gas prices may reduce obesity: people eat differently even at home because of income effects or changing food prices. The BRFSS contains data on the consumption of a variety of foods. I choose four types of foods that can unambiguously be considered unhealthy —sweets; french fries and fried potatoes; hamburgers, cheeseburgers, or meatloaf; and bacon or sausage—and four that are healthy—salad, carrots, other vegetables, and fruits—in an effort to

TABLE 7

Effect of Gasoline Price and Income on Number of Times Eating Out Per Year

	Breakfast		Lunch		Dinner		All	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Real gasoline price	−0.084	−3.799	−1.532	−3.077	−5.110	−0.811	−7.150	−7.310
	(1.784)	(1.213)***	(1.895)	(1.514)**	(2.156)**	(1.553)	(5.246)	(3.611)**
Real income	1.189	1.178	1.155	1.565	1.816	1.826	4.486	4.506
	(0.075)	(0.076)***	(0.114)***	(0.117)***	(0.102)***	(0.097)***	(0.246)***	(0.246)***
Real income squared	−0.000004	−0.000004	−0.000004	−0.000004	−0.000005	−0.000004	−0.00001	−0.00001
	(0.000000)***	(0.000000)***	(0.000001)***	(0.000001)***	(0.000001)***	(0.000001)***	(0.000002)***	(0.000002)***
R^2	0.053	0.058	0.088	0.089	0.110	0.113	0.115	0.118

Notes: (1) includes region and year fixed effects; (2) includes state fixed effects and a quadratic time trend. See other notes for Table 2. Also, all regressions include the state-level controls.

develop a robust story about how gasoline prices influence food consumption. My regression equation, which includes the individual- and state-level controls as well as state and year fixed effects, is

$$(9) \qquad FOOD_{ist} = \alpha_0 + \alpha_1 PGAS_{st} + \alpha_2 X_{ist} + \alpha_3 Z_{st} + \tau_t + \lambda_s + \varepsilon_{ist}$$

where *FOOD* represents consumption of one of the eight aforementioned types of food. The BRFSS allowed respondents to report either daily, weekly, monthly, or annual frequency of consumption of these foods; I convert all responses to weekly frequencies. Although the food variables are left-censored at zero, most respondents eat each of the eight types of food at least once per year. I therefore estimate OLS instead of Tobit models. The BRFSS contains the healthy food variables from 1990 to 2003, but the unhealthy food variables from only 1990 to 1994. Consequently, the sample size is much larger for the healthy foods (about 880,000) than the unhealthy foods (about 70,000). As food prices are one of the mechanisms through which gas prices may affect eating habits, I also estimate models without the food price controls.

TABLE 8

Effect of Gasoline Price on Frequency of Food Consumption: No Food Price Controls

	Sweets	Fries	Hamburgers	Bacon	Salad	Carrots	Vegetables	Fruits
Real gasoline price	0.192	−0.006	0.663	−0.097	−0.325	−0.334	−0.129	0.073
	(0.281)	(0.306)	(0.284)**	(0.240)	(0.288)	(0.247)	(0.717)	(0.600)
R^2	0.007	0.079	0.075	0.036	0.047	0.024	0.050	0.058

See notes for Table 2. Also, all regressions include year dummies, population density, and unemployment rate.

TABLE 9

Effect of Gasoline Price on Frequency of Food Consumption: Food Price Controls

	Sweets	Fries	Hamburgers	Bacon	Salad	Carrots	Vegetables	Fruits
Real gasoline price	0.402	−0.348	0.238	−0.481	−0.364	−0.337	−0.094	0.057
	(0.504)	(0.464)	(0.180)	(0.133)***	(0.298)	(0.246)	(0.721)	(0.602)
R^2	0.007	0.079	0.075	0.036	0.047	0.024	0.050	0.058

See notes for Table 2. Also, all regressions include year dummies and the state-level controls.

In Tables 8 and 9, I display the results for the regressions without food price controls and with them, respectively. Without food price controls, a rise in gas prices appears to increase the frequency of hamburger consumption, but the effects on the other three types of unhealthy foods are statistically insignificant. For healthy foods, the coefficient on gas price is negative in three regressions and positive in one, and statistically insignificant in all four. Adding the food price controls makes virtually no difference in the coefficient estimates for the healthy foods. For the unhealthy foods, the point estimates change somewhat, but remain within the 95% confidence intervals from the regressions without food prices. In all, I am unable to conclude that different food choices help to explain the negative effect of gas prices on obesity.

However, a potential problem with this analysis is that identifying α_1 from variation in gas prices between states over time will account for changes in disposable income but not necessarily changes in food prices. This is because the price of a food depends not only on the price of gas in the state of consumption, but also the price of gas in the state of production as well as the prices in all states the food travels through before reaching the consumer. In unreported regressions (results available upon request), I consider four alternative approaches based on hypotheses that may be true if food prices are an important mechanism through which gas prices affect food consumption—and therefore weight. First, the effect of gas prices on transportation costs should be stronger in larger states, so I estimate separate models for the 25 largest (in land area) states and the other states. Second, because foods are often shipped across state lines, gas prices in neighboring states should affect eating. I therefore include the average price of gas in the states bordering the respondent's state of residence. Third, national gas prices may be a better predictor of eating habits than state prices, so I use national instead of state prices and replace the year effects with a quadratic trend to prevent perfect collinearity. Finally, regional gas prices may be a better predictor than state prices, so I use regional gas prices and a quadratic trend. In all four cases, I continue to find no evidence that changes in the price of gas systematically affect eating habits.[20]

In all, my findings suggest that gas prices do not appear to affect the frequency of eating, but instead affect the location. Perhaps people do not consume fewer hamburgers when gas prices rise, but they cook their own

burgers instead of driving to Ruby Tuesday for a Colossal Burger, inevitably leading to the consumption of far fewer calories.[21] Likewise, people do not consume fewer salads, but prepare their own salads instead of eating salads served at restaurants that are loaded with dressing, cheese, and croutons.

The results in this section also help to rule out the possibility that my reduced-form results capture a general "price effect" instead of a gas price effect. If failing to adequately control for food prices in the reduced-form regressions led me to estimate a spurious negative correlation between gas price and weight, then I should have also found a negative relationship between gas price and food consumption, which I did not.

VI. CONCLUSION

In this paper, I use individual-level data from the 1984–2004 waves of the BRFSS matched with state-level gasoline price and tax data to provide evidence of a causal negative relationship between gasoline prices and body weight. I estimate that 8% of the rise in obesity in the United States over the period 1979–2004 can be attributed to falling gas prices during that time. Assuming that the gas price effect is symmetric, my estimates imply that a $1 increase in gas prices would, after 7 yr, reduce U.S. overweight and obesity by approximately 7% and 10%. The reduction in obesity would save approximately 11,000 lives and $11 billion per year, a magnitude which offsets 10% of fuel consumers' additional expenses. Finally, I find that a rise in gas prices increases walking and decreases the amount people eat out at restaurants, explaining their effect on weight.

The results of this paper support the argument of Lakdawalla, Philipson, and Bhattacharya (2005) that the growth in obesity can be explained largely by responses to changing economic incentives. Such a view would suggest that people are rationally "choosing" a weight that maximizes utility, and that policies designed to alter this choice would hurt welfare. However, there are a number of reasons to suspect that market failures cause personal choices to lead to an obesity rate that is higher than the social optimum. First, the fact that in the U.S. insurance system people rarely pay for their own health care costs means that medical expenditures create a negative externality (Bhattacharya and Sood 2005). Second, eating may be addictive to some degree, in which case government intervention could improve social welfare (Cawley 1999). Third, studies have found that listing nutritional information on restaurant menus alters food choices (Albright et al. 1990). The fact that decisions change in response to new information suggests that imperfect information may be creating inefficiencies in the weight market.

For these reasons, it is possible that revenue-neutral policies designed to alter gas price in such a way as to induce healthier eating and exercise decisions may improve social welfare. An example would be increasing gasoline taxes while subsidizing mass transit or reducing payroll taxes. However, given the recent sharp increases in gas prices, such a policy proposal is unlikely to be politically viable. An alternative would be to alter federal tax rates in such a way as to establish a gas price floor. I leave an analysis of the welfare effects of such policies to future research.

My analysis suffers from several caveats. First, my exercise, restaurant, and food consumption variables are flawed for the reasons discussed in Section III. Future work should use superior data to study the mechanisms through which gas prices affect weight. Second, the fact that my restaurant variable comes from a different data set than my exercise and food variables, plus my lack of additional instruments, prevents me from estimating a structural model to determine more precisely the contribution of the different mechanisms to the gas price effect. Next, further analysis is necessary to deter-mine exactly what percentage of the impact of gas prices on eating at restaurants is because of the income effect as opposed to the substitution effect. Also, further research is necessary to understand the relationship between gas prices and food prices and the resulting impact on health. Finally, my results hold only for as long as no widespread fuel substitutes exist for gasoline.

While much is therefore left to learn about the topic, my results suggest that there may be a "silver lining" to the large spike in gasoline prices that has occurred in recent years in the United States: we may experience a modest reduction in obesity, or at least a slowdown in its growth.

Notes:

1. Specifically, a person is considered obese if he or she has a body mass index (BMI = weight in kg/height in m^2) of greater than or equal to 30. A person is overweight if her or his BMI is greater than or equal to 25.
2. In a potentially relevant literature, Ewing et al. (2003), Giles-Corti et al. (2003), Saelens et al. (2003), and Frank et al. (2004) find that urban sprawl may have contributed to the rise in obesity by making walking and taking public transportation less feasible. However, Plantinga and Nernell (2007) and Eid et al. (2008) provide evidence that this relationship may not be causal.
3. For examples, see Philipson and Posner (1999), Lakdawalla and Philipson (2002), Chou, Grossman, and Sagger (2004), Rashad, Chou, and Grossman (2005), and Rashad (2006).
4. For a discussion, see http://www.eia.doe.gov/pub/ oil gas/petroleum/analysis publications/primer on gasoline prices/html/petbro.html.
5. See Cutler, Glaser, and Shapiro (2003) for a model that depicts this phenomenon.
6. The telephone nature of the BRFSS means that low-income individuals or individuals who only use cellular phones may be undersampled. However, it seems unlikely that this would systematically bias the results in this paper.
7. Owing to a lack of consistent data from the entire time period, I do not include state sales taxes. These only account for a small fraction of the variation in prices, so their omission should not substantially alter my results.
8. The cities included in the *ACCRA COLI* change somewhat from year to year. To ensure that the same cities are included each year, I drop cities for which prices are not reported in more than four of the survey years and impute the remaining missing prices by averaging the prices from the preceding and following years. Also, the *ACCRA COLI* reports prices quarterly instead of annually; I use the prices from the second quarter of each year.
9. Results are robust to the use of quadratic, log-linear, and log-log specifications. For ease of interpretation, I report the results from the linear models.
10. Ordered probit models with fixed effects are widely known to produce biased coefficient estimators because of the incidental parameters problem when the number of observations per group is small. As my regressions include an average of 16,000 observations per state and 48,000 observations per year, I do not expect that including state and year fixed effects will bias my estimators.
11. Note that these phenomena are unlikely to explain much of the variation in gas prices, and would theoretically bias the results away from the expected negative relationship between gas prices and weight.
12. I calculate ordered probit marginal effects using the Sata module "meoprobit" (Cornelissen 2006).
13. I convert BMI to pounds by assuming that one unit of BMI is equivalent to 6.5 pounds, which is the case at the sample mean height of 5'7 1/2". The sample mean height is similar across states.
14. Additionally, in unreported regressions, I use panel data from the National Longitudinal Survey of Youth (NLSY) to track the weight of individuals over a two-decade period of time. The NLSY is a smaller and less representative data set than the BRFSS, but its panel nature allowed me to eliminate both of these problems. Results are even stronger than those reported.
15. I convert the EIA's historical nominal gas price data to real using CPI data from the Bureau of Labor Statistics.
16. Using the estimates with the quadratic trend, this percentage rises to 11%.
17. The comment from footnote 10 applies to Tobit models as well.
18. See http://www.census.gov/datamap/fipslist/AllSt. txt. I classify counties in metropolitan statistical areas (MSAs), consolidated MSAs, primary MSAs, and New England county metropolitan areas as urban, and counties not in any metropolitan area as rural.
19. According to the U.S. Census Bureau, this was the number of households in 2002.
20. Specifically, even in large states gas price is only statistically significant at the 5% level in one of the eight regressions, while the effect in large states is generally statistically indistinguishable from that in small states. Average gas prices in border states are associated with increases in consumption of three types of food and decreases in five, and the variable is significant in only two of the eight regressions. National and regional gas prices are both associated with four increases and four decreases in food consumption, and both national and regional prices are significant in only one of eight regressions.

21. According to Hurley and Liebman (2007), a Colossal Burger contains 1,940 calories. In contrast, a homemade quarter-pound burger with a bun contains approximately 420 calories ("Calorie Content ... 2007").

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