Consumer Heterogeneity: Does It Affect Policy Responses to the Obesity Epidemic?

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Abstract

The fight against obesity in the U.S. has become a priority area for policy makers due to the additional health risks and health care costs. In developing policy to lower obesity rates, it is important to accurately characterize the impact that exercise, smoking and demographic characteristics have on BMI in order to draft effective policy. This analysis uses data from the Behavioral Risk Factor Surveillance System (BRFS) to evaluate the relationship between behavioral and demographic factors with BMI while explicitly accounting for individual heterogeneity by using a quantile analysis. Results suggest that the effect of exercise, smoking, occupation and race vary by BMI quantile, indicating that consumers should be treated as heterogeneous at least for these factors in obesity policy and related analyses.

Keywords: Obesity, Quantile Regression, Heterogeneity, Policy

JEL Classifications: I18

Introduction

Obesity is considered to have reached epidemic levels throughout the United States (US) with more than 34% of adults over age 20 and between 12-17% of children and adolescents being obese (National Center for Health Statistics, 2007). Current estimates indicate that obesity not only has a long range impact on the health and well-being of persons of all ages, but the impact also extends to economic issues including rapid escalation of health care costs and the loss of productivity within the economy. These costs and related quality of life effects have led to a number of research ideas and policy responses on obesity including taxing high calorie food (Schroeter and Lusk, 2008), physical activity (Roux, 2008), the food environment (Morland et al, 2006), advertising (Chou et al, 2004), and nutrition labeling (Kuchler et al, 2005).

A common potential problem in these approaches is that consumers are considered to be relatively homogeneous in their responses to prices and policy signals. An important distinction that needs to be better understood is how people respond differently to prices and policy signals. This information allows policy makers to draft more informed policy in order to more accurately link how a proposed policy might impact individuals at the individual-level, rather than at a more macro level. In this study, we use quantile regressions to more accurately evaluate the effect of behavior and demographics upon body mass index (BMI), while implicitly assuming that these relationships may change according to an individual's BMI. This offers more flexibility, than ordinary-least squares regression, for modeling data with heterogeneous conditional distributions (Chen, 2004). Data for this study are from the Behavioral Risk Factor Surveillance System (BRFS) which are collected on individuals in all 50 states using stratified sampling weights and include information regarding health factors (height, weight, access to health care, exercise, medical history, etc.), demographic factors (race, marital status, income, etc.), and location identifiers. Past studies have used this information to measure the impact of economic factors on health outcomes (Schroeter and Lusk, 2008; Chou et al, 2004).

Understanding the relationship between BMI and socio-demographic, economic and health factors is a key issue toward drafting effective successful polices. Therefore, the objective of this study is to quantify the effect of factors such as food prices, physical activity, and socio-demographic variables on BMI and allow for these marginal impacts to differ based on BMI. This study will stimulate the debate over potential policies to combat obesity by taking into account the heterogeneity of consumers in linking obesity and overweight with socio-demographic, economic, and health factors. This is crucial, as individuals from different socio-demographic and economic backgrounds have different behavior with regard to food consumption and exercise. Any action that aims to remedy the impact of obesity must take into consideration consumer heterogeneity.

Background

There have been several studies that aim to address the issue of the prevalence of obesity. These studies can be grouped in several categories. In one category, the focus is on identifying the determinants of increase in obesity rates. For instance, Chou *et al* (2004) test the hypothesis that an increase in the prevalence of obesity is the result of several economic changes that have altered the lifestyle of Americans. Such changes include the increase in women's' time value, increase in the demand for convenience and fast food, the rise in the cost of cigarette, and the increasing availability of fast-food restaurants. In this regard, Curie *et al*. (2009), in a study of the effect of fast food restaurants on obesity, find that at least a 5.2 % increase in obesity rates among 9th grade children is associated with the presence of a fast food restaurant within a tenth of a mile of a school. Similarly, Davis and Carpenter (2009) find that students attending schools with fast-food restaurants nearby consume fewer fruits and vegetables, more soda, and are more likely to be overweight than those whose schools are not near fast-food restaurants.

In addition, Chou *et al*. (2008) find a strong positive effect between the probability that children and adolescents are overweight and the exposure to fast-food restaurant advertising. Similarly, Robinson *et al*. (2007) find that the aggressive marketing to children of foods and beverages induce children 3 to 5 to choose items perceived to be from McDonald's. Another factor that has been linked to obesity in the literature is maternal employment. Anderson *et al*. (2003) find that the likelihood of a child being overweight is positively related to the number of hours per week and the intensity of work for the mother. Their findings are corroborated by Cawley and Liu (2007) study that concludes that women employment offers a valid explanation for the increase in childhood obesity.

Another category of factors that explain the increase in the prevalence of obesity concerns food prices, food availability and variety, and the price of physical activity. For a variety of reasons, food prices have been declining. For example, the ratio of food prices to the price of all other goods fell by 12 % between 1952 and 2003 (Variyam, 2005). According to Epstein *et al*. (2007), purchases of low-energy-density and high-density-energy foods are reduced when their prices are increased.[1] Asfaw (2006) uses an Egyptian integrated household survey to analyze the effect of the Egyptian food subsidy program on obesity prevalence among mothers. The study finds that BMI is inversely related to the price of subsidized energy-dense foods and directly related to the price of high diet quality. Schroeter and Lusk (2008) find that decreasing the price of food at home is a relatively efficient way of decreasing body weight.

Finally, many studies link the prevalence of obesity to physical activity and the increase in its cost. Varyiyam (2005) argues that the increase in the cost of physical activity either through direct

[1] In Epstein *et al*. (2007), mothers were randomly assigned to price conditions in a laboratory conditions.

cost (joining gym or health club) or through the opportunity cost (the value of the time foregone while exercising) alters the incentives for energy expenditure. Though no one argues about the benefit of physical activity in lowering the risk of many chronic diseases, over half of adults do not exercise consistently (CDC, 2009).

A second category of studies deals with policies that can alleviate the incidence of obesity and reduce its prevalence. For instance, Roux et al. (2008) show that physical activities reduce disease incidence and are cost-effective compared to other preventive strategies. Jacobson and Brownell (2000) suggest imposing taxes on soft drinks, snack, and foods of low nutritional value and using the revenues to fund health promotion programs. However, Kuchler *et al*. (2009) find that low tax rates of 1 cent per pound and 1 percent of value would not alter consumption of salty snack. Asfaw (2006) concludes that the Egyptian subsidy program should be redirected toward basic healthy foods by lowering prices of micronutrient-rich foodstuff not the starchy and fatty food items. Furthermore, Schroeter and Lusk (2008) conclude that taxing food away from home leads to weight increase.

Data

This paper utilizes the rich collection of health data from the Centers for Disease Control and Prevention's (CDC) Behavioral Risk Factor Surveillance System (BRFSS). Data are annually collected from all fifty states through cross-sectional telephone surveys targeting adults eighteen years or older. Demographic information, self-reported body weight and height, and other health-related information of individuals contained in the BRFSS' 2007 survey are combined with Consumer Price Indices from the U.S. Department of Labor-Bureau of Labor Statistics (BLS). Summary statistics are reported in table 1. The metropolitan city-level price indices considered in this paper are particular to the total expenditures for food at grocery stores and food prepared by the consumer unit on trips, or more commonly referred to as food-at-home, and to food-away-from-home, respectively. Food-away-from-home includes expenditures on all meals in fast-food, take-out, delivery, concession stands, buffet and cafeteria, full-service restaurants, and at vending machines and mobile vendors, among others. As pointed out in Schroeter and Lusk (2008), the distinction between the two price indices are used because at-home foods are thought to be healthier than away from home foods, which include food from restaurants and fast-food chains. To capture non-linear impacts from these prices, a squared term is used with each price index, as well as an interaction to capture similar movements in both prices.

A total of 430,902 individuals participated in the 2007 BRFSS survey. However, the merged data set was trimmed to 184,357 after eliminating observations due to omitted responses regarding relevant questions used in this analysis.[2] Further, regional binary variables were included and based on U.S. Census Bureau regional specifications for Northeast, Midwest, South, and West. Regional and MSA classifications are used in order to identify differences in regional location and population density, respectively.

BMI is computed based on reported height and weight and can be used to classify individuals into 4 main weight categories: underweight (< 19), ideal (19-25), overweight (25-30), and obese (> 30). In this data, 29.15% of the respondents are classified as obese, while 38.53% are classified as overweight, 29.44% are classified within the ideal BMI range, while 2.88% are underweight. This implies that the top 3 quantiles (.7, .8, .9) correspond to individuals in the obese category, while the 3 middle quantiles (.4, .5, .6) correspond to individuals in the overweight category. In our analysis, this allows us to focus on the difference in the marginal impacts from different factors for each group and

[2] Although BRFSS collects data from Puerto Rico, Guam, and U.S. Virgin Islands, observations from these countries were also not included in the final data set given that U.S. DOL-BLS measures of food-away-from home and food-at-home are not available for those locations.

within each group. An important question part of this analysis is evaluating which segments of the population are impacted by behavioral or price changes.

Methods

Typical least squares methods are based on finding optimal parameter estimates by minimizing the sum of squared errors, such that

$$\hat{\beta}_{ols} = arg\ min_{\beta} \sum_{i=1}^{n} \varepsilon_i{}^2 \quad (1)$$

where $\varepsilon_i = y_i - x_i\beta$ such that ε_i and y_i are individual scalar values and x_i is (*1xk*) while β is (*kx1*) and contain regressors that are expected to impact y_i. Estimates for β within this context can be thought of as average estimates across the population. However, a richer characterization of the data can be found through the use of quantile regressions. This is because individuals of different levels of BMI are hypothesized to respond differently to the regressor variables. For example, exercise may have a small marginal impact on individuals with low BMI and a significantly larger impact for individuals with higher BMI. Other advantages of quantile regressions include the additional robustness to outliers as well as the weak assumptions needed for consistent estimation (Cameron and Trivedi, 2005).

A quantile regression allows us to identify the heterogeneity regarding health outcomes from different economic factors and assess the differences in sensitivity to economic factors among BMI levels. In deriving the quantile regression it is important to point out that we can obtain the median of a random variable by minimizing the sum of absolute deviations. As Koenker and Hallock (2001) point out, we can also obtain the quantile (τ) by minimzing the sum of asymmetrically weighted absolute residuals, where positive residuals are weighted with τ and negative residuals are weighted with $(1-\tau)$. This can be written as

$$\hat{\beta}^{\tau} = arg\ min_{\beta} \sum_{i=1}^{n} \rho(\varepsilon_i) \tag{2}$$

where $\rho(\varepsilon_i) = \varepsilon_i\big(\tau - I(\varepsilon_i < 0)\big)$ is the asymmetrically weighted function with $I(\varepsilon_i < 0)$ equal to 1 when ε_i is negative and zero otherwise. Notice that there is an optimal $\hat{\beta}(\tau)$ for each specified quantile, which in the case of this study includes 9 quantile points:$\tau = \{0.1, 0.2, \dots, 0.8, 0.9\}$. The weighting function can alternatively be written as

$$\rho(\varepsilon_i) = \begin{cases} \tau|\varepsilon_i| & if\ \varepsilon_i \geq 0 \\ (1-\tau)|\varepsilon_i| & if\ \varepsilon_i < 0 \end{cases} \tag{3}$$

Within each quantile, BMI is conditional on X, which includes demographic, economic, and health factors that influence BMI. More specifically,

$$Q_{\tau}[BMI|X_d, X_e, X_h] = \beta_0^{\tau} + \beta_1^{\tau} X_d + \beta_2^{\tau} X_e + \beta_3^{\tau} X_h \tag{4}$$

where $Q_{\tau}[BMI|X_d, X_e, X_h]$ is the τth conditional quantile of *BMI*, β_0^{τ} is the regression intercept while X_d, X_e, X_h, which are of size *(nxk$_d$)*, *(nxk$_e$)*, and *(nxk$_h$)* such $k_d + k_e + k_h = k$, and are coefficients corresponding to demographic (age, gender, ethnicity), economic ("at-home" food price index, "away-from-home" food price index), and health (exercise, access to a health insurance plan) variables, respectively. The coefficients β^{τ} represent the marginal impact on *BMI* from covariates at the τth quantile.

Each quantile corresponds to a unique estimate for β, which allows for an examination into the economic impacts of obesity by BMI. For example, Schroeter and Lusk (2008) estimate the elasticity of BMI to changes in fast food price index to be -0.048 for all individuals in the survey. However, this elasticity can be viewed as an average elasticity across the population. From a policy perspective, it would also be useful to know which segments of the population have more elastic demands for such foods. Another example is the potential for a subsidy on foods deemed healthy such as food and vegetables. Would such a policy have the desired impacts on the high risk proportion of the population?

Estimation and Results

Table 2 shows the results of the quantile regression of key variables upon BMI, including exercise, the number of children in the household, food at home price index, food away from home price index, income, and education. Overall, the results show that the effect of many key variables clearly varies by quantile, indicating that there is substantial heterogeneity. Most significantly, a number of variables have increasingly strong effects upon BMI as quantile increases, and a few variables in which the sign changes as BMI quantile increases. Several results that are strongly relevant for obesity policy are highlighted.

First, notice that for all quantiles, the parameter of the variable *age* is positive and statistically significant, implying that the BMI increases as age increases. However, the effect of age increases as the BMI increases. As shown in Figure 1, the marginal effect of age (at the mean age of 56.5) on BMI for underweight individuals is slightly negative (-0.0065), while this effect is more substantial for the highest quantile (-0.1054), which includes obese individuals. While similar impacts are found for individuals with Age = 71, younger individuals have a larger increase in BMI with an additional year of age. This implies that natural growth patterns over one's life cycle are accentuated with age for people already having overweight or obesity problems.

On the other hand, physical activity or exercise allows decreasing the body mass index for all individuals, as indicated by the negatively statistically significant parameter of the variable *exercise.* The effect of exercise on BMI is more noticed with overweight and obese individuals than with underweight and normal weight individuals as the parameter estimate changes from -0.3052 to -0.9035 from the first to final quantile. This indicates the substantial effect of exercise on reducing BMI for obese individuals, and its importance as an effective behavior in reducing obesity.

Second, gender and marital status have some interesting effects. The results suggest that males have a lower BMI than females for obese individuals, and females have a relatively lower BMI for the lower weight categories. This implies that the prevalence of obesity is more accentuated for females than males. For marital status, the results indicate that for underweight, normal, and overweight individuals BMI is higher for married, separated/divorced and widowed persons than for single persons. Alternatively, for obese individuals, the prevalence of obesity is more accentuated for single than for married, divorced/separated and widowed persons. Compared with singles, divorced/separated and married persons appear to cope better with obesity and overweight. This change in effect may be based upon the changing family dynamics in obese and non-obese populations.

In addition, the results show that all categories of income have a positive and statistically significant effect on BMI, regardless of the quantile considered. Its important to note that these results are relative to the higher income bracket, implying that lower income brackets are found to have higher BMI levels. Similar conclusion could be drawn for access to a health, having children, having asthma, and race variables. Hence, all the race dummy variables affect positively BMI.[3] However, the prevalence of obesity is greater for African Americans than the other races.

[3] The dummy variable for Hispanic has a negative but not significant effect on BMI of 0.80 quantile and negative and significant effect on BMI of 0.90 quantile.

For categorical variables of employment, education, and smoking habits, the overall effect on BMI is negative for all quantiles. For instance, being a student, a self-employed, and homemaker has more reducing effect on BMI for obese individuals than the other categories, probably because of higher and frequent activities of these occupations; and the flexibility they offer in choosing and taking food. In terms of smoking habits, the results show that every day and someday smokers have lower prevalence to gain weight or be obese than non smokers.

Regarding geographical variables, the results of this study show that the regional dummy variables affect positively the BMI of all quantiles. However, the prevalence of obesity is not specific to any of the U.S regions. Similar conclusion can be drawn for the metropolitan statistical area (MSA) dummy variables, which affect the BMI negatively.

Finally, the marginal impacts from price levels are shown in Figure 2. Increases to food-away-from-home prices are shown to have a positive impact on the lower half and highly obese individuals. Food at-home has the oppositive impact for the lower 50% and is shown to have a similar impact to away-from-home prices for the .7 and .8 quantiles. These are surprising results as we assume that food consumed at home are supposed to be healthier than food away from home; and any increase in the price of these food would lead consumers to consume more food away from home, and increase BMI. This result implies that taxing food at home would decrease BMI for most populations, while taxing food away from home might actually increase the prevalence of obesity. However, the result should be carefully interpreted. First, food at home cannot be blindly assumed healthier than food away from home. Many foods prepared and taken at home include energy-dense and nutrient-poor food items such chips, sodas, canned food, and starchy foods that provide cheap sources of calorie intake. Therefore, taxing this type of food items would likely reduce the overweight and obesity prevalence. Second, many food away from home might include healthy food items such salads, vegetables, and nutrient-rich food items. Any tax increase on these food items would certainly decrease their consumption and therefore, increase the obesity prevalence. Unfortunately, the data at hand does not provide an appropriate tool to make policy decision in terms of taxing unhealthy food items and subsidizing healthy ones. Specific food intake and prices are needed in order to draft policy that could help prevent the obesity issue.

Conclusion

This research uses BRFSS data to evaluate to what extent consumers BMI were impacted by demographics, economic factors and choices. Unlike previous studies, this study takes into account the heterogeneity of individuals in the survey by using the quantile regression technique. The results show generally similar results to earlier studies, but obese respondents often are impacted substantially differently than other respondents with a greater impact of some variables (e.g. exercise, income, education, smoking) and a different relationship for other variables altogether (e.g. gender, marital status). These heterogeneous effects should be considered when developing policy that is designed to reduce obesity and suggests that a targeted and tailored approach would be most effective.

A key issue for future research is data designed to capture the effect of various potential policy changes upon BMI. Currently available data sets have limited information upon on food intake, exercise quality, prices and other factors that are known to impact BMI. Developing such data sets and appropriate analyses would thus be an important step in understanding the implications of obesity policy alternatives.

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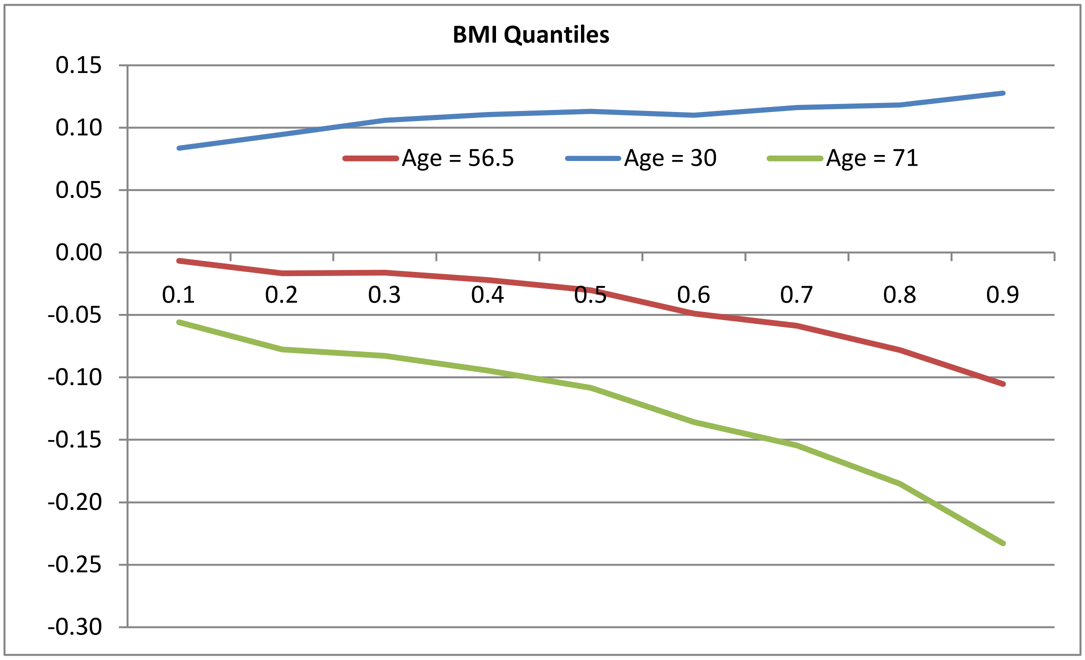
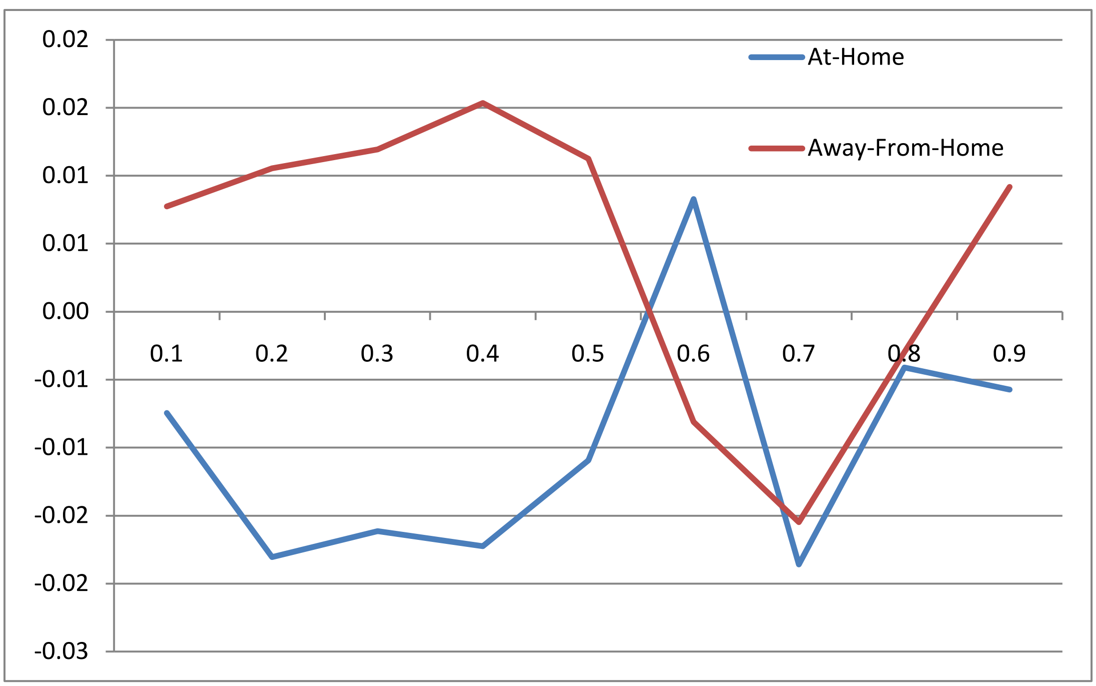
Figure 1. Marginal Impact on BMI from a One-unit Change in Age



Note: Marginal Impact is evaluate at mean age = 56.5 years.

Figure 2. Marginal Impact on BMI from a One-Unit Change in Price



Note: Marginal Impact is evaluate at mean price index levels; At-Home = 188.6, Away-From-Home = 194.8

Table 1. Summary Statistics for 2007 BFRRS (N = 184,357)

Variable	Units	Mean	Std. Dev.	Q1	Q3
BMI	kg/m^2	27.83	6.30	23.57	30.79
Age	Years	56.50	18.00	43.00	71.00
Children		0.48	0.99	0.00	0.00
Food At-Home Price	in 1998 $	188.60	27.10	177.00	208.20
Food Away From Home Price	in 1998 $	194.80	32.17	179.90	224.30
Proportion of Sample					
Exercise	1 = yes, if exercised within last 30 days; 0 = no	68.92%			
Health Plan	1 = yes, if health care coverage; 0 = no	84.74%			
Asthma	1 = yes, if ever had asthma; 0= no	14.05%			
Male	1 = yes, if male; 0 = no	33.72%			
Inc1	1 = yes, if annual household income < $15,000; 0=no	14.37%			
Inc2	1 = yes, if annual household income $15,000-$25,000; 0=no	24.22%			
Inc3	1 = yes, if annual household income $25,000-$35,000; 0=no	18.42%			
Inc4	1 = yes, if annual household income $35,000-$50,000; 0=no	24.54%			
Inc5	1 = yes, if annual household income > $50,000; 0=no	18.45%			
Employed	1= yes, if employed for wages; 0=no	34.65%			
Self-Employed	1 = yes, if self-employed; 0 = no	6.68%			
Out of Work	1 = yes, if out of work < 1 year; 0 = no	2.68%			
Homemaker	1 = yes, if homemaker; 0 = no	8.07%			
Student	1 = yes, if student; 0 = no	2.09%			
Retired	1 = yes, if retired; 0 = no	33.93%			
Unable To Work	1 = yes, if unable to work; 0 = no	11.90%			
High School Graduate	1 = yes, if completed; 0 = no	65.19%			
College Graduate	1 = yes, if completed; 0 = no	21.27%			
Northeast	1 = yes; 0 = no	20.20%			
Midwest	1 = yes; 0 = no	16.77%			
South	1 = yes; 0 = no	40.47%			
West	1 = yes; 0 = no	22.56%			

Table 1. (Continued)

Variable	Units	Mean
City Center	1 = yes; 0 = no	35.32%
Outside City Center	1 = yes; 0 = no	21.07%
Suburb	1 = yes; 0 = no	12.46%
No City Center	1 = yes; 0 = no	1.10%
Rural	1 = yes; 0 = no	30.05%
White	1 = yes; 0 = no	76.84%
African American	1 = yes; 0 = no	9.87%
Other race	1 = yes, if Asian, Native Hawaiian or other Pacific Islander, American Indian, Alaskan Native, multiracial, or from any other race; 0 = no	5.53%
Hispanic	1 = yes; 0 = no	7.76%
Married	1 = yes; 0 = no	42.29%
Divorces/Separated	1 = yes; 0 = no	21.25%
Widowed	1 = yes; 0 = no	19.32%
Single	1 = yes; 0 = no	17.14%
Everyday Smoker	1 = yes; 0 = no	17.24%
Someday Smoker	1 = yes; 0 = no	4.89%
Former Smoker	1 = yes; 0 = no	29.57%

Table 2. Quantile Regression Results from BMI regression

	BMI Quantile								
Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	15.715*	17.765*	18.8798*	20.203*	21.7453*	23.5857*	25.4653*	29.1542*	32.9759*
	(25.74)	(27.66)	(29.9)	(30.36)	(32.76)	(32.02)	(28.53)	(27.32)	(23.22)
Age	0.1856*	0.2206*	0.2438*	0.2606*	0.275*	0.2901*	0.3142*	0.3401*	0.3918*
	(36.58)	(49.79)	(53.22)	(49.41)	(51.55)	(56.3)	(50.25)	(44.38)	(38.03)
Age^2	-0.0017*	-0.0021*	-0.0023*	-0.0025*	-0.0027*	-0.003*	-0.0033*	-0.0037*	-0.0044*
	(-37.71)	(-51.78)	(-55.57)	(-54.16)	(-57.91)	(-63.21)	(-58.58)	(-56.37)	(-47.89)
Exercise	-0.3052*	-0.6585*	-0.8739*	-1.1384*	-1.3612*	-1.6064*	-1.917*	-2.3099*	-2.9035*
	(-9.94)	(-21.99)	(-24.26)	(-38.51)	(-38.18)	(-44.58)	(-42.35)	(-42.13)	(-41.26)
HealthPlan	0.1794*	0.2058*	0.1914*	0.203*	0.2223*	0.2772*	0.3382*	0.3285*	0.2299*
	(4)	(4.9)	(4.67)	(4.75)	(4.89)	(5.38)	(5.49)	(4.4)	(2.36)
Asthma	0.4166*	0.5938*	0.9117*	1.1223*	1.3672*	1.6088*	1.9088*	2.3124*	2.8054*
	(9.58)	(13.15)	(22.25)	(22.67)	(26.02)	(31.82)	(30.13)	(30.18)	(28.51)
Children	0.038*	0.0392*	0.0686*	0.0638*	0.075*	0.087*	0.0974*	0.0694*	0.0666
	(2.22)	(2.07)	(4.12)	(3.53)	(3.99)	(4.6)	(4.24)	(2.29)	(1.54)
Male	1.3869*	1.2697*	1.0496*	0.8295*	0.5841*	0.3328*	0.0876*	-0.2475*	-0.7152*
	(43.93)	(45.78)	(34.84)	(28.65)	(18.49)	(10.03)	(2.41)	(-5.28)	(-10.79)
Inc1	0.2431*	0.4979*	0.621*	0.7983*	0.981*	1.2207*	1.3396*	1.6321*	2.1897*
	(4.32)	(10.58)	(12.2)	(14.02)	(16.89)	(18.82)	(18.58)	(20.5)	(19.92)
Inc2	0.4057*	0.5772*	0.6187*	0.7412*	0.9073*	1.0138*	1.11*	1.2812*	1.6764*
	(9.39)	(14.94)	(14.96)	(17.85)	(20.02)	(18.41)	(19.97)	(20.04)	(15.69)
Inc3	0.4718*	0.5678*	0.6232*	0.6973*	0.7582*	0.8611*	0.9009*	0.9764*	1.2396*
	(10.96)	(13.63)	(13.89)	(17.98)	(16.07)	(15.33)	(15.08)	(13.67)	(12.98)
Inc4	0.4857*	0.5784*	0.5956*	0.6493*	0.7129*	0.7748*	0.7858*	0.8528*	1.1041*
	(11.99)	(14.37)	(14.85)	(17.02)	(15.54)	(16.29)	(13.78)	(12.78)	(12.41)
Employed	-0.0262	-0.288*	-0.5954*	-0.8328*	-1.1014*	-1.3999*	-1.7768*	-2.298*	-3.1762*
	(-0.52)	(-5.8)	(-10.66)	(-14.07)	(-17.15)	(-21.94)	(-21.79)	(-24.29)	(-22.67)
Self-Employed	-0.3223*	-0.7011*	-1.0852*	-1.3727*	-1.7452*	-2.1027*	-2.5434*	-3.2586*	-4.3418*
	(-4.73)	(-11.36)	(-16.41)	(-17.72)	(-21.49)	(-29.14)	(-26.86)	(-27.86)	(-26.12)

Table 2. (Continued)

Variables	BMI Quantile 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Out of Work	0.0160	-0.2421*	-0.4182*	-0.6197*	-0.9676*	-1.0687*	-1.3574*	-1.7247*	-2.3151*
	(0.2)	(-2.58)	(-4.42)	(-6.47)	(-8.45)	(-7.81)	(-8.46)	(-9.51)	(-8.44)
Homemaker	-0.3154*	-0.5611*	-0.8393*	-1.0847*	-1.3686*	-1.6063*	-1.8585*	-2.3291*	-3.1704*
	(-4.45)	(-7.86)	(-11.77)	(-14.46)	(-18.69)	(-19.94)	(-19.33)	(-19.09)	(-18)
Student	-0.3294*	-0.7382*	-1.2121*	-1.5545*	-2.0919*	-2.3801*	-2.7837*	-3.4205*	-4.4592*
	(-3.54)	(-8.67)	(-11.58)	(-13.84)	(-18.41)	(-16.72)	(-17.72)	(-18.76)	(-15.47)
Retired	0.0972	-0.1476*	-0.4269*	-0.6244*	-0.875*	-1.0989*	-1.4368*	-1.9171*	-2.6668*
	(1.75)	(-2.99)	(-7.54)	(-10.69)	(-14.42)	(-16.24)	(-18.42)	(-21.47)	(-18.19)
High School Graduate	-0.0519	-0.163*	-0.1946*	-0.2517*	-0.2784*	-0.3352*	-0.3928*	-0.3971*	-0.5748*
	(-1.05)	(-3.9)	(-4.37)	(-5.65)	(-6.19)	(-7.65)	(-6.6)	(-5.77)	(-5.56)
College Graduate	-0.6844*	-0.9258*	-1.0573*	-1.1436*	-1.1979*	-1.3121*	-1.4177*	-1.4873*	-1.6553*
	(-12.35)	(-20.08)	(-21.26)	(-23.28)	(-23.8)	(-24.56)	(-20.45)	(-17.87)	(-14.15)
White	0.4329*	0.3937*	0.3998*	0.3115*	0.2234*	0.1438	0.1181	0.1417	0.0818
	(6.35)	(6.83)	(7.49)	(4.64)	(3.16)	(1.83)	(1.21)	(1.46)	(0.46)
African American	1.5237*	1.7056*	1.9339*	2.0315*	1.9915*	2.0447*	2.1261*	2.2635*	2.0736*
	(19.19)	(20.07)	(23.02)	(24.26)	(21.71)	(20.52)	(16.58)	(17.69)	(10.05)
Hispanic	1.0283*	1.0195*	0.9296*	0.8034*	0.5882*	0.4026*	0.181	-0.0231	-0.5378*
	(12.11)	(13.11)	(13.03)	(9.58)	(6.95)	(4.08)	(1.5)	(-0.18)	(-2.85)
Married	0.5208*	0.4084*	0.3167*	0.2297*	0.1354*	0.0112	-0.2241*	-0.4323*	-0.9677*
	(11.04)	(8.98)	(7.59)	(4.8)	(2.85)	(0.22)	(-3.67)	(-5.74)	(-8.76)
Divorces/Separated	0.1471*	0.0307	-0.075	-0.1465*	-0.2225*	-0.3087*	-0.4344*	-0.5913*	-0.9703*
	(2.95)	(0.64)	(-1.55)	(-2.93)	(-4.16)	(-5.11)	(-6.45)	(-7.42)	(-7.52)
Widowed	0.3476*	0.2887*	0.2401*	0.213*	0.1399*	0.0426	-0.1443	-0.3005*	-0.7101*
	(6.17)	(5.52)	(4.34)	(3.5)	(2.47)	(0.76)	(-1.9)	(-3.24)	(-5.38)
Everyday Smoker	-1.4286*	-1.5614*	-1.6696*	-1.7481*	-1.8445*	-1.9746*	-2.1274*	-2.336*	-2.9011*
	(-32.99)	(-43.01)	(-43.21)	(-39.73)	(-40.33)	(-42.95)	(-39.97)	(-36.82)	(-32.95)
Someday Smoker	-1.0322*	-1.1432*	-1.231*	-1.3265*	-1.4387*	-1.5872*	-1.8865*	-2.1227*	-2.5455*
	(-15.34)	(-17.48)	(-18.63)	(-20.49)	(-20.51)	(-20.56)	(-23.05)	(-23.38)	(-17.68)

Table 2. (Continued)

	BMI Quantile								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Former Smoker	0.2500*	0.2184*	0.2412*	0.2422*	0.2673*	0.2718*	0.2724*	0.3338*	0.2702*
	(8.28)	(6.86)	(7.86)	(7.73)	(8.3)	(7.25)	(6.65)	(6.57)	(3.73)
Northeast	0.2116*	0.2155*	0.2302*	0.236*	0.1953*	0.1113*	0.048	0.07	-0.1123
	(4.33)	(5.29)	(4.91)	(5.85)	(4.25)	(2.14)	(0.79)	(1.04)	(-1.14)
Midwest	0.2490*	0.3411*	0.4113*	0.4756*	0.4756*	0.4542*	0.4871*	0.5776*	0.631*
	(5.17)	(7.61)	(8.33)	(10.51)	(9.56)	(7.85)	(7.59)	(7.55)	(5.9)
South	0.0893*	0.1659*	0.1636*	0.1942*	0.205*	0.1355*	0.0868	0.1086	0.1897
	(1.97)	(3.65)	(3.27)	(4.56)	(4.35)	(2.61)	(1.54)	(1.49)	(1.86)
City Center	-0.1409*	-0.1639*	-0.19*	-0.1957*	-0.2228*	-0.2712*	-0.2683*	-0.233*	-0.229*
	(-4.23)	(-5.46)	(-5.45)	(-6)	(-5.64)	(-6.52)	(-5.93)	(-4.08)	(-3.02)
Outside City Center	-0.0939*	-0.106*	-0.1411*	-0.1648*	-0.1685*	-0.2066*	-0.1537*	-0.0987	-0.0289
	(-2.41)	(-3.06)	(-3.98)	(-4.3)	(-3.99)	(-4.41)	(-3.22)	(-1.53)	(-0.36)
Suburb	-0.0918	-0.0764	-0.0963*	-0.0944*	-0.1603*	-0.1629*	-0.1427*	-0.1636*	-0.1749
	(-1.87)	(-1.7)	(-2)	(-2.39)	(-3.4)	(-2.96)	(-2.62)	(-2.3)	(-1.88)
No City Center	-0.1799	-0.1293	-0.2151	-0.2297	-0.2094	-0.3847*	-0.3869*	-0.3117	0.0672
	(-1.49)	(-1.08)	(-1.78)	(-1.78)	(-1.64)	(-2.8)	(-2.01)	(-1.55)	(0.25)
Food At-Home Price	-0.0062	-0.0168	-0.0149	-0.016	-0.0097	-0.0282	-0.0356	-0.0783*	-0.0617
	(-0.41)	(-1.03)	(-0.92)	(-0.92)	(-0.54)	(-1.56)	(-1.5)	(-2.92)	(-1.78)
(Food At-Home Price)^2	0.0001	0.0001*	0.0001	0.0001	0.0001	0.0002*	0.0002	0.0003*	0.0002
	(1.54)	(1.99)	(1.82)	(1.92)	(1.36)	(2.28)	(1.95)	(2.38)	(1.28)
Food Away From Home Price	0.0065	0.0093	0.0107	0.0141	0.01	0.0296*	0.0411*	0.0737*	0.067*
	(0.57)	(0.74)	(0.9)	(1.11)	(0.7)	(2.07)	(2.32)	(3.72)	(2.43)
(Food Away From Home Price)^2	0.0001	0.0001	0.0001	0.0001	0.0001	0	0	-0.0001	-0.0001
	(1.82)	(1.64)	(1.85)	(1.61)	(1.24)	(0.88)	(0.54)	(-1.02)	(-0.9)
(Food At-Home Price)* (Food Away From Home Price)	-0.0002	-0.0002*	-0.0002*	-0.0002*	-0.0002	-0.0002*	-0.0003	-0.0002	-0.0001
	(-1.96)	(-2.04)	(-2.09)	(-2.24)	(-1.66)	(-2.17)	(-1.82)	(-1.23)	(-0.52)

Note: t-values are reported in parenthesis and "*" indicates statistical significance at 0.05.