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Original Article

Using Quantile Regression to Measure the Differential Impact of Economic and Demographic Variables on Obesity

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Abstract

The fight against obesity in the U.S. has become a pressing priority for policy makers due to many undesirable outcomes including escalating health care costs, reduced quality of life and increased mortality. This analysis uses data from the 2007 Behavioral Risk Factor Surveillance System (BRFSS) to evaluate the relationship between behavioral, economic, and demographic factors with BMI while explicitly accounting for systematic heterogeneity using a quantile regression. Results suggest that the effect of exercise, smoking, occupation, and race vary by sizeable amounts from high to low BMI-quantiles. This strongly indicates that future research efforts and policy responses to obesity need to account for these differences in order to develop more effective policies.

Key words:Consumer Heterogeneity, Obesity, Quantile Regression

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INTRODUCTION

Obesity is considered to have reached epidemic levels throughout the United States (U.S.) 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 in health care costs and the loss of productivity. These costs and related quality of life effects have led to a number of research efforts and policy responses on obesity including taxing high calorie food (Schroeter and Lusk 2008), taxing sugar-sweetened beverages (Brownell et al. 2009), encouraging increased physical activity (Roux 2008), as well as changes to the food environment (Morland et al. 2006), advertising (Chou et al. 2004), and nutrition labeling (Kuchler et al. 2005). A common potential problem in estimating the relative effectiveness of these approaches is that consumers are considered to be relatively homogeneous as weight status changes. Conceptually, this would mean that individuals who are underweight would achieve the same result from a change in activity (e.g. nutrition changes, increasing activity, and smoking) as overweight or obese individuals. This assumption manifests itself in the form of using ordinary least squares (OLS) to regress BMI on demographic and economic factors, as in Chou et al. (2004).

To evaluate this conceptual and largely ignored issue, this article usesquantile regression. With quantile regression, systematic regressions are completed for each portion of the BMI distribution to enable a direct evaluation of the heterogeneity question. This paper demonstrates that considerable heterogeneity exists between BMI quantiles. This study aims to reveal the more comprehensive link between obesity and socio-demographic, economic, and health factors in order to assist in making potential policies to combat obesity more effective. Recent health-related studies that have used quantile regressions include topics such as the relationship between BMI and income (Joliffe 2010), child nutritional outcomes (Averett and Stifel 2009; Boorah 2005), and the relationship between sleep duration and BMI in Taiwan (Chen et al. 2011).

Information regarding consumer heterogeneity allows policy makers to draft more informed policy in order to more accurately link a proposed policy to thepotential impact on individuals at the individual-level, rather than at a more aggregated level. Further, it allows for policy to be more effectively linked to high-risk portions of the population. In this study, we use quantile regression 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 typical least squares regression approaches, for modeling data with heterogeneous conditional distributions (Chen 2004).

Data for this study are from the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is an annual telephone survey 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 data from the BRFSS to measure the average impact of economic factors on individual health outcomes (Schroeter and Lusk 2008; Chou et al. 2004).

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 age 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) who conclude that increases in female labor force participation led to an 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.However, Schroeter and Lusk (2008) find that decreasing the price of food at home (supposed to be healthier) 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 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. Whatever the cause, over half of adults do not exercise consistently (Centers for Disease Control, 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, Kuchleret al. (2009) find that lowering tax rates by 1 cent per pound and by 1 percent of value would not alter consumption of salty snacks. 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.

While a large body of research exists to support the impact of certain covariates on overall BMI, these estimates are typically found based on a single linear regression that does not fully characterize consumer heterogeneity.

For example,Goel and Ram (2004) determined that individuals who consume higher amounts of cigarettes have a significantly higher elasticity when compared to those who consume relatively low amounts. One can make the same argument regarding lifestyle choices such that individuals who tend to make relatively unhealthier choices are more likely to be less sensitive to make lifestyle choices that are more typical of healthier groups. In this study, we look to compare the sensitivity of individuals in higher BMI ranges with that of individuals in lower BMI ranges in order to determine the variability in modeling outcomes and policy responses.

DATA

This paper utilizes the rich collection of health data from the Centers for Disease Control and Prevention's 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). The BRFSS is a survey conducted by the Center for Disease Control (CDC) in cooperation with each state and uses a disproportionate stratified sampling design method.

Because the observations are not a random subsample, stratification weights are used in computing the summary statistics reported in Table 1. We also test whether the sample weighted and unweighted parameter estimates are statistically different as proposed by DuMouchel and Duncan (1983). Test results indicate that the two are not statistically differentwhen using quantile regression, meaning both are consistent and implying the unweightedquantile regression is preferred because it is more efficient. Further support for not using weights within the regressions is provided by DuMouchel and Duncan (1983) who state that weights are not necessary when samples are exogenously stratified, as in the case of quantile regression.

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. Both expenditure levels are stated in terms of $ in 1998. 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 respondents, 15.4% met both recommended levels for moderate and vigorous activities (All Act), while 33.1% met only one recommended level (Some Act), 38.7% reported 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.

A total of 430,902 individuals participated in the 2007 BRFSS survey. However, the merged data set was trimmed to 253,941 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 metropolitanstatistical areas (MSA) classifications are used in order to identify differences in regional location and population density, respectively. This variable identifies the difference between individuals living in city centers, outside city centers, in suburban counties, and MSA that do not have a center city. The inclusion of these variables is intended to identify differences in food availability and variety across different geographical areas.The number of fast food restaurants for each county was based on North American Industry Classification System (NAICS)code722211 of the U.S. Censusper 10,000 inhabitants. This includes fast food restaurants, pizza parlors, carryout restaurants, and any limited service restaurant.

BMI is computed based on reported height and weight and can be used to classify individuals into 4 main weight categories: underweight ($BMI< 19$), ideal ($19<BMI<25$), overweight ($25<BMI<30$), and obese ($BMI > 30$). As in Dunn (2010), we omit individuals with a BMI below 12 or above 90, eliminating 28 observations. In this data, 27.4% of the weighted respondents are classified as obese, while 36.9% are classified as overweight, 34.3% are classified within the ideal BMI range, while 1.5% 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 within each group. An important question part of this analysis is evaluating which segments of the population are impacted by behavioral or price changes.

Individuals are also asked questions regarding the servings of vegetables they consume as well as how much physical activity they participate in on a weekly basis. Daily servings of vegetables exclude carrots and potatoes, where the mean amount is 1.41 servings of vegetables per day. Physical activities are broken into moderate and vigorous physical activity, which has a recommended level of 30 minutes for 5 or more days of moderate activity and 20 minutes for 3 or more days for vigorous activities. Of the surveyed insufficient activity for both types of physical activity (Insufficient Act), and 12.8% reported no physical activity. Additional individual-specific information includes the use of a health care plan, diagnosis of asthma, and cigarette smoking frequency (everyday, someday, former, never). Also, demographic information, such as marital status, cultural heritage, education, gender, income, and type of employment are included in the data and provide important control variables for variation in BMI.

METHODS

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

$$\hat{\beta}_{ols} = ArgMin_{\beta} \sum_{i=1}^{n} {\varepsilon_i}^2 \qquad (1)$$

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. OLS 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 regression. 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 regression 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

$$\hat{\beta}^{\tau} = ArgMin_{\beta} \sum_{i=1}^{n} \rho(\varepsilon_i) \qquad (2)$$

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: $\tau = \{0.1, 0.2, \ldots, 0.8, 0.9\}$. Since we obtain parameters that are from a set of equations, we use the argmin function above. The weighting function can alternatively be written as

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

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

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

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. This implies that an increase of 10% in the price of fast food prices results in a drop in individual BMI by an average of about 0.5%. 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 fruits and vegetables. Would such a policy have the desired impacts on the high risk (obese or overweight) proportion of the population?

First, notice that for all quantiles and in the OLS estimate, the parameter of the variableage is positive and statistically significant, implying that the BMI increases as age increases. However, the positive association with age increases as the BMI increases in QR. Figure 1 (as well as Figures 2 and 3) plots the marginal effects associated with different quantiles, as well as the OLS results which are denoted with a dotted line. As shown in Figure 1, the marginal effect of age (at the mean age of 53.2) on BMI for individuals in lower quantilesis insignificant, while this effect is more substantial for the highest quantile (-0.0644), which includes obese individuals. This implies that a one-year increase in Age correlates with a reduction of 6.4% in BMI. Additionally, ages at the top and lowest quantiles were used to illustrate the nonlinear impact of age on BMI. For example, the impact for individuals 25-years old are quite different, where the average marginal

Table 1 2007 Weighted Summary Statistics (N =275,698)

Variable	Units	Mean	Q1	Q3
BMI	kg/m^2	27.61	23.62	30.43
Age	Years	53.17	41.00	65.00
Children	Number of children in household	0.62	0.00	1.00
Vegetable Servings	Servings per day	1.41	0.86	2.00
Fast Food Per Capita	stores per 1,000 residents	6.97	6.00	7.98
Food At-Home Price	in 1998 $	189.70	177.00	208.20
Food Away From Home Price	in 1998 $	195.90	179.90	224.80
Weighted Proportion of Sample				
HealthPlan	1 = yes, if health care coverage; 0 = no	86.38%		
All Act	1 = yes, if meets recommended moderate and vigorous physical activity levels; 0 = no	17.09%		
Some Act	1 = yes, if meets recommended moderate or vigorous physical activity levels; 0 = no	32.90%		
Insufficient Act	1 = yes, if insufficient moderate or vigorous physical activity; 0 = no	38.39%		
No Act	1 = yes, if no physical activity reported; 0 = no	11.61%		
Asthma	1 = yes, if ever had asthma; 0= no	12.85%		
Male	1 = yes, if male; 0 = no	50.92%		
Low Inc	1 = yes, if annual household income < $25,000; 0 = no	22.14%		
Mid Inc	1 = yes, if annual household income $25,000-$50,000; 0 = no	25.90%		
High Inc	1 = yes, if annual household income > $50,000; 0 = no	51.96%		
Employed	1= yes, if employed for wages; 0=no	55.48%		
Self-Employed	1 = yes, if self-employed; 0 = no	9.26%		
Out of Work	1 = yes, if out of work < 1 year; 0 = no	4.38%		
Homemaker	1 = yes, if homemaker; 0 = no	7.35%		
Student	1 = yes, if student; 0 = no	3.93%		
Retired	1 = yes, if retired; 0 = no	14.99%		
Unable To Work	1 = yes, if unable to work; 0 = no	4.60%		
Less than High School	1 = yes if no high school diploma; 0 = no	9.24%		
High School Graduate	1 = yes, if completed; 0 = no	52.90%		
College Graduate	1 = yes, if completed; 0 = no	37.86%		
Northeast	1 = yes; 0 = no	19.06%		
Midwest	1 = yes; 0 = no	20.97%		
South	1 = yes; 0 = no	33.88%		
West	1 = yes; 0 = no	26.09%		
City Center	1 = yes; 0 = no	42.42%		
Outside City Center	1 = yes; 0 = no	32.27%		
Suburb	1 = yes; 0 = no	12.98%		
No City Center	1 = yes; 0 = no	1.25%		
Rural	1 = yes; 0 = no	11.08%		
White	1 = yes; 0 = no	69.16%		
African American	1 = yes; 0 = no	9.77%		
Other race	1 = yes, if from any other race; 0 = no	7.54%		
Hispanic	1 = yes; 0 = no	13.53%		
Married	1 = yes; 0 = no	62.35%		
Divorces/Separated	1 = yes; 0 = no	11.28%		
Widowed	1 = yes; 0 = no	5.51%		

While past research has estimated the likelihood of obesity, conditional on economic and demographic factors using a binary choice model (Chou et al. 2004), the use of quantile regression seems to be more appropriate in the sense that it provides more details regarding all weight cate-goriesusing a parsimonious model. In order to compute standard errors associated with estimated parameters, we use the Markov chain marginal bootstrap (MCMB) method developed by He and Hu (2002). This resampling method overcomes many of the issues associated with other methods of computing standard errors for quantile regression, such as sparcity and rank inversion methods, and is preferred when the number of observations or independent variables is large. Further, the MCMB method is computationally more efficient than many other bootstrap methods because it avoids computing a full set of parameter estimates for each bootstrap sample; rather it relies on solving one-dimensional equations.

ESTIMATION AND RESULTS

Table 2 provides a direct comparison of the quantile regression (QR) results for BMI quantiles 0.1-0.9 against ordinary least squares regression (OLS) results. OLS implicitly assumes that the effects of the different variables have is consistent across BMI quantiles. Results show the parameter estimates and bootstrapped standard errors for the QR of key variables upon BMI, including exercise (All Act, Some Act, Insufficient Act), the number of children in the household (Children), food at home price index, food away from home price index, income (Low Inc, Mid Inc), and education (High School, College Graduate). Both QR and OLS parameter estimates are highly significant and have significance for key independent variables that have been known to affect BMI.Overall, the results show that the effect of many key variables clearly varies by quantile, indicating that there is substantial heterogeneity identified in the QR. 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. Results that are relevant for obesity studies and policy proposals are highlighted below.

Table 2 Quantile Regression Results from BMI regressions

Variables	OLS	BMI Quantile 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Intercept	25.9315*	16.852*	19.7744*	21.0071*	22.2866*	23.7614*	25.7021*	28.2030*	31.8883*	38.9622*
	(47.02)	(33.28)	(38.12)	(42.88)	(39.96)	(41.40)	(40.30)	(36.30)	(39.58)	(30.56) 0.4035*
Age	0.3115*	0.1827*	0.2143*	0.2363*	0.2553*	0.2760*	0.2981*	0.3196*	0.3526*	0.3115*
	(70.72)	(43.01)	(54.46)	(63.06)	(61.15)	(60.21)	(63.74)	(60.14)	(57.65)	(47.75)
Age^2	-0.0032*	-0.0017*	-0.0020*	-0.0022*	-0.0024*	-0.0027*	-0.003*	-0.0033*	-0.0037*	-0.0044*
	(-74.68)	(-40.72)	(-53.72)	(-63.49)	(-64.1)	(-60.73)	(-68.1)	(-65.95)	(-63.72)	(-58.79)
HealthPlan	0.1665*	0.1851*	0.1441*	0.1581*	0.1220*	0.0928	0.1455*	0.1889*	0.1780*	0.0532
	(4.14)	(4.74)	(3.74)	(3.73)	(3.00)	(1.92)	(3.04)	(3.40)	(2.38)	(0.52)
Vegetable	0.1063*	-0.0002	0.0134	0.0251*	0.0459*	0.0675*	0.0859*	0.1305*	0.1861*	0.2396*
	(9.45)	(-0.02)	(1.24)	(2.56)	(3.81)	(6.20)	(7.04)	(7.30)	(9.98)	(9.31)
All Act	-2.8206*	-0.5530*	-1.0272*	-1.4008*	-1.7862*	-2.2856*	-2.8183*	-3.3932*	-4.2033*	-5.5539*
	(-63.08)	(-13.13)	(-27.85)	(-33.82)	(-38.93)	(-53.62)	(-56.53)	(-59.47)	(-63.75)	(-52.24)
Some Act	-1.9101* (-49.99)	-0.2968*	-0.6651*	-0.9124*	-1.2050*	-1.5464*	-1.9536*	-2.3489*	-2.9618*	-3.962* (-42.50)
		(-7.40)	(-19.67)	(-23.56)	(-26.71)	(-39.11)	(-43.58)	(-44.97)	(-47.04)	(-49.99)
Insufficient Act	-0.8484*	0.1015*	-0.0796*	-0.1975*	-0.3644*	-0.5922*	-0.8403*	-1.0964*	-1.4894*	-2.256* (-23.99)
	(-22.87)	(2.57)	(-2.22)	(-5.23)	(-8.35)	(-14.62)	(-18.18)	(-19.27)	(-22.86)	1.4764*
Asthma	1.4764*	0.3545*	0.5850*	0.7976*	1.0059*	1.2302*	1.4323*	1.6979*	2.0489*	2.5248*
	(43.79)	(10.00)	(17.08)	(22.68)	(25.15)	(29.52)	(32.19)	(31.06)	(33.17)	(28.24) -0.0437
Children	0.0054 (0.43)	0.0033 (0.25)	0.0164 (1.51)	0.0247* (2.01)	0.0141 (1.11)	0.0216 (1.66)	0.0192 (1.23)	0.0073 (0.42)	-0.0017 (-0.07)	0.0054 (-1.53)
Male	0.981*	1.9382*	1.8801*	1.7371*	1.5647*	1.3666*	1.1642*	0.9140*	0.5763*	0.0661
	(40.1)	(85.68)	(92.95)	(80.37)	(66.28)	(53.03)	(42.82)	(27.88)	(16.16)	(1.29)

Table 2 (Continued)

		BMI Quantile								
Variables	OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Low Inc	0.8926*	-0.0709	0.1875*	0.3451*	0.5066*	0.672*	0.9013*	1.0558*	1.3163*	1.7393*
	(23.97)	(-1.86)	(5.49)	(9.27)	(13.52)	(16.08)	(21.53)	(23.02)	(20.42)	(17.55)
Mid Inc	0.5972*	0.1014*	0.2139*	0.3112*	0.4094*	0.4722*	0.5983*	0.638*	0.7389*	0.9722*
	(20.3)	(3.68)	(8.02)	(10.65)	(15.02)	(16.23)	(19.66)	(18.57)	(14.87)	(15.57)
Employed	-1.4801*	0.0934	-0.2930*	-0.6266*	-0.9121*	-1.1733*	-1.5528*	-1.8688*	-2.3905*	-3.2406* -1.4801*
	(-27.79)	(1.52)	(-5.33)	(-11.19)	(-14.91)	(-19.42)	(-20.26)	(-23.30)	(-21.75)	(-20.47)
Self-Employed	-2.0687*	-0.1956*	-0.6262*	-1.027*	-1.3701*	-1.7009*	-2.0991*	-2.4908*	-3.1347*	-4.2207*
	(-32.7)	(-2.97)	(-10.15)	(-16.30)	(-18.48)	(-23.8)	(-26.63)	(-27.79)	(-25.81)	(-26.31)
Out of Work	-1.223*	-0.0565	-0.3666*	-0.6728*	-0.9327*	-1.1824*	-1.4330*	-1.5347*	-1.9243*	-2.395*
	(-15.74)	(-0.68)	(-4.09)	(-8.34)	(-11.04)	(-11.55)	(-12.56)	(-12.04)	(-12.58)	(-10.48)
Homemaker	-1.9723*	-0.4102*	-0.8440*	-1.1688*	-1.5031*	-1.8058*	-2.1334*	-2.408*	-2.9345*	-3.8292*
	(-29.57)	(-5.80)	(-12.66)	(-16.04)	(-21.18)	(-24.2)	(-25.12)	(-23.31)	(-21.75)	(-21.61)
Student	-2.1657*	-0.2605*	-0.7245*	-1.1742*	-1.6127*	-1.9543*	-2.5156*	-2.7591*	-3.2539*	-4.1941*
	(-20.31)	(-2.28)	(-7.94)	(-12.5)	(-16.12)	(-20.09)	(-21.35)	(-16.84)	(-14.91)	(-15.39)
Retired	-1.3137*	0.0857	-0.2817*	-0.5882*	-0.8705*	-1.0986*	-1.449*	-1.7391*	-2.2424*	-3.0768*
	(-22.71)	(1.36)	(-4.85)	(-9.93)	(-13.1)	(-16.41)	(-18.55)	(-20.8)	(-20.89)	(-20.32)
High School Graduate	-0.2179*	-0.0446	-0.0537	-0.07	-0.1001*	-0.1265*	-0.1793*	-0.2522*	-0.3443*	-0.4689*
	(-4.86)	(-0.89)	(-1.2)	(-1.58)	(-2.02)	(-2.55)	(-3.06)	(-4.58)	(-4.82)	(-4.65)
College Graduate	-1.2677*	-0.678*	-0.8073*	-0.9467*	-1.0132*	-1.1342*	-1.21*	-1.3976*	-1.5833*	-1.9028*
	(-25.69)	(-12.64)	(-17.12)	(-20.76)	(-19.41)	(-19.98)	(-21.6)	(-22.92)	(-19.57)	(-17.16)
White	0.3124*	0.4208*	0.4379*	0.4146*	0.3702*	0.3277*	0.2535*	0.2108*	0.1893*	0.1528
	(5.88)	(8.93)	(8.32)	(7.86)	(6.87)	(5.23)	(3.7)	(2.79)	(1.98)	(1.30)
African American	2.0414*	1.5015*	1.8585*	2.0447*	2.1217*	2.1654*	2.1593*	2.2989*	2.3629*	2.4273*
	(30.44)	(22.67)	(25.73)	(28.35)	(31.17)	(28.65)	(25.23)	(24.72)	(18.84)	(13.87)
Hispanic	0.6789*	1.0047*	1.0367*	0.9771*	0.9373*	0.8785*	0.671*	0.6062*	0.3909*	0.0869
	(9.66)	(16.79)	(13.98)	(14.69)	(12.19)	(9.93)	(7.45)	(6.45)	(3.14)	(0.52)
Married	-0.3784*	0.3646*	0.2468*	0.1542*	0.064	-0.027	-0.165*	-0.3607*	-0.5996*	-1.1648*
	(-9.87)	(9.32)	(7.3)	(4.37)	(1.85)	(-0.6)	(-3.72)	(-7.41)	(-8.85)	(-11.98)
Divorces/Separated	-0.5768*	0.0935*	-0.0196	-0.1459*	-0.2088*	-0.3145*	-0.4099*	-0.5143*	-0.7276*	-1.1922*
	(-13.27)	(2.11)	(-0.48)	(-3.49)	(-4.79)	(-6.05)	(-7.46)	(-7.99)	(-10.36)	(-10.65)
Widowed	-0.2644*	0.3247*	0.2762*	0.2227*	0.1891*	0.0965	0.0092	-0.1906*	-0.4428*	-0.9711*
	(-5.02)	(5.91)	(5.84)	(4.60)	(3.73)	(1.54)	(0.14)	(-3.02)	(-5.32)	(-8.01)
Everyday Smoker	-1.6797*	-1.2303*	-1.286*	-1.2889*	-1.3327*	-1.3736*	-1.4602*	-1.5495*	-1.7073*	-2.0364*
	(-47.52)	(-34.49)	(-35.09)	(-36.63)	(-37.10)	(-32.60)	(-35.31)	(-34.10)	(-30.84)	(-28.1)
Someday Smoker	-1.2648*	-0.6951*	-0.7055*	-0.7166*	-0.7693*	-0.9189*	-1.0416*	-1.2343*	-1.4373*	-1.8482*
	(-22.74)	(-13.15)	(-11.91)	(-13.29)	(-16.50)	(-17.82)	(-16.65)	(-16.35)	(-17.89)	(-14.4)
Former Smoker	0.2859*	0.2773*	0.2714*	0.2798*	0.2694*	0.2971*	0.2889*	0.318*	0.3369*	0.3005*
	(10.74)	(10.67)	(12.44)	(13.26)	(11.82)	(10.62)	(10.16)	(9.94)	(8.75)	(5.43)
Northeast	-0.0065	0.0687*	0.0513	0.0686*	0.0711	0.0509	0.0003	-0.0702	-0.0666	-0.122
	(-0.18)	(2.04)	(1.74)	(2.02)	(1.94)	(1.43)	(0.01)	(-1.56)	(-1.22)	(-1.57)
Midwest	0.4826*	0.2158*	0.3059*	0.3741*	0.4395*	0.4722*	0.4964*	0.5504*	0.6656*	0.7355*
	(12.68)	(5.68)	(8.76)	(9.79)	(11.14)	(12.00)	(11.43)	(11.09)	(10.88)	(8.44)
South	0.1922*	0.1303*	0.1753*	0.2218*	0.2311*	0.2498*	0.2248*	0.2344*	0.2337*	0.2078*
	(5.45)	(3.71)	(5.94)	(6.35)	(6.57)	(7.11)	(5.67)	(5.1)	(4.53)	(2.84)
City Center	-0.2137*	-0.1402*	-0.1657*	-0.1863*	-0.1986*	-0.2364*	-0.2541*	-0.282*	-0.2682*	-0.2506*

Table 2 (Continued)

Variables	OLS	BMI Quantile 0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
City Center	-0.2137*	-0.1402*	-0.1657*	-0.1863*	-0.1986*	-0.2364*	-0.2541*	-0.282*	-0.2682*	-0.2506*
	(-7.14)	(-4.96)	(-5.6)	(-6.64)	(-7.63)	(-7.26)	(-7.79)	(-7.21)	(-4.81)	(-3.55)
Outside City Center	-0.1374*	-0.0513	-0.0662*	-0.0653*	-0.1152*	-0.1522*	-0.1602*	-0.1481*	-0.1367*	-0.1847*
	(-4.22)	(-1.79)	(-2.22)	(-2.29)	(-3.7)	(-4.73)	(-4.7)	(-3.57)	(-2.63)	(-2.67)
Suburb	-0.115*	-0.0414	-0.0627	-0.0854*	-0.0999*	-0.1246*	-0.133*	-0.1488*	-0.1612*	-0.1454
	(-3.03)	(-1.17)	(-1.73)	(-2.66)	(-2.83)	(-2.83)	(-2.92)	(-3.07)	(-2.71)	(-1.82)
No City Center	-0.0307	-0.0572	0.009	-0.092	-0.1278	-0.1566	-0.1	-0.0266	0.1063	0.1557
	(-0.27)	(-0.55)	(0.09)	(-1.04)	(-1.49)	(-1.3)	(-0.82)	(-0.2)	(0.5)	(0.6)
Fast Food per cap	-0.0798*	-0.0434*	-0.0599*	-0.0675*	-0.0694*	-0.0709*	-0.0758*	-0.0955*	-0.1021*	-0.1038*
	(-12.52)	(-7.61)	(-9.37)	(-11.93)	(-10.73)	(-10.07)	(-10.93)	(-11.96)	(-11.7)	(-7.68)
Food At-Home Price	-0.0664*	-0.0309*	-0.0521*	-0.0509*	-0.0485*	-0.0428*	-0.0466*	-0.0585*	-0.0739*	-0.1166*
	(-5.01)	(-2.54)	(-4.25)	(-4.53)	(-3.61)	(-3.17)	(-3.06)	(-3.03)	(-3.47)	(-3.7)
(Food At-Home Price)^2	0.0002*	0.0001*	0.0001*	0.0001*	0.0001*	0.0001*	0.0001*	0.0002*	0.0002*	0.0003*
	(5.16)	(2.46)	(4.38)	(4.65)	(3.64)	(3.36)	(3.23)	(3.22)	(3.62)	(3.88)
Food Away From Home Price	0.0362*	0.0211*	0.0251*	0.0253*	0.0252*	0.0202	0.0234*	0.0322*	0.039*	0.0585*
	(3.61)	(2.26)	(2.68)	(2.98)	(2.53)	(1.96)	(2.09)	(2.25)	(2.51)	(2.55)
(Food Away From Home Price)^2	-0.0001*	<0.0001*	-0.0001*	-0.0001*	-0.0001*	-0.0001	-0.0001*	-0.0001*	-0.0001*	-0.0001*
	(-3.63)	(-2.11)	(-2.54)	(-2.89)	(-2.43)	(-1.93)	(-2.18)	(-2.37)	(-2.63)	(-2.66)

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

is 0.11 and 0.17 for the highest 3 quantiles. This implies that individuals in higher BMI categories also increase weight over time at a significantly higher rate. In this context, a 10 year increase in age corresponds to an increase of 1.1% and 1.7%, respectively. This trend is inverted for individuals with ages of 70, where losses in BMI increase at a rate greater than 0.20, which is substantially larger than 0.06 for individuals in healthy weight quantiles. This is the difference between an increase of 10 years resulting in a 2.0% or 0.6% decrease in BMI. This implies that natural growth patterns over one's life cycle are accentuated with age for people already having overweight or obesity problems. These results underscore the importance of efforts to lower BMI for individuals of younger ages in order to minimize the natural increase in BMI due to age.Since OLS estimates are essentially an average estimate across the quantiles, OLS estimate overestimates the effect of age on BMI for underweight individuals and overestimates its effect on overweight individuals.

Physical activity is associated with a decrease inBMI for all individuals, except underweight individuals, as indicated by the negatively statistically significant parameter of the physical activity variables.The correlation between exercise and BMI is stronger with overweight and obese individuals than with underweight and normal weight individuals as shown in Figure 2. This is illustrated with the downward slope of each line showing that as BMI increases the marginal impact of additional exercise has a stronger impact on lowering BMI. For example, an individual in the highest

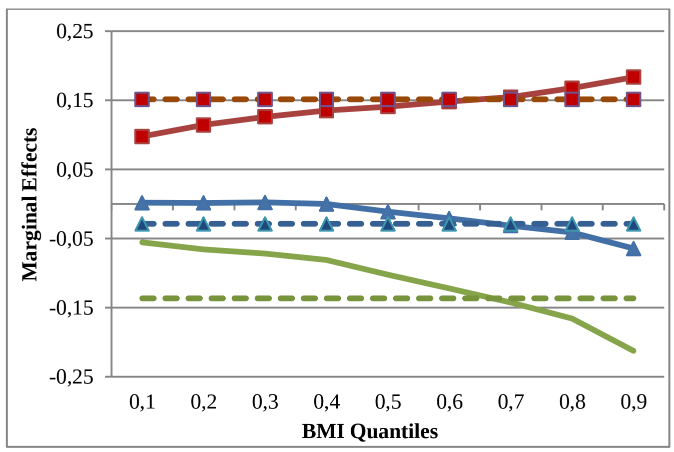

Figure 1 Marginal impact on BMI from a one-unit change in age, by BMI quantile

Age = 25 Age = 53.17
Age = 70 Age = 25 (OLS)
Age = 53.17 (OLS) Age = 70 (OLS)

weight category is expected to decrease BMI by 5.55 units when the individual goes from no exercise to exceeding recommended vigorous and moderate amounts of exercise (All Act). Some exercise, even if insufficient relative to recommended amounts (Insufficient Act), appears to have a significant impact on decreasing BMI for this highest BMI category. The reported marginal impacts are relative to no physical activity and demonstrate the importance of efficiently marketing policy aimed at using exercise to decrease obesity rates to be directed towards overweight and obese populations. This is because it is an area where large decreases in BMI can be made with lifestyle changes regarding exercise, which implies that it is an area where federal programs can be the most effective in targeting overall obesity. In comparison, OLS estimates show a constant negative effect of physical activity, but underestimates the effect of physical activity on overweight and obese populations.

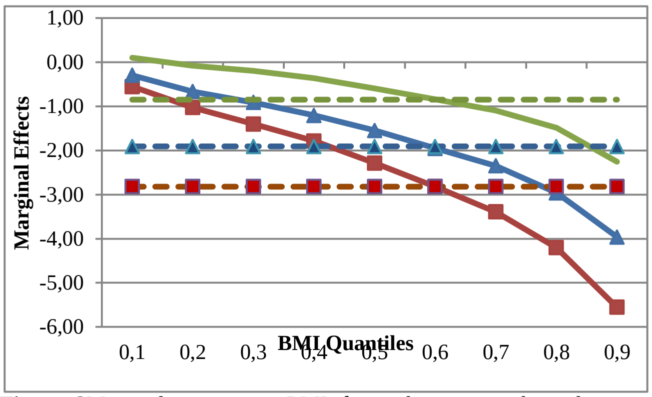

Figure 2 Marginal impact on BMI from changes in physical activity, relativeto 'No Activity'

MaV Act — MoV Act
Insufficient Act — MaV Act (OLS)
MoV Act (OLS) — Insufficient Act (OLS)

Second, gender and marital status have some interesting relationships with BMI. The results suggest that males have a higher BMI than females for individuals with relatively low BMI. This impact from gender (Male) diminishes for higher BMI individuals and is statistically insignificant for the highest BMI quantile. This implies that the prevalence of obesity is more accentuated for females than males. For marital status, the results indicate that for underweight and normal BMI quantiles, married and widowed individuals have a higher BMI than single persons. This difference is inverted for obese individuals as married and widowed individuals have significantly lower BMI levels. Compared with singles, divorced/separated and married persons may be better prepared to cope with being obeseor overweight, given the importance of a support system implicit in the family structure. This change in effect may be based upon the changing family dynamics in obese and non-obese populations.Since OLS estimates are an average across all quantiles, this information present in quantile results is not identified in OLS regression results.

In addition, the results show that the relationship between BMI and income is negative and statistically significant, regardless of the quantile considered. It is important to note that the results for Low Inc (less than $25,000) and Mid Inc ($25,000 - $50,000) are relative to the highest income bracket (>$50,000 per year), implying that lower income brackets are found to have higher BMI levels. This marginal impact is also increasing with BMI quantile, so that the negative relationship between income and BMI is amplified for overweight and obese individuals. For example, BMI is expected to be higher for those in the highest BMI quantile by 1.74 and 0.97 when income is respectively in the low or medium income bracket, relative to the highest.This particular result underscores the importance of obesity prevention programs in lower income areas and is not fully captured by the OLS regression.

While White and Hispanic populations have a higher BMI relative to the Other race category, this difference diminishes in higher quantiles and is not statistically different at the highest quantile. Alternatively, BMI for African American individuals is consistently higher for all quantiles. For categorical variables of employment, the overall effect is negative for all quantiles relative to individuals who cannot work. Additional education (relative to having no high school diploma), appears to be correlated with lower BMI levels, which is increasingly negative for higher BMI quantiles. The OLS estimates for these variables are at least consistent in sign and comparative magnitude to the QR regression.

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 larger negative relationship with 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. QR and OLS results are reasonably consistent.

Regarding geographical variation, the results of this study show that BMI is statistically higher in the Midwest and South regions, relative to the West,for all quantile levels.Population density appears to have a negative influence on BMI as those who live in or outside of a city center (as defined by the MSA) have statistically lower BMI levels than those who live in settings defined as Rural. Unlike Curie et al.(2009) and Davis and Carpenter (2009), the number of fast food restaurants per 10,000 population has a negative effect on the BMI. This difference in the conclusions may be due to the difference in the nature of the sample.In Curie et al.(2009) and Davis and Carpenter (2009), the sample is composed of children attending school; while this study uses BRFSS survey targeting adults eighteen years or older. Results for the OLS and QR regressions do not appear to be substantially different.

Finally, the marginal impacts from price levels are shown to be somewhat ambiguous and are shown in Figure 3. Increases to food-away-from-home prices are shown to have positive and negative impacts across BMI quantiles in a sharp fashion. Food at-home has a slightly more clear impact as most lowerquantiles (0.2 – 0.6) show a negative impact from prices, with a steep increase for the 0.7 quantile, while the impact of food at-home has a statistically insignificant impact on BMI for the highest two 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 the BMI. Results from the QR and OLS are consistent.

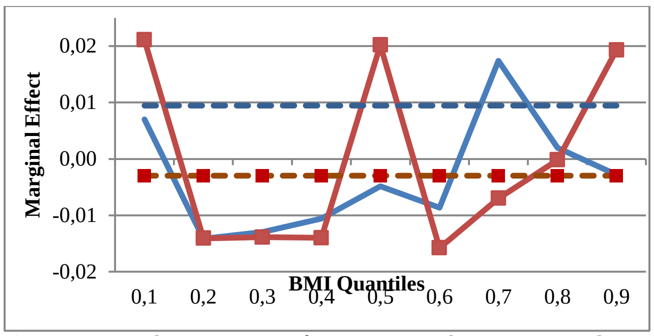

Figure 3. Marginal impact on BMI from a one-unit change in price indices, by BMI quantile
Note: Marginal Impact is evaluate at mean price index levels; At-Home = 189.7, Away-From-Home = 195.9.

At-Home
At-Home (OLS)
Away-From-Home
Away-From-Home (OLS)

This last result implies that taxing food typically consumed at home would decrease the BMI for quantiles 0.2 - 0.6 by an average of 0.19 for a 10% increase in the food at-home price index at the mean price level. Alternatively, this same tax increase is expected to correspond with an increase in BMI of 0.10 for the highest 3 quantiles which are defined as 'obese'. Taxing food away from home by 10% is expected to increase BMI by 0.40 for the median quantile while negatively related for most other quantiles. However, these results 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 certainly 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 the relationship between individual BMI levels with demographics, economic factors, and choices. Unlike previous studies, this study takes into account the heterogeneity of individuals in the survey by using quantile regression. 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 future research and policy that is designed to reduce obesity and suggests that a targeted and tailored approach would be most effective. For example, programs aimed at promoting exercise would have the largest impact if targeted toward obese and overweight populations. More specific data is needed to evaluate and simulate the effect of any pricing policy on obesity.

As with any study, marginal effects must be interpreted with care as they inform regarding correlations and not causal relationships. Thus, one limitation of this study is that results do not necessary indicate that changes in the independent variables of interest will lead to changes in BMI, but rather that these variables tend to move systematically together. A second limitation of this study is that it is based on data from a phone survey which may contain potential biases in how individuals report behavioral and individual characteristics.

A key issue for future research is utilizing data designed to capture the effect of various potential policy changes upon BMI. Available data sets, such as is available from BRFSS or NHANES among others, provide researchers mounds of individual information that has been used to inform policy makers and researchers regarding important questions in the fight against obesity. However, in order to model and draft policy that is able to effectively target high-risk segments of the population, research needs to be more specific in identifying policy instruments or latent sub-groups and their responsiveness to changes.

The analysis here strongly suggests that heterogeneity in responses by BMI weight category should be addressed. When informative data sources are coupled with the many recent advances in econometrics, economists are no longer constrained to make oversimplifying assumptions about a population when more information can be revealed.

Endnotes

1. In Epstein et al. (2007), mothers were randomly assigned to price conditions in a laboratory conditions.
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 these locations. Also, individuals who reported being pregnant were also omitted from this sample.

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