ANALYSIS OF ADULT OBESITY BASED ON NEW MEASURES OF FATNESS

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Abstract

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During the past three decades, the United States and most of the rest of the developed world have experienced a rapid and sustained rise in the obesity rate. This trend has stimulated a considerable amount of research by economists and other social scientists dealing with its causes and with policies to combat it. To date, the focus has been on obesity defined by a body mass index (BMI, weight in kilograms divided by height in meters squared) greater than or equal to 30. This measure has been criticized because it fails to distinguish body fat from lean body mass. It is the former that is responsible for the detrimental health effects of obesity. Therefore, in my dissertation I introduce the percentage body fat (PBF, the ratio of body fat to total weight multiplied by 100) and an obesity indicator based on PBF as alternative measures of body composition. I generate equations by gender and race to predict these measures from height, weight, and age in the Third National Health and Nutrition Examination Survey and use the estimated coefficients to obtain PBF and obesity based on PBF in the Behavioral Risk Factor Surveillance System for the period from 1984 through 2009. I then examine the effects of socioeconomic characteristics and state-level measures pertaining the per capita number of restaurants, the prices of a meal in fast-food and full-service restaurants, the price of food consumed at home, the price of cigarettes, and clean indoor air laws on BMI, PBF, BMI-defined obesity, and PBF-defined obesity. My results suggest that most of the determinants at issue have similar qualitative and quantitative effects on the outcomes at issue. Finally, I assume that PBF-defined obesity correctly identifies obese and non-obese individuals, but BMI-defined obesity results in error. I use these assumptions to estimate the parameters of a binary choice model by nonlinear least squares. My results show that this procedure successfully corrects the downward bias in the marginal effects of a probit model for BMI-based obesity.

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Table of Contents

1. Introduction.. 1

2. Background 4

3. Measurement of Fatness in the NHANES III.. 6

4. Empirical Strategy 9

1) Determinants of Obesity Based on Percent Body Fat 9

2) Determinants of Obesity with Misclassification Error 11

5. Data 14

6. Results 17

7. Conclusion 26

8. Bibliography 41

List of Tables

Table 1-1 Rates of misclassification caused by use of BMI to define obesity by gender and race 28

Table 1-2 Rates of misclassification caused by use of BMI to define obesity by gender and race 28

Table 2-1 Correction Equation of Weight in NHANES III........ 29

Table 2-2 Correction Equation of Height in NHANES III 29

Table 3-1 Predicting Body Fat (BF) in Kilograms, from NHANES III 30

Table 3-2 Predicting Fat-Free Mass from NHANES III 30

Table 4 Descriptive Statistics 31

Table 5-1 OLS regression of BMI and PBF........ 33

Table 5-2 OLS regression of BMI-defined obesity and PBF-defined obesity........ 35

Table 6-1 Marginal Effects of selected continuous variables for the first model at the mean values 37

Table 6-2 Marginal Effects of selected continuous variables for the second model at the mean values 37

Table 6-3 Elasticity of selected continuous variables for the first model at the mean values 38

Table 6-4 Elasticity of selected continuous variables for the second model at the mean values 38

Table 7-1 Marginal effect of selected continuous variables at the mean values........ 39

Table 7-2 Elasticity of selected continuous variables for the probit and NLS at the mean values.. 39

Table 8-1 Marginal effect of selected continuous variables at the mean values for 1984-1999 40

Table 8-2 Elasticity of selected continuous variables for the probit and NLS at the mean values for 1984-1999 40

1. Introduction

During the past three decades, the United States and most of the rest of the developed world have experienced a rapid and sustained rise in the obesity rate. This trend has stimulated a considerable amount of research by economists and other social scientists dealing with its causes and with policies to combat it. To date, the focus has been on obesity defined by a body mass index (BMI, weight in kilograms divided by height in meters squared) greater than or equal to 30. This measure has been criticized because it fails to distinguish body fat from lean body mass.

The World Health Organization (WHO) defines obesity as abnormal or excessive fat accumulation that may impair health.[1] That is, the definition of obesity depends on the accumulation of fat in a body. However, currently existing social science datasets do not include measurements of the accumulation of fat. Hence, as a proxy for the fat accumulation in a body, social scientists usually use Body Mass Index (BMI), which is defined as a person's weight in kilograms divided by his height in meters squared. If BMI is greater than 30, it is classified as obese. By using this BMI-defined obesity, researchers explained the relationship of obesity with other economic and medical factors.

However, as a proxy for fat accumulation, BMI is not sufficiently able to distinguish the Body Fat (BF) from body muscle (Burkhauser and Cawley 2008). WHO also indicates that BMI should be considered only a rough guide for obesity because the same BMI does not indicate the same degree of fat in different individuals. Therefore, the direct measurements of BF could significantly improve the detection and diagnosis of obesity (Gallager et al. 1996). Burkhauser and Cawley (2008) introduces more accurate measures of fatness such as Fat-Free Mass (FFM)

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[1] "Obesity and Overweight," World Health Organization, last modified September 2006, http://who.int/mediacentre/factsheets/fs311/en/index.html.

and Percent Body Fat (PBF) using the Bioelectrical Impedance Analysis(BIA) information in NHANES III, and suggested that researchers could calculate PBF as an alternative measure of fatness using prediction equations instead of relying on BMI. Wada and Tekin (2010) use the same data to identify the BF and FFM using BIA information for creating the direct measurement of fatness.

According to Burkhauser and Cawley (2008), the BMI-defined obesity has considerably misclassified rates of obesity compared to the PBF-defined obesity, and the prevalence of obesity based on BMI may not be a correct conclusion. To study the determinants of the prevalence of obesity over time, Chou et al. (2004) use BMI and BMI-defined obesity as dependent variables using Behavioral Risk Factor Surveillance System (BRFSS) data. Also, Rashad et al. (2006) investigate the determinants of BMI and BMI-defined obesity using NHANES I, II, III and 99 data. Therefore, to study the determinants of the prevalence of obesity over time, PBF-defined obesity could be introduced as an alternative of BMI-defined obesity.

In this paper, I employ Burkhauser and Cawley's more accurate measures of fatness to investigate the determinants of the prevalence of obesity in the United States using BRFSS data from 1984 to 2009. I introduce the prediction equations using NHANES III to generate more accurate measures of fatness such as FFM and PBF in BRFSS data. By comparing the OLS results among BMI, BMI-defined obesity, PBF and PBF-defined obesity, I can reinvestigate the determinants of the prevalence of obesity in the U.S. and determine whether there is any considerable difference between the marginal effects or elasticities of BMI-defined obesity and PBF-defined obesity in order to explain the prevalence of obesity over time. Also, in order to check the bias caused by the misclassification error of BMI-defined obesity, I check the marginal effects of probit models of BMI-defined obesity and PBF-defined obesity and then find the misclassification error using BMI-defined obesity and PBF-defined obesity to correct the bias using the Nonlinear Least Squares (NLS) model with misclassification error.

Section II will introduce the small background of this research and Section III will introduce a more accurate measure of fatness from NHANES III. I will estimate FFM using BIA resistance value and then derive PBF. Between PBF-defined obesity and BMI-defined obesity, I calculate misclassification rates of BMI-defined obesity and obtain the misclassification error of BMI-defined obesity. Section IV will show two empirical strategies for estimating determinants of the prevalence of obesity. The first strategy is to introduce the prediction equations of BF from NHANES III to generate PBF in the 1984-2009 BRFSS data. Using BMI, PBF, BMI-defined obesity, and PBF-defined obesity, I will run OLS regressions on individual characteristics, time trends, and state-specific variables. The second strategy is to combine the binary-choice model originated by Hausman et al. (1998) with the misclassification error obtained from Section III. Nonlinear Least Squares (NLS) with the obtained misclassification error will be run using BRFSS data from 1984 to 2009. Then, I will compare the marginal effects and elasticities of probit models using BMI-defined obesity and PBF-defined obesity with those of NLS models with misclassification error. Section V describes the BRFSS data from 1984 to 2009 and the augmented state-level data obtained from various sources. Section VI shows the results of two empirical strategies. A short conclusion will follow in Section VII.

2. Background

BMI is widely used to measure and define the obesity, but it has shortcomings to distinguish fat from fat-free mass. So, a lot of researchers tried to develop more accurate measures of fatness instead of BMI. One new measure of fatness is body fat and fat-free mass using NHANES III dataset through BIA information. However, unfortunately these measures can be obtained only from NHANES III dataset until now. Therefore, researchers tried to transport these measures to other social science datasets, which have more social science variables such as labor market outcomes. In order to do that, they created the prediction equations of body fat and fat-free mass in NHANES III dataset. Even though different researchers used different specifications of prediction equations, commonly they included height, weight and age variables. So in the short run, the predictions equations of body fat measures in NHANES III are useful tool to create new measures of fatness in social science datasets.

Burkhauser and Cawley (2008) introduced body fat measures using NHANES III, and found that BMI-defined obesity is weakly correlated with PBF-defined obesity, causing the substantial misclassification of obesity. Also they found that African Americans are particularly misclassified using BMI and that the obesity prevalence difference between black and white is highly sensitive to the measure of fatness to define obesity. They also created their own prediction equations to transport the body fat measure to other social sciences dataset. Especially, they used Panel Survey of Income Dynamics (PSID) to show the correlation of fatness with labor market outcomes using predicted body fat measures. Finally they suggested that social science datasets should include more accurate measures of fatness in the long run (Burkhauser and Cawley 2008).

Wada and Tekin (2010) also used NHANES III data to create the body fat measure, and then generated the prediction equations of body fat in order to transport to the National Longitudinal Survey of Youth 1979 (NLSY79). They estimated wage models for white respondents in NLSY79, and found that calculated body fat is associated with wage decrease for white males and white females and that the fat-free mass is associated with wage increase. They also showed that their results are robust to numerous specifications and to a number of alternative BIA prediction equations that are used for deriving the body fat measures.

In this paper, I also use NHANES III data to create new measures of fatness and generate the prediction equations of body fat in order to transport to BRFSS data. Especially, I employ Burkhauser and Cawley's specifications of prediction equations to generate more accurate measures of fatness in BRFSS data. Then, I investigate the determinants of the prevalence of obesity in the United States using BRFSS data from 1984 to 2009. Section III introduces more details of body fat measures in NHANES III dataset.

3. Measurement of Fatness in the Third National Health and Nutrition Examination Survey

The Third National Health and Nutrition Examination Survey (NHANES III) is a nationally representative cross-sectional survey from 1988 to 1994. In this survey, a trained physician examined the BIA resistance in the mobile examination center (MEC) and recorded the BIA measures in the Body Measurements section. Examinees include persons 12 years of age and older, excluding candidates who had a pacemaker or were pregnant (NCHS 1996). I can obtain the BF information from the BIA resistance using predictive equations introduced by clinical researchers.

I estimate FFM using BIA resistance. Sun et al. (2003) provided the prediction equations of FFM using BIA resistance measurements. Since Sun's team used an RJL system to measure BIA resistance and a Valhalla system to measure the BIA resistance in NHANES III, the Valhalla system should be converted to the equivalent RJL system for each NHANES III respondent (Burkhauser and Cawley 2008).[2] The prediction equations of Sun et al. (2003) are as follows:

$$\text{For males: FFM} = -10.678 + 0.262\ \text{weight} + 0.652\frac{\text{stature}^2}{\text{resistance}} + 0.015\ \text{resistance}$$

$$\text{For females: FFM} = -9.529 + 0.168\ \text{weight} + 0.696\frac{\text{stature}^2}{\text{resistance}} + 0.016\ \text{resistance}$$

where weight is measured in kilograms, stature (height) measured in centimeters, and the resistance measured in ohms.[3] The R-squared was 0.90 for males and 0.83 for females (Sun et al. 2003). Sun et al. calculated BF with difference between total weight and FFM. They calculated

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[2] For males, RJL resistance = 2.5 + 0.98 Val resistance. For females, RJL resistance = 9.6 + 0.96 Val resistance. The R-squared was 0.996 for men and 0.993 for women. See the appendix in Chumlea et al. (2002).

[3] Wada and Tekin (2007) showed 47 alternative BIA conversion equations estimated by clinical researchers and found that the expected sign of the models is the same for all 47 cases.

PBF using the formula (BF/Weight) × 100. They used the same prediction equations for whites as they did for African Americans since there is no significant difference in goodness of fit for race (Sun et al. 2003). However, Sun et al. (2003) show that the above prediction equations underpredict African-American males' FFM and African American females' FFM by 2.1kg and 1.6kg, respectively, and overpredict white males' FFM and white females' FFM by 0.4kg and 0.3kg, respectively.[4] Therefore, I adjusted the FFM of NHANES III by these amounts.

In order to obtain the measure of BF and PBF in NHANES III, I use data from adults aged 18 to 65. This data includes self-reported weight and height, measured weight and height, age, and BIA readings. If the self-reported height is either under four feet (0 observation) or over seven feet (0 observation) and if the self-reported weight is under 80 pounds (1 observation), I drop the observations. Our total sample size is 7751 respondents; the sample sizes for white males, white females, African-American males, and African-American females are 1961, 2186, 1690, and 1914, respectively.

I generate two obesity variables in this paper. I define obese1 using BMI; if BMI is greater than 30, a person is classified as obese. I define obese2 based on PBF; if a man's PBF is greater than 25% or a woman's PBF is greater than 30%, the respondent is classified as obese (NIDDK 2001). Since the BMI-defined obesity is weakly correlated with the PBF-defined obesity, the BMI-defined obesity results in substantial misclassification.[5]

Burkhauser and Cawley (2008) show that the misclassification of BMI-defined obesity varies by gender[6] with controlling the threshold effect. He also demonstrates the false positive and false negative classification of BMI-defined obesity by race and gender with control of the

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[4] Sun et al. (2003) did not include a Hispanic sample in the study, so I focus only on white Americans and African-Americans.

[5] See Burkhauser and Cawley 2008.

[6] The difference by gender is due to men's considerably greater muscle mass than that of women; the BMI cannot distinguish muscle from fat.

threshold effect, which means that BMI is a poor measure of determining whether a person is obese. Tables 1-1 and 1-2 show the rates of misclassification caused by BMI-defined obesity by race and gender and the misclassification error. Table 1-1 compares the variables obese1 and obese2 that is, the misclassification of BMI-defined obesity without controlling for threshold effects. Table 1-2 shows the rates of misclassification when threshold effects are controlled. Both tables also show the false positive error and false negative error, which I will define below in Section IV. In Table 1-1, I find the false negative error is big and the false positive error is small, so I can infer that the true obesity rate would be greater than the BMI-defined obesity rate. This result is confirmed in Table 1-2. Therefore, it is not clear that the BMI-defined obesity is the right prevalence of obesity (Burkhauser and Cawley 2008).

Chou et al. (2004) analyze the determinants of the prevalence of adult obesity from 1984 to 1999 in the U.S. Their work is based on BMI and BMI-defined obesity over time using BRFSS data augmented with state-level measures such as the number of fast-food and full-service restaurants, full-service and fast-food prices, the price of food served at home, the price of cigarettes, and clean indoor-air laws. I investigate the work of Chou et al. by comparing PBF and PBF-defined obesity with the results of BMI and BMI-defined obesity using two different econometric models. The first model generates BF in BRFSS data using the prediction equations of BF in NHANES III and then creates PBF and PBF-defined obesity for OLS regression. The second model uses the false positive and false negative errors of BMI-defined obesity. Using the binary-choice model with misclassification error in the dependent variable and the values of misclassification error in Tables 1-1, I run the NLS model to estimate the marginal effects with fixed error values. I will compare the results with the marginal effects of the probit model. Section IV shows the details of the above econometric models.

4. Empirical Strategy

1) Determinants of Obesity Based on Percent Body Fat

To analyze adult obesity using BRFSS data, I need to transport BF in NHANES III to BRFSS because BRFSS does not contain BIA information. Different researchers may use different prediction equations for this.[7] In this paper, I use Burkhauser and Cawley's specification of the prediction equation. Burkhauser and Cawley (2008) regress BF and FFM on weight, weight^2, height, height^2, age, and age^2 by race and gender (white males, white females, African-American males, and African-American females) to generate the prediction equations for them.

However, before I generate the prediction equations, I have to correct the reporting error inherent in the self-reported weights and heights (Burkhauser and Cawley 2008). I regress actual weight on reported weight, weight^2, age, and age^2 by race and gender. I repeat this process for height. Then, I multiply the coefficients of these results by the self-reported values in NHANES III to generate the predicted weight and height corrected for reporting error. Tables 2-1 and 2-2 present these correction equations. Then, I regress BF and FFM on corrected self-reported weight and its square, corrected self-reported height and its square, and age and its square separately for white males, white females, African-American males, and African-American females in NHANES III. These regressors are also available in BRFSS. I report the results in Table 3-1; R-squared values range from 0.78 to 0.91. Table 3-2 shows the prediction equation of FFM.

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[7] Wada and Tekin (2010) predicted the body fat and fat-free mass using the self-reported variables: age, age^2, age^3, weight, weight^2, weight^3, height, height^2, height^3, and height × weight by regression for white males and white females and then created the prediction equations for BF and FFM.

Also, I corrected self-reported weight and height in BRFSS data using the coefficients of Tables 2-1 and 2-2 to generate the predicted weight and height, which I multiplied by the coefficients of Tables 3-1 and 3-2 to construct the predicted BF and FFM in BRFSS. Then, I generated PBF by the formula (BF/predicted weight) × 100. I generate the PBF-defined obesity based on National Institutes of Health (NIH) classification: a man is obese if his PBF exceeds 25% and a woman is obese if her PBF exceeds 30% (NIDDK 2001).

Then, I investigate a paper by Chou et al. (2004) to compare the results of OLS regression using PBF with those of BMI. Chou et al. analyze how much of the trend in the prevalence of the obese population can be accounted for by state-specific variables. However, it is not clear that the BMI-defined obesity shows the right prevalence (Burkhauser and Cawley 2008), so the accountability of the state-specific variables for the prevalence of obesity should be investigated using PBF-defined obesity. Therefore, I investigate the effects of the state-specific variables for the prevalence of PBF-defined obesity using the OLS, and then compare the results with BMI-defined obesity.

According to Chou et al. (2004), if the regressions include the pure trend terms, the multicollinearity between state-specific variables and time makes it difficult to investigate the effects of the state-specific variables for the prevalence of obesity. Hence, Chou et al. suggest three forms for OLS regressions. The first form includes only variables obtained in BRFSS, time, and the time squared. The second form excludes the trend terms and includes the state-specific variables. The third form includes all variables. This paper employs the second and third specifications. I use the quadratic specification for each continuous variable for consistency of trend effects. Also, I include state dummy variables in all regressions to control for the state-specific fixed effects of obesity. Finally, I calculate the marginal effects and elasticities of selected continuous variables.[8]

2) Determinants of Obesity with Misclassification Error

In this section, I employ the binary-choice model of Hausman et al. with misclassification error in the BMI-defined obesity. According to Hausman et al. (1998), I can estimate and correct for the misclassification error in the binary-choice model for finding marginal effect if the misclassification error in the dependent variable is independent of covariates. Let y^* be the latent variable, given by

$y_i^* = x_i\beta + \varepsilon_i where \varepsilon_i \sim Normal(0,1)$

$y_i = 1\ [y_i^* > 0]$

Then, I can use the probit model to estimate the coefficients. According to Hausman et al., if the misclassification of the dependent variable does not depend on covariates, I can construct the following misclassification errors.

False Positive Error: $\alpha_0 = \Pr(y_i = 1|y_i^* < 0)$

False Negative Error: $\alpha_1 = \Pr(y_i = 0|y_i^* > 0)$

In terms of BMI-defined obesity, α_0 indicates false positive error of obese and α_1 indicates false negative error of not obese.

The expected value of the observed dependent variable is:

$$E(y_i|x_i) = \Pr(y_i = 1|x_i) = (1-\alpha_1)F(x_i\beta) + \alpha_0[1-F(x_i\beta)] = \alpha_0 + (1-\alpha_0-\alpha_1)F(x_i\beta),$$

---

[8] Due to the quadratic specification of continuous variables, the marginal effects and elasticities of continuous variables are obtained as in the following example: If $y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2$, the marginal effect with respect to x_1 is $\beta_1 + 2\beta_2\bar{x}_1$ and the elasticity of x_1 is $(\beta_1 + 2\beta_2\bar{x}_1)\frac{\bar{x}_1}{\bar{y}_i}$, where $\bar{x}_1$ and $\bar{y}_i$ are mean values of x_1 and y_i, respectively.

which will be $F(x_i\beta)$, if there is no misclassification error $(\alpha_0 = \alpha_1 = 0)$. The marginal effect is

$$\frac{\partial \Pr(y_i = 1 \mid x_i)}{\partial x_i} = (1 - \alpha_0 - \alpha_1) f(x_i\beta)\beta_i,$$

which will be $f(x_i\beta)\beta_i$ if there is again no misclassification error. Therefore, the marginal effects of the simple probit model will be biased downward due to the misclassification error compared to the true effect.

In order to estimate$(\alpha_0, \alpha_1, \beta)$, I can employ the NLS method by minimizing

$$\sum_{i=1}^{n} (y_i - \alpha_0 - (1 - \alpha_0 - \alpha_1)F(x_i\beta))^2 .$$

Alternatively, I can estimate $(\alpha_0, \alpha_1, \beta)$ with Maximum Likelihood Estimation (MLE) by maximizing the log likelihood function

$$L(\alpha_0, \alpha_1, \beta) = n^{-1} \sum_{i=1}^{n} \{y_i \ln(\alpha_0 + (1 - \alpha_0 - \alpha_1)F(x_i\beta)) + (1 - y_i)\ln(1 - \alpha_0 - (1 - \alpha_0 - \alpha_1)F(x_i\beta))\} .$$

One more assumption for identification is $\alpha_0 + \alpha_1 < 1$.[9]

In this paper, I consider the PBF-defined obesity and the BMI-defined obesity as y_i^* and y_i, respectively. That is, I assume that the PBF-defined obesity is close to a true classification and that the BMI-defined obesity has a misclassification error. Based on this assumption, I can obtain the values of α_0 and α_1 from Table 1-1. The value of $\alpha_0 + \alpha_1$ is clearly less than 1, so the above assumption is satisfied. Also, when I compare the misclassification error of four different groups in Table 1-1, the values are similar over four groups with a consistent small false positive error and large false negative error. Therefore, I can use the misclassification error of total sample for α_0 and α_1.

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[9] According to Hausman et al. (1998), if $\alpha_0 + \alpha_1 > 1$, it results in estimates of coefficients (and marginal effects) of the wrong sign.

The marginal effect on the BMI-defined obesity should be less than the marginal effect on the true classification by a factor of $(1 - \alpha_0 - \alpha_1)$ (Hausman et al. 1998). I run the probit model of BMI-defined obesity and PBF-defined obesity and the NLS model using the BMI-defined obesity. The NLS model uses the obtained α_0 and α_1 values. The marginal effect of probit model using the BMI-defined obesity should be biased downward compared to the marginal effect of probit model using PBF-defined obesity due to the misclassification error. Also, in order to compare these results with those of the above linear probability model, I calculate the marginal effect and elasticities of selected continuous variables for the probit model and the NLS model at the mean values of variables.[10] I exclude state dummy variables in order to simplify the model. I also omit time trends because the state-specific variables already include such trends (Chou et al. 2004).

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[10] Due to the quadratic specification of continuous variables, the marginal effects and elasticities of continuous variables are obtained as follows. For the NLS model, if $E(y_i|x_i) = \alpha_0 + (1 - \alpha_0 - \alpha_1)F(\beta_0 + \beta_1 x_1 + \beta_2 x_1^2)$, the marginal effect with respect to x_1 is $(1 - \alpha_0 - \alpha_1)f(\beta_0 + \beta_1 x_1 + \beta_2 x_1^2)(\beta_1 + 2\beta_2 \bar{x}_1)$ and the elasticity of x_1 is $(1 - \alpha_0 - \alpha_1)f(\beta_0 + \beta_1 x_1 + \beta_2 x_1^2)(\beta_1 + 2\beta_2 \bar{x}_1)\frac{\bar{x}_1}{\bar{y}_i}$, where $\bar{x}_1$ and $\bar{y}_i$ are mean values of x_1 and y_i, respectively. For the probit model, the marginal effect and elasticity of x_1 will be $f(\beta_0 + \beta_1 x_1 + \beta_2 x_1^2)(\beta_1 + 2\beta_2 \bar{x}_1)$ and $f(\beta_0 + \beta_1 x_1 + \beta_2 x_1^2)(\beta_1 + 2\beta_2 \bar{x}_1)\frac{\bar{x}_1}{\bar{y}_i}$, respectively.

5. Data

In order to analyze adult obesity based on the research of Chou et al., I employ the BRFSS data from 1984 through 2009, which are augmented with state-level measures such as the per-capita number of restaurants, the average prices of fast-food meals and meals at full-service restaurants, the price of food eaten at home, the price of cigarettes, and clean indoor-air laws.

The Census of Retail Trade has collected the number of fast-food restaurants and that of full-service restaurants for the years 1982, 1987, 1992, 1997, 2002, and 2007. For other years, I used interpolations and extrapolations of state-specific logarithmic time trends as Chou et al. did. I added the fast-food restaurants to the full-service restaurants and used the per-capita number by state in estimation. The Census of Retail Trade has sorted the average cost of a meal at a full-service restaurant into categories of less than $2.00, $2.00-$4.99, $5.00-$6.99, $7.00-$9.99, $10.00-$14.99, $15.00-$19.99, $20.00-$29.99, and $30.00 and over for the years 1982, 1987, 1992, 1997 and 2002[11]. I found the midpoints of each category, using $1.50 for the smallest category and $45.00 for the highest category. Then, each cost was computed as a weighted average of the average cost in each category, using the number of restaurants in each category by state for weights.

The American Chamber of Commerce Researchers Association (ACCRA) *Cost of Living Index* has collected the respective prices of fast-food meals and of meals at home from 1984 to 2009. Chou et al. provide the data from 1984 to 1999, so I added the data from 2000 to 2009 for both prices. The fast-food price is a population-weighted average price of cities for three dishes: hamburger, pizza and fried chicken. I obtained quarterly state prices and then

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[11] Data for the average cost of a meal in 2007 has not yet been published.

averaged the prices from each year's four quarters for annual prices. ACCRA reports the weight of each item in a household's typical budget. The weights of the three fast-food items were equal to each other from 1984 through 2009, so the fast-food price is a simple average of the three items divided by the annual Consumer Price Index (CPI) for the U.S. as a whole (1982-84=1) of the Bureau of Labor Statistics.

The price of food at home comes from 13 food prices in ACCRA's *Cost of Living Index*. This price is also a population-weighted average price of states. I obtained quarterly state prices and then averaged them over the four quarters for annual prices. The final food-at-home price is a weighted average of the 13 items, where the weights are reported by ACCRA from 1984 through 2009. Chou et al. provided the data from 1984 to 1999, which informed us that the weights are fixed over time. However, the weights are different for 2002 and 2003, 2004, 2005, 2006 and 2007, and 2008 and 2009, so the final food at home price for these years is a weighted average of 13 items, where weights are the year-specific average expenditure shares of these items.

I use the price of cigarettes given by the Tobacco Institute's *Tax Burden on Tobacco* (Vol. 44). This price is a weighted-average price per pack including federal and state excise taxes. The clean indoor-air regulations are those noted by the Centers for Disease Control and Prevention from 2000 through 2009.[12] Chou et al. provide the data for previous years.

I report the descriptive statistics in Table 4. The total sample size is 2,518,627. The average BMI for the whole sample is 26.6 and the average PBF is 29.9, which is greater than the average BMI by 3.3%. Thus, the BMI under-measures the BF by an average of 3.3%. Also, the probability of BMI-defined obesity (obese1) is 0.215 on average and the probability of PBF-

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[12] State Tobacco Activities Tracking and Evaluation (STATE) System," Department of Health and Human Services, Centers for Disease Control and Prevention, accessed Month Date, Year, http://apps.nccd.cdc.gov/statesystem/TrendReport/TrendReports.aspx.

defined obesity (obese2) is 0.624. The true prevalence of obesity will be higher than I thought. That is, the false negative error of BMI-defined obesity is considerable.

For the model in Section IV-1, I use the BRFSS data from 1984 to 2009 data to estimate two models of OLS regression for BMI, PBF, obese1, and obese2. I add the state dummy variables to remove the state-fixed effect. I also add to this the squared terms of the continuous variables. I report the results in Tables 5-1 and 5-2. For the model in Section IV-2, I use the same dataset as Section IV-1 and Chou’s dataset for comparison. However, I exclude all state dummy variables and time trends from this model.

6. Results

Tables 5-1 and 5-2 show the ordinary least squares regressions of BMI, PBF, the BMI-defined obesity, and the PBF-defined obesity for two different models. The first model includes the individual characteristics and the state-specific variables. The second model includes the individual characteristics, the time trends, and the state-specific variables. As shown in Chou's paper, the OLS of BMI and obese1 (BMI-defined obesity) shows low explanatory power with R squares between 6 and 9 percent. But the OLS of PBF and obese2 (PBF-defined obesity) show a very improved explanatory power with R squares between 17 to 51 percent. In the preliminary results of OLS using Chou's data (1984-1999), I reach the same improved explanatory power of PBF and obese2. The PBF measures the fatness percentage in the body to determine the obesity, but the BMI measures the body mass by using weights and heights. Therefore, the direct comparison of coefficients between BMI and PBF in Table 5-1 is not available.

In Table 5-1, the second and third columns are the results of OLS regression of BMI. In terms of the effects of the individual characteristics, age has an inverted U-shaped effect for BMI, as in Chou's result. Whites show higher BMIs than African Americans and males show higher BMIs than females for the two models. In terms of marital status, our results mirror Chou's work. Married and widowed persons show higher BMIs than do single persons, and divorced persons show lower BMIs than single persons. In terms of the education level of respondents, persons with some high school education show higher BMIs than persons with only lower levels of schooling, but this difference is not significant. High school graduates, persons with some college attendance, and college graduates show lower BMIs than do persons with only lower-level schooling. I find that the effect of education effect on BMI is negative and that its effect increases as the level of education increases. Household income has a negative effect on BMI and its square term shows positive effect on BMI. That is, household income has a U-shape effect on BMI, as in Chou’s result. The time and its square term show positive effects on BMI, consistent with the steady rise of obesity in the U.S. over time.

For the state-specific variables, the first model excluding time trends shows positive effects of the number of restaurants and the average cigarette price on BMI, and negative effects of the average price of fast food, the price of a meal at a full-service restaurant, and the average price of a meal at home on BMI. However, in the second model, the full-service restaurant price shows a positive effect on BMI. For the clean indoor-air law, restrictions on private and government workplaces as well as other public places have a positive effect on BMI. The restriction on restaurants has a negative effect on BMI in the first model. However, the second model shows the negative effect of restrictions on government workplaces on BMI.

Columns 4 and 5 in Table 5-1 show the results of OLS regression of PBF. In terms of individuals’ characteristics, whites tend to have higher PBF than do African Americans and males tend to have lower PBF than do females. As it does on BMI, age also has an inverted U-shape effect on PBF. Also as with BMI, in terms of marital status, married and widowed persons show higher PBFs than do single persons, and divorced persons show lower PBFs than do single persons. Regarding schooling, all four dummy variables (some high school, high school graduation, some college, and college graduation) show negative effects on PBF. That is, an increased education level lowers the PBF with college graduation having the highest effect. Household income shows a negative effect and its square term shows a positive effect on PBF, as it does on BMI. Time has a positive effect on PBF, while time’s square term has a negative effect on it, suggesting that obesity increases at a decreasing rate. For the state-specific variables, as on BMI, the first model shows positive effects of the number of restaurants and the cigarette price on PBF, and negative effects of the average price of a fast-food meal, the average price of a meal at a full-service restaurant, and the average price of a meal at home. However, the second model shows a positive effect of the full-service restaurant price on PBF, as on BMI. The clean indoor-air law shows the same effect on PBF as it does on BMI.

Even though the BMI model does not directly compare with the PBF model, the comparison between obese1 and obese2 could be very useful in understanding the true prevalence of obesity and its determinants. Table 5-2 shows the results of OLS regression of BMI-defined obesity (obese1) and PBF-defined obesity (obese2). In terms of the effects of individual characteristics, obese1 shows that African Americans tend to be more obese than whites and that males tend to be more obese than their female counterparts. However, obese2 shows that, based on PBF, African Americans are less obese than are whites and that males are less obese than are females. These results could be due to males having more muscle than do females and to African Americans having more muscle or less body fat than do whites. In terms of the effects of schooling, obese1 and obese2 show same negative effects except for respondents with only some high-school education. That is, as one’s level of education increases, one’s probability of obesity will decrease based on both classifications. In the case of marital status, obese1 and obese2 both show that married persons and widowed persons are more obese than single persons and that divorced persons are less obese than single persons. In terms of the age effect, obese1 and obese2 both exhibit the same inverted U-shape effect. Obese1 shows that the time and time’s squared terms have positive effects on obesity, but obese2 shows that the time has a positive effect and that the time’s squared term has a negative effect on obesity. In other words, as time increases, obese1 increases at the increasing rate and obese2 increases at the decreasing rate.

Household income holds different effects on obese1 and obese2. Household income negatively affects obese1, while its squared term positively affects obese1. The variable of household income also positively affects obese2, while its squared term negatively affects obese2. That is, as household income increases, obesity decreases based on BMI-defined obesity, but increases based on PBF-defined obesity. However, when I check the marginal effect of household income from quadratic form, household income has negative marginal effects on obese1 and obese2.

Regarding the state-specific variables, the first model of obese1 and obese2 shows the same signs of coefficients with Chou's work. The number of restaurants and the average cigarette price show positive effects on obesity, and the average price of a fast-food meal, the average price of a meal at a full-service restaurant, and the average price of food for a meal at home show negative effects on obesity. There is no big difference between obese1 and obese2, but the coefficient of the price for food at home of obese2 becomes downsized in comparison to obese1 and returns to a positive effect at the second model. For the second model, the difference between obese1 and obese2 is shown in the coefficients of the average price of a full-service restaurant and the price of food at home. The full-service restaurant price shows a positive effect on obese1 and a negative but not significant effect on obese2. The price of a meal eaten at home has a negative but not significant effect on obese1 and a positive effect but not significant on obese2. For the clean indoor-air law, there is no notable difference between obese1 and obese2. The restrictions on private or governmental workplaces and other public places have a positive effect on obesity and the restrictions on restaurants have a negative effect on obesity in the first model. However, the second model shows that restrictions on governmental workplaces have a negative effect on obesity.

When the obesity is classified using the PBF, the rate of obesity increases to 0.624, which means 62% of the sample classified as obese compared to a rate of 0.215 when obesity is defined by BMI. In 1984, the rate of obese2 was 0.528 and in 2009, the rate was 0.788, an increase of just 0.26 in 26 years. In 1984, the rate of obese1 was 0.1, which increased to 0.338 by 2009. The change over this 26-year period is thus 0.238, not very different from the change of obese2. The determinants of obesity explain these respective changes in obese1 and obese2 over time instead of the difference between obese1 and obese2. Therefore, because the changes of obese1 and obese2 are similar, the coefficients of obese1 and obese2 do not differ very much even though the sample means of obese1 and obese2 greatly differ from each other.

Tables 6-1 through 6-4 show the marginal effects and elasticities calculated at the sample mean from Tables 5-1 and 5-2 for four outcomes using the quadratic specification. Table 6-1 and 6-3 are based on the OLS regression using individual characteristics and state-specific variables excluding time trends. Out of five state-specific variables, the number of restaurants shows the highest elasticity in size for all regressions. Since the sample means of BMI and PBF are similar, their elasticities do not differ very much. However, the sample mean of obese1 is 0.215 and the sample mean of obese2 is 0.624, so the elasticities of the obese2 model show considerably lower values than those of the obese1 model.

Table 6-2 and 6-4 portray the marginal effects and elasticities of the OLS regression using individual characteristics, time trends, and state-specific variables. After introducing the time trends together with state-specific variables, the price of a meal at a full-service restaurant shows a positive elasticity for BMI. The situation is similar when obesity is defined by PBF, in which case the price of such a meal has a positive elasticity for PBF and the number of restaurants shows a negative elasticity. The number of restaurants in the case of obese2 has a negative elasticity, but the price of a meal at a full-service restaurant shows a positive elasticity. The average price of a meal eaten at home has a positive elasticity. According to Chou et al., these results are due to factors including time trends and state-specific variables simultaneously, which cause multicollinearity.

The low elasticity of obese2 compared to obese1 is due to the initial rate of obese2 in 1984 being so high even though the changes over time are similar between obese1 and obese2. Therefore, the direct comparison of elasticities between obese1 and obese2 is not a good strategy to determine the effects of selected continuous variables. In order to explain the determinants of the increase in the obesity rate over time using obese1 and obese2, I need to remove the gap of the initial obesity rate between obese1 and obese2 in 1984. Therefore, I made obese3 variable with $pbf \geq 40$ for women and $pbf \geq 28$ for men to generate the mean value of 0.228 that is similar to 0.215 of mean value of obese1. This corrected mean value of obese3 is applied to the calculation of marginal effects and elasticities of selected continuous variables. I present the results of these calculations in the last columns of Tables 6-1 through 6-4 and find that the elasticities of obese2 corrected for initial value do not differ greatly from obese1, though they are still somewhat lower in size than obese1. I also apply the corrected mean value of obese3 to Table 7-1 and 7-2.

Even though I could not find any considerable difference between OLS regressions of BMI-defined obesity and PBF-defined obesity because the regressors explain the changes of obesity over time instead of explaining the obesity rate itself, the misclassification error of obesity causes a downward bias in the marginal effects of the probit model using BMI-defined obesity (Hausman et al. 1998). In Tables 7-1 through 8-2, I find the results of the probit models of obese1, obese2 and obese3 and the binary-choice model with the misclassification error. To simplify calculation, I did not include state dummies. For comparison, I calculate the marginal effects and elasticities of three probit models using obese1, obese2 and obese3 and the NLS model using obese1 for selected continuous variables from quadratic specification. According to Hausman et al., the marginal effect of the probit model using obese1 should be biased downward compared to the marginal effect of the probit model using obese2 due to the misclassification error, and the NLS model with the misclassification error should correct this downward bias.

Table 7-1 shows the marginal effects of four models. The average price of a meal at a full-service restaurant and the average price of cigarettes show higher effects in the probit model using obese2 than the probit model using obese1 in size, but an average number of restaurants, the average price of a fast-food meal, and the average price of a meal eaten at home show lower marginal effects of the first probit model than the second probit model in size. Therefore, I can find that for some variables, the probit model using obese1 has a downward bias in marginal effects compared to the probit model using obese2, but it is not consistent for all variables. The NLS model correcting the misclassification error using the value from Table 1-1 shows higher marginal effects in size than the first probit model using obese1 since it corrects the downward bias.

Table 7-2 shows the elasticities of three models calculated using the marginal effects of Table 7-1 and the sample means. In the calculation of elasticity at the sample mean, marginal effects are same with Table 7-1 and the sample means of independent variables are the same for the three models. The only difference is the sample mean of obese1 and obese2. Because the sample mean of obese2 is much higher than the sample mean of obese1, elasticities of the second probit model using obese2 are considerably lower than those of the probit model using obese1 and even the NLS model. Therefore, I provide additional elasticities of obese3 using the above corrected sample mean (0.228) in the fourth column. Even so, I find that the elasticities of obese2 are lower in size than those of obese1 except for the number of restaurants. The NLS model correcting the misclassification error shows higher elasticities than the probit model using obese1 in size. In the first probit model, the fast food price shows the highest elasticity out of five variables, and cigarette price and the price of food consumed at home follow in order. The number of restaurants shows the smallest elasticity. This rank of elasticities of five continuous variables can be found in the second probit model using obese2 except for the food at home price, even though the size of elasticities is very small. In the NLS model, the rank of elasticities of five continuous variables is same. Still the number of restaurants shows the smallest elasticity.

Table 8-1 shows the marginal effect of selected continuous variables at the sample means for the three models using Chou's data (BRFSS 1984-1999). The second probit model using obese2 mostly shows higher marginal effects in size than the first probit model using obese1, excluding the price of food eaten at home which shows different sign. That is, I find that the first probit model using obese1 is biased downward due to misclassification error as expected, but still this model is not consistent for all variables. In the second probit model, the price of food eaten at home shows a positive marginal effect.[13] The NLS model shows the correction of this downward bias using the obtained misclassification error values again.

Table 8-2 shows the elasticities of selected continuous variables at the sample mean for BRFSS data from 1984 through 1999. Again, due to the very high sample mean of obese2, the elasticities of the second probit model using obese2 are lower than those of other models. Therefore, I provide additional elasticities of obese3 using the corrected sample mean (0.172) in the fourth column. The elasticities of obese3 are higher in size than the first probit model using

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[13] In the quadratic specification, the marginal effect of the price of food eaten at home is negative and the marginal effect of this price squared is positive, as in Chou's result, but the marginal effect calculated from the quadratic specification is positive.

obese1 and the NLS model. By correcting the downward bias, the NLS model shows higher elasticities than the first probit model using obese1 in size. In this sample, the highest elasticity is in the fast-food price and the second highest is in the cigarette price. The lowest elasticity is in the food at home price, although the number of restaurants also shows a small elasticity. Again, in Tables 8-1 and 8-2, I find that the NLS model corrects the downward bias caused by the misclassification error of BMI-defined obesity.

The difference between Table 7-1 and Table 8-1 could result from a lot of reasons. But one possible explanation can be the applicability of coefficients of Tables 3-1 and 3-2 to different time period. Tables 3-1 and 3-2 show the prediction coefficients of BF using NHANES III dataset, which is for 1988-1994. Table 7-1 dataset is for 1984-2009 and Table 8-1 is for 1984-1999. So Table 8-1 time period is close to NHANES III, but Table 7-1 time period is very far from NHANES III. If the prediction coefficients of BF change over time, applying these coefficients to different time period may cause errors. It can be one possible reason why Table 7-1 shows unclear downward bias while Table 8-1 shows clear downward bias.

7. Conclusion

In conclusion, when I use PBF to define obesity, the mean rate of obesity for BRFSS data from 1984 through 2009 increases to 0.624 compared to 0.215 when I use BMI to define obesity. By comparing the determinants of BMI-defined obesity with those of PBF-defined obesity using OLS regression, I found that males are less obese than their female counterparts and that African Americans are less obese than white Americans. The effects of education levels, age, and marital status on obesity conceived by either PBF or BMI are similar. The coefficients of household income and its squared term on both conceptions of obesity show different signs, but the marginal effect of household income is the same. For the state-specific variables, the first model without time trends has coefficients with the same signs for both obesity concepts as in Chou's work. The second model also did not find any considerable difference between the two obesities. This is because even though the sample mean (0.624) of obese2 is greater than that of obese1 (0.215), the change of obese2 over time (0.26) is not far from that of obese1 over time (0.238); the determinants of obesity explain this change.

However, when I compare the elasticities between obese1 and obese2 for selected continuous variables, I find that because of this considerable difference between the sample mean of obese1 and that of obese2, the elasticities of obese2 are considerably lower in size than those of obese1 even though the marginal effects of the variables are similar between these two models. Further, when I use obese3, I find that the elasticities of obese3 remain slightly lower in size than those of obese1.

Even though I cannot find any considerable difference between OLS regressions of BMI-defined obesity and PBF-defined obesity because the regressors explain the changes of obesity over time instead of the obesity rate itself, the misclassification error of obesity causes a downward bias in marginal effects of the probit model using BMI-defined obesity (Hausman et al. 1998). Thus, when I apply the binary-choice model with the misclassification error and compared it with the probit models of obese1 and obese2 using the BRFSS data from1984 through 2009 and Chou's BRFSS data from 1984 through 1999, I find that for some variables, the probit model of BMI-defined obesity has a downward bias in marginal effects compared to the probit model of PBF-defined obesity for the selected continuous variables. This result is due to the misclassification error of BMI-defined obesity, but it is not consistent for all variables. I also find that the NLS model using the obtained misclassification error could correct this downward bias in marginal effects and elasticities. Therefore, applying the NLS model with the misclassification error could contribute to finding more accurate marginal effects of determinants on the prevalence of obesity over time.

Table 1-1 Rates of misclassification caused by use of BMI to define obesity by gender and race

	Total	Females		Males	
		White	African American	White	African American
True positives (%)	23.49	23.24	36.10	17.80	16.15
False positives (%)	1.59	0.00	0.10	2.09	4.73
True negatives (%)	40.76	27.36	25.24	48.95	66.15
False negatives (%)	34.16	49.41	38.56	31.16	12.96
False Positive Error: α_0	0.04	0.00	0.00	0.04	0.07
False Negative Error: α_1	0.59	0.68	0.52	0.64	0.45

Note: (1) Data, NHANES III. Sample sizes—White females: 2186; African American females: 1914; White males: 1961; African American males: 1690. (2) No controls for the threshold effect; obese for PBF≥25% for male and PBF≥30% for female of NIH classification. (3) True obesity status determined using percent body fat, measured using BIA. (4) False positive means that PBF indicates Non-obese but BMI indicates Obese, and False negative means that PBF indicates Obese but BMI indicates Non-obese.

Table 1-2 Rates of misclassification caused by use of BMI to define obesity by gender and race

	Total	Females		Males	
		White	African American	White	African American
True positives (%)	16.45	18.85	23.72	12.39	9.82
False positives (%)	8.63	4.39	12.49	7.50	11.07
True negatives (%)	69.49	71.36	61.86	69.81	75.33
False negatives (%)	5.43	5.40	1.93	10.30	3.79
False Positive Error: α_0	0.11	0.06	0.17	0.10	0.13
False Negative Error: α_1	0.25	0.22	0.08	0.45	0.28

Note: (1) Data, NHANES III. Sample sizes—White females: 2186; African-American females: 1914; white males: 1961; African-American males: 1690. (2) Controls for the threshold effect; obese for PBF≥29% for male and PBF≥41% for female corresponding to the same obesity rate of BMI≥30. (3) True obesity status determined using percent body fat, measured using BIA. (4) False positive means that PBF indicates Non-obese but BMI indicates Obese, and False negative means that PBF indicates Obese but BMI indicates Non-obese.

Table 2-1 Correction Equation of Weight in NHANES III

	(1) White male	(2) White female	(3) African-American male	(4) African-American female
Self-reported weight(lbs)	0.963^{***}	1.184^{***}	0.991^{***}	1.351^{***}
	(32.56)	(41.35)	(23.96)	(31.19)
Self-reported weight(lbs) squared	0.000172^{*}	-0.000405^{***}	0.000186	-0.000782^{***}
	(2.45)	(-4.99)	(1.88)	(-6.79)
Age in years	0.157	0.0459	0.0411	0.307^{*}
	(1.78)	(0.53)	(0.34)	(2.31)
Age in years squared	-0.00167	-0.00117	-0.000705	-0.00480^{**}
	(-1.62)	(-1.15)	(-0.48)	(-2.96)
Constant	-3.403	-14.72^{***}	-7.803	-35.36^{***}
	(-1.03)	(-5.27)	(-1.71)	(-8.04)
Observations	1961	2186	1690	1914
R-squared	0.954	0.954	0.934	0.925

t statistics in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 2-2 Correction Equation of Height in NHANES III

	(1) White male	(2) White female	(3) African-American male	(4) African-American female
Self-reported height(inches)	-0.334	0.379	-1.016^{***}	-1.241^{***}
	(-1.27)	(1.54)	(-3.72)	(-6.03)
Self-reported height(inches) squared	0.00878^{***}	0.00389^{*}	0.0130^{***}	0.0158^{***}
	(4.68)	(2.04)	(6.66)	(9.83)
Age in years	0.0399^{***}	0.0622^{***}	0.0348^{**}	0.0526^{***}
	(3.99)	(6.56)	(2.82)	(4.27)
Age in years squared	-0.000587^{***}	-0.000900^{***}	-0.000516^{***}	-0.000745^{***}
	(-4.99)	(-8.03)	(-3.43)	(-4.95)
Constant	49.27^{***}	22.93^{**}	76.40^{***}	77.82^{***}
	(5.33)	(2.91)	(8.00)	(11.81)
Observations	1961	2186	1690	1914
R-squared	0.881	0.871	0.853	0.800

t statistics in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3-1 Predicting Body Fat (BF) in Kilograms, from NHANES III

	(1) White male	(2) White female	(3) African-American male	(4) African-American female
Corrected self-reported weight (kg)	0.399^{***}	0.715^{***}	0.291^{***}	0.669^{***}
	(12.36)	(25.82)	(8.09)	(19.45)
Corrected self-reported weight (kg) squared	0.000556^{***}	-0.000262	0.00120^{***}	-0.0000188
	(3.38)	(-1.54)	(6.49)	(-0.09)
Corrected self-reported height (cm)	1.434^{*}	-1.292^{*}	0.660	-1.216
	(2.51)	(-2.55)	(0.95)	(-1.84)
Corrected self-reported height (cm) squared	-0.00477^{**}	0.00317^{*}	-0.00269	0.00293
	(-2.97)	(2.05)	(-1.38)	(1.46)
Age in years	-0.0136	-0.0528	0.0259	-0.0566
	(-0.30)	(-1.40)	(0.49)	(-1.12)
Age in years squared	0.000485	0.000860	-0.000106	0.000779
	(0.90)	(1.94)	(-0.16)	(1.27)
Constant	-120.7^{*}	104.1^{*}	-47.28	98.57
	(-2.39)	(2.52)	(-0.77)	(1.82)
Observations	1961	2186	1690	1914
R-squared	0.782	0.908	0.777	0.883

t statistics in parentheses. $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$

Table 3-2 Predicting Fat-Free Mass from NHANES III

	(1) White male	(2) White female	(3) African-American male	(4) African-American female
Corrected self-reported weight (kg)	0.621^{***}	0.295^{***}	0.745^{***}	0.323^{***}
	(18.98)	(13.30)	(20.60)	(12.78)
Corrected self-reported weight (kg) squared	-0.000616^{***}	0.000225	-0.00132^{***}	0.0000711
	(-3.70)	(1.66)	(-7.09)	(0.48)
Corrected self-reported height (cm)	-1.284^{*}	0.00132	-0.422	0.360
	(-2.22)	(0.00)	(-0.60)	(0.74)
Corrected self-reported height (cm) squared	0.00423^{**}	0.000727	0.00183	-0.000303
	(2.60)	(0.59)	(0.93)	(-0.21)
Age in years	0.00882	0.0558	-0.0172	0.0581
	(0.19)	(1.85)	(-0.32)	(1.57)
Age in years squared	-0.000473	-0.000910^{*}	-0.0000655	-0.000785
	(-0.87)	(-2.56)	(-0.10)	(-1.74)
Constant	110.0^{*}	2.347	30.36	-28.77
	(2.15)	(0.07)	(0.49)	(-0.72)
Observations	1961	2186	1690	1914
R-squared	0.821	0.820	0.812	0.812

t statistics in parentheses. $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$

Table 4 Descriptive Statistics (Mean and Standard Deviation) for 1984-2009 BRFSS

Variable	Definition	Mean and standard deviation*
Body mass index (BMI)	Weight in kg divided by height in meters squared	26.607 (5.599)
Percent body fat (PBF)	(Estimated body fat in kilogrmas divided by weight in kilograms) ×100	29.915 (7.896)
Obese1	Dummy variable=1 if $BMI\geq30$	0.215 (0.411)
Obese2	Dummy variable=1 if $PBF\geq25$ for male and $PBF\geq30$ for female	0.624 (0.484)
Black	Dummy variable=1 if race=black	0.120 (0.326)
Male	Dummy variable=1 if sex=male	0.523 (0.500)
Some high school	Dummy variable=1 if formal schooling is greater than 9 years and less than 12 years	0.035 (0.184)
High-school graduate	Dummy variable=1 if formal schooling is exactly 12 years	0.141 (0.348)
Some college	Dummy variable=1 if formal schooling is greater than 13 years and less than 16 years	0.758 (0.428)
College graduate	Dummy variable=1 if formal schooling ends with graduation from college	0.055 (0.228)
Married	Dummy variable=1 if marital status is married	0.618 (0.486)
Divorced	Dummy variable=1 if marital status is divorced	0.101 (0.301)
Widowed	Dummy variable=1 if marital status is widowed	0.023 (0.151)
Household income	Real household income in thousands of 1982-84 U.S. dollars	33.459 (26.086)
Age	Age in years	39.961 (13.002)
Time	Time in years where 1984=1	14.960 (7.053)
Restaurants	Number of fast-food and full-service restaurants per ten thousand persons by state	13.264 (1.541)
Fast-food price	Real fast food meal price by state in 1982-84 U.S. dollars	2.797 (0.508)
Full-service restaurant price	Real full-service restaurant meal price by state in 1982-84 U.S. dollars	5.927 (1.234)
Food-at-home price	Real food at home price by state in 1982-84 U.S. dollars	1.244 (0.123)
Cigarette price	Real cigarette price by state in 1982-84 U.S. dollars	1.719 (0.588)
Observations		2518627

* Sample weighted mean and standard deviation.

Table 4 Descriptive Statistics (Mean and Standard Deviation) for 1984-2009 BRFSS (Continued)

Variable	Definition	Mean and standard deviation*
Private	Dummy variable=1 if smoking is prohibited in private workplaces by state	0.453 (0.498)
Government	Dummy variable=1 if smoking is prohibited in state and government workplaces by state	0.706 (0.456)
Restaurant	Dummy variable=1 if smoking is prohibited in restaurants by state	0.594 (0.491)
Other	Dummy variable=1 if smoking is prohibited in other public places such as public transportation by state	0.803 (0.398)
Observations		2518627

* Sample weighted mean and standard deviation.

Table 5-1 OLS regression of BMI and PBF

	(1) BMI	(2) BMI	(3) PBF	(4) PBF
Black	1.642***	1.635***	-0.783***	-0.789***
	(25.12)	(25.55)	(-11.90)	(-12.20)
Male	1.024***	1.024***	-10.40***	-10.40***
	(23.23)	(23.23)	(-175.46)	(-175.56)
Some high school	0.00475	0.0148	-0.0213	-0.0195
	(0.04)	(0.13)	(-0.16)	(-0.14)
High school	-0.230*	-0.224*	-0.205	-0.210
	(-2.47)	(-2.26)	(-1.64)	(-1.62)
Some college	-0.340***	-0.434***	-0.282*	-0.403**
	(-3.66)	(-4.53)	(-2.22)	(-3.18)
College	-0.914***	-0.823***	-0.945***	-0.862***
	(-8.66)	(-7.40)	(-7.10)	(-6.22)
Married	0.235***	0.246***	0.316***	0.327***
	(7.44)	(7.74)	(10.89)	(11.18)
Divorced	-0.379***	-0.370***	-0.340***	-0.333***
	(-9.30)	(-8.92)	(-8.86)	(-8.49)
Widow	0.279***	0.286***	0.341***	0.347***
	(4.74)	(4.84)	(6.20)	(6.27)
Household income	-0.0397***	-0.0406***	-0.0266***	-0.0270***
	(-20.15)	(-20.86)	(-13.22)	(-13.41)
Household income squared	0.000227***	0.000234***	0.000106***	0.000108***
	(12.31)	(13.05)	(5.44)	(5.63)
Age	0.318***	0.317***	0.286***	0.285***
	(46.47)	(46.07)	(44.71)	(43.60)
Age squared	-0.00284***	-0.00284***	-0.00203***	-0.00202***
	(-36.38)	(-36.10)	(-26.54)	(-25.99)
Time		0.108***		0.137***
		(11.06)		(10.63)
Time squared		0.00109**		-0.000158
		(3.07)		(-0.39)
Restaurants	0.525***	0.351**	0.493**	0.238
	(3.70)	(2.89)	(3.12)	(1.73)
Restaurants squared	-0.00869	-0.0133**	-0.00960	-0.0100*
	(-1.89)	(-2.96)	(-1.87)	(-2.09)
Fast-food price	-0.874**	-0.0294	-0.873**	0.0136
	(-3.35)	(-0.27)	(-3.04)	(0.10)
Fast-food price squared	0.0396**	0.00105	0.0398**	-0.000660
	(3.33)	(0.21)	(3.05)	(-0.11)
Full-service restaurant price	-0.512**	0.196*	-0.540**	0.0720
	(-3.31)	(2.08)	(-2.93)	(0.54)
Full-service restaurant price squared	0.0356***	-0.00943	0.0340**	-0.00265
	(3.94)	(-1.67)	(2.96)	(-0.34)
Food -at-home price	-6.336*	-0.654	-5.580*	-0.761
	(-2.34)	(-0.58)	(-2.12)	(-0.50)
Food at home price squared	2.079*	-0.0232	1.768	0.00158
	(2.13)	(-0.06)	(1.91)	(0.00)
Observations	2518627	2518627	2518627	2518627
R-squared	0.090	0.091	0.507	0.508

Note: *t* statistics in parentheses. $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$. State dummies are included in all regressions.

Table 5-1 OLS regression of BMI and PBF (Continued)

	(1) BMI	(2) BMI	(3) PBF	(4) PBF
Cigarette price	2.603***	0.887***	2.629***	0.860***
	(14.57)	(6.45)	(13.05)	(6.66)
Cigarette price squared	-0.438***	-0.208***	-0.458***	-0.197***
	(-9.77)	(-7.21)	(-9.53)	(-7.07)
Private	0.316***	0.0461	0.321***	0.0962
	(5.17)	(1.10)	(4.20)	(1.54)
Government	-0.0118	-0.0413	0.0141	-0.0483
	(-0.19)	(-0.84)	(0.21)	(-0.91)
Restaurant	-0.198*	-0.00909	-0.249**	-0.0586
	(-2.58)	(-0.19)	(-2.96)	(-1.15)
Other	0.0571	0.0822	0.0708	0.0665
	(0.94)	(1.65)	(1.13)	(1.38)
Observations	2518627	2518627	2518627	2518627
R-squared	0.090	0.091	0.507	0.508

Note: *t* statistics in parentheses. $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$. State dummies are included in all regressions. Standard errors were calculated using sample weights and clustered by State.

Table 5-2 OLS regression of BMI-defined obesity and PBF-defined obesity

	(1) Obese1	(2) Obese1	(3) Obese2	(4) Obese2
Black	0.0985***	0.0980***	-0.0651***	-0.0654***
	(27.13)	(27.52)	(-18.77)	(-19.09)
Male	0.0100***	0.0101***	-0.303***	-0.303***
	(5.14)	(5.17)	(-102.57)	(-102.36)
Some high school	0.000368	0.00135	-0.00465	-0.00497
	(0.05)	(0.17)	(-0.48)	(-0.49)
High school	-0.0218**	-0.0210**	-0.0113	-0.0121
	(-3.39)	(-3.07)	(-1.30)	(-1.33)
Some college	-0.0333***	-0.0378***	-0.0138	-0.0227**
	(-5.15)	(-5.69)	(-1.87)	(-2.97)
College	-0.0631***	-0.0572***	-0.0850***	-0.0802***
	(-8.29)	(-7.17)	(-8.27)	(-7.45)
Married	0.0111***	0.0118***	0.0497***	0.0503***
	(7.16)	(7.52)	(32.80)	(32.96)
Divorced	-0.0233***	-0.0226***	-0.00976***	-0.00934***
	(-11.01)	(-10.56)	(-5.17)	(-4.85)
Widow	0.0141***	0.0146***	0.00639*	0.00677*
	(3.60)	(3.70)	(2.11)	(2.22)
Household income	-0.00286***	-0.00295***	-0.0000486	-0.0000425
	(-23.35)	(-24.26)	(-0.38)	(-0.34)
Household income squared	0.0000176***	0.0000183***	-0.00000492***	-0.00000509***
	(13.92)	(14.71)	(-3.60)	(-3.84)
Age	0.0134***	0.0134***	0.0168***	0.0167***
	(34.97)	(35.39)	(47.53)	(46.55)
Age squared	-0.000113***	-0.000113***	-0.000101***	-0.000100***
	(-26.40)	(-26.75)	(-21.79)	(-21.32)
Time		0.00525***		0.0102***
		(7.25)		(13.55)
Time squared		0.000122***		-0.0000737**
		(4.74)		(-3.17)
Restaurants	0.0312**	0.0242**	0.0292**	0.00906
	(3.16)	(3.41)	(2.87)	(1.20)
Restaurants squared	-0.000430	-0.000895***	-0.000604	-0.000417
	(-1.34)	(-3.50)	(-1.80)	(-1.67)
Fast-food price	-0.0597***	-0.00998	-0.0608***	-0.00296
	(-4.27)	(-1.35)	(-3.55)	(-0.47)
Fast-food price squared	0.00270***	0.000434	0.00279***	0.000146
	(4.24)	(1.28)	(3.57)	(0.51)
Full-service restaurant price	-0.0256**	0.0219**	-0.0380**	-0.00452
	(-2.84)	(3.44)	(-2.96)	(-0.56)
Full-service restaurant price squared	0.00192***	-0.00120**	0.00247**	0.000601
	(3.79)	(-2.80)	(2.81)	(1.19)
Food-at-home price	-0.451*	-0.0655	-0.215	0.0438
	(-2.66)	(-0.89)	(-1.46)	(0.59)
Food-at-home price squared	0.151*	0.00743	0.0649	-0.0290
	(2.44)	(0.29)	(1.28)	(-1.12)
Observations	2518627	2518627	2518627	2518627
R-squared	0.056	0.057	0.165	0.165

Note: *t* statistics in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. State dummies are included in all regressions.

Table 5-2 OLS regression of BMI-defined obesity and PBF-defined obesity (Continued)

	(1) Obese1	(2) Obese1	(3) Obese2	(4) Obese2
Cigarette price	0.156***	0.0536***	0.166***	0.0517***
	(15.23)	(5.87)	(10.46)	(5.37)
Cigarette price squared	-0.0253***	-0.0127***	-0.0295***	-0.0115***
	(-9.75)	(-6.31)	(-8.01)	(-5.77)
Private	0.0200***	0.00148	0.0121**	0.000367
	(4.78)	(0.38)	(3.41)	(0.13)
Government	-0.00224	-0.00259	0.00335	-0.00225
	(-0.57)	(-0.66)	(0.77)	(-0.76)
Restaurant	-0.00988*	0.00156	-0.0130**	-0.00100
	(-2.04)	(0.33)	(-2.73)	(-0.34)
Other	0.00482	0.00766	0.00626	0.00448
	(0.91)	(1.23)	(1.30)	(1.26)
Observations	2518627	2518627	2518627	2518627
R-squared	0.056	0.057	0.165	0.165

Note: *t* statistics in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. State dummies are included in all regressions. Standard errors were calculated using sample weights and clustered by State.

Table 6-1 Marginal Effects of selected continuous variables for the first model at the mean values

	(1) BMI	(2) PBF	(3) Obese1	(4) Obese2	(5) Obese3 (0.228)[a]
Restaurants	0.2945	0.2383	0.0198	0.0132	0.0191
Fast-food price	-0.6525	-0.6504	-0.0446	-0.0452	-0.0423
Full-service restaurant price	-0.0900	-0.1370	-0.0028	-0.0087	-0.0034
Food-at-home price	-1.1634	-1.1812	-0.0753	-0.0535	-0.0706
Cigarette price	1.0972	1.0544	0.0690	0.0646	0.0718

a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 6-2 Marginal Effects of selected continuous variables for the second model at the mean values

	(1) BMI	(2) PBF	(3) Obese1	(4) Obese2	(5) Obese3 (0.228)[a]
Restaurants	-0.0018	-0.0273	0.0005	-0.0020	-0.0009
Fast-food price	-0.0235	0.0099	-0.0076	-0.0021	-0.0028
Full-service restaurant price	0.0842	0.0406	0.0077	0.0026	0.0078
Food at home price	-0.7117	-0.7571	-0.0470	-0.0284	-0.0405
Cigarette price	0.1719	0.1827	0.0099	0.0122	0.0103

a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 6-3 Elasticity of selected continuous variables for the first model at the mean values

	(1) BMI	(2) PBF	(3) Obese1	(4) Obese2	(5) Obese3 (0.228)[a]
Restaurants	0.1468	0.1057	1.2211	0.2801	1.1108
Fast-food price	-0.0686	-0.0608	-0.5802	-0.2026	-0.5191
Full-service restaurant Price	-0.0200	-0.0271	-0.0783	-0.0828	-0.0873
Food-at-home price	-0.0544	-0.0491	-0.4358	-0.1067	-0.3851
Cigarette price	0.0709	0.0606	0.5518	0.1779	0.5412

a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 6-4 Elasticity of selected continuous variables for the second model at the mean values

	(1) BMI	(2) PBF	(3) Obese1	(4) Obese2	(5) Obese3(0.228)[a]
Restaurants	-0.0009	-0.0121	0.0282	-0.0426	-0.0523
Fast-food price	-0.0025	0.0009	-0.0982	-0.0096	-0.0345
Full-service restaurant price	0.0188	0.0080	0.2116	0.0247	0.2021
Food at home price	-0.0333	-0.0315	-0.2720	-0.0565	-0.2212
Cigarette price	0.0111	0.0105	0.0795	0.0335	0.0777

a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 7-1 Marginal effect of selected continuous variables at the mean values

	(1) Probit Obese1	(2) Probit Obese2	(3) Probit Obese3 (0.228)[a]	(3) NLS Obese1 α_0=0.04 α_1=0.59
Restaurants	0.0022	0.0014	0.0018	0.0029
Fast-food price	-0.0678	-0.0598	-0.0654	-0.0822
Full-service restaurant price	-0.0115	-0.0170	-0.0122	-0.0127
Food-at-home price	-0.0690	-0.0501	-0.0702	-0.0999
Cigarette price	0.0855	0.0869	0.0881	0.1013

Note: State dummies are NOT included in all regressions.
a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 7-2 Elasticity of selected continuous variables for the probit and NLS at the mean values

	(1) Probit Obese1	(2) Probit Obese2	(3) Probit Obese3 (0.228)[a]	(4) NLS Obese1 α_0=0.04 α_1=0.59
Restaurants	0.1335	0.0303	0.1024	0.1777
Fast-food price	-0.8823	-0.2679	-0.8018	-1.0698
Full-service restaurant price	-0.3159	-0.1616	-0.3181	-0.3490
Food-at-home price	-0.3991	-0.0999	-0.3830	-0.5782
Cigarette price	0.6835	0.2394	0.6644	0.8098

Note: State dummies are NOT included in all regressions.
a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 8-1 Marginal effect of selected continuous variables at the mean values for 1984-1999

	(1) Probit Obese1 (0.160)	(2) Probit Obese2 (0.566)	(3) Probit Obese3 (0.172)[a]	(3) NLS Obese1 (0.160) α_0=0.04 α_1=0.59
Restaurants (13.203)	0.0031	0.0057	0.0031	0.0034
Fast-food price (2.895)	-0.0796	-0.1263	-0.0799	-0.0851
Full-service restaurant price (5.892)	-0.0092	-0.0177	-0.0096	-0.0096
Food-at-home price (1.260)	-0.0043	0.0496	-0.0021	-0.0195
Cigarette price (1.277)	0.0751	0.0992	0.0768	0.0825

Note: State dummies are NOT included in all regressions. Sample size is 847277. Parentheses are mean values of variables.

a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

Table 8-2 Elasticity of selected continuous variables for the probit and NLS at the mean values for 1984-1999

	(1) Probit Obese1 (0.160)	(2) Probit Obese2 (0.566)	(3) Probit Obese3 (0.172)[a]	(4) NLS Obese1 (0.160) α_0=0.04 α_1=0.59
Restaurants (13.203)	0.0016	0.0026	0.2403	0.0017
Fast-food price (2.895)	-0.0090	-0.0126	-1.3453	-0.0096
Full-service restaurant price (5.892)	-0.0021	-0.0036	-0.3302	-0.0022
Food-at-home price (1.260)	-0.0002	0.0022	-0.0153	-0.0010
Cigarette price (1.277)	0.0037	0.0044	0.5701	0.0041

Note: State dummies are NOT included in all regressions. Sample size is 847277. Parentheses are mean values of variables.

a. The mean value of obese3 with PBF≥40 for women and PBF≥28 for men.

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