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Abstract: This paper uses quantile regression and alternate measures of overweight to examine the relationship between income and the body-mass index (BMI). In contrast to the prevalence measure of overweight, the alternate measures considered are sensitive to changes in the body-mass index (BMI) distribution and continuous in BMI at the overweight threshold. The standard prevalence measure indicates that there has been no association between poverty and overweight during the last 30 years of the 20th century. The most recent data from 2004 indicate that the prevalence of overweight for poor people is more than 5 percentage points lower than for the nonpoor. The alternative measures indicate though that the BMI distribution of the poor has been much more positively skewed over this time period, indicating a more severe overweight problem. Quantile regression analysis indicates that the strongest relationship between income and BMI is observed at the tails of the (conditional) distribution. There is a strong negative income gradient in BMI at the obesity threshold and some evidence of a positive gradient at the underweight threshold.

Classification: I1, I18, I32
Key Words: Overweight, Obesity, Body Mass Index, Robust Measurement, Foster-Greer-Thorbecke Poverty Measures, NHANES

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1. **Introduction**

Mortality and morbidity rates for many health outcomes are inversely related to income (Deaton and Paxson, 1999; Deaton, 2001). Deaton (2002) notes that people in the U.S. with family income less than $5,000 (in 1980 dollars) have a life expectancy that is around 25 percent lower than those with family income above $50,000. He further notes that the negative income gradient in health has a long history, first documented in France in the 1820s and the United Kingdom as early as 1851. Perhaps the most prominent recent public health concern in the U.S. has been the rapid rise of overweight. Ogden et al. (2006) estimate that 66 percent of U.S. adults are overweight based on data from 2003 and 2004.[1] The potential health consequences from being overweight or obese include being at increased risk of morbidity from hypertension, stroke, type 2 diabetes, osteoarthritis, respiratory problems, and breast, prostate, and colon cancers.[2] A reasonable and common assumption then is that the poor suffer significantly higher rates of overweight. The aim of this paper is to determine whether this is an accurate portrayal of income and overweight prevalence, and then to examine the nature of the income gradient in weight status.

There are important policy implications linked to correctly understanding this relationship. In both the popular and academic press, there is the argument that the growth of fast food and energy-dense food has been an important cause of the overweight epidemic in the U.S. and that this has disproportionately affected poor people. Drewnowski and Specter (2004, p. 14) argue that limited economic resources may shift dietary choices toward a diet that provides maximum calories at the least cost. Critser (2003) in his book Fat Land, similarly argues that cheap fats and sugars are the primary cause of overweight and notes that "… one fact stuck out above all others

[1] This estimate is age standardized by the direct method to the 2000 Census data and based on three age categories.

…In late-twentieth-century America, it was the poor, the underserved, and the underrepresented who were most at risk from excess fat” (p.109). An implication of this line of research is that the poor can not afford healthy diets.

A different line of reasoning suggests that Federal food assistance programs are exacerbating the overweight health crisis. In the Washington Post, Besharov (2002) argues that programs such as food stamps are increasing the food budgets of the poor, who are already over-consuming. In Congressional testimony he states that “Today, as many as 70 percent of low-income adults are overweight, about 10 percent more than the nonpoor” (2003). In the National Review Online, O’Beirne (2003) asks “with rates of excess weight and obesity highest among low-income households, budget officials should be asking themselves why tens of billions of dollars are being spent each year by Federal nutrition programs aimed at boosting food consumption by the poor.”

2. Data and Descriptive Statistics

The aim of this section is to examine the assertions in the popular press that the rates of overweight and obesity are highest among the poor. The official estimates of overweight and obesity come from the National Health and Nutrition Examination Survey (NHANES), which is conducted by the National Center for Health Statistics of the Centers for Disease Control. The NHANES samples are representative of the U.S. civilian, non-institutionalized population and observations are selected following a stratified, multi-stage design. I use six rounds of the NHANES data: 1971-1974 (NHANES I), 1976-1980 (NHANES II), 1988-1994 (NHANES III), 1999-2000, 2001-2002, and the 2003-2004 files. Body weight and height measures were obtained by trained health technicians, and effective sample sizes of those persons between 20

[2] See National Heart, Lung, and Blood Institute (1998, Chapters 1 and 2) for a more complete list of

and 75 years of age range from 3,647 in the 1999-2000 cycle to 12,901 from NHANES I.

Current medical research indicates that excess accumulation of body fat, as a percent of total body weight, is the primary source of health concerns associated with being overweight. Federal guidelines use the body mass index (BMI), which is body weight in kilograms divided by the square of height in meters, as an approximation for measuring body fat.[3] In 1998, the U.S. Federal Government adopted the recommendations of the World Health Organization Expert Committee (1995) and defined a person as overweight if they had a BMI greater than or equal to 25, and obese as greater than or equal to 30.

[INSERT TABLE 1 APPROXIMATELY HERE]

Table 1 lists rates of overweight and obesity from 1971 to 2004 by poor and non-poor categories. Throughout this paper, I categorize an individual as poor if their income is less than 130 percent of the poverty line. I use this income cutoff primarily because it matches the (gross) income eligibility criterion for the food stamp program, the largest of the Federal food assistance programs.[4] In terms of BMI, Table 1 indicates that there has historically been no relationship at all between being poor and being overweight. Between 1971 and 2002, there are no statistically significant differences in the rates of overweight between the poor and nonpoor. The first statistically significant result is from the most recent data, 2003-2004, but this reveals that the overweight rate for the poor is 5.6 percentage points lower than for the nonpoor.

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health problems associated with being overweight and for citations for each of the listed health problems.

[3] The National Heart, Lung, and Blood Institute (1998, Chapter 4) asserts that BMI provides an acceptable approximation for large groups. This view is also supported by the American Society for Clinical Nutrition (1998) and the World Health Organization (1995). Nagaya *et al*. (1999) also show that BMI is well correlated with body fat.

[4] Using 130 percent of the poverty line to split the sample between poor and nonpoor also has the advantage of having a greater sample of poor observations (relative to using the poverty line).

The findings change if we ignore overweight and just consider obesity. Panel B of Table 1 now reveals a story that is somewhat more consistent with the assertions in the popular press. Between 1971 and 2002, the poor did have higher rates of obesity and the difference in the rates ranged from 3.6 to 6.7 percentage points higher than for the nonpoor. The most recent data though suggest a convergence in obesity rates--33 percent of the nonpoor are obese compared to 32 percent of the poor. While this recent convergence might reflect sampling variance, we should be aware of the possibility that the correlation between the dichotomous measures of obesity and poverty has disappeared.

The message then is significantly less clear than suggested in the popular press. If overweight is the relevant health indicator, then there never has been an association between this measure of wellbeing and poverty until very recently, and this recent development suggests that the poor are modestly healthier than the nonpoor in this indicator. If on the other hand, obesity is the relevant measure of excess fat, then the poor have historically been less well off but this relationship appears to no longer exist.

3. Distribution-sensitive Measures of Overweight[5]

Part of the reason for this mixed message is due to an attempt to simplify a fairly complex relationship. The decision to discuss overweight and obesity in terms of prevalence rates requires that the continuous Body Mass Index (BMI) be converted into discrete outcomes indicating whether it is above or below some threshold. Converting this continuous measure into discrete outcomes for overweight and obese has the important advantage that it is easy for the general public to understand prevalence rates, but it also has disadvantages.

[5] Parts of this section are drawn from Jolliffe (2004).

First, research indicates that the risks of health problems for adults associated with being overweight are increasing in BMI (Willett, Dietz and Colditz, 1999). For example, the risk of heart failure increases 5 percent in adult men and 7 percent in adult women with a unit increase in BMI (Kurth et al., 2002). Similarly, a one-unit increase in BMI is associated with a 6 percent increase in the relative risks of total, ischemic and hemorrhagic stroke for men (Kenchaiah et al., 2002). The decision to convert BMI to a dichotomous outcome for overweight, is a decision to ignore the case that someone whose BMI is twice the overweight threshold is likely to be at higher risk of negative health outcomes than someone whose BMI is 5 or 10 percent greater than the overweight threshold.

A second, and related issue, is that when the outcome is dichotomous; the selection of the threshold value becomes more important. There is no research that literally argues that there is some razor's edge at a BMI of 25 or 30 (the current thresholds for overweight and obese). That is, there is no evidence indicating that someone with a BMI of 24.99 is in significantly better health than someone whose BMI is 25; yet the discontinuity at the threshold implies this is the case. When the measurement methodology imposes assumptions such as discontinuity at an important public health threshold, the public health debate may well place unnecessary emphasis on the threshold points at the expense of discussion about the shifting distribution of BMI.

3.1 Alternative Measures of Overweight

These issues of the discontinuity of the welfare measure and disagreement about the appropriate threshold are also faced in the measurement of poverty and the general solution to these measurement issues is to consider distribution-sensitive measures. Drawing from the poverty literature, I use a family of indices introduced by Foster, Greer and Thorbecke (1984, hereafter referred to as FGT) to measure poverty. Slightly modifying the FGT index, one can express a class of overweight indices, OW_α, as:

$$OW_\alpha = 1/n \sum_i I(BMI_i \geq f)[(BMI_i - f)/f]^\alpha \qquad (1)$$

where n is the sample size, i subscripts the individual, f is the cutoff point identifying who is overweight, and I is an indicator function which takes the value of one if the statement is true and zero otherwise. When α=0 the resulting measure, OW_0, is the proportion of the population that is overweight, or the overweight *prevalence*. When α=1, the FGT index results in the overweight-gap index, or OW_1, which can be described as revealing the *depth* of the problem. A useful interpretation of the overweight-gap index is to recognize that it is equal to the product of the prevalence rate and the average value of excess BMI of the overweight (expressed as a fraction of the overweight cutoff point). When α=2, the resulting measure is the average of the squared values of the individual overweight-gaps and is sensitive to (mean-preserving) changes in the bodyweight distribution of the overweight. Due to its distribution sensitivity, and using the poverty semantics, OW_2 can be described as reflecting the *severity* of the overweight problem.

The merit of these measures can be illustrated by considering an overweight person who gains weight. This weight gain has no effect on the overweight prevalence, but the health of this person has changed and this change is reflected in the overweight-gap and squared overweight-gap indices. As another example, consider a mean-preserving, increasing spread of the bodyweight distribution of the overweight (and assume there is no change in the prevalence). In this case the overweight-gap index will not reflect a change in the overall welfare of the population, but the squared overweight-gap index will be sensitive to this change in the distribution. In terms of shaping public-health policy, OW_1 and OW_2 provide important information. Policies that focus on helping the extremely overweight to loose some weight would likely have no effect on OW_0, yet could possibly have important public-health benefits.

[INSERT FIGURE 1 APPROXIMATELY HERE]

The first indication that there have been important changes in the distribution of BMI that would be masked by prevalence measures but revealed by the FGT measures can be seen in Figure 1. This figure plots the density function of BMI in the early 1970s and also the most recent BMI density function, from 2003 – 2004. The most striking change is the significant shift to the right of BMI over time. It is clear from this figure that significantly more of the BMI distribution for 2003-2004 lies to the right of the cutoff at 25. This shift is reflected in the increased prevalence of overweight from 47 percent in the 1970s to the most recent estimate of 66 percent. What is also clear from the figure is that BMI in 2003-2004 is significantly less-peaked indicating greater spread in the tails. The changing shape of the density functions indicates that the variance in BMI is now greater. This change is largely hidden in the prevalence measures, but will be revealed in the depth and severity measures.

3.2 Sampling Variance of the Measures

To test whether changes in OW_α over time or across demographic characteristics are reflective of true changes in the population, it is necessary to estimate the sampling variance of (1). FGT show that their index is additively decomposable. This characteristic greatly simplifies the derivation of design-corrected estimates of the sampling variance. To illustrate this, consider any BMI vector, broken down into M subgroups, $BMI^{(1)}, \ldots, BMI^{(M)}$. Because OW is additively decomposable with population share weights, it can be written as:

$$OW_\alpha(BMI;f) = \sum_{j=1}^{M} (n_j / n)\, OW_{\alpha,j}(BMI^j; f) \qquad (2)$$

where n is the sample size, n_j is the size of each subgroup, and f is again the overweight threshold. By extension, each observation can be treated as a subgroup and then the overweight index is the weighted mean of the individual-specific measures, or: $OW_\alpha = \sum OW_{\alpha,i}/n$. Following Kish (1965) and noting that OW_α can be considered a sample mean, the estimated sampling variance of the FGT indices from a weighted, stratified, clustered sample is given by:

$$V(OW_{\alpha,w}) = \sum_{h=1}^{L} n_h (n_h - 1)^{-1} \sum_{i=1}^{n_h} \Big(\sum_{j=1}^{m_{h,i}} w_{h,i,j}\ OW_{\alpha,h,i,j} - \sum_{i=1}^{n_h} \sum_{j=1}^{m_{h,i}} w_{h,i,j}\ OW_{\alpha,h,i,j} \Big)^2 \qquad (3)$$

where the h subscripts each of the L strata, i subscripts the cluster or primary sampling unit (PSU) in each stratum, j subscripts the ultimate sampling unit (USU), so w_{hij} denotes the weight for element j in PSU i and stratum h. The number of PSUs in stratum h is denoted by n_h, and the number of USUs in PSU (h, i) is denoted by m_{hi}.[6]

3.3 Results from the Alternate Measures

Table 2 presents the three overweight indices by income for each round of the NHANES, starting with estimates from 1971-1974 and ending with the 2003-2004 data. The prevalence rates, based on the dichotomous indices of overweight and obese, can be compared with the distribution-sensitive depth and severity measures. While the OW_0 measure indicates that the poor have never had a greater prevalence of overweight (and in fact currently have a statistically significant lower rate), the depth and severity measures portray a different picture. Throughout the 1970s and 1980s, these measures were larger for the poor than the nonpoor; but the magnitude of the difference has now diminished and the difference is currently not statistically significant.

In terms of differences in BMI across the poor and nonpoor, it is also worth noting the difference in growth rates of these measures. In the early 1970s, the nonpoor had lower levels for all three measures and the percentage change in each of these measures has been markedly larger for the nonpoor than the poor. For example, the severity measure for the poor has increased by 92 percent, while this measure for the nonpoor has more than tripled in size. To some extent, this difference in relative changes is driven by the lower levels for the nonpoor to begin with. But an examination of the absolute levels suggests that the nonpoor are quickly converging. For example, the severity measure for the poor was 83 percent greater than for the nonpoor in the first NHANES. The data indicate that this index for the poor is now only 14 percent greater than for the nonpoor.

There is one dimension in which the distribution-sensitive measures indicate a similar pattern for both the poor and nonpoor. Between the early 1970s (NHANES I) and the current estimates from 2003-04, all three measures have increased for the poor and nonpoor. Further, while the prevalence measure has increased by 28 percent for the poor, OW_1 has increased by 66 percent and OW2 by 92%. For the nonpoor, the OW_1 index has increased by more than the OW_0 index, and OW_2 has grown faster than OW_1. Noting that as the α subscript increases in magnitude, the OW_α measures are more distribution sensitive, this pattern indicates that the increases in the prevalence rates fails to reveal that an important component of the change over the last three decades has been a large shift out of the right tail of the BMI distributions for both the poor and nonpoor. For example, while median BMI has increased less than 3 units between NHANES I

[6] The indices and sampling variance estimates are documented in more detail in Jolliffe and Semykina (1999) who also provide a program to estimate equations (1) and (3) in the *Stata* software for the FGT poverty indices.

and the recent estimates from 2003-2004 (increasing from 24.6 to 27.3), the 95th percentile has increased by more than 6 units in this period (increasing from 34.1 to 40.3). To put this increase in terms of pounds, consider an average-height male at 1.77 meters (or 5 feet, 10 inches). An increase of BMI by 6 means a weight gain of 18.8 kilograms (or 41 pounds).

[INSERT TABLE 2 APPROXIMATELY HERE]

Gender adds an additional important dimension to the correlation between poverty and BMI which indicates seemingly very different associations for men and women (see Table 3). In order to highlight some of these differences, I contrast low-income (less than 130 percent of the poverty line) to high-income (more than 300 percent of the poverty line) for men and women. Over the last 30 years, in stark contrast to the income-BMI relationship portrayed in the popular press, high-income men had much higher overweight prevalence rates than poor men. In the 2003-04 data, 76 percent of high-income men (income greater than 300 percent of the poverty line) were overweight as compared to 57 percent of poor men. For women, the story is the opposite. Poor women have consistently had a higher prevalence of overweight than nonpoor women. Currently, 66 percent of low-income women are overweight compared to 58 percent for high-income women.

The distribution-sensitive measures again provide a more detailed profile of overweight by sex and income. Over each sub-sample considered (men and women by high-income and low-income status), the relative change in the indices over time is greater for high-income men and high-income women relative to their low-income counterparts. Similarly, the growth rates in each of the indices are increasing in α, meaning systematic changes in the shape of the distributions over time.

The distribution-sensitive indices add further detail to the profile of BMI by income and gender that complicate simplifying descriptions. For example, one might note that more than three fourths of high income men are overweight, in contrast to 58 percent for high-income women, and suggest that being overweight is much more of a problem for high-income men than women. The severity measure reveals that this would overly simplify the picture. The OW_2 measure for high-income women is higher than for high-income men, indicating that for those high-income people who are overweight, women are overweight by much greater amounts.[7] There is a similar story contrasting high-income men with low-income men. The prevalence of overweight is close to 20 percentage points greater for high-income men than for low-income men. In contrast, the OW_2 measure suggests very little difference in the severity of overweight for these two groups.

[INSERT TABLE 3 APPROXIMATELY HERE]

Despite the lack of empirical evidence to support the conventional wisdom that the poor have a higher prevalence of overweight, Tables 2 and 3 provide some indications to a potential reason for this misperception. While it is the nonpoor who have a greater prevalence of overweight, the overweight poor are heavier. The ratio OW_1/OW_0 provides a measure of the extent to which BMI of the overweight surpasses the overweight threshold of 25. Using the 2003-2004 estimates, this ratio indicates that the overweight poor are 28 percent overweight (i.e. their BMI is on average 28 percent greater than 25), while this estimate for the nonpoor is 25 percent. Comparing overweight high-income women with overweight poor women provides a similar finding. Poor,

[7] More specifically, high-income, overweight women exceed the overweight threshold by 28 percent. High-income, overweight men exceed this threshold by 21 percent on average.

overweight women are on average 32 percent overweight; while high-income, overweight women exceed the overweight threshold by 28 percent on average. Figure 2 plots the most recent BMI density functions for the poor and nonpoor and graphically illustrates this point. There is more mass in the density function for the overweight nonpoor near the threshold of 25 (the nonpoor density function lies above the poor density for BMI between about 25 and 33). Similarly, the density function for the poor lies above the nonpoor at the extreme values of BMI, between about 40 and 50.

[INSERT FIGURE 2 APPROXIMATELY HERE]

4. Is there an Income Gradient in BMI?

An important motivation for the alternative measures of overweight considered above is the argument that the dichotomous (prevalence of overweight) measure fails to reveal any information about the changing distribution of those who are overweight. Similarly, treating income as dichotomous (poor and not poor) could very well also be failing to reveal important aspects of the relationship between income and BMI. Case, Lubotsky and Paxson (2002, p. 1308) note that the income gradient in health status "is evident throughout the income distribution." For example, the decision to treat all of the poor as the same might hide important differences between those who are in severe poverty compared to those whose income is closer to the poverty line. In this section, I avoid converting either the BMI or income measures into dichotomous outcomes, and consider the relation between continuous measures of each.

There is a large literature on the income gradient in health outcomes which fairly uniformly documents positive correlation between bad health outcomes and decreases in income. See for example, Pappas et al. (1993), Sorlie et al. (1995), Deaton and Paxson (1999), Deaton (2001).

Essentially all of this analysis is based on estimating the correlation between the probability of a negative health outcome and income. BMI as a health outcome has an important complicating factor relative to many other health outcomes (or at least for how these outcomes are typically measured). At high levels of BMI, decreases in BMI indicate health improvements; but at low levels of BMI, increases in BMI indicate health improvements (the Centers for Disease Control and Prevention, CDC, consider 18.5 as the threshold for underweight status).

Given the current epidemic of overweight, it's natural to assume that a negative correlation between income and BMI indicates that higher income levels are associated with better BMI outcomes. But for measurement purposes it is important to consider that for the underweight, negative correlation would indicate that deteriorating BMI outcomes are associated with increases in income.

An OLS regression of BMI on income and other controls, X, provides an estimate of the correlation between BMI (conditional on X) and income, or:

$$\partial\, E(\text{BMI} \mid \text{Income}, X) \,/\, \partial\, \text{Income} \tag{4}$$

The OLS estimator provides an estimate of the change in the conditional mean of BMI from a change in income. A nonparametric (or lowess, or spline) estimator would allow the estimated partial derivative to vary at different levels of income, but it would continue to estimate the change in the conditional mean of BMI from a change in income. Estimates such as these fail to allow for the possibility that income could have very different effects on BMI at different points on the conditional distribution of BMI. This is the same point made by Chamberlain (1994) who compares OLS and quantile estimators to measure the wage premium from union participation. The OLS estimates indicate that union participation has a positive effect on the conditional mean of wages, but the quantile estimates allow one to see that the premium is much larger for low (conditional) wage earners than high earners and the OLS estimate falls between the two.

In contrast to the union example, where the union effect is diminished at higher points on the conditional wage distribution, one might expect the income effect on BMI to potentially reverse signs. In other words, if there is an income gradient in BMI which indicates a positive relationship between income and improvements in BMI, then there should be positive correlation at low levels of BMI and negative correlation at high levels. The OLS estimator is unable to reflect this diversity, but the quantile estimator allows for marginal effects to differ over different parts of the conditional distribution.

Typically when using the quantile estimator, marginal effects are compared at fixed points on the conditional distribution, such as the 10^{th}, 50^{th}, 90^{th} quantiles. (See for example, Chamberlain, 1994, Nguyen et al., 2007, Patrinos and Sakellariou, 2006.) To examine the relationship between income and BMI using data from different points in time, I argue that this approach will produce estimates that are unnecessarily difficult to interpret. For example, a median regression on the data from 1988 and later would estimate the relationship between income and BMI at some point above the overweight threshold. But for the earlier years, this median regression would be for BMI levels below the overweight threshold, and the public health literature is fairly silent as to whether we believe health is positively or negatively affected for BMI changes between 18.5 and 25.

The current medical literature designates primarily three points on the BMI distribution as key thresholds. Underweight is defined as 18.5 or less, overweight at 25 and higher, and obese is defined as 30 and over.[8] As these are the thresholds for defining this public health concern, I examine the marginal correlation of income and BMI at these three points, or:

$$\partial\, Q_{BMI}(\tau_{BMI=30,25,18.5} \mid \text{Income}, X) \,/\, \partial\, \text{Income} \tag{5}$$

Following the notation of Koenker (2005), Q_{BMI} is the conditional quantile function of BMI and τ represents the quantile corresponding to the three BMI thresholds. For each year, I estimate (5) at the quantile, τ, equal to the population prevalence of obesity, overweight, and underweight.[9] The regression parameters therefore are evaluated at different quantiles, but reflect the marginal change in BMI from a change in income at the key thresholds for each year. While the thresholds represent different percentiles of the BMI distribution in each year, I argue that the relevant question is not whether there is relationship between income and BMI at some fixed percentile, but rather if there is a relationship at the public health thresholds (underweight, overweight, obese).

Table 4 reports the regression coefficients from the OLS and quantile estimators of BMI on just income, while Table 5 replicates this but adds controls for age, square of age, and indicator variables for race, and education levels. In all of the analysis, income is measured relative to the poverty line and scaled to one (e.g. a value of two indicates that income is twice the poverty line). For the regression estimates, I pool together the three cross sections of data from 1999 to 2004 to increase the sample size. While the quantile estimator at the overweight threshold performs well for smaller samples, the power of the estimator declines at the extremes of the distribution. In the case of underweight in the U.S., this has stayed at approximately two percent over the last three decades. Estimating the marginal effect of income on BMI at the second

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[8] Obesity is sometimes further decomposed into different categories, including morbid (or class 3) obesity defined as a BMI greater than 40.

[9] In sex-specific regressions, I estimate (5) at the quantile corresponding to the sex-specific prevalence rate.

percentile for the last round of data for 2003-04 would mean estimating this quantile with 3,600 observations. By pooling the last three rounds, the sample size increases to 10,412. (Sample sizes for NHANES I, II, III range from 10,952 to 13,212.)

All estimates are weighted with the exam sample weights, allowing inferences to be drawn to the reference population (U.S. civilian, non-institutionalized population). I use the *qreg* command in Stata (version 9.2) for all quantile regressions, but this program can not correct the variance-covariance matrix for the clustering and stratification. To provide an estimate for this adjustment, I use the estimated design effects for each of the OLS regressions and scale the estimated standard errors for the quantile estimates accordingly. For example, if the design effect for the male regression in panel B of Table 5 for a given year is 4, I scale up the quantile standard errors by a factor of 2 (the square root of the design effect). The design effect for means (Kish, 1965) and conditional means (Scott and Holt, 1982) is a function of the observation matrix, number of clusters, and the intra-cluster correlation coefficient. Considering the same specification, the relevant characteristic that can change is the intra-cluster coefficient, which suggests that this adjustment is based on the assumption that the level of the residual intra-cluster correlation is similar at different points on the conditional distribution.[10]

[INSERT TABLES 4 AND 5 APPROXIMATELY HERE]

Panel A in Table 4 reports the income gradient in (unconditional) BMI for all adults between the ages of 20 and 75 from 1971-74 to 1999-2004. The naïve approach of using the OLS estimator would show a negative and statistically significant income gradient in BMI. The magnitude of the point estimate ranges from -0.14 to -0.17. Recalling that income is measured in poverty line units (where an income of 1 means income equal to the poverty line), the OLS estimates suggest a unit increase in income is associated with a reduction of BMI by approximately 0.16 in the latest rounds.

The quantile estimates in Panel A though, reveal that the OLS estimates are averaging over important differences across the distribution. At the underweight threshold, there is a positive and statistically significant (in 3 of the 4 periods) income gradient in BMI. The latest rounds of data indicate that a one unit increase in income is associated with an increase in BMI of 0.26 when evaluated at the underweight threshold. The data also indicate that there has never existed a (statistically significant) income gradient in BMI at the overweight threshold, when evaluated for all adults. Finally, at the obese threshold, the income gradient is negative and statistically significant in all periods. A one unit increase in income is associated with a reduction in BMI by 0.27 in the latest rounds of the data. The magnitude of this effect is 70 percent greater than the OLS estimate. It is striking that the point estimates at the obese threshold are more than twice as large as the OLS estimates in the other 3 time periods.

An important measurement issue in these findings then is that because the OLS estimator assumes a constant gradient at all points on the distribution, it mis-estimates the sign of the effect for the underweight and significantly underestimates the magnitude of the gradient for the obese. The findings for the conditional estimates are quite similar, with the OLS estimates indicating a smaller income gradient than the quantile estimator evaluated at the obesity threshold. It is also useful to note that OLS overestimates the effect at the overweight threshold (BMI=25). There is essentially no statistically significant correlation between income and (either conditional or unconditional) BMI evaluated at the overweight threshold when considering the adult population.

[10] A further assumption is that the adjustment factor for the conditional quantile is similar in form to the

Given the significant gender differences in the relationship between BMI and income observed in Table 3, it is not that surprising that Tables 4 and 5 show differences in the income gradient by gender. For males, over much of the last thirty years, there has been a positive gradient in BMI running from the underweight threshold through the overweight threshold. This positive gradient then disappears at the threshold for obesity. For women, there is essentially no gradient at the underweight threshold; but a large and statistically significant negative gradient for BMI when evaluated at the overweight and obese thresholds.

The OLS results indicate a positive gradient in BMI for men and a negative gradient for women. If we consider a naïve interpretation of the income gradient literature, one might argue that this is evidence that the 'expected' gradient doesn't exist for men, but does for women. The argument here is that a naïve interpretation focuses on high BMIs and expects income to be correlated with BMI as it is with many other health outcomes. While this interpretation would not be completely off the mark, a more complete interpretation based on the quantile estimates would emphasize that the relationship is as expected for men with low BMIs. Increases in income are associated with increases in BMI for underweight men. And, similarly the interpretation for women would be modified by noting that increases in income appear to have no BMI benefits for the underweight.

As a final extension on this examination of the correlation between income and BMI, I relax the linearity assumption imposed on the specification of income. I consider a specification with income and income squared, and I also consider a spline estimator with knots at 135 and 250 percent of the poverty line. I report on both of these specifications in Table 6 using the pooled data from 1999 through 2004, and compare OLS estimates with quantile estimates at the underweight, overweight and obese thresholds. The spline estimator allows for the slope

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adjustment for the conditional mean derived by Scott and Holt (1982).

parameters to vary across the different income ranges for each of the estimators. Relaxing the functional form assumptions placed on income appears to fairly significantly reduce the power of the estimators. There are few statistically significant point estimates. The one finding that is consistent and significant is simply that the joint income effect (the joint significance of the slope coefficients on the three splines) is statistically significant at each of the three thresholds.

The specification considering income and income squared imposes more form on the income variable, but does allow for nonlinearity. Panel A of Table 6 now provides evidence that there is a positive income gradient in BMI at the overweight threshold for low-income persons and this gradient declines in magnitude up to about three times the poverty line at which point it becomes negative. The evidence is somewhat similar for the income gradient evaluated at the obesity threshold, except the inflection point is at 1.8 times the poverty line.

Table 7 estimates these gradients separately for men and women, and the interpretation is fairly similar. Both men and women appear to have a positive income gradient in BMI for low income levels when evaluated at the overweight threshold. For men this appears to taper off around 4.7 times the poverty line, but the negative coefficient on income squared, providing evidence of the concavity, is not statistically significant. For women, the positive coefficient on income and negative coefficient on income squared are both statistically significant, indicating a positive income gradient in BMI up through 2.2 times the poverty line and thereafter a negative income gradient.

The point estimates for the male and female income gradients when evaluated at the obesity threshold also indicate a concave function. But in this case, the positive coefficient on income for women is not statistically significant, and the inflection point is at quite a low level of income (1.2 times the poverty line). For men, both coefficients are statistically significant and the point of inflection is at 3 times the poverty line.

[INSERT TABLES 6 & 7 APPROXIMATELY HERE]

4. Conclusion

Understanding the relationship between income and BMI is important for policies directly aimed at the nutritional intake of low-income persons as well as policies aiming to reduce the prevalence of overweight and obesity in the US. Current portrayals of the relationship between income and BMI, in the popular press, policy briefings and academic writings, suggest that the poor have much higher rates of overweight and obesity. The basic descriptive statistics do no support this assertion. NHANES data from 2003-04 indicate that the prevalence of overweight for poor people (income less than 130 percent of the poverty line) was almost 5.6 percentage points lower than for the nonpoor. In terms of obesity, the most recent prevalence rates are not statistically different for the poor and nonpoor. Despite these descriptive statistics refuting the portrayal of the poor as having higher rates of overweight, this paper provides some support to the conventional wisdom that the poor are more overweight.

The first part of this paper examines the relationship between poverty status and continuous measures of BMI. The choice to use an overweight index that is continuous in BMI is based primarily on a desire to use a measure that reflects the view the severity (or probability) of negative health outcomes associated with being overweight are increasing in BMI (i.e. someone who is 50 pounds overweight has a higher probability of a BMI-related, negative health outcome than someone who is a pound overweight). If one considers the overweight depth measure (OW_1), which measures the average amount by which the population exceeds the overweight threshold, there is no longer a statistically significant difference between the poor and nonpoor.

This index also reveals that overweight and poor people exceed the overweight threshold (BMI=25) by 28 percent. In contrast, the nonpoor and overweight exceed this threshold by 25 percent. While the prevalence of overweight is greater for the nonpoor, the depth and severity measures indicate that the BMI distribution for the poor is more positively skewed with more mass at higher BMI levels.

The next step of the analysis regresses BMI on a continuous measure of income (rather than looking at the poor and nonpoor categories). The parameter estimates from most all regression functions provide some estimate of the marginal change in the conditional expected value of the dependent variable from a change in an explanatory variable. With many nonlinear, or nonparametric estimators, it is possible to allow for this effect to vary for different values of the explanatory variable, but the change is always evaluated at the conditional mean of the dependent variable. In the context of BMI, this is not a useful descriptive tool. If there is a relationship between rising income and improving health as measured by BMI, then we should expect to see a positive marginal effect of income on BMI for the underweight and a negative effect for the overweight. The quantile estimator allows for the marginal effect to vary at different points on the conditional distribution of the dependent variable, and proves to be a useful tool for measuring the income gradient in BMI.

When considering the adult population, the OLS estimate from regressing BMI on income indicates that a one unit increase in income (e.g. increasing income from the poverty line to twice this level) reduces the average BMI by .16 points. The quantile estimates reveal that at the underweight threshold (BMI=18.5), a one unit increase in income increases BMI by .26 points and at the obese threshold (BMI=30), the same increase in income reduces BMI by .27 points. The OLS estimate is essentially showing an average effect and therefore can not reflect the changing signs of the income gradient.

In the final extension to this paper, income is introduced nonlinearly with a squared term. With this specification for all adults, there is initially an upward sloping gradient when evaluated at the quantile corresponding to the overweight threshold. The gradient then becomes negative at about 1.8 times the poverty line. This implies that for poor and lower income people, increases in income are associated with increases in BMI, but for those with incomes greater than 1.8 times the poverty line, income gains are associated with declines in BMI.

Finally, this specification is the only specification that suggests some similarities between men and women. When evaluated at the overweight and obese thresholds, the point estimates for the gradients indicate the same pattern for men and women, an increasing gradient at low income levels which then becomes negative at higher income levels. For men, both the coefficients on both income terms are statistically significant when evaluated at the obese threshold, and for women, they are significant at the overweight threshold. The primary difference for the male and female specifications is that the inflection point is at a much lower income level for women. So, for example, when evaluating at the overweight threshold, the gradient is positive for men up to 4.7 times the poverty line, where as for women, the gradient becomes negative at 2.2 times the poverty line.

In summary, this paper provides evidence that the cross tabulation of overweight and not overweight on poor and not poor provides a very incomplete picture of the association between income and BMI. The cross tabulation indicates that the poor have a significantly lower prevalence of overweight. The continuous measures of overweight indicate though that the BMI density function for the poor has more mass at the higher levels of BMI than the nonpoor density. The overweight poor have a higher average BMI than the overweight nonpoor. The quantile regression analysis further suggests that there is some evidence of a positive income gradient in BMI for the underweight and a negative gradient for the obese.

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Table 1: Overweight and Obese by Income

OW_α Indices of Overweight	1971 - 1974	1976 - 1980	1988 - 1994	1999 - 2000	2001 - 2002	2003 - 2004	% Change 1971-2004
Panel A: Overweight, BMI > 25							
Overweight, Poor	48.3	46.5	55.7	64.1	63.5	62.0	28%
	(1.54)	(1.40)	(1.40)	(2.57)	(1.45)	(1.87)	
Overweight, Not Poor	46.5	45.9	53.9	64.5	65.6	67.6	45%
	(0.77)	(0.84)	(1.09)	(2.09)	(0.80)	(1.33)	
Difference : (% points)	1.8	0.6	1.8	-0.4	-2.1	-5.6**	
Panel B: Obese, BMI > 30							
Obese, Poor	19.8	19.0	26.8	33.2	35.8	32.4	64%
	(1.09)	(1.02)	(1.38)	(1.25)	(2.13)	(1.47)	
Obese, Not Poor	13.3	13.5	21.3	29.6	29.1	32.8	147%
	(0.55)	(0.41)	(0.87)	(1.97)	(1.19)	(1.47)	
Difference: (% points)	6.5***	5.5***	5.5***	3.6	6.7***	-0.4	

Note: For all analysis in this paper, poor is defined as less than or equal to 130% of the poverty line. Statistical significance indicated with *, **, or *** for p-values less than 0.1, 0.05, and 0.01, respectively. Standard errors corrected for complex sample design using the NHANES pseudo design variables. All years exclude pregnant and breastfeeding women.

Table 2: Adult Overweight by Income

OW_α	Indices of Overweight	1971 - 1974	1976 - 1980	1988 - 1994	1999 - 2000	2001 - 2002	2003 - 2004	% Change 1971-2004
Panel A: Income < 130% poverty line								
OW_0	Prevalence	48.3	46.5	55.7	64.1	63.5	62.0	28%
		(1.54)	(1.40)	(1.40)	(2.57)	(1.45)	(1.87)	
OW_1	Depth	10.4	10.2	13.6	17.7	19.7	17.3	66%
		(0.46)	(0.48)	(0.68)	(0.66)	(1.15)	(0.79)	
OW_2	Severity	4.4	4.3	6.1	8.6	10.7	8.4	92%
		(0.35)	(0.39)	(0.51)	(0.59)	(1.04)	(0.67)	
Panel B: Income ≥ 130% poverty line								
OW_0	Prevalence	46.5	45.9	53.9	64.5	65.6	67.6	45%
		(0.77)	(0.84)	(1.09)	(2.09)	(0.80)	(1.33)	
OW_1	Depth	7.5	7.4	11.1	15.9	15.2	16.9	124%
		(0.22)	(0.18)	(0.43)	(1.07)	(0.45)	(0.62)	
OW_2	Severity	2.3	2.3	4.4	6.9	6.3	7.4	215%
		(0.14)	(0.1)	(0.33)	(0.77)	(0.36)	(0.48)	

Note: All overweight measures are multiplied by 100. Standard errors for OW_0, OW_1, and OW_2 are also multiplied by 100 and in parentheses. See notes for Table 1.

Table 3: Adult Overweight by Sex and Income

OW_α	Indices of Overweight	1971 - 1974	1976 - 1980	1988 - 1994	1999 - 2000	2001 - 2002	2003 - 2004	% Change 1971-2004
Panel A: Low Income Men (<130% poverty)								
OW_0	Prevalence	43.8	42.8	51.5	62.9	62.1	56.8	29%
		(2.18)	(1.99)	(1.97)	(2.67)	(3.17)	(3.22)	
OW_1	Depth	7.0	6.8	10.2	14.8	16.4	12.6	79%
		(0.5)	(0.44)	(0.68)	(1.18)	(1.48)	(0.88)	
OW_2	Severity	2.2	2.1	3.6	6.4	8.7	5.0	133%
		(0.3)	(0.27)	(0.48)	(0.91)	(1.60)	(0.66)	
Panel B: Low Income Women (<130% poverty)								
OW_0	Prevalence	51.7	49.0	59.0	65.1	64.7	66.1	28%
		(1.94)	(1.75)	(1.91)	(3.40)	(2.09)	(2.12)	
OW_1	Depth	12.9	12.5	16.4	20.0	22.3	21.0	62%
		(0.64)	(0.79)	(0.94)	(0.98)	(1.25)	(1.04)	
OW_2	Severity	6.0	5.8	8.0	10.3	12.3	11.1	84%
		(0.51)	(0.67)	(0.68)	(0.82)	(1.19)	(1.00)	
Panel C: High Income Men (≥300% poverty)								
OW_0	Prevalence	55.3	53.3	60.8	68.5	73.0	75.5	37%
		(1.73)	(1.10)	(1.29)	(1.81)	(1.40)	(2.06)	
OW_1	Depth	7.5	6.7	9.8	14.4	14.7	16.0	112%
		(0.39)	(0.23)	(0.43)	(1.24)	(0.67)	(0.89)	
OW_2	Severity	2.0	1.6	3.3	5.7	5.2	5.7	182%
		(0.31)	(0.10)	(0.36)	(1.10)	(0.72)	(0.58)	
Panel D: High Income Women (≥300% poverty)								
OW_0	Prevalence	34.4	34.9	44.0	57.1	56.1	58.4	70%
		(1.17)	(1.52)	(2.49)	(3.77)	(1.68)	(2.83)	
OW_1	Depth	6.0	6.7	10.1	14.7	14.8	16.5	172%
		(0.36)	(0.46)	(0.35)	(1.57)	(0.94)	(1.16)	
OW_2	Severity	2.1	2.6	4.1	6.5	6.6	8.4	300%
		(0.23)	(0.32)	(0.19)	(1.03)	(0.6)	(1.01)	

Note: See note for Table 2.

Table 4: BMI and Income, correlation coefficients

Income gradients, OLS and Quantile estimators	1971-1974	1976-1980	1988-1994	1999-2004
Panel A: All Adults, BMI				
OLS	-.14***	-.15***	-.17***	-.16***
	(.03)	(.03)	(.05)	(.05)
Quantile: Underweight	.16***	.18***	.07	.26***
	(.05)	(.05)	(.10)	(.10)
Quantile: Overweight	-.08	-.05	-.07	.03
	(.06)	(.05)	(.10)	(.07)
Quantile: Obese	-.38***	-.57***	-.36***	-.27***
	(.11)	(.08)	(.12)	(.08)
Sample size	*12,397*	*11,295*	*13,274*	*10,422*
Panel B: Males, BMI				
OLS	.13***	.13***	.05	.16**
	(.04)	(.03)	(.05)	(.07)
Quantile: Underweight	.41***	.31***	.11	.50*
	(.14)	(.08)	(.37)	(.28)
Quantile: Overweight	.18**	.18***	.10	.31***
	(.07)	(.05)	(.06)	(.09)
Quantile: Obese	-.13	-.24***	-.10	.07
	(.13)	(.07)	(.13)	(.11)
Sample size	*4,793*	*5,406*	*6,392*	*5,314*
Panel C: Females, BMI				
OLS	-.43***	-.45***	-.39***	-.46***
	(.05)	(.06)	(.06)	(.08)
Quantile: Underweight	.04	.12**	.00	.08
	(.07)	(.06)	(.11)	(.11)
Quantile: Overweight	-.43***	-.41***	-.36***	-.41***
	(.08)	(.07)	(.11)	(.09)
Quantile: Obese	-.78***	-.93***	-.65***	-.63***
	(.19)	(.16)	(.16)	(.14)
Sample size	*7,604*	*5,889*	*6,882*	*5,108*

Note: Standard errors corrected for complex sample design. Design effect for quantiles is assumed to be the same as for the means.

Table 5: Conditional BMI and Income, correlation coefficients

Income gradients, OLS and Quantile estimators	1971-1974	1976-1980	1988-1994	1999-2004
Panel A: All Adults, BMI				
OLS	-.10**	-.09**	-.20***	-.22***
	(.04)	(.04)	(.05)	(.06)
Quantile: Underweight	.10	.18***	.01	.27***
	(.07)	(.07)	(.11)	(.09)
Quantile: Overweight	-.07	.01	-.10	.05
	(.07)	(.04)	(.07)	(.07)
Quantile: Obese	-.20*	-.39***	-.35***	-.34***
	(.11)	(.09)	(.13)	(.10)
Sample size	*11,975*	*10,952*	*13,212*	*10,412*
Panel B: Males, BMI				
OLS	.09**	.08**	-.05	.06
	(.05)	(.04)	(.06)	(.09)
Quantile: Underweight	.42**	.22*	.05	.54
	(.18)	(.13)	(.39)	(.35)
Quantile: Overweight	.04	.11**	-.02	.25**
	(.06)	(.05)	(.08)	(.1)
Quantile: Obese	-.06	-.20**	-.24	-.04
	(.09)	(.08)	(.15)	(.16)
Sample size	*4,626*	*5,248*	*6,354*	*5,309*
Panel C: Females, BMI				
OLS	-.29***	-.27***	-.33***	-.48***
	(.06)	(.06)	(.07)	(.07)
Quantile: Underweight	-.02	.11*	-.01	.11
	(.08)	(.07)	(.14)	(.08)
Quantile: Overweight	-.25***	-.26***	-.22**	-.25***
	(.09)	(.08)	(.10)	(.07)
Quantile: Obese	-.50***	-.55***	-.54***	-.60***
	(.17)	(.14)	(.19)	(.11)
Sample size	*7,349*	*5,704*	*6,858*	*5,103*

Note: Conditioning on age, square of age, race and education levels. Standard errors corrected for sample design effects. Design effect for conditional quantiles is assumed to be the same as for the conditional means.

Table 6: 1999-2004 Income coefficients, Extensions

	OLS	Quantile (2%) Underweight	Quantile (35%) Overweight	Quantile (69%) Obese
Panel A: Income squared				
Income	.25	.33	.62**	.49
	(.22)	(.33)	(.27)	(.34)
Income^2	-.08**	-.01	-.10**	-.14**
	(.04)	(.06)	(.05)	(.06)
H_0: β_1=β_2=0	.001	.0004	.02	.0001
Inflection point	1.6	15.5	3.1	1.8
Panel B: Income spline, 3 knots				
Income, low (under 135%)	.16	-.06	.10	.31
	(.36)	(.51)	(.45)	(.60)
Income, mid (135%-250%)	-.05	.51	.63*	-.04
	(.25)	(.38)	(.32)	(.45)
Income, high (≥ 250%)	-.35***	.21	-.22	-.55***
	(.11)	(.14)	(.11)	(.15)
H_0: β_1=β_2=β_3=0	.005	.0003	.024	.001
H_0: β_1=β_2=β_3	.197	.676	.014	.075
Sample size	*11,975*	*10,952*	*13,212*	*10,412*

Note: Regressions condition on age, square of age, race and education levels. Income is relative to the poverty line. Standard errors corrected for sample design, design effect for conditional quantiles is assumed to be the same as for the conditional means. P-values are listed for tests that income coefficients are jointly equal to zero, and joint tests of significance. P-values for the quantile estimators are uncorrected.

Table 7: 1999-2004 Income coefficients, Extensions

	OLS	Quantile (1%) Underweight	Quantile (31%) Overweight	Quantile (71%) Obese
Panel A: Income squared, Male				
Income	.61**	.45	.60**	1.13**
	(.29)	(1.09)	(.29)	(.51)
Income squared	-.09*	.02	-.06	-.19**
	(.05)	(.18)	(.05)	(.09)
H_0: β_1=β_2=0	.11	.36	.0001	.028
Inflection point	3.3	-14.6	4.7	3.0
Sample size	*4,626*	*5,248*	*6,354*	*5,309*
Panel B: Income squared, Female				
	OLS	Quantile (3%)	Quantile (38%)	Quantile (66%)
Income	.16	.16	.72**	.44
	(.30)	(.36)	(.34)	(.48)
Income squared	-.11**	-.01	-.17***	-.18**
	(.05)	(.07)	(.06)	(.09)
H_0: β_1=β_2=0	<.0001	.38	.0001	<.0001
Inflection point	.7	9.0	2.2	1.2
Sample size	*7,349*	*5,704*	*6,858*	*5,103*

Note: See notes for Table 6.

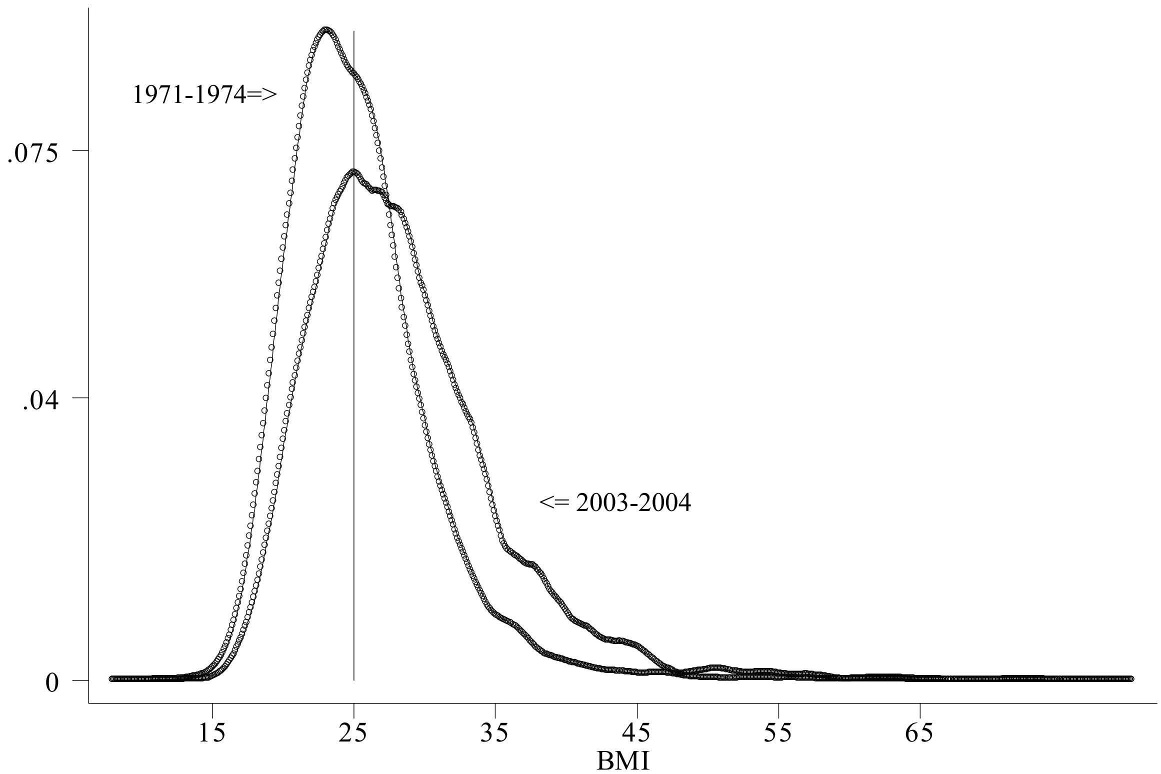

Figure 1: BMI density from 1971-1974 and 2003-2004

Notes: The Epanechnikov kernel is used to estimate the density functions with the smoothing parameter set to 0.75.

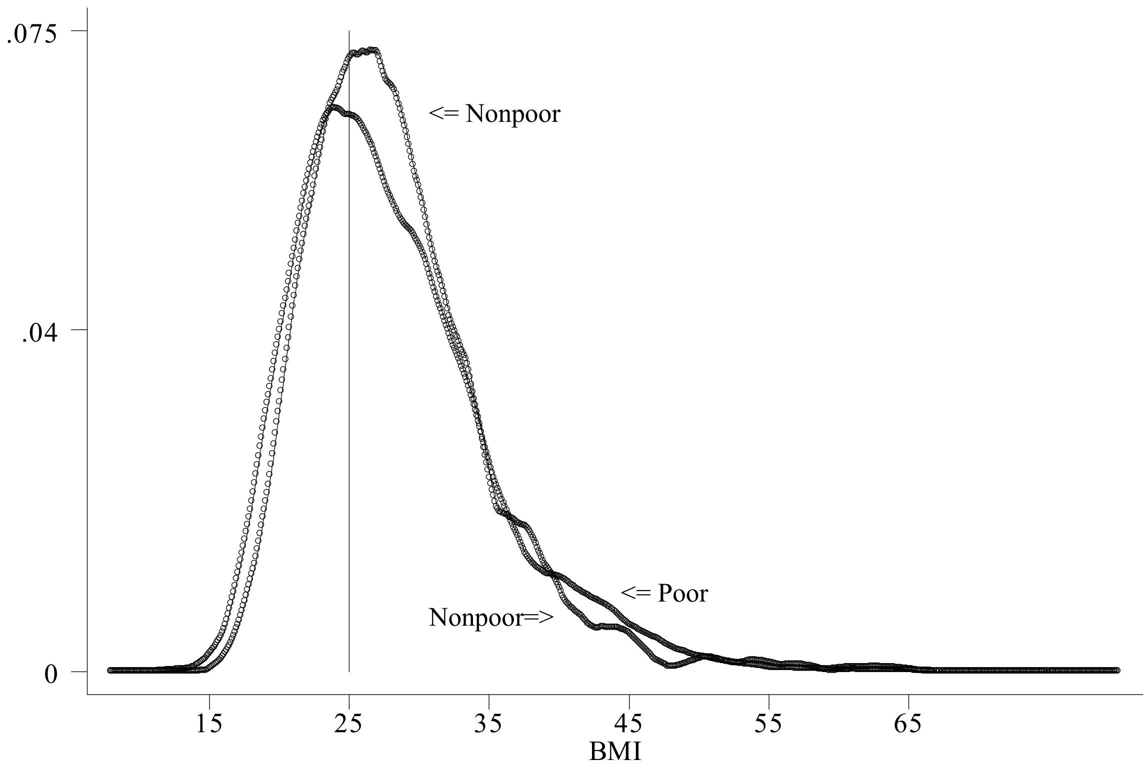

Figure 2: BMI density in 2003-2004 by income

Notes: Poor persons are those with incomes less than 130 percent of the poverty line, nonpoor are those with incomes greater than 130 percent. The Epanechnikov kernel is used to estimate the density functions with the smoothing parameter set to 0.75 for the nonpoor and 1.5 for the poor.