Race-Ethnicity and Unhealthy Body Mass: A Quantile Regression Analysis*

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Abstract

This paper examines how race-ethnicity and other social factors stratify BMI among American men and women in 2005. Building on social stratification theory, we launch an investigation into the stratification at the CDC pre-set standards for malnourishment, overweight, obesity, and extreme obesity as well as the full distribution of BMI, applying quantile regression models to the 2005 NHIS data. Our study offers a few major findings. First, black men do not differ from white men in BMI whereas black women have a much higher BMI than white women throughout the full BMI distribution, with a stronger effect in the overweight and obese ranges. Second, being Hispanic increases BMI for both genders and over the full BMI distribution: Hispanic men are particularly heavier in the extreme obese range while Hispanic women are so in the overweight and obese ranges. Third, being Asian is protective but acts differently by gender and across BMI standards. Asian men are thinner than white men at the overweight and obese ranges whereas Asian women are thinner at the obese and extreme obese ranges. Fourth, not only does income act independently of race for men but confound with race for women, but also exerts the opposite effect for men vs. women. High income men tend to be overweight whereas high income women tend to less overweight and less obese. Finally, immigration variables play a consistent role for both men and women and systematically become stronger with higher BMI. Although acculturation to American lifestyle erodes the immigrant advantage, be it diets, cultures, or self-selection, acculturation does not completely take this advantage away within the first generation.

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Introduction

The high prevalence and rapid growth of obesity among Americans pose a significant health threat to society. At the same time, people in deep poverty, who are more likely racial minorities, may suffer from malnourishment due to food insecurity. Both obesity and malnourishment can lead to serious health consequences. Body mass index (BMI), a spectrum of people's weight relative to their height, is a widely used health indicator. The disparities in obesity by race-ethnicity has been well documented. Less attention has been paid to the whole distribution of body mass index, in particular, the between- and within- racial group disparities of the entire spectrum of body mass index. We know very little whether and how racial-ethnic hierarchy shapes the lower tail (malnourishment) and upper tail (obesity) of the BMI distribution. The objectives of the paper are to bridge these gaps.

Using quantile functions, we document the between- and within racial-ethnic disparities patterns of BMI. Based on social stratification theory, we conceptualize the effect of racial-ethnic hierarchy on BMI, taking into account other stratification factors. Because quantile regression techniques offer appealing properties for inequality studies, we use quantile regression to estimate the total, partial, and interactive effects of race-ethnicity over the full distribution of BMI.

Our analysis draws data from the National Health Interview Survey (NHIS 2005), a large-scale nationally representative data. With our appropriate analytic tools for inequality studies and the most recent data, this research will provide fresh evidence for an important dimension of racial-ethnic inequality--health inequality.

Background

Obesity Prevalence

The prevalence of overweight and obesity has steadily increased over the years. Only about 15% of adult Americans were obese in the late 1970s, whereas about 31% were so in 2000. According to the Center for Disease Control and Prevention (CDC), obesity is related to other detrimental health and costly economic consequences. The Surgeon General's Call to Action to Prevent and Decrease Overweight and Obesity (2001) stated that in 2000, the indirect and direct costs of obesity totaled approximately $117 billion. The majority of these costs are due to obesity-associated health problems such as type 2 diabetes, coronary heart disease, and hypertension.

Race/Class Obesity Disparities

The most striking pattern of obesity is racial-ethnic disparities. Non-Asian racial-ethnic minorities are more likely to be overweight than their white counterparts. The National Health and Nutrition Examination Survey (NHANES) 1999-2000 reported the following racial-ethnic patterns of obesity: 69.6% of blacks and 73.4% of Mexicans compared to 62.3% of non-Hispanic whites were overweight (BMI greater than 25). Also, in comparison to 28.7% of whites, 39.9% of blacks and 34.4% of Mexicans had a BMI greater than 30 or were obese. Another striking pattern of obesity is income group disparities, but the relationship between income and obesity may be curvilinear. An earlier review summarizes that a monotonic, inverse relationship between socioeconomic status and obesity does not apply to the whole population (Sobal and Stunkard 1989). A curvilinear relationship is found between education and obesity (Zhang and Wang 2004). Hofferth (2004, 2006) warns us that people in deep poverty may be underweight due to food insecurity whereas people with moderate income may have the highest BMI. Gender and age further complicate the obesity disparities by race and class. Although gender disparities in obesity may be related to biomedical antecedents, social structural forces are also responsible for gender disparities.

Importance of Immigration

The trend of increasing immigrant inflows coincides with the trend of obesity. Of the 1990 total population, 8% were foreign born. By 2005, the percent of immigrants increased to 12.4. (Census Bureau, 1991, 2006). Contemporary immigration features continuous replenishment, mainly from Latin America and Asia, greatly expanding the Hispanic and Asian population shares. Correspondingly, recent immigrants' skills have concentrated at the bottom or top tails of the skill distribution, widening the U.S. class differentiation. As a result, most the immigrants today are Hispanics and Asians with moderate income. They bring in their original cultures of food, diet, taste, and physical exercise, but also adopt the American culture at varying speeds over time. This process of adapting to the new environment or culture or acculturation, can offer various benefits. However, acculturation may convert immigrants' dietary behaviors to those of the native born such as the American habit of frequent snacking (Nielsen, Siega-Riz, & Popkin, 2002). Thus, studies show that immigrants who spent less than 10 years in the U.S. generally have healthier weights than those with a longer duration of residence (Kaplan et al., 2004; Goel et al., 2004; Lauderdale & Rathouz, 2000). Hence, lengths of U.S. residence can be an additional factor that stratify the BMI of American population.

Theoretical Consideration

Social stratification theory underscores the role of social hierarchies according to race, class, and gender in determining the life chances of individuals who occupy specific structural positions in society (Weber 1947; Grusky 1994). Because race confounds with class, studies on race stratification of individual life chances must consider class stratification simultaneously. Racial minorities are more likely to have lower education, lower labor market skills, lower occupational prestige, lower income, and lower wealth, all of which have profound impact on health (Williams and Collins 1995). These aspect of disadvantage of racial minorities are essentially class stratification. With the same human capital, however, racial minorities face discrimination in the labor, housing, lending markets, resulting in spatial structure of race--racial residential segregation.

Two theories contend with one another on the relative importance of race and class in the formation of the underclass. On the one side, Wilson (1987) posits the rising significance of class in the making of black underclass. On the other side, Massey and Denton (1993) advocate the overwhelming importance of race. The contention over the relative significance of race and class has been focused on the black population but has not been extended to the non-black population. Studies on Hispanic-white segregation show that, unlike middle-class blacks who are segregated from middle-class whites, upwardly mobile Hispanics are integrated with whites so that Hispanic-white segregation is essentially class segregation (Farley and Frey 1994). Class, then, may play a more important role than race for the non-black population.

Racial residential segregation theory focuses on the multiple forms of discrimination against blacks. Slavery, Jim Crow laws, and housing market redlining were institutions, which historically isolated blacks from whites. Segmented labor markets, ethnic queuing in job market, racially differential treatments in housing and lending markets, welfare policies, and public housing projects have contributed to the increasing confinement of blacks to inner city neighborhoods. Massey and Denton (1993) argue that residential segregation has played an important role in exacerbating social stratification. Residential segregation enables other forms of racial discrimination beyond institutional racial discrimination in the labor, lending, and housing markets. In particular, health resources (public services, retail businesses, food industry, health care facilities, and physical exercise facilities) are spatially distributed to favor white neighborhoods. Traditionally, racial segregation focused on black-white segregation because the urban underclass was primarily a black phenomenon. As the population has become more diverse with the rapid growth of the Hispanic population, more recent segregation research extends the focus to Hispanic-white segregation (Frey and Farley 1996).

The reason why race/class hierarchies may shape BMI can be closely linked to spatial structure of race/class. Black and Hispanic neighborhoods as well as moderate-income neighborhoods exposure to excessive advertisements of fast foods and other unhealthy foods (Harrison and Marske 2005; Austin et al 2005). Race/class segregation is a structural source of the uneven and unfair distribution of health resources across neighborhoods. Race/class residential segregation restricts the disadvantaged from sufficient and good-quality health resources that promote positive health outcomes. Health resources include access to and quality of health care and preventive and diagnostic services (Kirby and Kaneda 2005), healthy foods (Horowitz et al 2004; Moore and Roux 2006), quality housing (Acevedo-Garcia 2000), and adequate facility and environment for physical activities (Saelens et al 2003; Giles-Corti and Donovan 2002). Not only does the accessibility to but also the price of health resources favor whites over blacks and the better-off over the disadvantaged. For example, suburban neighborhoods have chain supermarkets offering reasonable food prices on a variety of whole-grain products, low-fat dairy foods, and fresh fruits and vegetables; in contrast, inner city neighborhoods have small, old grocery stores with a large share of revenues from Food Stamps, where healthy foods are less available and more costly (Chung and Myers 1999; Morland et al 2002).

Williams and Collins (1995) in their review article propose additional social structures and processes by which race-ethnicity affect health. These include work, occupation, acculturation, migration, and childhood SES, which are unevenly distributed across racial-ethnic groups.

The above reasoning suggests that an assessment of racial stratification must take into account class, gender, and other related variables. In addition, racial effects may differ by class and gender, which must be rigorously examined. Our major goal is to pinpoint not only the partial effects of race but also the potential differential racial effects for different class groups and gender groups over the sections of unhealthy body mass along the BMI distribution.

Data Sources

The study draws data from the 2005 NHIS, which is a nationally representative survey of 38,509 households (102,467 persons) conducted by the National Center for Health Statistics. One adult per household is randomly selected to answer detailed questions on topics regarding demographic, socioeconomic, and health conditions. We confine our sample to respondents aged 25 to 54 to avoid the complications of child and young adult developmental and aging.[1] The resulting sample include 7,169 men and 8,461 women.

Measurement

According to the CDC, BMI=(weight in kilograms)/(height in meters)^2. For the U.S. system, BMI=703·(weight in pounds)/(height in inches)^2. Our analysis uses the CDC's absolute standards for malnourished (18.5), overweight (25), obese (30), and extreme obese (40). Given the different biomedical and social experiences between men and women, we perform separate analyses for the two gender groups and compare their patterns. Race-ethnicity is measured with three non-Hispanic groups—white, black, and Asian—and Hispanics. Class status is indicated by educational levels (lower than high school, high school graduate, some college, college graduate,

[1] We exclude pregnant women from the sample.

and beyond college) and categories of income-to-needs ratios (below 1, between 1 and 1.5, between 1.5 and 2.5, between 2.5 and 3.5, and above 3.5). We distinguish between the native-born and immigrants and among immigrants by years in the U.S. (less than 5 years, 5 to 10 years, 10 to 15 years, and more than 15 years). Marital status is measured by married, divorced/widowed/separated, never-married, and cohabiting statuses. We consider participation in the Food Stamps program because of the direct linkage of food with BMI. We control for life cycle effect by including age and age-squared. Also controlled is number of children. See Appendix Table for descriptive statistics for variables used in analyses. On average, American adult population is overweight and a typical man is more overweight than a typical woman: the mean BMI is 27.4 for men and 26.7 for women. Compared to men, women are less likely to have an income-to-needs ratio over 3.5 and more likely to be divorced/widowed/separated. In addition, fewer women immigrants have stayed in the U.S. for more than 15 years. Other explanatory variables are quite evenly distributed between men and women.

Analytic Strategies

Quantile Functions

We use quantile functions to describe the between- and within race-ethnicity disparities. The median is a special *quantile*, the one which describes the central location of a distribution. Other quantiles can be used to describe non-central positions of a distribution. The *quantile* notion generalizes specific terms like quartile, quintile, decile and percentile. The p^{th} quantile denotes a value of the response, below which the proportion of the population is $p \sim (0,1)$. Thus, quantiles can be specified at any points of a distribution. For example, 2.5% of the population lies below the .025$^{\text{th}}$ quantile. Quantile functions express quantiles as a function of p. Producing the quantile function of BMI for different racial-ethnic groups and by other stratification variables, we can compare between-group differences using the median and within-group inequality at any specific quantiles along the distribution (e.g., the $.05^{th}$ and $.95^{th}$ quantiles).

Quantile Regression

The empirical model used for analysis in this paper is quantile regression (Keonker and Bassett 1978; Keonker 2005; Hao & Naiman forthcoming 2007). Though relatively new to research on BMI, the quantile regression technique has been applied to studies on economic inequality by race-ethnicity (Buchinsky 1994; Chay & Honore, 1998; Hao 2006). Let y_i be the BMI for individual i, and x_i is a vector of race-ethnicity, class, other stratification factors, individual characteristics, and the constant, the quantile regression model can be expressed as: $y_i = \beta^{(p)} x_i + \varepsilon_i^{(p)}$, where $0 < p < 1$ indicates the cumulative proportion of the population. $Q_t^{(p)}(y_i \mid x_i) = \beta^{(p)} x_t$ denotes the conditional p^{th} quantile given x_i. The p^{th} conditional quantile is estimated with the quantile-specific parameters, $\beta^{(p)}$, and the values of the covariates x_i. We will identify the quantiles corresponding to the CDC's 4 standards regarding BMI and estimate quantile regression models at these specific quantiles. To understand the impact of stratification on the full BMI distribution, we also estimate equal-interval quantiles over the entire BMI distribution.[2] By testing the equivalence of quantile regression coefficients of a covariate across quantiles, we can determine whether a covariate has significantly different effects on different quantiles.

Quantile regression models are appropriate in our research for two reasons. First, the conventional OLS models assume that the effects of covariates on the conditional mean of the response are constant on any points of the response distribution. Since we are interested in the stratification effects on the points corresponding to the CDC's 4 standards, we need to actually

[2] We use Stata "sqreg" to perform simultaneous quantile regression estimation with bootstrap standard errors. We are then able to test the equivalence of coefficients for a covariate among quantiles.

estimate the potential differential effects of stratification factors on these different quantiles. Second, self-reported height and weight may be biased downward for extremely obese persons (Plankey et al. 1997; Ezzati et al. 2006). In addition, a common practice to protect confidentiality of sensitive survey data is to top- or bottom-code BMI at the two extremes (NCHS 2005). Both will seriously distort OLS estimates. The robustness property of quantile regression, however, helps overcome these problems so long as the quantiles are not specified beyond the under-reported or top-coded at the upper tail and beyond the bottom-coded at the lower tail (Keonker 2005; Hao and Naiman 2007).

Results

Gendered Patterns of Unhealthy Body Mass

Table 1 shows the gendered patterns of body mass categories. Although the percentage for malnourishment is small, more women (2.07%) than men (0.17%) are malnourished. The female advantage is observed in the normal weight category: more women (46.68%) than men (28.08%) have normal weight. The percentage for overweight reverses and becomes much larger for men (46.61%) than for women (28.31%). Women continue to have an advantage over men at the obese category, 20.8% vs. 24.43%, respectively. However, women take the lead to be more extremely obese at 2.14% than men at 0.7%.

(Table 1 about here)

To examine the full BMI distribution, we present two types of graphs. The familiar histograms (density functions) for men and women with a normal curve imposed are presented in Figure 1. We mark the 4 CDC standards in the histograms. The distribution for women is more right-skewed than men's, contributed by women's higher density over the normal weight range. In addition, the women's distribution has a heavier top tail than the men's.

(Figure 1 about here)

The inverse cumulative distribution functions are quantile functions. Graphically, the x-axis indicates the cumulative proportion of the population (p) and the y-axis indicates the quantiles, the BMI scores at each p. Figure 2 presents the quantile functions for men (the solid line) and women (the dashed line). Four horizontal lines represent the 4 CDC standards for BMI. Regarding the familiar median, we find BMI of 27 for men and BMI of 25 for women. The percentages of population below each CDC standard for BMI can be easily seen in quantile functions. For example, the overweight standard at BMI of 25 is corresponding to $p = .30$ for men and about $p = .47$ for women, meaning that about 30% of men and 47% of women are below the standard of overweight. While quantile functions serve as an alternative descriptive tool for group patterns, they are preferred for their direct relationship to quantile regression. That is, the quantiles corresponding to the 4 CDC standards, rather than the mean, will be estimated in our quantile regression models, conditional on the explanatory variables. These quantiles have precise medical, epidemiological meanings for us to pinpoint the impact of social stratification variables.

(Figure 2 about here)

The drastic gender differences in BMI suggest a need to take a closer look at the potential differential patterns of BMI by other stratification variables. For men, we examine the BMI patterns by race, education, immigration, and Food Stamps participation whereas for women we add income-to-needs and marital status, which do not clearly differentiate BMI for men but do so for women. The overall impression from the four graphs for men is that these social stratification variables do not greatly stratify men's BMI. One clear pattern is that Asian men have much lower BMI than other racial-ethnic groups, as the Asian curve lies much below the lines for other racial groups. Such an extent of differences is not observed for education, years in the U.S., or Food

Stamps status. By contrast, social stratification variables play a much more important role in women's BMI. The racial patterns rank black women at the top, followed by Hispanic, white, and Asian at the bottom, meaning that Asian women have the lowest BMI among the racial groups. Education levels at college and above give women an advantage, so do higher income, shorter lengths in the U.S. and nonuse of Food Stamps. Marital status only moderately differentiates women's BMI. These observed patterns may or may not hold in the multivariate framework, to which we now turn.

(Figures 3 and 4 about here)

Replication of OLS Analysis

We begin our analysis by replicating conventional OLS models, using the continuous measure of BMI, rather than obese status, because we are interested in making a full use of the variation in BMI. The OLS model also serves as a basis to compare with quantile regression models. If the explanatory variables contribute to only the group mean differences without changing the shape of the group distribution, OLS results would be consistent with quantile regression results, assuming no data contamination such as under-reporting and top-coding.

Our goal here is to understand whether race is confounded with other social stratification variables, including class, immigration, family, and welfare participation. Our five nested models progressively introduce these variables to assist a better understanding of the race effect when other social factors are partial out step by step. We perform separate analysis for men and women. We focus our interpretation both within and between gender groups.

Table 2 presents the results from the OLS nested Models 1 through 5 for men. Overall, these models explain only a small percentage (2 to 5%) of the variation in men's BMI. Model 1 reports the effect of race on BMI, using whites as the reference, controlling for age and age-squared. Black and white men are not statistically significantly different; but Hispanic men have a higher BMI and Asian men have a lower BMI than white men. Specifically, on average, Hispanic men' BMI is .584 points higher while Asian men's BMI is 2.024 points lower than white men's.

(Table 2 about here)

Model 2 adds education and income to Model 1. Higher educational attainment is beneficial for healthy weight status. The negative effects of college education (-.649) and beyond college education (-1.074) results in lower average BMI. With education being controlled, however, men with higher income-to-needs ratio (2.5 and above) are significantly more likely to be heavier than those in poverty. This perplexing finding suggests that higher income does not help men obtain healthy food and physical exercise as we previously thought. As we will see later, this effect reverses for women. Education and income appear to affect BMI independently of race since the effects of race remain statistically the same as those in Model 1.

Model 3 adds years of residence in the U.S. to Model 2. Recent immigrants who have arrived in the U.S. within 5 years are less likely to be overweight/obese and the effect is very strong. Their average BMI is 2.053 points lower than the native-born. Different from previous research that found a 10-year threshold for immigrant health decline (Goel et al. 2006), we find that immigrants who have stayed in the U.S. for as long as more than 15 years still have a significantly lower BMI than natives, although this advantage reduces with the increasing years in the U.S. With the introduction of immigrants' U.S. residence, the effect of being Hispanic increases from .542 in Model 2 to 1.2 in Model 3, because the proportion of immigrants is much higher among Hispanics than the population as a whole. Similarly, Asian men do not have as much an advantage over white men as found in Model 2 once the immigration variables are included. These results about the confounding effects of race and immigration suggest that it is very important to separate out immigration effects while examining race effects .

Model 4 further includes marital status and number of children as part of the explanatory variables. Because the effects of number of children are by and large insignificant in all the models estimated in this paper, we did not present them in the tables. Unmarried statuses, including divorced/widowed/separated and single/never-married, significantly lowers BMI by about .8 points, compared to married status. Controlling marital status turns the effect of being black to become significant because black men are more likely to be unmarried than the whole population. However controlling for marital status does not change the effects of being Hispanic or Asian. In addition, family factors take away the income effects for men.

Finally, Model 5 includes receiving Food Stamps and finds that men receiving food stamps tend to be heavier. Introducing the Food Stamps variable changes the effect of moderate income from insignificant to positive. However, this welfare participation effect is independent of race effects. The partial race effects estimated in Model 5 are likely to come from sources not measured in the model, including racial residential segregation, distribution of healthy food, obesigenic environment, dietary and exercise behavior, and biomedical factors.

The OLS nested regression estimates for women are shown in Table 3. The explanatory power of each model is greater for women than for men (the R-squared ranging from 6% to 10%). Model 1 reports that black women are significantly more likely to have higher BMI than do white women (2.771). Though not as strong as the effect for blacks, Hispanic women also have significantly higher BMI than do white women (1.943). A reverse effect is reported for Asian women, who have significantly lower BMI compared to white women (-2.223).

(Table 3 about here)

In Model 2, women with college or beyond college education are significantly more likely to have lower BMI (-1.649 and -2.001, respectively). As for income-to-needs ratios, the protective effect increases monotonically with the level of income-to-needs. The effects of education and poverty are independent from race for Asians and blacks, but confound with being Hispanic. Controlling for education and income significantly lowers the effect of being Hispanic from 1.943 in Model 1 to 1.217 in Model 2, primarily due to the fact that Hispanic women are lower educated than white women.

Model 3 results indicate that the effects are particularly strong for recent immigrants who significantly more likely to have lower BMI than natives. Increased years in the U.S. takes away some of the protective effect by reducing the negative effect from -2.460 (less than 5 years) to -.730 (15+ years). Nonetheless, being an immigrant definitely helps healthy weight status for women. Because more than half of Asians and Hispanics are immigrants, controlling for immigration makes the detrimental effect of being Hispanic greater (from 1.217 to 1.859) and the beneficial effect of being Asian smaller (from -1.971 to -.863). Model 4 further takes into account marital status and children, which play no role in stratifying women's BMI. However, when using Food Stamps is introduced to model 5, divorced/widowed/separated women have lower BMI and women who receive Food Stamps have 1.193 points higher in BMI than those who do not. Introducing the Food Stamps variable takes away the protective effect of moderate income but gives significance to the negative effect of being divorced.

Models 1 to 5 examine the potential confounding between race and other stratification factors, the intersections of which are yet to be considered as suggested by the intersectional approach. Moving beyond those models, we explored a full set of potential interactions between race and each of the following: education, income, lengths of U.S. residence, marital status, and Food Stamps participation for both men and women. The only significant interaction effect we found was the interaction between the indicator for blacks and the indicator for college and beyond education for women only, with a coefficient at 1.600 significant at the .001 level. In this interactive model, the coefficient of being black becomes 1.885, the college education coefficient becomes -1.784 and that for beyond college becomes -2.078, all of which are significant. Combining a main effect with the interaction effect, we find that college-educated black women are 1.885+1.600=3.465 points higher in BMI than their white counterparts. High education does not protect black women any more: $-1.784+1.600=-.184$, which is insignificant. This is also true for black women with beyond college education. This finding warrant careful interpretations of the race-class intersection. However, given this is the only evidence to support intersectional approach, our comparisons between the two genders and the next step of analysis using quantile regression will focus on Model 5.

After examining the two gender groups separately, we now highlight the major gender differences revealed in Model 5 of Tables 2 and 3. First, black men are just slightly heavier than white men whereas black women are much heavier than white women. The gender difference in the effect of being Hispanic is similar. Second, men with moderately higher income tend to be heavier than their poorer or wealthier counterparts, suggesting a curvilinear income effect that is absent for women. By contrast, when the income-to-needs reaches 3.5, higher income protects women and reduces their BMI. Third, men who are single/never-married have lower BMI than those who are married. This effect is absent for women. Beyond these differences in signs and significance levels, gender groups also differ in the magnitudes of effects: stronger education and welfare effects for women than men. The only variable that does not differ between gender is the immigration effect, protecting both men and women to the same degree.

Quantile Regression Analysis

The OLS regression models assume that the effects of covariates on the conditional mean of BMI are the same for other points throughout the entire distribution. This is a strong assumption. When the substantive interest does not actually fall in the mean but pre-set, absolute standards along the distribution, such as the 4 CDC standards for malnourished, overweight, obese, and extreme obese statuses, it is necessary to test whether the OLS assumption stands true. Quantile regression models allow estimation at any points of the response distribution and thus, is appropriate for our purpose. Our quantile regression models specify 4 quantiles corresponding to the 4 CDC: .03th, .30th, .76th, and .97th for men and .03th, .47th, .75th, and .97th for women. The quantile corresponding to the overweight standard differs by gender was discussed in the descriptive results section. The bottom and top quantiles are set at .03th and .97th for both men and women to take advantage of the robustness property of quantile regression and to allow sufficient statistical power from the two tails.[3] The model specification include explanatory variables used in Model 5 of the OLS analysis. Because the different nature between malnourishment and overweight/obesity, we expect that the explanatory variables have opposite effects on the .03th quantile for malnourishment from those on the other quantiles for heavy body mass statuses.

Table 4 presents the quantile coefficients for the 4 quantiles of men's BMI. We first examine the first column for the .03th quantile coefficients. Three variables are found significant: positive (protective) for being Hispanic and having high income-to-needs and negative (detrimental) for being single/never married. Looking across columns, these effects do not change sign as we expected. For instance, being Hispanic is protective against malnourishment but increases the BMI at the overweight standard and above. A similar interpretation is true for having high income-to-needs. The significance level of having high income does change and becomes insignificant at the higher quantiles. The single status, too, becomes insignificant at the top quantile. All other grouping variables have no significant impact on malnourishment, many which do have a significant different role for other heavy-status quantiles and many do reverse

[3] The estimation of a tail quantile uses all the sample data points, rather than just the tail data points, but uses a greater weight for the tail.

their signs. These results strongly suggest that the effect of explanatory variables on the BMI bottom tail are different from the quantiles indicating heavy weight statuses. They suggest that the OLS assumption of constant effects of covariates throughout the BMI distribution does not hold and quantile regression provides more valid estimates for overweight and obese problems.

(Table 4 about here)

For higher quantiles than the .03th, negative coefficients signify lower BMI and thus protective, while positive coefficients imply greater BMI and thus detrimental. At the .30th quantile, race is an important factor since Hispanic men are more likely to be overweight (1.128), and Asian men are less likely to be overweight than whites (-.695). Education does not play a role at this quantile. Men who have moderate and high income are significantly more likely to be overweight than men in poverty or near poverty. Shorter or longer lengths in the U.S. are protective. Although the effect appears to be stronger for those who lived in the US for 5 to 10 years (-1.228) than less than 5 years (-.996), but decreases for 10 to 15 years (-.796) and for 15+ years (-.553), a test indicates that there is only a significant decrease from 5 to 10 years to 15+ years. In addition, divorced/widowed/separated and single men are less likely to be overweight than their married peers.

At the .76th quantile for obese status, we focus on significantly differential effects from those at the .30th quantile, marked by "d" based on between-quantile coefficient tests. Three variables have a significantly different effect on the .76th quantile vs. the .30th quantile. Beyond-college education reduces BMI only at the .76th quantile; having arrived within 5 years and within 10-15 years become much more protective at the obese level than at the overweight level. These results provide further evidence that the OLS assumption of constant effects of covariates throughout the BMI distribution does not hold.

Moving to the .97th quantile estimates, we look for differential effects across the three heavy-status standards. The between-quantiles tests shows that many of the effects on extreme obesity become significantly stronger than those on obesity and overweight. For example, the effects of being Hispanic, having college or above education, and various lengths of U.S. residence become much stronger. Single/never-married status, however, loses its significant negative effect at the top tail. These results provide one more set of evidence to reject the OLS assumption and provide more accurate estimates for the stratification of BMI by social stratification variables.

Do the results about the differential coefficients across quantiles for men also hold for women? We move to Table 5 for women. At the .03th malnourishment quantile, only race plays a role: black and Hispanic women are less likely to be malnourished. As for men, many coefficients at the lower tail are significantly different from those at heavy-status quantiles. Examining the differential effects across overweight, obese, and extreme obese quantiles, we find three variables with significantly different effects across the three quantiles: the protective effect of being Asian is the strongest at the top tail and the immigrant protective effects become much stronger at the obese quantile and remain similar at the extreme obese quantile. Compared with the results for men, fewer differential effects are found for women. Yet, the OLS assumption still does not hold for women since OLS models underestimate the Asian effect and immigrant effects for the epidemic of obesity and extreme obesity and its implication for diseases such as diabetics, hypertension, coronary heart disease and others.

(Table 5 about here)

A Graphic View for the Stratification of the Full Distribution of BMI

Our quantile regression models have thus far addressed the 4 CDC standards. How do social stratification variables stratify the full distribution of BMI? We answer this question by estimating 19 equal-interval quantiles (every 5% from .05th to .95th) plus the .03th and .97th quantiles. The results are presented in Figures 5 and 6 for men and women, respectively.

(Figures 5 and 6 about here)

The setup of the figures is similar to the quantile function graphs we previously examined, except that the coefficients for the series of quantiles are mapped against the cumulative proportions at the x-axis. The solid curve is for the point estimates and the shaded area indicates the 95% confidence envelope estimated with 100 bootstrap samples. We draw a thick horizontal line through 0 at the y-axis. If the CI envelope crosses this line, the coefficients within the envelope are not significant. We also draw 4 vertical lines to indicate the 4 CDC standards, which divide the full distribution into health status ranges. We examine the shape of the coefficient line: a near-horizontal line indicates that OLS estimate is robust and a deviation from it indicates that the effect of the variable in question differs across the full distribution of the conditional quantile function.

Figure 5 shows race effects and several selected variables with significant effects. Blacks have a near-horizontal line and the CI envelope cross the zero horizontal line, indicting a lack of overall significance. The Asian effects are significant in the overweight range and the line is near-horizontal. The Hispanic effect is significantly positive throughout the distribution, with a much greater effect at the top tail. By contrast, the lines for higher education and immigrants' lengths of U.S. residence are below the zero horizontal line, and have a down-sloping line, indicating the steadily increasing negative (protective) effects of these variables as we move toward the right tail. The non-married status effects are curvilinear: strongest at the middle-upper ranges than the two tails. The welfare participation effects are significant only at a small range of the top half of the distribution.

Turning to Figure 6 for women, a general impression is that all the presented variables have differential effects for the full distribution of the conditional quantile function. Moreover, these are not straight lines. The detrimental effects of being black and Hispanic are stronger at the middle range than the two tails whereas the protective effect of being Asian is strong and significant only for the obese range. The effect of education and income become stronger as moving rightward but reduce when reaching the obese range. Similar findings are shown for 3 out of 4 variables for immigrants' lengths of U.S. residence and Food Stamps use. Divorced women tend to have lower BMI only at the normal and moderately overweight range.

These patterns add rich information to what we learned from the 4-quantile estimates in Tables 4 and 5. They pinpoint the stratification by each factor for each range of the BMI-related health status. Among findings from many interesting patterns, we stress that a complete view of the full distribution, rather than at only the conditional mean, is important for both men and women.

Conclusions

This paper examines how racial-ethnic hierarchy and other social stratification factors stratify BMI among American men and women in 2005. Building on social stratification theory, we launch an investigation into the stratification patterns at the CDC pre-set standards for malnourishment, overweight, obesity, and extreme obesity as well as the full distribution of BMI.

Our study uses a simple specification of main social grouping variables. This approach facilitates us to untangle potential confounding relationships among race-ethnicity, class, and gender. With the profound transformation of American population due to a 4-decade mass immigration, we also consider variables distinguishing between natives and immigrants and lengths of U.S. residence among immigrants as a stratification variable, which may confound with race-ethnicity. Moreover, efforts are made to detect potential differential effects of race-ethnicity for different class groups, gender groups, and U.S. resident length groups. With this focus, our study does not tackle biomedical and health care factors, nor does it look at intermediate processes such as dieting and exercising.

Methodologically, we use quantile regression models, which is more appropriate than the conventional OLS regression models or logistic regression model for our objective to pinpoint the exact stratification pattern by each social stratification factor while controlling for others, at the CDC standards for BMI and for the full BMI distribution.

Our descriptive analysis shows that 20% more women than men are in the normal weight range while 20% more men than women are in the obese range. This drastic gender difference raises the need for separate analysis for men and women. The within-gender observed stratification patterns by race, however, is more salient for women than for men and so are class, immigration, and other variables.

Our replication of OLS analysis sorts out the potential confounding relationships among major stratification factors. Our analysis shows that the effect of race-ethnicity is independent of the effect of class for men but not for women. The gendered confounding pattern is important for future research to take different strategies in searching for the sources of racial disparities among men vs. among women. Immigration variables, by contrast, confound with indicators for Hispanics and Asians. The unaffected black effect, particularly detrimental among women, suggests a harder effort should be made for health policy makers, health professionals, and the public at large to curb the obesity epidemic. Although many of the stratification variables are confounding with each other, they do not interact to produce differential effects as suggested by the intersectional approach (Williams and Collins 1996). The only exception is the interaction between black and college education among women, which finds black women with college and above education actually have a higher BMI, adding another paradox to the obesity and health literature.

Our quantile regression analysis for the 4 CDC standards and the full BMI distribution provides strong evidence that the OLS assumption about the constant effect of a factor throughout the BMI distribution does not hold. The stratification effects of social factors do vary between the bottom quantile and the heavy-status quantiles and many effects vary across the heavy-status quantiles.

We highlight our substantive findings around the role of race-ethnicity. First, when other major stratification factors are controlled, being black does not significantly affect men in most part of the BMI distribution. By contrast, black women have a much higher BMI than white women through out the full BMI distribution, with stronger effects in the overweight and obese ranges. Second, being Hispanic increases BMI for both genders and over the full BMI distribution. The ranges of BMI being affected most heavily differ between men and women: Hispanic men are particularly heavier in the extreme obese range while Hispanic women are so in the overweight and obese ranges. Third, being Asian is protective but acts differently by gender and across BMI standards. Asian men are thinner than white men at the overweight and obese ranges whereas Asian women are thinner at the obese and extreme obese ranges.

Our findings about income differ greatly between the two gender groups. Not only does income act independently of race for men but confound with race for women, but also exert opposite effect for men vs. women. High income men tend to be overweight whereas high income women tend to less overweight and less obese.

The largest effect among stratification factors is found of immigration variables, which play a consistent role for both men and women and systematically become stronger with higher

BMI. All immigrant men and women, particularly those who arrived more recently, are more likely to have a normal weight. Although acculturation to American lifestyle erodes the immigrant advantage, be it diets, cultures, or self-selection, acculturation does not totally take this advantage away within the first generation.

These accurately identified stratification effects will provide the health community with important information as to which particular groups to focus in order to curb the obesity epidemic in America. Further research will need to identify the sources of racial disparities in obesity, including racial residential segregation and the distribution of healthy, affordable food.

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Table 1. Gendered Patterns of Body Mass Categories

Gender	Malnourished	Normal	Overweight	Obese	Extreme Obese
Male	0.17	28.08	46.61	24.43	0.70
Female	2.07	46.68	28.31	20.80	2.14
Total	1.12	37.31	37.52	22.63	1.42

Data source: National Health Interview Survey (NHIS) 2005, National Center for Health Statistics.

Table 2. Nested Regression Models for BMI: Male, 2005

Variable	(1)	(2)	(3)	(4)	(5)
Race (reference: whites)					
Black	0.219	0.153	0.234	0.366*	0.348*
	(0.153)	(0.155)	(0.154)	(0.154)	(0.154)
Hispanic	0.584**	0.542**	1.200**	1.149**	1.147**
	(0.127)	(0.137)	(0.162)	(0.161)	(0.161)
Asian	-2.024**	-1.757**	-0.863**	-0.836**	-0.850**
	(0.263)	(0.264)	(0.287)	(0.286)	(0.286)
Education (reference: < H.S.)					
High school	--	0.083	-0.030	0.005	0.031
		(0.162)	(0.162)	(0.161)	(0.162)
Some college	--	0.243	0.081	0.122	0.154
		(0.161)	(0.162)	(0.161)	(0.162)
College	--	-0.649**	-0.746**	-0.682**	-0.646**
		(0.177)	(0.177)	(0.177)	(0.178)
Beyond college	--	-1.074**	-1.084**	-1.115**	-1.082**
		(0.221)	(0.220)	(0.219)	(0.219)
Income-to-needs ratio (reference: < 1.0)					
1.0-1.5	--	-0.004	0.035	-0.121	-0.028
		(0.269)	(0.269)	(0.268)	(0.271)
1.5-2.5	--	0.124	0.085	-0.044	0.098
		(0.223)	(0.223)	(0.222)	(0.231)
2.5-3.5	--	0.583**	0.519*	0.393	0.545*
		(0.226)	(0.226)	(0.226)	(0.237)
3.5+	--	0.516*	0.413*	0.245	0.397
		(0.206)	(0.206)	(0.209)	(0.220)
Years in the U.S. (reference: natives)					
< 5 years	--	--	-2.053**	-2.125**	-2.082**
			(0.323)	(0.322)	(0.323)
5-10 years	--	--	-1.429**	-1.564**	-1.530**
			(0.271)	(0.270)	(0.270)
10-15 years	--	--	-1.295**	-1.405**	-1.376**
			(0.302)	(0.300)	(0.300)
15+ years	--	--	-0.869**	-0.967**	-0.949**
			(0.187)	(0.186)	(0.187)
Marital Status (reference: married)					
Divorced/widowed/separated	--	--	--	-0.787**	-0.796**
				(0.151)	(0.151)
Single/never married	--	--	--	-0.848**	-0.856**
				(0.149)	(0.149)
Cohabiting	--	--	--	-0.316	-0.357
				(0.209)	(0.209)
Receiving food stamps	--	--	--	--	0.530*
					(0.244)
Constant	21.135**	21.072**	21.403**	23.287**	23.110**
	(1.142)	(1.150)	(1.152)	(1.177)	(1.180)
n	7169	7169	7169	7169	7169
R-squared	0.02	0.03	0.04	0.05	0.05

Note: All models control for age and age-squared. Models (4) and (5) also control for number of children.
* p < .05 ** p <. 01

Table 3. Nested Regression Models for BMI: Female, 2005

Variable	(1)	(2)	(3)	(4)	(5)
Race (reference: whites)					
Black	2.771**	2.323**	2.355**	2.317**	2.249**
	(0.165)	(0.168)	(0.167)	(0.173)	(0.173)
Hispanic	1.943**	1.217**	1.859**	1.841**	1.838**
	(0.152)	(0.164)	(0.188)	(0.188)	(0.188)
Asian	-2.223**	-1.971**	-0.863*	-0.867*	-0.879*
	(0.345)	(0.342)	(0.373)	(0.374)	(0.373)
Education (reference: < H.S.)					
High school	--	-0.367	-0.505*	-0.482*	-0.394*
		(0.196)	(0.197)	(0.197)	(0.197)
Some college	--	-0.233	-0.399*	-0.365	-0.256
		(0.192)	(0.193)	(0.193)	(0.194)
College	--	-1.649**	-1.740**	-1.721**	-1.571**
		(0.219)	(0.219)	(0.220)	(0.221)
Beyond college	--	-2.001**	-2.052**	-2.030**	-1.881**
		(0.258)	(0.258)	(0.259)	(0.260)
Income-to-needs ratio (reference: < 1.0)					
1.0-1.5	--	-0.623*	-0.567*	-0.535	-0.195
		(0.276)	(0.275)	(0.276)	(0.283)
1.5-2.5	--	-0.551*	-0.581*	-0.526*	-0.037
		(0.234)	(0.233)	(0.236)	(0.253)
2.5-3.5	--	-0.923**	-0.978**	-0.927**	-0.416
		(0.249)	(0.249)	(0.254)	(0.272)
3.5+	--	-1.322**	-1.389**	-1.357**	-0.876**
		(0.220)	(0.220)	(0.233)	(0.250)
Years in the U.S. (reference: natives)					
< 5 years	--	--	-2.460**	-2.442**	-2.314**
			(0.419)	(0.420)	(0.420)
5-10 years	--	--	-1.936**	-1.924**	-1.817**
			(0.329)	(0.330)	(0.331)
10-15 years	--	--	-1.764**	-1.756**	-1.684**
			(0.351)	(0.352)	(0.352)
15+ years	--	--	-0.730**	-0.743**	-0.669**
			(0.235)	(0.236)	(0.236)
Marital Status (reference: married)					
Divorced/widowed/separated	--	--	--	-0.285	-0.367*
				(0.157)	(0.158)
Single/never married	--	--	--	0.233	0.125
				(0.178)	(0.179)
Cohabiting	--	--	--	0.126	0.054
				(0.276)	(0.275)
Receiving food stamps	--	--	--	--	1.193**
					(0.225)
Constant	21.792**	23.130**	23.529**	23.326**	22.369**
	(1.368)	(1.357)	(1.357)	(1.388)	(1.397)
n	8461	8461	8461	8461	8461
R-squared	0.06	0.09	0.10	0.10	0.10

Note: All models control for age and age-squared. Models (4) and (5) also control for number of children.
* p < .05 ** p <. 01

Table 4. Quantile Regression Models for BMI at Malnourishment, Overweight, Obese, and Extremely Obese Standards: Male, 2005

Variable	Q.03	Q.30	Q.76	Q.97
Race (reference: whites)				
Black	-0.125 [b]	0.250	0.563*	1.020
	(0.228)	(0.142)	(0.248)	(0.614)
Hispanic	0.843** [c]	1.128**	1.021**	2.125** [f]
	(0.287)	(0.157)	(0.241)	(0.582)
Asian	0.134 [a b]	-0.695**	-1.420**	0.662
	(0.385)	(0.252)	(0.364)	(1.208)
Education (reference: < H.S.)				
High school	0.439	0.198	0.467	-0.623 [f]
	(0.251)	(0.172)	(0.256)	(0.545)
Some college	0.198	0.168	0.379	-0.491
	(0.219)	(0.162)	(0.262)	(0.581)
College	0.286 [b c]	-0.239	-0.806**	-1.915** [e]
	(0.300)	(0.187)	(0.289)	(0.666)
Beyond college	-0.128 [c]	-0.434	-1.394** [d]	-2.381** [e]
	(0.369)	(0.231)	(0.327)	(0.697)
Income-to-needs ratio (reference: < 1.0)				
1.0-1.5	-0.105	0.009	0.084	-0.395
	(0.375)	(0.263)	(0.399)	(0.888)
1.5-2.5	-0.313	0.114	0.026	0.707
	(0.315)	(0.229)	(0.375)	(0.908)
2.5-3.5	0.287	0.582*	0.623	0.144
	(0.337)	(0.246)	(0.337)	(0.906)
3.5+	0.805*	0.641**	0.073	-0.267
	(0.318)	(0.213)	(0.329)	(0.895)
Years in the U.S. (reference: natives)				
< 5 years	-0.188 [b c]	-0.966**	-2.692** [d]	-5.773** [e f]
	(0.717)	(0.296)	(0.382)	(0.817)
5-10 years	-0.643 [b]	-1.228**	-2.045**	-2.789*
	(0.385)	(0.256)	(0.431)	(1.384)
10-15 years	0.337 [a b c]	-0.796*	-2.053** [d]	-4.247** [e f]
	(0.462)	(0.316)	(0.412)	(1.106)
15+ years	-0.210 [a b]	-0.553**	-1.147**	-2.481** [e f]
	(0.296)	(0.164)	(0.279)	(0.723)
Marital Status (reference: married)				
Divorced/widowed/separated	-0.454	-0.715**	-1.142**	-0.620
	(0.249)	(0.175)	(0.233)	(0.462)
Single/never married	-0.657**	-0.898**	-1.021**	0.161 [e f]
	(0.246)	(0.154)	(0.262)	(0.441)
Cohabiting	-0.133	-0.375	-0.655	0.006
	(0.390)	(0.213)	(0.387)	(0.602)
Receiving food stamps	-0.150 [b]	0.301	0.960*	0.651
	(0.299)	(0.283)	(0.387)	(0.908)
Constant	17.451**	21.303**	25.508**	42.126**
	(1.918)	(1.465)	(1.977)	(3.997)
n	7,169	7,169	7,169	7,169

Note: All models control for age, age-squared, and number of children.
Indications for significant difference between-quantile coefficients at the .05 level:
a: between the .03th and .30th quantiles
b: between the .03th and .76th quantiles
c: between the .03th and .97th quantiles
d: between the .30th and .76th quantiles
e: between the .30th and .97th quantiles
f: between the .76th and .97th quantiles
* p < .05 ** p <. 01

Table 5. Quantile Regression Models for BMI at Malnourished, Overweight, Obese, and Extremely Obese Standards: Female, 2005

Variable	Q.03	Q.47	Q.75	Q.97
Race (reference: whites)				
Black	0.805** [a b]	2.846**	2.671**	1.543*
	(0.265)	(0.234)	(0.302)	(0.665)
Hispanic	1.175** [a b]	1.999**	2.185**	1.371*
	(0.175)	(0.247)	(0.343)	(0.676)
Asian	0.066 [b]	-0.469	-1.035*	-3.534** [e f]
	(0.386)	(0.384)	(0.436)	(1.103)
Education (reference: < H.S.)				
High school	-0.251	-0.399	-0.296	0.164
	(0.283)	(0.219)	(0.377)	(0.627)
Some college	-0.197	-0.267	-0.179	0.300
	(0.267)	(0.211)	(0.355)	(0.555)
College	-0.316 [a]	-1.805**	-2.027**	-1.319
	(0.263)	(0.215)	(0.388)	(0.760)
Beyond college	-0.323 [a b]	-1.902**	-2.544**	-2.110*
	(0.270)	(0.232)	(0.372)	(1.057)
Income-to-needs ratio (reference: < 1.0)				
1.0-1.5	-0.061	-0.232	-0.424	-0.806
	(0.372)	(0.376)	(0.571)	(0.958)
1.5-2.5	0.410	-0.074	-0.071	0.165
	(0.366)	(0.337)	(0.473)	(0.874)
2.5-3.5	0.670 [a b]	-0.569	-0.787	-0.422
	(0.364)	(0.348)	(0.485)	(0.904)
3.5+	0.276 [a]	-0.868**	-1.652**	-1.188
	(0.312)	(0.318)	(0.443)	(0.793)
Years in the U.S. (reference: natives)				
< 5 years	-0.426 [a b]	-1.629**	-3.148** [d]	-3.826
	(0.359)	(0.413)	(0.494)	(2.000)
5-10 years	-0.341 [a b c]	-1.420**	-2.671**	-3.138**
	(0.280)	(0.296)	(0.427)	(1.121)
10-15 years	-0.431 [b]	-1.336**	-2.492** [d]	-3.694**
	(0.412)	(0.340)	(0.662)	(0.974)
15+ years	0.274 [a]	-0.703**	-0.892*	-0.301
	(0.235)	(0.253)	(0.412)	(0.903)
Marital Status (reference: married)				
Divorced/widowed/separated	-0.068 [a]	-0.724**	-0.457	0.448
	(0.162)	(0.167)	(0.298)	(0.597)
Single/never married	-0.012	-0.288	0.547 [d]	1.309 [e]
	(0.255)	(0.193)	(0.386)	(0.695)
Cohabiting	0.079	0.160	-0.105	1.322
	(0.367)	(0.280)	(0.548)	(0.837)
Receiving food stamps	0.174 [a]	1.548**	1.959**	1.715*
	(0.336)	(0.243)	(0.437)	(0.830)
Constant	18.282**	21.003**	21.860**	34.061**
	(1.609)	(1.466)	(2.615)	(5.254)
n	8,461	8,461	8,461	8,461

Note: All models control for age, age-squared, and number of children.
Indications for significant difference between-quantile coefficients at the .05 level:
a: between the .03th and .47th quantiles
b: between the .03th and .75th quantiles
c: between the .03th and .97th quantiles
d: between the .47th and .75th quantiles
e: between the .47th and .97th quantiles
f: between the .75th and .97th quantiles
* $p < .05$ ** $p < .01$

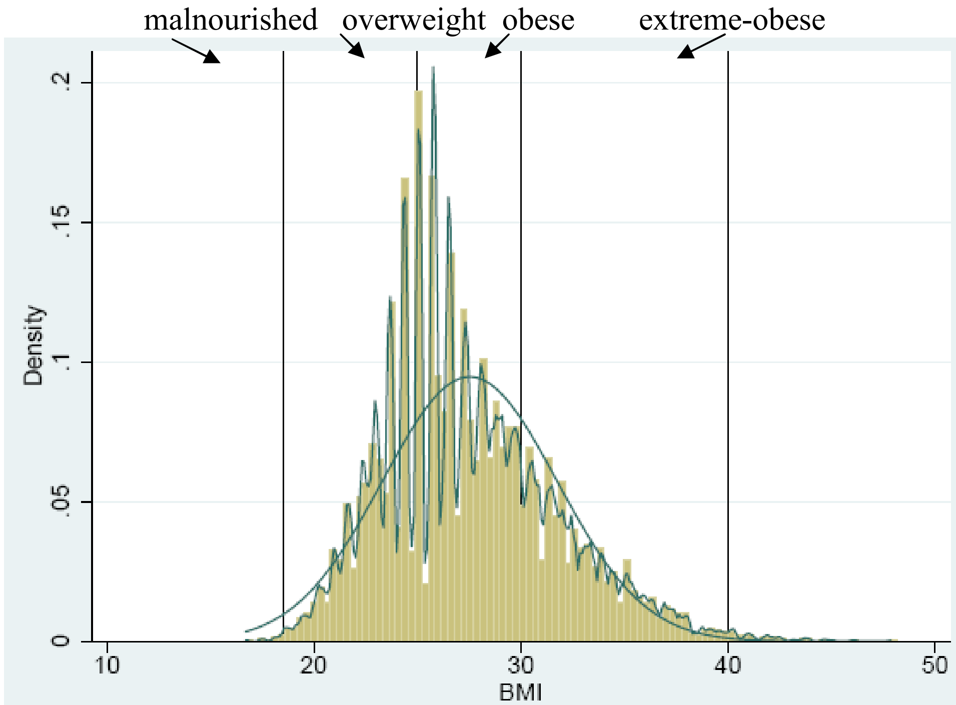
Appendix Table. Descriptive Statistics for Variables Used in Analyses

Variable	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Body Mass Index (BMI)	27.40	4.21	26.66	5.63
Race (reference: white)				
Black	0.12	0.33	0.16	0.37
Hispanic	0.20	0.40	0.21	0.41
Asian	0.04	0.19	0.03	0.17
Education (reference: less than high school)				
High school	0.25	0.43	0.23	0.42
Some college	0.27	0.45	0.30	0.46
College	0.21	0.41	0.19	0.40
Beyond college	0.09	0.28	0.10	0.30
Income-to-Needs Ratio (reference: <1.0)				
1-1.5	0.06	0.23	0.07	0.26
1.5-2.5	0.14	0.35	0.15	0.35
2.5-3.5	0.14	0.35	0.12	0.33
3.5+	0.41	0.49	0.35	0.48
Years in United States (reference: natives)				
Less than 5 years	0.03	0.16	0.02	0.15
5-10 years	0.04	0.20	0.04	0.19
10-15 years	0.03	0.17	0.03	0.18
15+ years	0.11	0.31	0.09	0.29
Marital Status (reference: married)				
Divorced/widowed/separated	0.17	0.37	0.22	0.42
Single/never married	0.23	0.42	0.19	0.39
Cohabiting	0.06	0.24	0.05	0.22
Welfare participation				
Receiving Food Stamps	0.05	0.22	0.11	0.31
Life cycle				
Age	39.67	8.45	39.51	8.52
Age-squared	1644.81	670.83	1633.87	675.64
Children (reference: no children)				
1-2 children	0.33	0.47	0.43	0.50
3 or more children	0.09	0.29	0.15	0.35
n	7,169		8,461	

Data source: National Health Interview Survey (NHIS) 2005, National Center for Health Statistics.

Figure 1. Histogram for BMI by Gender

(a) Male



(b) Female

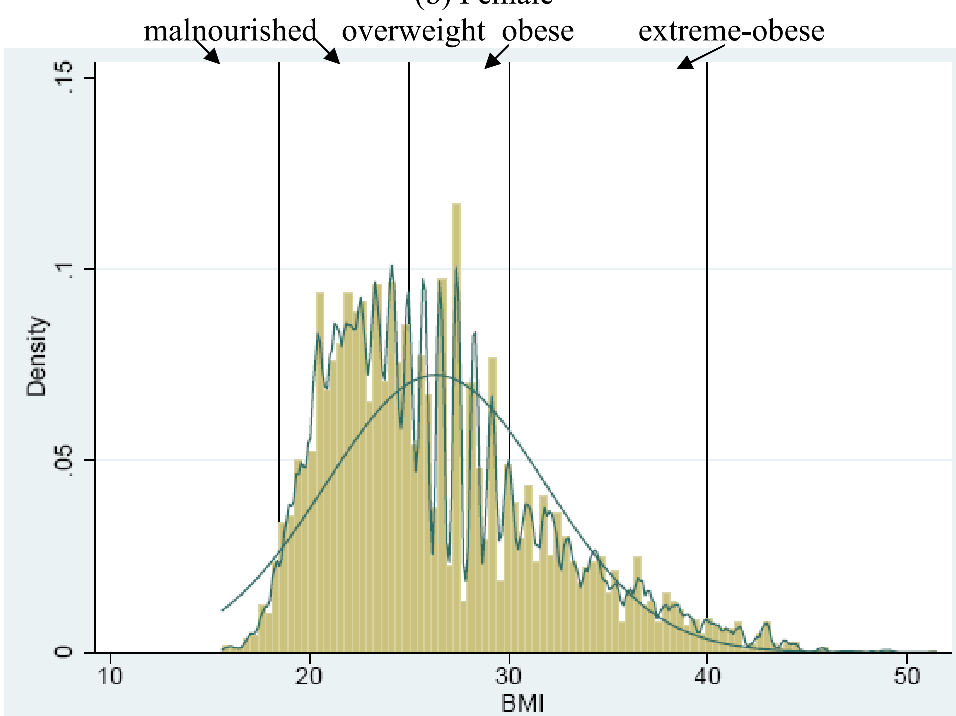


Figure 2. Quantile Functions for BMI by Gender

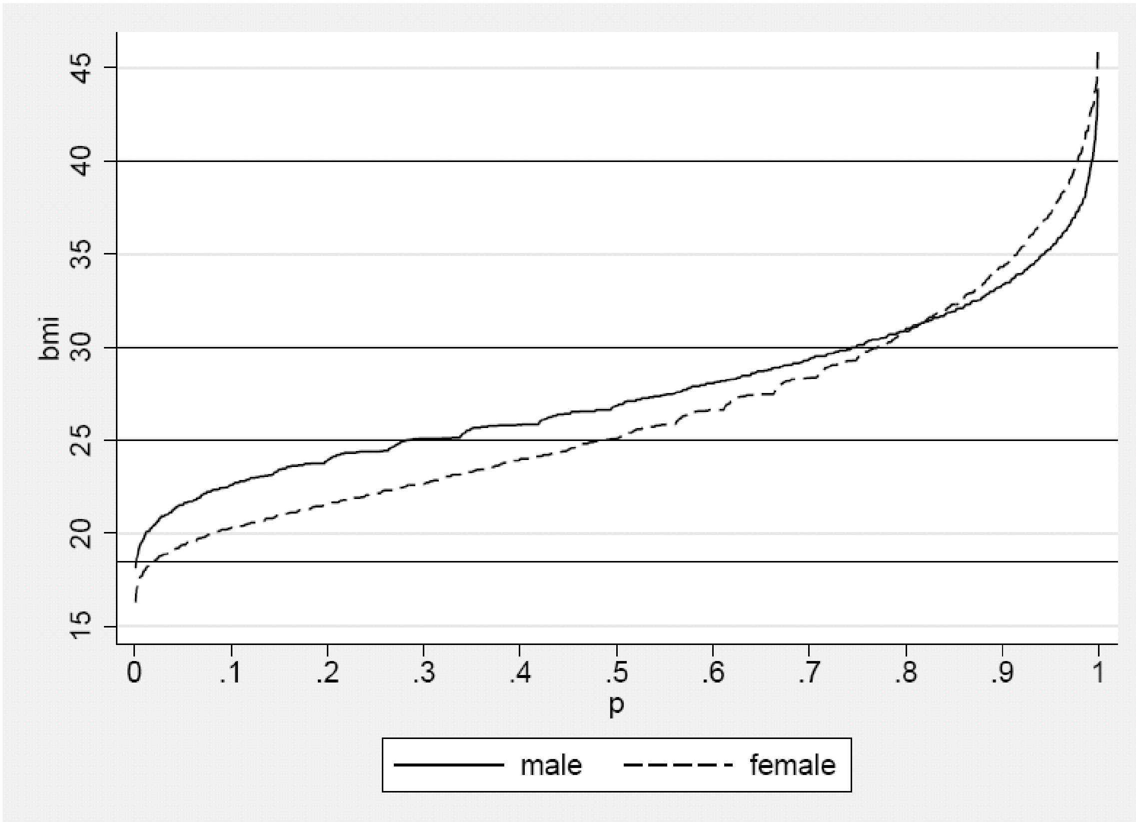
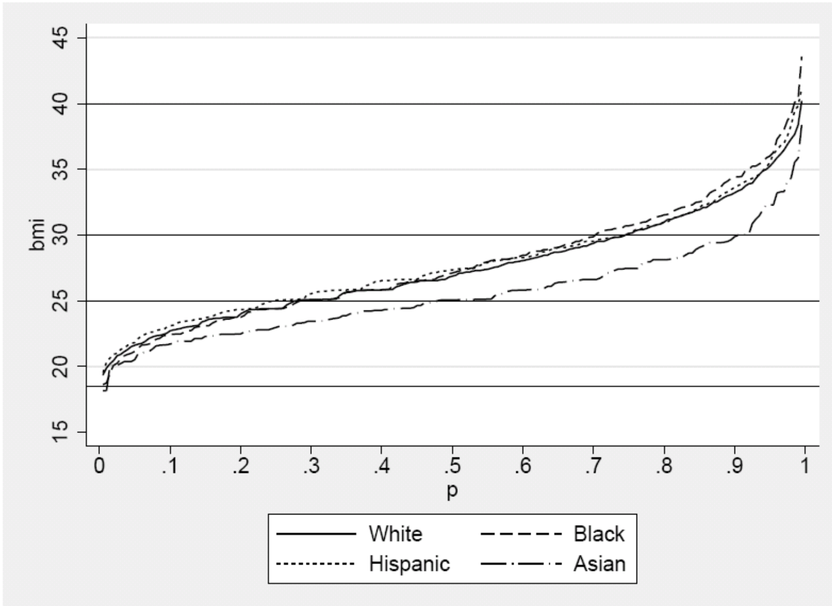
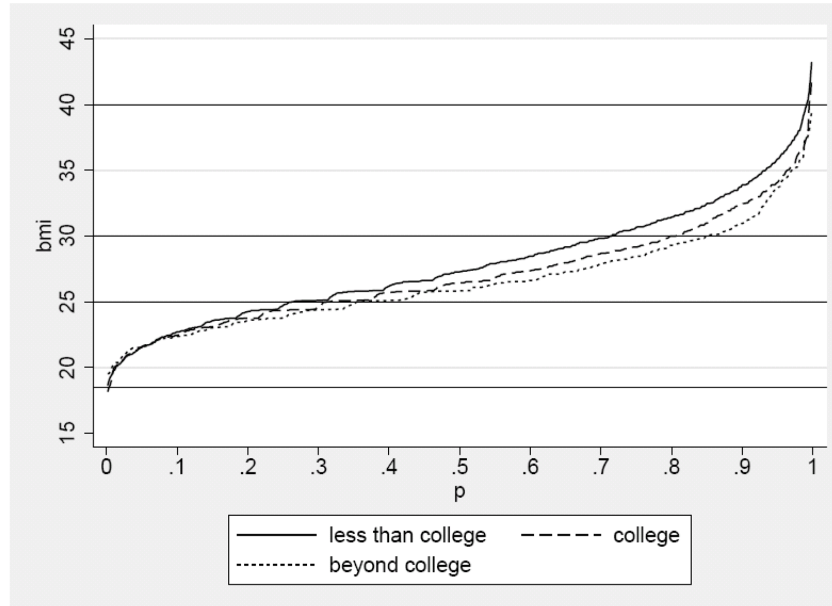


Figure 3. Quantile Functions by Grouping Variables: Male

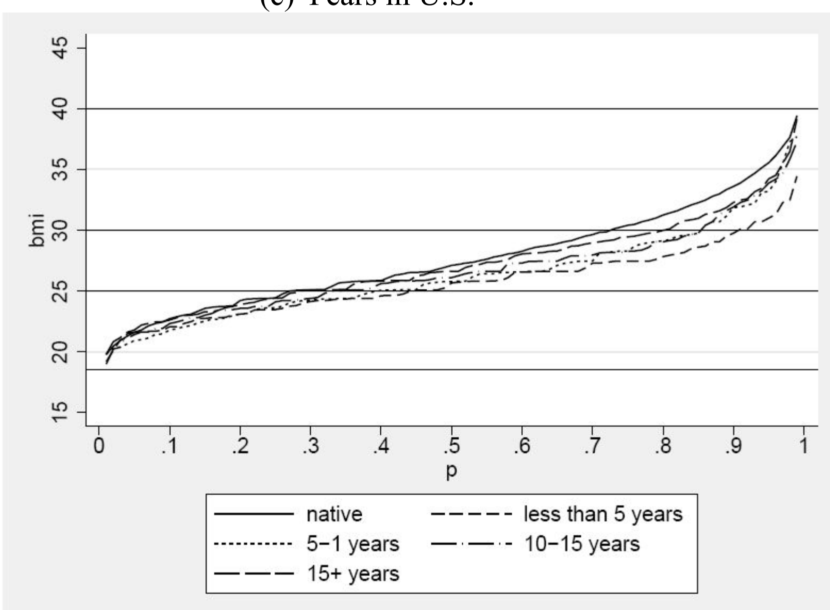
(a) Race



(b) Education



(c) Years in U.S.



(d) Food Stamps

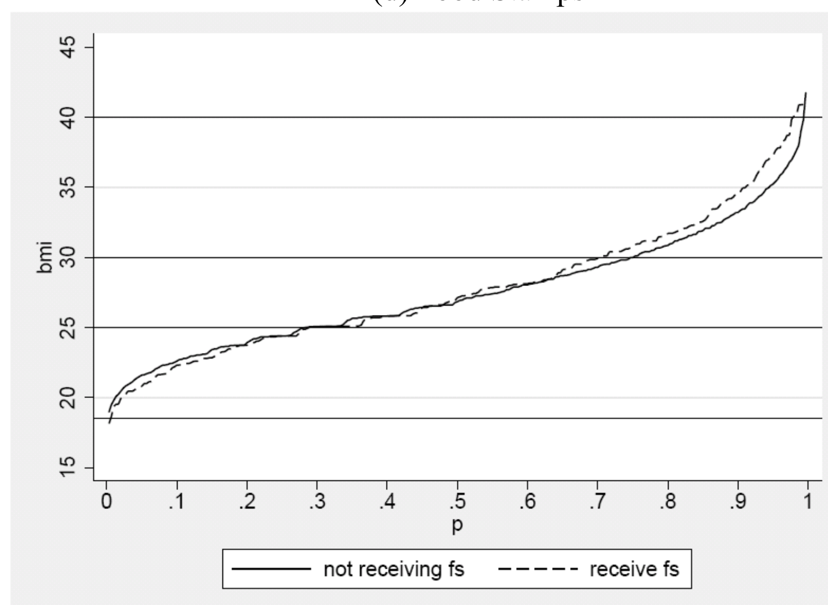
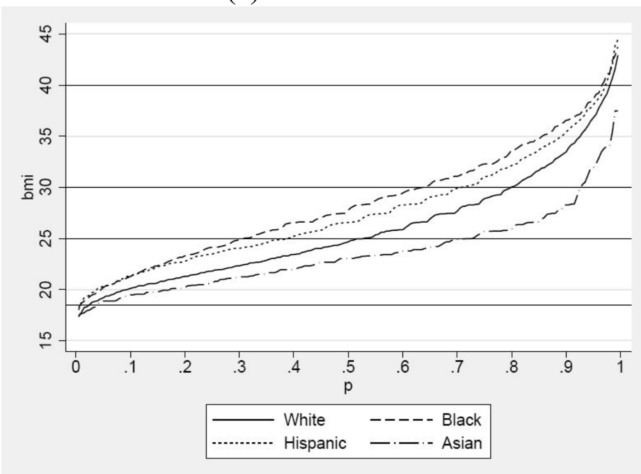
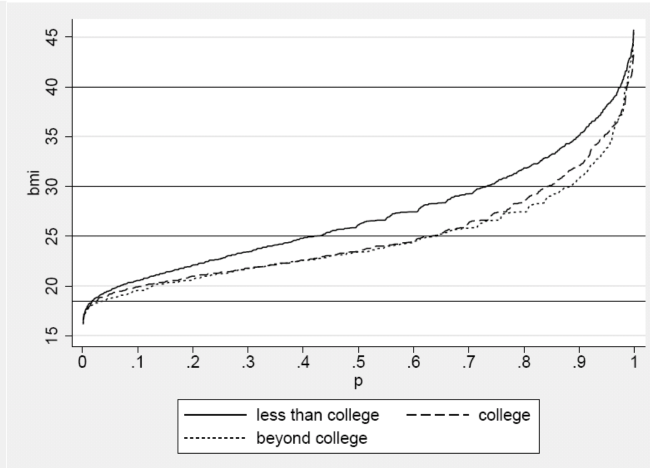


Figure 4. Quantile Functions by Grouping Variables: Female

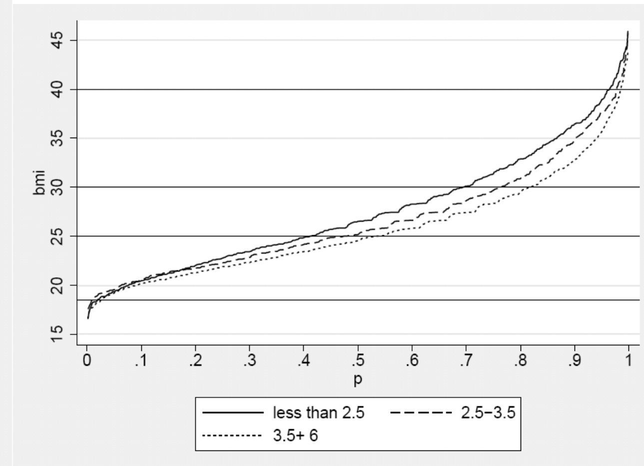
(a) Race



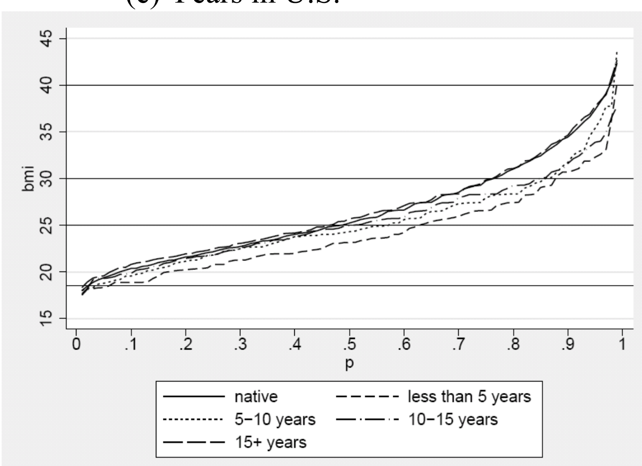
(b) Education



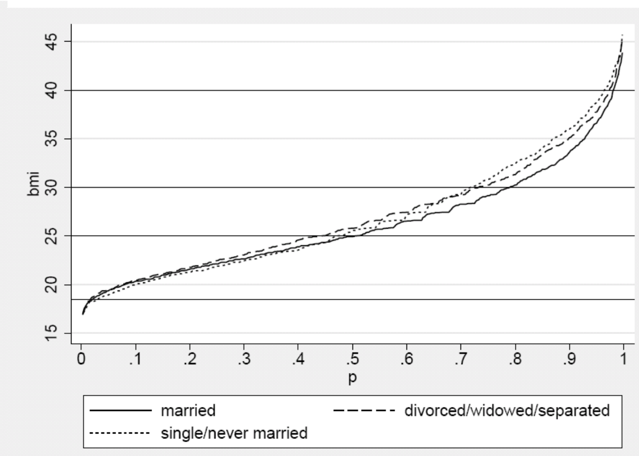
(c) Income-to-Needs Ratio



(e) Years in U.S.



(b) Marital Status



(c) Receiving Food Stamps

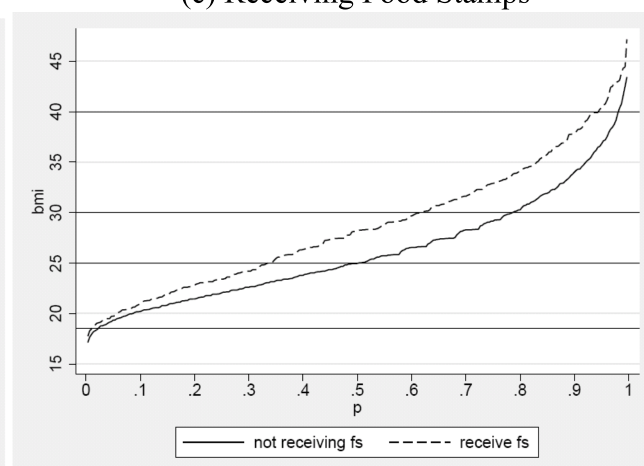


Figure 5. Quantile Coefficients at 21 quantiles for BMI: Male, 2005

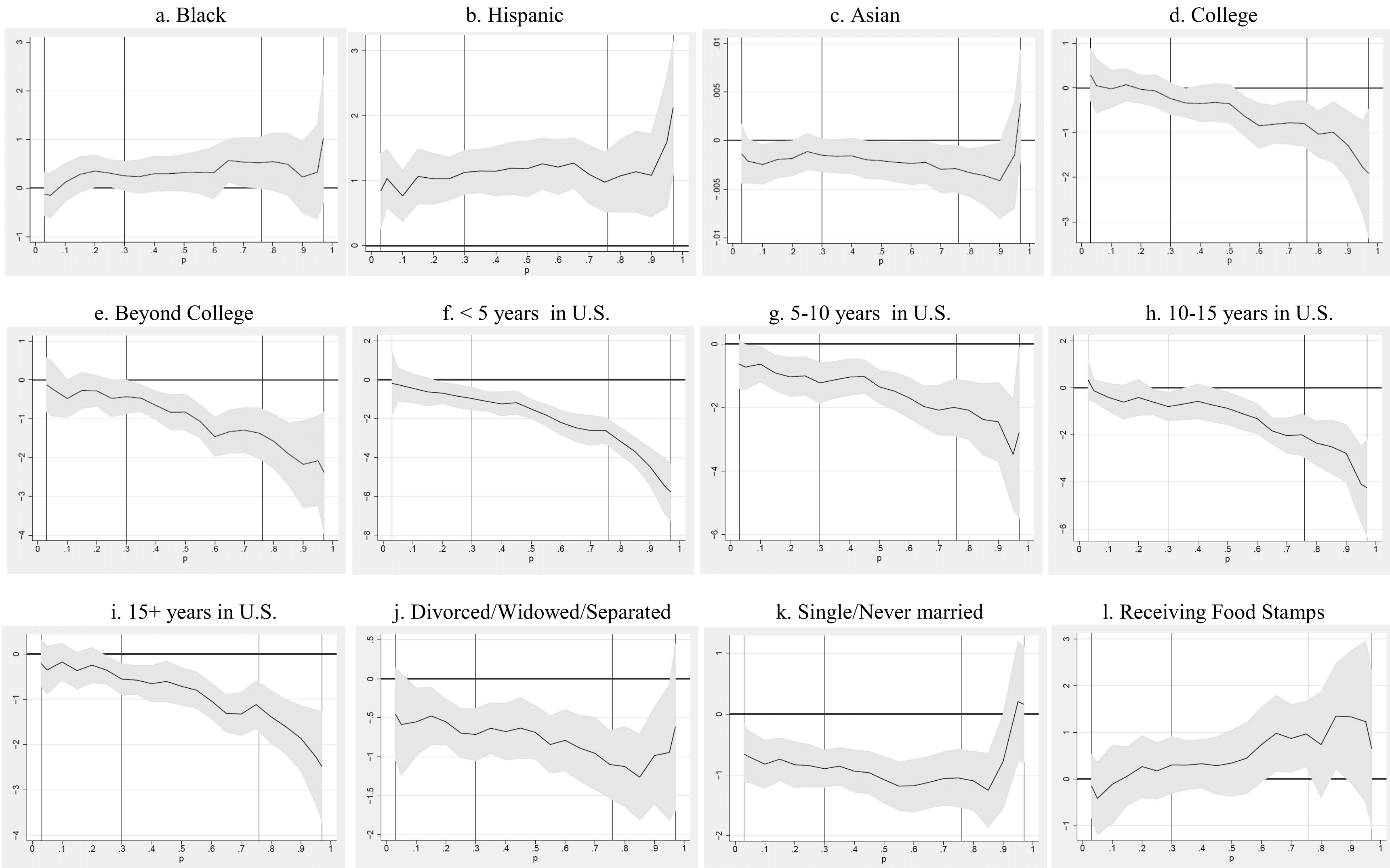


Figure 6. Quantile Coefficients at 21 quantiles for BMI: Female, 2005