Explaining Gender-Specific Racial Differences in Obesity Using Self-Reports of Food Intake and Physical Activity

Abstract

In NHANES data (waves 1999–2006), we initially observe a very weak relationship between self-reported measures of caloric intake and physical activity and either BMI or obesity risk, and these behaviors appear to explain only a small fraction of the black-white BMI gap (or obesity gap) among women. Using an innovative method to mitigate the widely recognized problem of measurement error in self-reported behaviors—proxying for measurement error using the ratio of reported caloric intake to estimated caloric expenditure—we obtain much stronger relationships between behaviors and BMI (or obesity risk). We find that the combination of lower physical activity levels and higher caloric intakes among black women compared to white women accounts for almost half of the difference in mean BMI between these groups and accounts for nearly two-thirds of black women's excess obesity risk. Observed behaviors among men are consistent with the presence of much smaller BMI/obesity gaps between blacks and whites.

Keywords: obesity, race, gender, self-reporting bias, caloric intake, physical activity

JEL Classifications: I12, J15, J16

1 Introduction

Since at least the 1960s, obesity has been significantly more prevalent among non-Hispanic African-American women (henceforth "black women") than among non-Hispanic white American women (henceforth "white women").[1] Table 1 gives age-adjusted obesity rates for white women and black women, ages 20 to 74 years, over various time intervals between 1976 and 2006. These rates are based on the National Health and Nutrition Examination Surveys, hereafter NHANES. The data are based on NHANES II, which covers 1976–1980, NHANES III (1988–1994), and NHANES 1999–2004. (Age-adjusted data by race and sex are not available in surveys prior to NHANES II.) In the 1976–1980 data, the obesity rate among black women exceeds that of white women by 15.6 percentage points. This gap is roughly unchanged in the 1988–1994 data (15.8 points) and becomes even greater in subsequent periods, reaching a maximum of 21.8 percentage points in the 2003–2006 data. In contrast, black men do not consistently exhibit higher obesity rates than white men. In periods in which black men's obesity rate exceeds that of white men by a significant margin, the gap in rates falls far short of the difference observed among women—witness, for example, the 3.3 percentage-point gap among men in the 2003–2006 data, versus the 21.8 percentage-point gap among women during the same period.

A recent editorial (Ogden 2009) draws attention to black women's higher obesity rate in relation to other sociodemographic groups, and argues that a greater understanding of disparities in obesity risk is critical for the design of appropriate policy interventions. While policymakers and researchers from a broad array of disciplines are well aware of differences in obesity prevalence and mean body mass index (BMI) by race and sex, systematic research into the causes of these patterns has been scarce and the facts underlying the disparities remain poorly understood.

In this paper, using NHANES 1999–2006 data, we perform a gender-specific multivariate analysis of obesity and BMI to determine the extent to which variation in relevant behaviors—including food intake, physical activity, and smoking—contribute to gender-specific racial differences in out-

[1] The definition of obesity employed by the Centers for Disease Control (CDC) is a body mass index (BMI) value of 30 or greater. BMI is the ratio of weight, measured in kilograms, to squared height, measured in meters.

comes. NHANES data are advantageous in that weight and height values (and therefore BMI) are measured rather than self-reported, and hence not subject to systematic bias. The surveys also contain extensive data on food intake and physical activity patterns, although these data are largely self-reported and subject to systematic biases in addition to random noise.[2]

Following existing methods for addressing self-reporting bias in behaviors, we first eliminate implausible self-reports from the sample. In addition, we construct a continuous proxy for measurement error in behaviors to include as an additional control variable. The proxy method results in large increases in the estimated effects of caloric intake and physical activity on BMI and in the ability of these factors to account for gender-specific racial differences in mean BMI and obesity. The data-elimination method alone appears to be much less effective in mitigating self-reporting biases. We confirm the validity of the proxy method using simulations. Our proxy method and simulations are derived from a conceptual model of BMI which highlights the importance of capturing behaviors accurately.

We find that a combination of greater caloric intake and lower levels of physical activity among black women can account for 52% of the black-white gap in female mean BMI and 65% of black women's excess obesity risk. Of the difference in outcomes that is explained by the model, unmeasured variation in behaviors—some combination of caloric intake and physical activity—accounts for a significant share. We find that smoking patterns contribute at best only marginally to race-by-gender patterns in BMI (or obesity) when measurement error in caloric intake and physical activity are mitigated. This result occurs because smoking acts on BMI only indirectly, via its influences on caloric intake and/or caloric expenditure.

Numerous studies across various disciplines have documented the presence of racial disparities in mean BMI and obesity prevalence in the United States over various time periods. Kuczmarski et al. (1994) document trends in obesity prevalence and mean BMI by race and sex for NHANES surveys spanning the years 1960–1991. Flegal et al. (1998) update these trends for the NHANES

[2]Accelerometer-based measures of physical activity are available for some subjects in NHANES 2003–2006; these also are subject to measurement error based on user compliance, in addition to potential sample-selection bias. See, for example, Beyler et al. 2008.

III (1988–1994) survey, and Ogden et al. (2006) describe the trends for NHANES 1999–2004. Ljungvall and Zimmerman (2012) provide the most comprehensive analysis to date of trends in obesity risk and mean BMI by race/ethnicity and gender, covering the period 1960–2008. Komlos and Brabec (2010) examine obesity trends by birth cohort and race for the period 1882–1986. Some of these have pointed out the gender specificity of the black-white patterns in particular, such as Burkhauser and Cawley (2008). Other studies (Kumanyika 1987) have offered numerous hypotheses to explain black women's excess obesity prevalence, yet do not come to any firm conclusions and do not address the problem of gender specificity. A number of studies have investigated the contribution of socioeconomic status to racial and/or race-by-gender patterns in BMI and/or obesity risk, and have concluded, nearly uniformly, that the demographics of obesity are highly robust to controls for household income, educational attainment. (See, for example, Burke and Heiland (2008), Mujahid et al. (2005), Chang and Lauderdale (2005), Chou et al. (2004), Denney et al. (2004), and Zhang and Wang (2004).)

Rashad (2006) also uses self-reported data on caloric intake and physical activity from NHANES surveys (waves I, II, and III) to estimate a model of BMI determination. Her main objective is to identify the contributions to BMI of exogenous variation in food intake and cigarette smoking, as predicted by instruments such as restaurant prices and cigarette taxes. She acknowledges potential measurement error in self-reported caloric intake and attempts to mitigate it by assuming that self-reporting bias in caloric intake can be proxied by self-reporting bias in BMI, where the latter can be observed in the NHANES data. In gender-specific, ordinary-least-squares (OLS) models that use (adjusted) caloric intake measures directly, the estimated effects of caloric intake on BMI are an order of magnitude smaller than our own best estimates.

This finding of weak effects—which we reproduce in models that fail to control for measurement error—indicates that Rashad's correction for measurement error is inadequate. The use of instruments might in principle be expected to mitigate attenuation bias, but Rashad's estimated effects of caloric intake on BMI are in most cases smaller—and have lower or no significance—in the instrumental variables (IV) models compared to OLS models. Rashad attributes the decline to the removal of endogeneity bias in the IV specification. However, we argue below that endogeneity of weight-related behaviors is most likely to result in a downward bias on the effect of calories on BMI, and therefore we would expect IV effects to be greater than OLS effects.

Our findings significantly enhance the understanding of the contribution of individual behaviors to the gender-specific racial disparities in obesity, an important step towards addressing the associated health disparities (e.g., Finkelstein et al. 2010; Flegal et al. 2005). Furthermore, our use of rigorous strategies to mitigate measurement error is shown to be a critical component in producing such understanding. In the absence of such strategies, one is led to believe that caloric intake and physical activity play at best a minor role in BMI determination, despite voluminous scientific evidence to the contrary.

The remainder of the paper is organized as follows: Section II presents the empirical model of BMI and describes the methods for mitigating measurement error. Section III describes the data and sample selection. Section IV describes the empirical analysis and Section V concludes.

2 Empirical methodology

Equation 1 below represents a linear approximation of a structural model of BMI. It can be shown formally that a linear model offers a reasonable approximation to an underlying (nonlinear) structural model of BMI, which is described in Appendix A.

$$BMI_i^s = \alpha + \beta EI_i^s + \gamma PAL_i^s + \mu * \epsilon_i. \tag{1}$$

This model assumes that all variables, including BMI, energy intake (EI), and the physical activity level (PAL), are observed at their respective "steady state" (stable or habitual) values. That is, neither BMI nor relevant behaviors fluctuate over time. PAL is defined as the ratio of total daily energy expenditure, TEE_i (in kcal), to the basal metabolic rate, BMR_i (also measured in kcal). The basal metabolic rate refers to the calories expended per day in maintaining basic involuntary bodily functions while in a resting and fasting state. The term ϵ_i represents the idiosyncratic metabolic endowment, which has marginal effect μ on BMI, where $\mu < 0$ implies that individuals with a large metabolic shock (i.e. faster basal metabolic rate) will have lower BMI, all else equal.

In reality, of course, behaviors, and also BMI, may fluctuate significantly over time within an individual and may exhibit long-term trends. Ignoring trends, fluctuations imply that snapshots of behaviors and BMI at a point in time—even if perfectly accurate—constitute noisy measures of steady state behaviors and BMI. Given this potential for random error in measurement of stable values, the estimated relationships between behaviors and BMI are likely to be attenuated.[3] This "snapshot problem" applies to any attempt to estimate relationships between behaviors and BMI using large, representative data sets, in which data on behaviors are necessarily limited to a small sample of days.

The BMI values we use are based on weight and height as measured by trained NHANES examiners. While not subject to self-reporting bias, a given BMI value may nonetheless deviate from its habitual value; however, any given one-day fluctuation in energy intake (or energy expenditure) will result in a much smaller (percentage) change in BMI over the day. For example, an individual who fasts for a day, thereby reducing caloric intake by 100%, will lose less than 1% of body weight.[4] Given these facts, we assume that observed BMI values constitute reasonable approximations to habitual BMI values.

Evidence from previous studies finds that self-reported dietary intakes tend on average to understate true food intake (Macdiarmid and Blundell 1998). There are several reasons for self-reporting bias: first, individuals may have an imperfect recall of food intake; second, individuals may deliberately fail to report certain food items and/or may understate portion sizes; third, prior to the interview people may eat less than normal.[5] In cases of deliberate underreporting,

[3] Given the design of NHANES, data on caloric intake are potentially more noisy than data on physical activity: in our sample, caloric intake data represent only a single day's calories, whereas physical activity data refer to activities in a "typical" day, week, or month.

[4] Weight loss percentage will vary by individual; the figure is an approximate upper-bound, assuming no change in physical activity level from normal habits.

[5] In the NHANES surveys, individuals are asked to report all items consumed in previous 24-hour period. They know in advance they will be asked to recall intake but are not instructed to write things down as they go, because

individuals may be ashamed to report true consumption—an example of a "social desirability" effect or bias toward giving a socially normative response.[6] In cases of deliberate undereating, subjects may feel compelled to eat a socially normative amount of food based on the knowledge that they will have to reveal that intake.

Given its motivating causes, underreporting is likely to be more severe among individuals with higher true caloric intake, resulting in non-classical measurement error (Macdiarmid and Blundell 1998). Therefore, we expect a negative covariance between true caloric intake and its error (defined as self-reported calories minus true calories). When measurement error has this property, Black et al. (2000) show that, under relatively weak conditions, the estimated coefficient on reported calories will be biased towards zero.[7] Therefore, both sources of measurement error in caloric intake—random fluctuations and systematic self-reporting bias—are expected to bias the coefficient on calories in the same direction.

There is evidence that self-reports of physical activity overstate true activity levels, due to imperfect recall and social desirability effects (Beyler et al. 2008). Similar to the predicted biases in caloric intake, measurement error in physical activity might be negatively correlated with true activity. Therefore, we expect that the effects of physical activity on BMI will be biased towards zero based on the potential for both noise and systematic reporting biases.

To mitigate biases caused by measurement error in self-reported behaviors, we adopt two strategies. First, following Black (2000), we identify self-reports of food intake that appear invalid in relation to the reported physical activity level and exclude these observations from the regression. We cannot determine whether reported food intake is too low or too high in an absolute sense, only whether it appears inconsistent with the reported physical activity level, which may also be biased. Second, we construct a continuous proxy for the measurement error in food intake relative to physical activity and add this as a control variable in some regressions.

doing so may induce restraint relative to habitual intake.

[6]Social desirability effects are a long-standing concern in organizational research (see, e.g., Streb et al. 2008).

[7]The necessary condition is that the sum of the variance of the measurement error and the (negative) covariance of true intake and measurement error must be positive. Our results suggest that the coefficient on self-reported calories is indeed biased towards zero relative to the coefficient on true caloric intake.

Method 1. Exclusion of invalid observations

Black (2000) describes a method for identifying observations of food intake which appear highly inconsistent with the individual's physical activity level (PAL) and BMI. In our application of Black's method, we estimate both the energy-intake ratio and the PAL value using NHANES data. The energy-intake ratio is calculated by dividing self-reported caloric intake by an estimate of the basal metabolic rate (BMR). To construct this estimate, we take a predicted value of BMR due to Mifflin, et al. (1990) and to this value add a random shock based on the gender-specific empirical distribution of residuals in Mifflin, et al. (1990). The justification for estimating BMR in this manner is provided in Appendix B. We construct PAL values (and associated confidence intervals) that are specific to each individual, based on responses to the NHANES physical-activity questionnaire.[8] Each confidence interval allows for (homoscedastic) within-subject variance in caloric intake and caloric expenditure, respectively. These variance estimates are based on previous studies (cited in Black 2000) in which individual energy intake and/or expenditure were measured over extended periods using sophisticated methods. The fewer days on which caloric intake is observed, the wider the confidence interval. Using this confidence-interval approach, we exclude roughly 25% of relevant observations among women and 22% among men.

Method 2. Measurement error proxy ("EB-Ratio Method")

We contribute an additional method for mitigating measurement bias. We construct a continuous proxy variable for the joint measurement error in self-reported behaviors, termed "EB-Ratio," short for "energy-balance ratio." To compute EB-Ratio, we divide the energy-intake ratio by the PAL. Since in steady state these two latter quantities are equal to each other, we obtain the following result:

$$EBRatio^s \equiv (EI_i^s/BMR_i^s)/PAL_i^s = 1. \tag{2}$$

Note that this condition holds for all individuals in steady state, regardless of the individual's BMI.

[8]We map the NHANES physical-activity data into PAL values using guidelines drawn from the NHANES and from the World Health Organization (FAO/WHO/UNU 2001). See Appendix C.2 for details.

For convenience of exposition, we multiply EB-Ratio by 100 with no loss of generality. Ignoring the normalization, the measure is equivalent to the ratio of (daily) energy intake to (daily) energy expenditure. If all individuals were observed in steady state, we should obtain EB-Ratio values of 100 uniformly, as in Eq. (2). A value less than 100 indicates that the energy intake ratio falls short of the PAL, which will occur if energy intake is understated, holding PAL at its steady state value, or if physical activity is overstated, holding intake at its steady state value. For analogous reasons, EB-Ratio will exceed 100 when self-reported energy intake is overstated relative to self-reported physical activity. As such, EB-Ratio acts as an index of the joint measurement error in self-reported behaviors. If behaviors deviate randomly from their habitual values, the average value of EB-ratio should approach 100 in a large sample. However, as a result of systematic self-reporting errors of the types described above, EB-Ratio may either exceed or fall short of 100 on average.

Including EB-Ratio in the regression should alleviate the expected biases on the coefficients on caloric intake and physical activity under certain conditions. We illustrate how the control works by writing a modified version of Eq. (1) as follows:

$$BMI_i^s = \hat{\alpha} + \hat{\beta} EI_i^{SR} + \hat{\gamma} PAL_i^{SR} + \mu * \epsilon_i + \omega_i. \tag{3}$$

In the above, EI_i^{SR} and PAL_i^{SR} refer to self-reported (SR) behaviors, and the coefficients are denoted $\hat{\beta}$ (and $\hat{\alpha}$, and so on), rather than simply β, to reflect potential biases in the empirical estimation of the model. The term ω_i represents the joint contribution of unmeasured variation in behaviors (both energy intake and physical activity) to BMI. Referring back to Eq. (1), any two individuals with the same *true* (steady-state) values of food intake and physical activity (age and gender constant) have the same BMI in expectation; their respective steady-state BMI values will differ from each other only if the individuals have different metabolic endowments (different ϵ_i). Among individuals with the same set of *self-reported* behaviors, however, variation in BMI may reflect either variation in endowments or variation in measurement error in behaviors. Because we observe neither ϵ_i nor ω_i, variation in BMI conditional on the observed factors could reflect either of these unobserved effects.

If ϵ_i is orthogonal to the observed variables, the only potential source of bias is measurement error. In particular, ω_i may be correlated with self-reported energy intake and/or physical activity. EB-Ratio acts as a proxy for ω_i, the purpose of which is to pick up the variation in BMI—conditional on self-reported behaviors—that can be attributed to the joint measurement error in behaviors. With EB-Ratio in the regression, the estimated relationship between self-reported caloric intake (or physical activity) and BMI should be closer to its expected value in the absence of measurement error. We confirm that this pattern of results holds using simulations, described in Appendix B.

A caveat is in order. To calculate EB-Ratio, we use estimates of the basal metabolic rate as described above and in Appendix B, because measurements of BMR are unavailable in NHANES. Therefore, our estimates of EB-Ratio are themselves subject to error. For example, an individual with a low EB-Ratio would appear to be understating her food intake relative to her expenditures, but she may simply have a lower-than-expected BMR and therefore lower-than-expected caloric expenditures. As a result, the proxy method may attribute too much variation in BMI to variation in measurement error and too little to variation in metabolic endowments. However, Pryer et al. 1997 measure energy expenditures directly and find that self-reported energy intakes generally fall short of expenditures. Such evidence suggests that variation in metabolic endowments is not large enough to explain the variation in EB-Ratio, lending further support to our method.

3 Data and Sample Selection

The empirical analysis is conducted using data from NHANES, a nationally representative series of cross-sectional studies conducted by the Centers for Disease Control (CDC). The NHANES data include observations of weight, height, and other physical features measured by direct examination, as well as demographic and socioeconomic characteristics, life circumstances, behavioral choices, and health conditions, collected via in-person interviews. The empirical analysis uses NHANES surveys from the years 1999–2006. We pool the data as recommended in the NHANES analytical guidelines (National Center for Health Statistics 1996). Complex survey design is accounted for using Stata's "svy" commands. Data for 2007 and later are also available, but changes in the questionnaire make it difficult to compare activity levels in the later data with the earlier data.

We restrict the samples to individuals ages 20 to 65 who had their height and weight examined in person. We calculate BMI as examined weight in kilograms divided by the square of examined height in meters. We determine obesity status using the standard criterion of BMI ≥ 30. Included individuals also provided a detailed (in-person) self-report of food intake for a single day and provided at least some information about physical activity patterns. Imposing a maximum age of 65 years helps to minimize differences in age distributions across demographic groups and survey periods. We impose a minimum age of 20 years because a uniform adult criterion for obesity begins to apply at that age. We do not exclude any racial categories from the analysis, although our study focuses on the discrepancies between just two groups: non-Hispanic whites and non-Hispanic blacks. Pregnant women are excluded from the sample on the grounds that BMI during pregnancy is likely to be above its typical value. The sample that results from these criteria will be called the "full" sample. We impose additional selection criteria related to the validity of self-reports of behaviors, as described above, to create a "validity-restricted" sample. The respective sample sizes are 6,225 (full) and 4,676 (validity-restricted) for women and 6,208 (full) and 4,861 (validity-restricted) for men. Construction of remaining variables is described in Appendix C.

4 Empirical Analysis

The goal of the empirical analysis is to identify behaviors that may account for gender-specific racial variation in BMI and obesity. We first describe raw differences in food intake, physical activity, and smoking behavior by race and sex. Then we estimate empirical models of BMI and obesity status separately for men and women as functions of these behavioral measures. Descriptive statistics and regression are performed for each of the full sample and the validity-restricted sample.

4.1 Descriptive analysis of behavior

Table 3 shows the mean values of the variables of interest by sex and race, calculated for each full regression sample and validity-restricted regression sample, respectively. As expected, statistically significant differences in mean BMI and obesity rates between blacks and whites are specific to women. White women are significantly more likely to fall into the "vigorous activity" category (highest level of leisure-time physical activity) than black women. White men are also more likely to achieve "vigorous activity" than black men, although the gap in the men's shares is smaller and only marginally significant (p-value is 0.066 in the validity-restricted sample). These comparisons must be qualified by the fact that the sample contains a significant fraction of missing observations for leisure-time physical activity, where the share with missing data is significantly higher among blacks (especially black women) than among whites. In data pertaining to "normal daily activities" not including leisure-time exercise—for which missing observations are not a problem—black women are significantly more likely than white women to sit most of the time (31% versus 25%, in either sample). In contrast, black men and white men are about equally likely (21% and 22%, respectively) to sit for most of the day. Daily caloric intake appears marginally higher among black women than white women in the complete sample and modestly higher in the restricted sample, but the difference is not statistically significant in either sample. Black men report lower caloric intake than white men, and the difference is significant in the full sample (p-value 0.000) and marginally significant in the restricted sample (p-value 0.054). In either sample, white women are significantly more likely to smoke (26% are current smokers) than black women (22%), while the opposite holds for men—31% of white men and 35% of black men are smokers.

In the full sample, the mean EB-Ratio is significantly less than 100 (the benchmark value for valid reporting) for each of the four demographic groups of interest, indicating underreporting of caloric intake and/or overreporting of physical activity. For each group, the mean EB-Ratio moves closer to 100 in the restricted sample. In the restricted sample, black women have a lower average, at 92.7, than white women, at 94.9, although the difference is only marginally significant (p-value .099). For both samples, black men report a significantly lower mean EB-Ratio than white men, indicating a greater tendency to underreport intake and/or overreport activity.

4.2 Regression analysis

Table 4 shows the results of linear (OLS) regressions of female BMI against various groups of regressors, including all women aged 20-65 years who reported at least one day of food intake and with non-missing values for all other regressors. The first four columns of the table report results pertaining to the unrestricted or "full" samples and columns 5 through 8 report results pertaining to the restricted sample. The data include indicators for the day of the week on which a given day's food intake was reported. The results are robust to controlling for these indicators and they had no significant effects (results not shown).

The first row in each column of Table 4 gives the difference in mean BMI between black women and white women conditional on the other covariates. The baseline difference (controlling for age and foreign-born status) is 4.0 units in the full sample (model 1)—roughly 23.5 pounds for a woman of average height (5 feet 4 inches). Model 3 includes the leisure-time physical activity categories, daily activities, smoking status, and food intake, in addition to the baseline controls. While many of the behavior variables have significant effects on BMI in the directions we would expect, the black-white difference in mean BMI remains large and significant, at 3.5 units.

Models 2 and 4 are similar to models 1 and 3, respectively, but in each case we add EB-Ratio as a control. When EB-Ratio is included, the effects of (most) behaviors become larger and/or more precise. For example, between models 3 and 4 the effect of the variable "stands"—which refers to standing rather than sitting during normal daily activities—increases in absolute value by a factor of roughly 2.5, from -0.9 to -2.4. The effect of caloric intake increases from zero to a statistically significant value of 0.011. (The effects of smoking, discussed below, constitute an exception to this pattern.) The conditional black-white gap in female mean BMI is significantly smaller in model 4 (2.5 units), which conditions on behaviors and EB-Ratio, than in model 3 (3.5 units), which conditions on behaviors only.

R-squared values (adjusted) are substantially higher when EB-Ratio is included. Between models 1 and 2 the increase in R-squared reflects the (negative) correlation between BMI and EB-Ratio. Between models 3 and 4, the increase reflects the fact that the explanatory power of some behaviors is enhanced when EB-Ratio is included. The negative coefficient on EB-Ratio (in models 2 and 4) means that, all else equal, an individual with a lower EB-Ratio—that is, for whom reported caloric intake appears lower in relation to her physical activity level—has a higher BMI than an individual with a higher EB-Ratio. This result agrees with previous findings (e.g., Pryer et al. 1997) that high-BMI individuals underreport caloric intake more than low-BMI individuals.

Columns 5 through 8 in Table 4 show results of linear regressions of female BMI for the restricted sample. R-squared values are in most cases greater under the restricted samples (in all but model 6), an expected consequence of using less noisy data. Compared to the estimates from corresponding models on the full sample, the point estimates of the black-white difference in (conditional) mean BMI are smaller for the restricted sample (for each of models 5 through 8), reaching a low of 1.7 in model 8. The latter estimate is significantly different from the corresponding coefficient in model 4. The effect of caloric intake becomes significant in model 7 due to the sample restriction alone, but the effect remains attenuated compared to model 8, which includes EB-Ratio. We infer that sample restrictions alone do not fully mitigate the measurement error in reporting of food intake.

Table 5 shows the results of Poisson models of obesity risk for women for each of the complete and restricted samples.[9] The first row in each column indicates the estimated ratio of relative obesity risk for black women compared with white women, conditional on the other covariates. Subsequent rows indicate the remaining coefficients of relative risk. The results follow the same basic patterns seen in the linear models.

Between model 1 and model 4, the marginal effect of black race on female obesity risk falls significantly, from 1.65 to 1.27. Again, the effects of caloric intake and physical activity on BMI are

[9]Given the high prevalence of obesity in the subject population, odds ratios from a logistic regression do not approximate relative risks of obesity and are therefore hard to interpret. Poisson regression produces reliable estimates of relative risks and conservative confidence intervals (e.g., McNutt et al. 2003). Logistic regressions with identical right-hand side variables yield qualitatively similar results (available upon request).

stronger and/or more significant when EB-Ratio is included, and the augmented model accounts for a greater portion of the black-white obesity gap. Restricting the sample (columns 5 through 8) increases the estimated effect of caloric intake on obesity risk (comparing model 7 to model 3), but including EB-Ratio results in an even greater amplification of food's effect (compare model 3 to model 4 or model 7 to model 8). Sample restriction alone does not typically have significant consequences for the impact of physical activity on obesity risk.

Tables 6 and 7 provide analogous results for men. In all specifications point estimates indicate that black men have a somewhat higher mean BMI than white men, although the differences are not statistically significant. A significantly higher obesity risk for black men is observed in models 1, 3, 5, and 7 of Table 7, but this difference becomes insignificant in models which include EB-Ratio. Again, including EB-Ratio (models 8) strengthens the effects of caloric intake and physical activity on BMI (and obesity risk) and results in large increases in explanatory power. In general, the marginal effects of caloric intake and physical activity categories (such as "vigorous" leisure-time activity) on BMI (or obesity risk) are weaker for men than for women and R-squared values are also lower for men. The coefficient on EB-Ratio is negative and significant in all models, but the point estimates are smaller for men than for women.

In models that exclude EB-Ratio, being a smoker (as opposed to a nonsmoker) is associated with significantly lower BMI for both men and women. Unlike the effects of caloric intake and physical activity, the effects of smoking on BMI generally become smaller and/or lose significance when EB-Ratio is included. As explained above, smoking has no effect on BMI in a model that includes perfect measures of caloric intake and caloric expenditure. In empirical estimation, however, smoking may proxy for unmeasured variation in intake and/or expenditure. (See, for example, Perkins et al. 1989, Perkins 1992, and Stamford et al. 1986.) By including EB-Ratio as a proxy for measurement error, smoking's proxy effect is apparently reduced.

Taking the estimated effects of behaviors on obesity risk, combined with the demographic patterns in the behaviors, we get a quantitative sense of how these behaviors help to account for the black-white obesity risk gap among women. In results for the restricted sample shown in Table 5, the excess risk of obesity for black women (compared to white women) falls by approximately 65% (about 14 percentage points) between the baseline model (model 5) and the most inclusive model (model 8). Of this decline in excess risk, roughly 22.5% (3.3 percentage points) is accounted for by the 34-calorie-per-day gap in mean caloric intake between black women and white women (seen in Table 3). Lower levels of physical activity among black women jointly account for about 52.6% (7.6 percentage points), while the contribution from smoking is negligible. The lower EB-Ratio among black women accounts for 28.0% of the decline in excess risks, which means that the contributions (calculated just above) of racial differences in behaviors to excess obesity risk represent lower-bound estimates.[10] However, we cannot separate out the respective contributions of measurement error in caloric intake and measurement error in physical activity, nor can we rule out the possibility that EB-Ratio proxies for unmeasured variation in basal metabolism.

Among men, we observe only small obesity risk gaps between blacks and whites, and they are mostly not significant at conventional levels (Table 7). Lower caloric intake by black men (in the restricted sample) predicts a lower relative risk of obesity. However, the latter effect is more than offset by the fact that black men have a lower EB-Ratio than white men, a difference which predicts a greater relative obesity risk for black men and calls into question their lower reported caloric intakes. Black men are also significantly less likely to engage in moderate or vigorous physical activity than white men, and this difference predicts some excess obesity risk.

5 Discussion and Conclusion

Using NHANES data from 1999–2006, we describe the contribution that behavioral factors make to explaining the gender-specific differences in mean BMI and obesity risk between blacks and whites in the United States. Using an innovative strategy to mitigate measurement error in self-reported behaviors, we find that a combination of lower physical activity levels and higher caloric intakes can account for almost half of the difference in mean BMI between black women

[10] The total portion of the decline in the obesity gap explained by the aforementioned factors exceeds 100%. This occurs because the effects of the control variables (age group and Not U.S.-born) weaken in most cases between the baseline model and the most-inclusive model.

and white women and nearly two-thirds of black women's excess obesity risk. Among men, the relatively small black-white gaps in BMI and obesity in uncontrolled data are most likely due to black men's lower physical activity levels, a difference which may be offset partly by lower caloric intake among black men. When measurement error in caloric intake and physical activity are mitigated, smoking's contribution to racial differences in BMI, among both women and men, becomes small-to-negligible.

Our analysis shows that measurement error, if uncontrolled, may severely limit the ability to explain variation in BMI on the basis of self-reported caloric intake and physical activity. When we take steps to mitigate measurement error, the effects of calories consumed and physical activities on outcomes become much stronger (and smoking's effects become weaker), enabling these behaviors to account for a larger share of the black-white BMI gap (or obesity gap) for women and enabling higher R-squared values in all linear regressions. If we were to take at face value the results of the uncontrolled models, we might infer that the female obesity gap is driven by systematic black-white differences in relatively immutable physiological factors such as basal metabolism. We note also that there is no scientific consensus that blacks (and black women in particular, as would have to be the case) have lower metabolic endowments than whites. (Studies that test for such differences include Martin et al. 2004; Sharp et al. 2002; Weyer et al. 1999; Carpenter et al. 1998; Foster et al. 1997; and Yanovski et al. 1997).

The fact that patterns in caloric intake and physical activity can account for a significant portion of the female obesity gap is important from a policy perspective. While wholesale behavioral change is hard to achieve, our findings suggest that a combination of modest, sustained adjustments on both sides of the energy balance equation may go a long way towards closing the BMI and obesity gaps between black women and white women. For example, our results imply that a relatively small reduction in caloric intake—such as 50 calories per day—could reduce excess obesity risk among black women by 5 percentage points. While black women engage in significantly less leisure-time physical activity than white women, interventions aimed at increasing black women's participation in such activities only address one portion of overall physical activity. Our results indicate that normal daily activities, which likely pertain to actions on the job or related to home production, may have a significant impact on BMI and obesity risk. If leisure-time is scarce, targeting leisure-time activities may be less effective than, for example, encouraging employers to facilitate physical activity during the workday among workers required to sit most of the time.

Our findings raise the obvious question of why behaviors differ between black women and white women. A number of studies find evidence that black women hold a higher ideal BMI than white women (e.g., Anderson et al. 1992 and Burke and Heiland 2008). Other studies find that black women face lower social and economic penalties associated with obesity (e.g., Averett and Korenman 1996 and Cawley 2004). While socioeconomic status is widely cited as an important determinant of BMI and obesity risk, both black women and black men have significantly lower socioeconomic status than their white counterparts, rendering the explanation insufficient to capture gender specificity. In any event, previous research has shown that the stylized facts are largely robust to controls for socioeconomic status (e.g., Burke and Heiland 2008 and Denney et al. 2004). Previous research has also shown that African-Americans tend to live in neighborhoods that provide greater exposure to fast food restaurants, reduced access to fresh produce, and restricted opportunities for safe exercise (e.g., Currie et al. 2009). However, it is not known whether the differences in such constraints apply to (or influence) African-American women to a greater extent than African-American men.

While so far we have emphasized the female-specificity of the black-white obesity gap, this fact breaks down among the younger cohorts in our sample. As seen in Table 2, black men in the youngest age group (20–29 years) have a 50% higher obesity rate than white men the same age (full sample) and black men ages 30–39 years have a roughly 22% higher obesity rate than their white counterparts. The relative risks are still significantly smaller than those observed among women in the same age groups, but the emergence of excess obesity risk among young black men raises important questions for public policy and future research.

REFERENCES

Anderson, J., C. Crawford, J. Nadeau, and T. Lindberg. 1992. "Was the Duchess of Windsor Right? A Cross-Cultural Review of the Socioecology of Ideals of Female Body Shape." *Ethology and Sociobiology* 13(3): 197–227.

Averett, S., and S. Korenman. 1996. "The Economic Reality of the Beauty Myth," *Journal of Human Resources* 31: 304–330.

Beyler, N., S. Nusser, W. Fuller, and G. Welk. 2008. "Relating Self-report and Accelerometer Physical Activity with Application to NHANES 2003–2004." *Proceedings of the Survey Research Methods Section.* American Statistical Association. Available at http://www.amstat.org/sections/srms/proceedings/allyearsf.html.

Black, A. 2000. "Critical Evaluation of Energy Intake Using the Goldberg Cut-Off for Energy Intake:Basal Metabolic Rate. A Practical Guide to its Calculation, Use and Limitations." *International Journal of Obesity* 24(9): 1119–1130.

Black, D., M. Berger, and F. Scott. 2000. "Bounding Parameter Estimates with Nonclassical Measurement Error." *Journal of the American Statistical Association* 95(451): 739–748.

Burke, M., and F. Heiland. 2007. "Social Dynamics of Obesity." *Economic Inquiry* 45(3): 571–591.

Burke, M., and F. Heiland. 2008. "Race, Obesity, and the Puzzle of Gender Specificity." Federal Reserve Bank of Boston, Working Paper No. 08-7. Available at http://bos.frb.org/economic/wp/wp2008/wp0808.pdf

Burkhauser, R., and J. Cawley. 2008. "Beyond BMI: The Value of More Accurate Measures of Fatness and Obesity in Social Science Research." *Journal of Health Economics* 27(2): 519–529.

Carpenter, W., T. Fonong, M. Toth, P. Ades, J. Calles-Escandon, J. Walston, and E. Poehlman. 1998. "Total Daily Energy Expenditure in Free-Living Older African-Americans and Caucasians." *American Journal of Physiology* 274(37): E96–E101.

Cawley, J. 2004. “The Impact of Obesity on Wages,” *Journal of Human Resources* 39: 451–74.

Chang, V., and D. Lauderdale. 2005. “Income Disparities in Body Mass Index and Obesity in the United States, 1971–2002,” *Archives of Internal Medicine* 165: 2122–2128.

Chou, S., M. Grossman, and H. Saffer. 2004. “An Economic Analysis of Adult Obesity: Results from the Behavioral Risk Factor Surveillance System.” *Journal of Health Economics* 23(3): 565–587.

Cunningham, J. 1991. “Body composition as a determinant of energy expenditure: a synthetic review and a proposed general prediction equation,” *American Journal of Clinical Nutrition* 54: 963–969.

Currie, J., S. Della Vigna, E. Moretti, and V. Pathania. 2009. “The Effect of Fast Food Restaurants on Obesity and Weight Gain.” NBER Working Paper No. 14721. Cambridge, MA: National Bureau of Economic Research.

Denney, J., P. Krueger, R. Rogers, and J. Boardman. 2004. “Race/Ethnic and Sex Differentials in Body Mass Among US Adults.” *Ethnicity & Disease* 14: 389–398.

Finkelstein, E., D. Brown, L. Wrage, B. Allaire, and T. Hoerger. 2010. “Individual and Aggregate Years-of-life-lost Associated with Overweight and Obesity. *Obesity* 18(2): 333–339.

Flegal, K., M. Carroll, R. Kuczmarski, and C. Johnson. 1998. “Overweight and Obesity in the United States: Prevalence and Trends, 1960–1994.” *International Journal of Obesity* 22(1): 39–47.

Food and Agricultural Organization of the United Nations. 2004. *Human Energy Requirements: Report of a Joint FAO/WHO/UNU Expert Consultation*. FAO Food and Nutrition Technical Report Series 1. Rome: Food and Agricultural Organization of the United Nations. Available at ftp://ftp.fao.org/docrep/fao/007/y5686e/y568e00.pdf.

Foster, G., T. Wadden, and R. Vogt. 1997. “Resting Energy Expenditure in Obese African American and Caucasian Women,” *Obesity Research* 5: 1–8.

Goldberg, G., A. Black, S. Jebb, T. Cole, P. Murgatroyd, W. Coward, and A. Prentice. 1991. "Critical Evaluation of Energy Intake Data using Fundamental Principles of Energy Physiology. Derivation of Cut-Off Values to Identify Under-Recording." *European Journal of Clinical Nutrition* 45: 569–581.

Grunberg, N. 1982. "The Effects of Nicotine and Cigarette Smoking on Food Consumption and Taste Preferences." *Addictive Behaviors* 7(4): 317–331.

Horgan, G., and J. Stubbs. 2003. "Predicting basal metabolic rate in the obese is difficult." *European Journal of Clinical Nutrition* 57: 335–340.

Komlos, J., and M. Brabec. 2010. "The Trend of Mean BMI Values of U.S. Adults by Centiles, Birth Cohorts 1882–1986." Working Paper No. 16252. Cambridge, MA: National Bureau of Economic Research.

Kuczmarski, R., K. Flegal, S. Campbell, and C. Johnson. 1994. "Increasing Prevalence of Overweight Among U.S. Adults: The National Health and Nutrition Examination Surveys, 1960 to 1991." *Journal of the American Medical Association* 272(3): 205–211.

Kumanyika, S. 1987. "Obesity in Black Women." *Epidemiologic Reviews* 9(1): 31–50.

Ljungvall, Å., and F.J. Zimmerman. 2012. "Bigger Bodies: Long-Term Trends and Disparities in Obesity and Body-Mass Index among U.S. Adults, 1960–2008," *Social Science & Medicine* 75: 109–119.

Macdiarmid, J., and J. Blundell. 1998. "Assessing Dietary Intake: Who, What, and Why of Under-reporting." *Nutrition Research Reviews* 11(2): 231–253.

Martin, K., P. Wallace, P. Rust, and W. Garvey. 2004. "Estimation of Resting Energy Expenditure Considering Effects of Race and Diabetes Status." *Diabetes Care* 27(6): 1405–1411.

McNutt, L., C. Wu, X. Xue, and J. Paul Hafner. 2003. "Estimating the Relative Risk in Cohort Studies and Clinical Trials of Common Outcomes." *American Journal of Epidemiology* 157(10): 940–943.

Mifflin, M., S. Jeor, L. Hill, B. Scott, S. Daugherty, and Y. Koh. 1990. "A New Predictive Equation for Resting Energy Expenditure in Healthy Individuals." *American Journal of Clinical Nutrition* 51(2): 241–247.

Miyata, G., M. Meguid, S. Fetissov, G. Torelli, and H. Kim. 1999. "Nicotine's Effect on Hypothalamic Neurotransmitters and Appetite Regulation." *Surgery* 126(2): 255–263.

Mujahid, M., A. Diez Roux, L. Borrell, and F. Nieto. 2005. "Cross-Sectional and Longitudinal Associations of BMI with Socioeconomic Characteristics." *Obesity Research* 13(8): 1412–1421.

National Center for Health Statistics Centers for Disease Control and Prevention. 1996. *Analytic Reporting Guidelines. The Third National Health and Nutrition Examination Survey. NHANES III 1988–1994.* Hyattsville, MD: Center for Disease Control. Available at http://www.cdc.gov/nchs/data/nhanes/nhanes3/nh3gui.pdf.

Ogden, C. 2009. "Disparities in Obesity Prevalence in the United States: Black Women at Risk." *American Journal of Clinical Nutrition* 89(4): 1001–102.

Ogden, C., M. Carroll, L. Curtin, M. McDowell, C. Tabak, and K. Flegal. 2006. "Prevalence of Overweight and Obesity in the United States, 1999–2004." *Journal of the American Medical Association* 295(13): 1549–1555.

Perkins, K. 1992. "Metabolic Effects of Cigarette Smoking." *Journal of Applied Physiology* 72(2): 401–409.

Perkins, K. 1993. "Weight Gain Following Smoking Cessation." *Journal of Consulting and Clinical Psychology* 61(5): 768–777.

Perkins, K., L. Epstein, R. Stiller, B. Marks, and R. Jacob. 1989. "Acute Effects of Nicotine on Resting Metabolic Rate in Cigarette Smokers." *American Journal of Clinical Nutrition* 50(3): 545–550.

Pryer, J., M. Vrijheid, R. Nichols, M. Kiggins, and P. Elliott. 1997. "Who Are the 'Low Energy Reporters' in the Dietary and Nutritional Survey of British Adults?" *International Journal of Epidemiology* 26(1): 146–154.

Rashad, I. 2006. "Structural Estimation of Caloric Intake, Exercise, Smoking, and Obesity." *Quarterly Review of Economics and Finance* 46(2): 268–283.

Scrimshaw, N., J. Waterlow, and B. Schurch, eds., 1994. Energy and Protein Requirements, Proceedings of an IDECG workshop. http://unu.edu/unupress/food2/UID01E/UID01E08.HTM.

Sharp, T., M. Ball, G. Grunwald, K. Schmitz, S. Sidney, C. Lewis, K. Tolan, and J. Hill. 2002. "Differences in Resting Metabolic Rate between White and African-American Young Adults." *Obesity Research* 10(8): 726–732.

Stamford, B., S. Matter, R. Fell, and P. Papanek. 1986. "Effects of Smoking Cessation on Weight Gain, Metabolic Rate, Caloric Consumption, and Blood Lipids." *American Journal of Clinical Nutrition* 43(4): 486–494.

Streb, M., B. Burrell, B. Frederick, and M. Genovese. 2008. "Social Desirability Effects and Support for a Female American President." *Public Opinion Quarterly* 72(1): 76–89.

Sun, S., W. Chumlea, S. Heymsfield, H. Lukaski, D. Schoeller, K. Friedl, R. Kuczmarski, K. Flegal, C. Johnson, and Van S. Hubbard. 2003. "Development of Bioelectrical Impedance Analysis Prediction Equations for Body Composition With the Use of a Multicomponent Model for Use in Epidemiologic Surveys." *American Journal of Clinical Nutrition* 77: 331–40.

Weyer, C., S. Snitker, C. Bogardus, and E. Ravussin. 1999. "Energy Metabolism in African Americans: Potential Risk Factors for Obesity." *American Journal of Clinical Nutrition* 70(1): 13–20.

Yanovski, S., J. Reynolds, A. Boyle, and J. Yanovski. 1997. "Resting Metabolic Rate in African-American and Caucasian Girls," *Obesity Research* 5(4): 321–325.

Zhang, Q., and Y. Wang. 2004. "Socioeconomic Inequality of Obesity in the United States: Do Gender, Age, and Ethnicity Matter?" *Social Science and Medicine* 58(6): 1171–1180.

Table 1: Obesity Rates (in Percentages) of U.S. Adults Ages 20–74 years, by Gender, Race, and Poverty Status[1]

	1960–62	1971–74	1976–80	1988–94	1999–02	2003–06
			20–74 Years, Age adjusted[3]			
Total population:						
Both sexes	13.3	14.6	15.1	23.3	31.1	34.1
Male	10.7	12.2	12.8	20.6	28.1	33.1
Female	15.7	16.8	17.1	26.0	34.0	35.2
Not Hispanic or Latino:						
White, male	—	—	12.4	20.7	28.7	33.0
White, female	—	—	15.4	23.3	31.3	32.5
Black/African American, male	—	—	16.5	21.3	27.9	36.3
Black/African American, female	—	—	31.0	39.1	49.6	54.3
Percent of poverty level:[2]						
Below 100%	—	20.7	21.9	29.2	36.0	35.9
100%–less than 200%	—	18.4	18.7	26.6	35.4	36.7
200% or more	—	12.4	12.9	21.4	29.2	33.1

Sources: NHES I, NHANES II, NHANES III, NHANES 1999–2006

Notes: —Data not available. [1]Based on CDC Trend tables and Chartbook Tables in Excel format, 2006 Edition, Table 73 (http://www.cdc.gov/nchs/hus.htm). [2]Poverty level is based on family income and family size. Persons with unknown poverty level are excluded. [3]Age adjusted to the 2000 standard population using five age groups: 20–34 years, 35–44 years, 45–54 years, 55–64 years, and 65 years and over (65–74 years for estimates for 20–74 years).

Table 2: Obesity Rates (in Percentages) of U.S. Adults Ages 20-65 years, by Gender, Race, and Regression Sample, NHANES 1999–2006

	Women				**Men**			
	Whites		Blacks		Whites		Blacks	
	Full N=2,817	Restricted N=2,177	Full N=1,403	Restricted N=967	Full N=2,920	Restricted N=2,386	Full N=1,311	Restricted N=943
Age								
Ages 20–29 Years	21.3	16.6	47.7	44.2	21.4	19.6	32.6	30.8
	(2.2)	(2.4)	(3.9)	(5.2)	(2.3)	(2.3)	(3.3)	(3.5)
Ages 30–39 Years	27.7	25.3	50.3	49.0	27.5	26.3	33.5	34.5
	(2.6)	(2.9)	(3.5)	(5.0)	(2.0)	(2.4)	(3.2)	(4.4)
Ages 40–49 Years	36.5	35.5	52.1	50.4	33.9	32.9	31.8	26.9
	(2.2)	(2.5)	(3.0)	(3.7)	(2.3)	(2.7)	(2.7)	(3.0)
Ages 50–65 Years	37.5	36.1	53.8	49.8	36.0	32.9	33.9	31.9
	(1.9)	(2.0)	(2.9)	(3.6)	(1.8)	(2.0)	(2.6)	(3.4)
Foreign-born Status								
Not U.S.-born	17.6	15.3	27.6	29.1	26.0	26.4	13.5	12.3
	(3.4)	(3.4)	(4.1)	(4.9)	(4.3)	(4.8)	(2.8)	(3.6)
U.S.-born	32.7	30.6	53.0	50.2	30.8	28.8	35.2	33.3
	(1.3)	(1.4)	(1.8)	(2.5)	(1.3)	(1.3)	(1.8)	(2.1)
Education								
High School Dropout	38.7	33.6	50.6	44.2	33.9	32.1	29.6	29.0
	(2.6)	(3.1)	(3.1)	(4.5)	(3.9)	(4.6)	(2.4)	(2.9)
High School Graduate	37.1	33.6	53.0	51.6	31.8	29.8	34.4	31.2
	(1.8)	(2.0)	(3.4)	(4.2)	(1.7)	(2.1)	(2.7)	(3.0)
Some College	28.9	27.9	50.5	49.4	29.5	27.8	34.3	32.2
	(1.5)	(1.6)	(2.3)	(3.1)	(1.6)	(1.6)	(2.9)	(3.2)
Income								
Low Income	37.8	33.2	53.0	48.4	28.6	27.6	29.3	27.8
	(1.7)	(2.3)	(2.5)	(3.2)	(1.9)	(2.4)	(2.3)	(2.8)
Middle Income	35.1	33.5	55.0	54.3	33.6	31.5	36.2	31.2
	(2.8)	(2.9)	(3.4)	(4.0)	(2.7)	(3.0)	(2.8)	(3.5)
High Income	28.0	26.7	43.2	43.0	30.0	27.8	35.5	34.7
	(1.5)	(1.5)	(3.3)	(3.5)	(1.6)	(1.7)	(2.8)	(3.6)
Physical Activity								
Missing Activity	41.1	38.5	52.9	49.6	35.6	33.0	29.6	28.1
	(1.6)	(1.5)	(2.4)	(2.8)	(2.0)	(2.3)	(2.3)	(3.2)
Light Activity	38.4	36.8	57.3	57.0	31.8	31.6	31.6	31.6
	(2.1)	(2.3)	(4.5)	(5.6)	(2.2)	(2.5)	(3.4)	(3.9)
Moderate Activity	29.1	25.3	47.5	51.2	30.4	28.9	41.4	38.3
	(3.0)	(3.0)	(5.0)	(4.6)	(3.3)	(3.4)	(4.5)	(4.7)
Vigorous Activity	20.3	18.1	43.3	35.0	26.5	24.0	34.8	31.7
	(1.7)	(1.9)	(2.8)	(3.3)	(1.8)	(2.0)	(2.8)	(3.2)
Sits	39.9	39.8	51.7	49.1	36.5	35.2	33.1	33.2
	(2.3)	(2.7)	(3.2)	(3.7)	(2.3)	(2.5)	(3.8)	(4.1)
Stands	32.2	29.4	52.1	50.4	31.0	28.8	34.5	32.6
	(1.6)	(1.9)	(2.2)	(3.1)	(2.1)	(2.4)	(2.3)	(2.7)
Light Lifting	21.2	18.3	47.5	42.2	25.4	23.7	33.5	26.6
	(2.2)	(2.1)	(3.4)	(5.4)	(2.2)	(2.3)	(4.1)	(4.1)
Heavy Lifting	34.1	30.9	42.2	36.6	27.8	26.2	24.9	25.5
	(6.8)	(7.8)	(8.9)	(11.5)	(2.0)	(2.5)	(3.9)	(4.5)
Smoking								
Nonsmoker	32.5	31.7	52.0	49.8	31.5	30.3	37.2	35.2
	(1.7)	(2.0)	(2.2)	(3.2)	(1.9)	(2.0)	(2.5)	(3.2)
Former Smoker	34.7	32.9	56.9	56.5	37.1	34.1	37.4	33.3
	(2.2)	(2.5)	(4.2)	(4.6)	(1.9)	(2.2)	(4.0)	(4.6)
Current Smoker	28.7	23.7	45.4	40.6	23.6	21.8	24.7	23.8
	(1.7)	(1.7)	(3.3)	(4.4)	(1.8)	(1.8)	(2.3)	(2.8)

Source: Authors' calculations based on NHANES 1999–2006.

Notes: Standard errors given in parentheses.

Table 3: Sample Means, Dependent and Independent Variables, by Gender, Race, and Regression Sample, NHANES 1999-2006

	Women				**Men**			
	Whites		Blacks		Whites		Blacks	
	Full N=2,817	Restricted N=2,177	Full N=1,403	Restricted N=967	Full N=2,920	Restricted N=2,386	Full N=1,311	Restricted N=943
BMI	27.84	27.41	31.59	30.76	28.18	27.95	28.47	28.05
	(0.21)	(0.23)	(0.31)	(0.34)	(0.16)	(0.17)	(0.26)	(0.27)
Obese	0.32	0.30	0.51	0.49	0.31	0.29	0.33	0.31
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Age	42.56	42.50	40.41	40.54	41.87	42.01	39.57	39.29
	(0.32)	(0.33)	(0.38)	(0.39)	(0.31)	(0.37)	(0.45)	(0.49)
Ages 20–29 Years	0.19	0.18	0.22	0.22	0.21	0.20	0.26	0.27
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Ages 30–39 Years	0.23	0.23	0.26	0.25	0.23	0.23	0.24	0.25
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Ages 40–49 Years	0.26	0.27	0.26	0.27	0.25	0.26	0.25	0.24
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Ages 50–65 Years	0.33	0.32	0.26	0.26	0.32	0.32	0.25	0.24
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Not U.S.-born	0.05	0.05	0.08	0.08	0.05	0.05	0.11	0.11
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Missing Activity	0.29	0.29	0.48	0.50	0.27	0.27	0.39	0.38
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Light Activity	0.24	0.25	0.19	0.21	0.19	0.20	0.15	0.17
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Moderate Activity	0.14	0.15	0.11	0.10	0.15	0.15	0.10	0.11
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Vigorous Activity	0.33	0.31	0.22	0.19	0.39	0.38	0.35	0.34
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Sits	0.25	0.25	0.31	0.31	0.22	0.22	0.21	0.21
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Stands	0.53	0.54	0.53	0.53	0.43	0.42	0.52	0.53
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Light Lifting	0.20	0.19	0.14	0.13	0.21	0.22	0.16	0.16
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Heavy Lifting	0.03	0.03	0.02	0.03	0.14	0.14	0.11	0.11
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Total Kcal	1878.80	2030.89	1894.14	2072.12	2767.56	2874.95	2587.42	2787.98
	(15.59)	(15.18)	(29.89)	(26.06)	(23.71)	(21.88)	(34.33)	(40.39)
Nonsmoker	0.51	0.51	0.66	0.65	0.43	0.43	0.49	0.50
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Former Smoker	0.23	0.23	0.12	0.12	0.26	0.26	0.16	0.17
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Current Smoker	0.26	0.26	0.22	0.23	0.31	0.30	0.35	0.34
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
EB-Ratio	87.23	94.92	84.63	92.69	95.40	99.28	88.38	95.49
	(0.76)	(0.54)	(1.53)	(1.18)	(0.82)	(0.71)	(1.19)	(1.14)

Source: Authors' calculations based on NHANES 1999–2006.

Notes: Standard errors given in parentheses.

Table 4: Determinants of BMI, Linear Regressions, Females Aged 20–65 Years

	Full Sample				Restricted Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	4.004***	3.880***	3.532***	2.458***	3.611***	3.515***	2.905***	1.745***
	(0.335)	(0.308)	(0.342)	(0.268)	(0.366)	(0.339)	(0.389)	(0.280)
Aged 30–39 Years	1.208**	1.194**	0.879*	1.230***	1.696***	1.624***	1.562***	1.798***
	(0.365)	(0.361)	(0.361)	(0.310)	(0.398)	(0.391)	(0.393)	(0.294)
Aged 40–49 Years	2.422***	2.394***	1.927***	2.758***	2.882***	2.789***	2.709***	3.322***
	(0.388)	(0.376)	(0.382)	(0.301)	(0.401)	(0.388)	(0.383)	(0.272)
Aged 50–65 Years	3.028***	2.835***	2.353***	4.356***	3.473***	3.341***	3.492***	5.142***
	(0.338)	(0.353)	(0.349)	(0.309)	(0.423)	(0.420)	(0.409)	(0.318)
Not U.S.-born	-2.799***	-2.603***	-3.190***	-1.246***	-2.786***	-2.759***	-2.715***	-1.010**
	(0.345)	(0.370)	(0.308)	(0.308)	(0.391)	(0.400)	(0.342)	(0.314)
Missing Activity			0.232	0.159			0.198	0.146
			(0.295)	(0.222)			(0.311)	(0.240)
Moderate Activity			-1.818***	-1.288***			-1.888***	-1.567***
			(0.401)	(0.303)			(0.410)	(0.342)
Vigorous Activity			-2.169***	-4.393***			-2.549***	-4.453***
			(0.306)	(0.236)			(0.348)	(0.257)
Current Smoker			-1.305***	-0.352			-1.561***	-0.690**
			(0.219)	(0.198)			(0.264)	(0.247)
Former Smoker			0.602	0.376			0.369	0.081
			(0.406)	(0.348)			(0.428)	(0.339)
Stands			-0.943***	-2.269***			-1.251***	-2.380***
			(0.247)	(0.244)			(0.290)	(0.251)
Light Lifting			-2.035***	-4.341***			-2.661***	-4.578***
			(0.393)	(0.321)			(0.422)	(0.370)
Heavy Lifting			-1.332*	-5.658***			-2.603***	-6.527***
			(0.625)	(0.535)			(0.655)	(0.539)
Total Kcal			0.0002	0.0110***			0.0027***	0.0113***
			(0.0002)	(0.0005)			(0.0002)	(0.0005)
EB-Ratio		-0.041***		-0.241***		-0.040***		-0.234***
		(0.003)		(0.009)		(0.005)		(0.010)
Constant	26.080***	29.697***	28.225***	29.578***	25.272***	29.152***	22.467***	27.802***
	(0.310)	(0.427)	(0.526)	(0.362)	(0.334)	(0.627)	(0.658)	(0.466)
R^2 (adj.)	0.067	0.113	0.105	0.421	0.073	0.096	0.169	0.466
N	6,225	6,225	6,225	6,225	4,676	4,676	4,676	4,676

Source: Authors' calculations.

Notes: Standard errors are reported in parentheses. All regressions also control for Mexican, other Hispanic, and other Race/Ethnicity.

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.

Table 5: Determinants of Obesity, Poisson Regressions, Females Ages 20–65 Years

	Full Sample				**Restricted Sample**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	1.654***	1.602***	1.522***	1.266***	1.689***	1.664***	1.493***	1.244***
	(0.074)	(0.065)	(0.071)	(0.057)	(0.102)	(0.096)	(0.095)	(0.082)
Age 30-39	1.238***	1.243***	1.170**	1.194**	1.396***	1.380***	1.332***	1.327***
	(0.100)	(0.098)	(0.092)	(0.081)	(0.150)	(0.146)	(0.134)	(0.116)
Age 40-49	1.499***	1.506***	1.386***	1.495***	1.730***	1.711***	1.637***	1.682***
	(0.117)	(0.112)	(0.107)	(0.083)	(0.158)	(0.151)	(0.143)	(0.111)
Age 50-65	1.566***	1.530***	1.418***	1.734***	1.801***	1.767***	1.754***	2.008***
	(0.109)	(0.110)	(0.101)	(0.116)	(0.169)	(0.166)	(0.160)	(0.160)
Not U.S.-born	0.574***	0.589***	0.538***	0.744***	0.567***	0.568***	0.575***	0.769***
	(0.048)	(0.050)	(0.044)	(0.061)	(0.050)	(0.052)	(0.049)	(0.065)
Missing Activity			1.009	0.972			0.990	0.953
			(0.052)	(0.048)			(0.055)	(0.052)
Moderate Activity			0.765***	0.830***			0.732***	0.786***
			(0.060)	(0.055)			(0.063)	(0.063)
Vigorous Activity			0.615***	0.394***			0.552***	0.371***
			(0.040)	(0.026)			(0.044)	(0.034)
Current Smoker			0.850***	0.978			0.769***	0.893*
			(0.040)	(0.048)			(0.046)	(0.055)
Former Smoker			1.027	1.014			0.994	0.983
			(0.056)	(0.050)			(0.065)	(0.054)
Stands			0.942	0.808***			0.865**	0.756***
			(0.045)	(0.039)			(0.052)	(0.045)
Light Lifting			0.705***	0.540***			0.594***	0.485***
			(0.064)	(0.045)			(0.064)	(0.046)
Heavy Lifting			0.869	0.477***			0.709*	0.408***
			(0.139)	(0.073)			(0.140)	(0.080)
Total Kcal			1.0000	1.0017***			1.0004***	1.0017***
			(0.0000)	(0.0001)			(0.0000)	(0.000)
EB-Ratio		0.993***		0.960***		0.993***		0.962***
		(0.001)		(0.002)		(0.001)		(0.002)
N	6,225	6,225	6,225	6,225	4,676	4,676	4,676	4,676

Source: Authors' Calculations.

Notes: Coefficients represent relative risks. Standard errors are reported in parentheses. All regressions also control for Mexican, other Hispanic, and other Race/Ethnicity.

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.

Table 6: Determinants of BMI, Linear Regressions, Males Ages 20–65 Years

	Full Sample				Restricted Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.536	0.344	0.514	0.173	0.38	0.269	0.423	0.029
	(0.298)	(0.292)	(0.310)	(0.259)	(0.326)	(0.325)	(0.319)	(0.287)
Aged 30–39 Years	1.208***	1.333***	0.939***	1.508***	1.238***	1.317***	1.027***	1.584***
	(0.246)	(0.233)	(0.247)	(0.224)	(0.259)	(0.255)	(0.265)	(0.267)
Aged 40–49 Years	2.083***	2.138***	1.780***	2.637***	2.216***	2.250***	2.069***	2.923***
	(0.276)	(0.271)	(0.276)	(0.266)	(0.284)	(0.279)	(0.276)	(0.260)
Aged 50–65 Years	2.013***	1.846***	1.486***	2.882***	1.910***	1.823***	1.828***	3.282***
	(0.284)	(0.263)	(0.281)	(0.217)	(0.276)	(0.264)	(0.268)	(0.210)
Not U.S.-born	-2.062***	-2.174***	-2.256***	-1.458***	-2.058***	-2.152***	-1.981***	-1.195***
	(0.347)	(0.327)	(0.347)	(0.283)	(0.336)	(0.333)	(0.341)	(0.303)
Missing Activity			0.187	0.149			-0.008	0.12
			(0.240)	(0.212)			(0.279)	(0.236)
Moderate Activity			-0.037	-0.322			-0.045	-0.291
			(0.282)	(0.236)			(0.320)	(0.265)
Vigorous Activity			-0.618*	-3.016***			-1.004***	-3.201***
			(0.259)	(0.256)			(0.271)	(0.246)
Current Smoker			-1.657***	-0.814**			-1.655***	-0.915***
			(0.250)	(0.252)			(0.249)	(0.239)
Former Smoker			0.075	0.083			0.005	0.061
			(0.248)	(0.233)			(0.281)	(0.234)
Stands			-0.842**	-1.456***			-0.895**	-1.516***
			(0.286)	(0.245)			(0.316)	(0.259)
Light Lifting			-1.309***	-2.723***			-1.571***	-2.946***
			(0.327)	(0.296)			(0.347)	(0.315)
Heavy Lifting			-0.817**	-3.969***			-1.344***	-4.385***
			(0.302)	(0.327)			(0.354)	(0.337)
Total Kcal			-0.0001	0.0057***			0.0009***	0.0060***
			(0.0001)	(0.0003)			(0.0001)	(0.0003)
EB-Ratio		-0.027***		-0.169***		-0.029***		-0.177***
		(0.002)		(0.007)		(0.003)		(0.006)
Constant	26.846***	29.392***	28.736***	29.944***	26.589***	29.454***	25.987***	29.603***
	(0.228)	(0.325)	(0.440)	(0.394)	(0.224)	(0.385)	(0.529)	(0.463)
R^2 (adj.)	0.032	0.068	0.058	0.278	0.034	0.055	0.082	0.310
N	6,208	6,208	6,208	6,208	4,861	4,861	4,861	4,861

Source: Author's calculations.

Notes: Standard errors are reported in parentheses. All regressions also control for Mexican, other Hispanic, and other Race/Ethnicity.

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.

Table 7: Determinants of Obesity, Poisson Regressions, Males Ages 20–65 Years

	Full Sample				**Restricted Sample**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	1.132**	1.079	1.121**	0.999	1.145*	1.116	1.148**	1.015
	(0.064)	(0.061)	(0.064)	(0.050)	(0.078)	(0.076)	(0.076)	(0.065)
Age 30-39	1.245***	1.284***	1.175**	1.313***	1.333***	1.361***	1.270**	1.411***
	(0.096)	(0.099)	(0.090)	(0.105)	(0.130)	(0.133)	(0.122)	(0.141)
Age 40-49	1.436***	1.462***	1.344***	1.671***	1.536***	1.554***	1.487***	1.857***
	(0.117)	(0.119)	(0.108)	(0.130)	(0.157)	(0.156)	(0.147)	(0.178)
Age 50-65	1.479***	1.433***	1.323***	1.819***	1.512***	1.482***	1.495***	2.085***
	(0.129)	(0.121)	(0.112)	(0.142)	(0.151)	(0.146)	(0.141)	(0.187)
Not U.S.-born	0.585***	0.576***	0.559***	0.690***	0.595***	0.584***	0.600***	0.730***
	(0.065)	(0.063)	(0.064)	(0.073)	(0.072)	(0.070)	(0.074)	(0.082)
Missing Activity			1.084	1.048			1.021	1.023
			(0.075)	(0.067)			(0.082)	(0.071)
Moderate Activity			0.951	0.879			0.920	0.843
			(0.092)	(0.082)			(0.100)	(0.091)
Vigorous Activity			0.878*	0.477***			0.785**	0.437***
			(0.068)	(0.039)			(0.075)	(0.044)
Current Smoker			0.723***	0.865**			0.711***	0.848**
			(0.052)	(0.059)			(0.059)	(0.066)
Former Smoker			1.019	1.007			0.964	0.951
			(0.061)	(0.061)			(0.071)	(0.067)
Stands			0.893	0.819***			0.854*	0.777***
			(0.069)	(0.056)			(0.079)	(0.061)
Light Lifting			0.783***	0.622***			0.724***	0.568***
			(0.069)	(0.049)			(0.073)	(0.051)
Heavy Lifting			0.846**	0.471***			0.774***	0.431***
			(0.058)	(0.037)			(0.073)	(0.042)
Total Kcal			1.0000	1.0012***			1.0002***	1.0012***
			(0.0000)	(0.0001)			(0.0000)	(0.0001)
EB-Ratio		0.994***		0.962***		0.993***		0.960***
		(0.001)		(0.002)		(0.001)		(0.002)
N	6,208	6,208	6,208	6,208	4,861	4,861	4,861	4,861

Source: Authors' calculations.

Notes: Coefficients represent relative risks. Standard errors are reported in parentheses. All regressions also control for Mexican, other Hispanic, and other Race/Ethnicity.

*Statistically significant at the .10 level; **at the .05 level; ***at the .01 level.

Appendix A. Structural model of BMI

In the proximate or structural sense, body weight at a point in time, denoted W_i^T, is a stock that reflects lifetime energy balance, or caloric intake net of caloric expenditure, as follows:

$$W_i^T = W_i^0 + \kappa \sum_{t=1}^{T} (EI_i^t - TEE_i^t). \quad (4)$$

W_i^0 in Eq. (4) refers to weight at birth (measured in kilograms), EI_i^t is total energy intake or food consumption in a given period (measured in kilocalories or kcal), and TEE_i^t is total energy expenditure in a given period (also measured in kcal). The term κ is a constant that translates energy balance in a given period (measured in kcal) into change in body weight (measured in kilograms). For example, if EI_i^t exceeds TEE_i^t, energy balance is positive and body weight increases over the period. Ignoring childhood and adolescence, when weight and height are generally increasing, we focus on adulthood and adopt the stylized assumption that weight is largely stable over time. Holding height constant, we can apply the energy balance equation to BMI as well, although the value of κ will differ. While it is more realistic to think of a life-cycle path of BMI than a fixed value, we abstract from age in the discussion immediately following. However, we control for age differences in the empirical analysis. In order to maintain weight or BMI at a stable value over time, a necessary condition is that $EI_i^t = TEE_i^t$ within each period.

The following equation represents BMI as the joint product of individual choices and biological factors, subject to an implicit stability condition:

$$BMI_i^s = G(EI_i^s, PAL_i^s, g_i, \epsilon_i). \quad (5)$$

BMI_i^s in Eq. (5) refers to the stable BMI value that results when the individual adopts a daily caloric intake level equal to EI_i^s and a daily physical activity level equal to PAL_i^s. The physical activity level (PAL) is defined formally as the ratio of total daily energy expenditure, TEE_i^s (in kcal), to the basal metabolic rate, BMR_i^s (also measured in kcal). The basal metabolic rate refers to the calories expended per day in maintaining basic involuntary bodily functions, such as breathing, while in a resting and fasting state. The term "resting metabolic rate" or RMR is sometimes used interchangeably with BMR. However, measurement standards are stricter for basal metabolism than for resting metabolism. See, for example, http://www.caloriesperhour.com/tutorial_BMR.php. The PAL represents the average energy-intensity of physical activities performed in a typical day, where energy-intensity is expressed in relation to energy expended at rest. The PAL is equivalent to the average MET score of activities in a day, where a MET, or metabolic equivalent, is defined as the calories expended per minute of an activity relative to calories expended per minute at rest. The estimated range of PAL values for sustainable lifestyles runs from 1.2 to 2.5, where 1.2 is indicative of a bed-bound or chair-bound individual and 2.5 represents a very physically active individual (Scrimshaw et al. 1994). Intuitively, PAL increases with either the time spent in or the intensity of physical activities.

Beginning from any initial BMI value, an individual who fixes her daily choices at EI_i^s and PAL_i^s will stabilize at BMI_i^s. This stable BMI value also depends on the individual's gender, denoted g_i, and on an idiosyncratic metabolic endowment, ϵ_i, which is described below. We posit that the individual chooses a physical activity level (PAL) rather than total energy expenditure (TEE) — based on the fact that it is harder to observe caloric expenditure than to observe time spent and intensity of physical activities. Total energy expenditure is chosen indirectly, however, as a function of PAL and other factors, and can be expressed as follows:

$$TEE_i^s = PAEE_i^s(PAL_i^s, BMI_i^s, g_i) + BMR_i^s(BMI_i^s, g_i, \epsilon_i). \tag{6}$$

The stable value of total energy expenditure, TEE_i^s (in kcal), is separated into two components: physical-activity-related energy expenditure, denoted $PAEE_i^s$, which depends on the (stable) physical activity level (PAL_i^s), the (stable) BMI value, and gender, g_i; and the basal metabolic rate (BMR_i^s), defined above. BMR depends on current BMI, gender, and the idiosyncratic metabolic endowment. The dependence of energy expenditure on BMI reflects the fact that a larger body requires more energy to perform a given amount of work. The mutual dependence between BMI and energy expenditure means that stable BMI must satisfy a fixed-point condition. The idiosyncratic endowment, ϵ_i, acts as a random shock to the relationship between BMR and BMI. Given this heterogeneity, stable BMI may vary across individuals for identical behavior choices. PAEE may also vary idiosyncratically. We abstract from such variation with no meaningful change in results.

Individuals have preferences over food intake, physical activity level, and BMI itself. In addition, they face constraints such as income, food prices, and the cost of engaging in physical activity. Taking the BMI production function, $G[.]$, as given, individuals jointly choose BMI, food intake, and physical activity level to maximize utility subject to constraints. For a given individual and a given BMI value, we assume there is a unique combination of behavioral choices that maximize utility subject to achieving the given BMI. Given indirect (maximized) utility as a function of BMI, individuals choose BMI to maximize utility globally, and optimal behaviors consistent with the chosen BMI are implied. Optimal BMI is taken to be unique subject to individual parameters. Burke and Heiland (2007) describe necessary and sufficient conditions for the existence of optimal and stable BMI.

Optimal BMI is a function of behaviors, preferences, endowments, and constraints, as follows:

$$BMI_i^* = K[EI_i^*(\mu_i, p_i, \epsilon_i), PAL_i^*(\mu_i, p_i, \epsilon_i)]. \tag{7}$$

Gender has been dropped from Eq. (7) for simplicity and the relationship is assumed to be gender-specific. The function $K[.]$ differs from the function $G[.]$ in Eq. (5) because the latter equation imposes optimality conditions in addition to stability. The term μ_i denotes a vector of preferences over food, physical activity, and BMI. Such preferences may reflect physiological factors (an inherent taste for various foods) as well as social and cultural factors such as body size norms and the importance of sports in social life, all of which are taken as exogenous. Constraints are given by p_i, a vector that includes income, food prices, and the cost of engaging in physical activity.

Our framework can be readily extended to include smoking behavior. While smoking should have no independent effect on energy balance once total caloric intake and total caloric expenditure are taken into account, it is often found to have a significant (negative) association with BMI (e.g., Chou et al. 2004). Previous research has found that nicotine may raise the resting metabolic rate (Perkins et al. 1989) and inhibit food consumption (Miyata et al. 1999 and Grunberg 1982). Since caloric intake and caloric expenditure are typically measured with error, smoking likely acts as a proxy for unmeasured variation in these factors. The choice to smoke is likely to be simultaneous with BMI if individuals perceive the effects of smoking on body weight.

Appendix B. Simulation analysis

To assess the validity and robustness of the "balance-ratio" method, we apply the method to simulated data on BMI and behaviors under a variety of data conditions. We also compare the method used in the paper to two alternative methods, described below.

B.1 Setup

The simulated data are generated using two fictional yet reasonable structural models. The first is a model of individual BMI as a function of steady-state caloric intake, $kcal_i$, steady-state physical activity level, PAL_i, and the metabolic endowment, ϵ_i, as follows:

$$BMI_i = \frac{kcal_i}{\beta * PAL_i} - \frac{\alpha}{\beta} - \frac{\epsilon_i}{\beta} \tag{8}$$

In the above, the parameters α and β are strictly positive constants. The second model relates an individual's basal metabolic rate (BMR), or daily calories expended in a resting state, to her body mass index (BMI) and metabolic endowment (ϵ_i), as follows:

$$BMR_i = \alpha + \beta * BMI_i + \epsilon_i \tag{9}$$

The same parameters appear in both equations: the model of BMI is derived using the model of BMR, along with the condition that BMI and behaviors are stable and mutually consistent.

We calibrate the model to women, but results are qualitatively similar for a model calibrated to men. We abstract from age. To generate a population distribution for BMI, we generate distributions of behaviors ($kcal$ and PAL) and endowments (ϵ_i) and then use equation (8) to determine associated BMI values. We assume that $kcal_i$ is independent of PAL_i, and that the metabolic endowment is independent of both of these factors. A given behavior (or the endowment) is drawn from the same distribution for all individuals. The simulated distributions of BMI, caloric intake, and physical activity levels are similar, in terms of means and variances, to the corresponding empirical distributions in the NHANES 1999–2006 data for women ages 20-65. Given simulated BMI and simulated endowments, we construct simulated BMR using equation (9).

Using the simulated data, we estimate a model of BMI that is linear in $kcal$ and PAL, treating the endowment as an omitted variable. Due to the specification error, the estimated coefficients on behaviors do not match the coefficients of the nonlinear structural model, but they represent the "correct" coefficients under the linear specification and are used as benchmarks in the assessment of various linear models below.

We introduce noise into caloric intake and physical activity to produce simulated "self-reported" data. In one case, we perturb true behaviors with classical noise, adding a mean-zero, homoscedastic disturbance. In a second case, we let self-reporting bias depend on the true behaviors. In the case of caloric intake, we impose a bias toward underreporting which is more extreme, on average, the higher is true caloric intake. However, random perturbations ensure that self-reported calories are not wholly predictable on the basis of true calories. For physical activity, the average tendency is to overreport and moreso the lower is true activity. Again, the relationship is perturbed at random. Under either type of noise, the disturbances used to generate self-reported caloric intake and physical activity level, respectively, are independent within an individual.

Recall that, as applied to the NHANES data, the EB-Ratio is computed as follows:

$$EBRatio_i = \frac{kcal_i^{sr}/\hat{BMR}_i}{PAL_i^{sr}} \qquad (10)$$

In the above, $kcal_i^{sr}$ refers to self-reported $kcal$, $\hat{BMR}_i$ is an estimated value of BMR, and PAL_i^{sr} is an estimate of PAL based on self-reported physical activity. In the method used in the paper, $\hat{BMR}_i$ represents the sum of a predicted BMR value (based on the Mifflin equation) and a random disturbance based on the distribution of residuals in Mifflin et al. (1990). Using the simulated data, we construct three slightly different versions of EB-Ratio: the first mimics the one just described, the second represents an ideal benchmark, and the third represents a feasible alternative. We include each version (alternately) as a control variable in a linear regression of BMI against self-reported behaviors. Comparing these results, we show that our preferred method performs better in relation to the ideal benchmark than the feasible alternative.

The three versions of EB-Ratio differ only in the value of BMR. In the ideal benchmark ("true BMR") version, we use true (simulated) BMR, which should yield the best results and yet is not feasible in NHANES. In the version that mimics the one applied to NHANES data ("estimated BMR"), we act as if BMR is unknown and use an estimate that constitutes a predicted value plus a random shock. To generate this estimate, we regress simulated BMR against simulated BMI, omitting the endowment. This regression is analogous to the Mifflin equation used to estimate BMR in the actual data. This regression produces a downward-biased estimate of the (simulated) structural coefficient on BMI because, by construction, BMI is endogenous in the unobserved endowment. This same bias likely affects the Mifflin equation, which therefore should not be interpreted as a structural model of BMR. We use the resulting regression equation to predict BMR as a function of BMI, and then add a random disturbance drawn from the distribution of residuals of the same regression. In the third version ("predicted BMR"), we let BMR take its predicted value rather than the prediction plus a shock.

For each method of constructing EB-Ratio and for each type of noise, we run 20 iterations of the model, each involving different values for the various shocks. Results represent averages across runs. We observe minimal variance in results within a given method.

Table Appendix B: Simulation Results, Energy-Balance Ratio Approach

	No noise			**Classical noise**			**Non-classical noise**		
Data condition	Kcal coef.	PAL coef.	R^2	Kcal coef.	PAL coef.	R^2	Kcal coef.	PAL coef.	R^2
EB-Ratio omitted	0.038	-55.0	0.72	0.009	-20.5	0.21	0.012	0.68	0.10
EB-Ratio, true BMR				0.036	-52.6	0.69	0.041	-43.1	0.62
EB-Ratio, predicted BMR				0.049	-71.1	0.93	0.055	-57.2	0.83
EB-Ratio, estimated BMR				0.033	-50.2	0.65	0.04	-36.5	0.58

Source: Authors' calculations.

Notes: See text of Appendix B for explanation.

B.2 Results

Table A shows estimated (linear) model coefficients under various data conditions and methods, as labelled in the table. The "no-noise" condition indicates the benchmark coefficients of a linear model using the true data, which are 0.038 on kcal and -55 on PAL, respectively. For each noise condition, we show coefficients on kcal and PAL (and R-squared values) for a model with no correction measures (EB-Ratio omitted) and for models including, in turn, each of the 3 versions of EB-Ratio. We discuss results for classical noise first and then turn to the non-classical case.

With EB-Ratio omitted (and classical noise), coefficients on behaviors are biased downward substantially (in absolute magnitude) relative to benchmark values; explanatory power is weak—R-squared is less than one-third of its value in the no-noise case. Using EB-Ratio with true BMR, the coefficients come close to their no-noise benchmarks, despite displaying residual attenuation bias, and R-squared also approaches the benchmark value. These results indicate that the method works as intended, if imperfectly, under the ideal scenario. Using EB-Ratio with predicted BMR, the model overestimates the magnitudes of both structural coefficients and so ascribes too much explanatory power to behaviors and too little to the endowment. Finally, under EB-Ratio with estimated BMR, the structural coefficients are still too low, but attenuation is far less severe than in the absence of any control, and R-squared is not far from its benchmark. Comparing the two feasible EB-Ratio methods, we should prefer the "estimated BMR" to the "predicted BMR" method, since the former produces conservative (yet decent) estimates of the structural coefficients whereas the latter overestimates them.

Under non-classical noise, when EB-Ratio is omitted the coefficient on kcal is biased downward while the coefficient on PAL is biased sharply upward, taking a positive value. Using EB-Ratio with true BMR, the coefficient on *kcal* is moderately overestimated, while the coefficient on PAL is underestimated (in magnitude) and yet far closer to its true value than in the absence of control. Therefore, the method encounters some difficulty in the presence of non-classical noise, even in the best-case scenario. Using EB-Ratio with predicted BMR, as in the classical noise case both coefficients are too large in absolute value, although the R-squared is not as severely overstated. Using the estimated BMR version, again the effect of *kcal* is overestimated, but to a lesser extent than it is using either of the other versions. Also, the effect of PAL is underestimated and R-squared falls short of the benchmark. Comparing feasible EB-Ratio methods, the "estimated BMR" version again performs best.

These results justify use of the "estimated BMR" method for EB-Ratio in the NHANES data. While the method is imperfect and biases are more severe under non-classical noise, it results in estimated effects of behaviors that are much closer to their benchmark values than we obtain in the absence of any mitigation method. Furthermore, when applying the method to the NHANES data, the estimated coefficients for both kcal and PAL increase in absolute value with the inclusion of EB-Ratio. These latter results suggest that there is a strong classical component to measurement error in self-reported behaviors which most likely dominates the non-classical component.

Appendix C. Data

This appendix describes the construction of variables used in the empirical analysis. All variables are constructed using data from the NHANES, survey years 1999–2006. Methods used conform to those in the NHANES analytical guidelines.

C.1 Physical activity

We construct two discrete variables to capture physical activities: a variable that describes typical daily activities, and a variable that measures leisure-time physical activity (LTPA). The former variable consists of responses to a survey question asking subjects to characterize their "usual daily activities" in the course of paid work, housework, attending classes if a student, or the typical activities of retired persons. Available responses, among which subjects must choose only one, include "mostly sitting," "mostly standing or walking with little heavy lifting," "lifting light loads and/or stair-climbing," and "lifting heavy loads or other heavy work." The leisure-time activity variable draws on a series of questions pertaining to "moderate" and "vigorous" leisure-time physical activities. For each of these two categories, respondents are first asked whether they engaged in any such activity for at least 10 minutes during the past 30 days; if so, they report the frequency and typical duration of each qualifying activity.

We aggregate the set of LTPA-related responses for an individual into a measure of total intensity-weighted LTPA per month using the concept of MET-minutes. A MET, or metabolic equivalent, is the ratio of energy expended in an activity to energy expended at rest (but not asleep). MET-minutes are calculated as the product of minutes spent in an activity and the MET value of the activity, where 30 minutes of a 2-MET activity, such as washing dishes, represents the same total MET-minutes (60) as 15 minutes of a 4-MET activity, such as walking briskly. Using the recommended MET values for activities provided by NHANES, together with the frequency and duration data, we compute total MET-minutes (per month) across all leisure-time physical activities and assign each individual to one of four categories: the "light activity" category includes those with fewer than 2000 MET-minutes per month of LTPA; the "moderate activity" category includes those with at least 2,000 MET-minutes per month but less than 4,000; the "vigorous activity" category includes those with 4,000 or greater MET-minutes per month of LTPA; a fourth category includes those with missing values for leisure-time physical activity. The three non-missing categories correspond roughly to the three levels of physical activity described in the U.S. Department of Health and Human Services' physical activity guidelines for adults. See http://www.health.gov/paguidelines/pdf/paguide.pdf for details.

We create a separate category for individuals with missing data, rather than excluding them from the sample, for several reasons. First, the share of individuals in NHANES 1999–2006 for whom LTPA data are missing is large and therefore discarding these observations would entail a significant loss in sample size. Second, missing values for LTPA are more common among African-Americans than whites. Therefore, omitting the observations would impair the representativeness of the data. In results described in the main text, we find that individuals with missing values for LTPA are not significantly different—in terms of either their BMI or their obesity risk—from individuals in the "light activity" category. Therefore those with missing data are likely to have low levels of LTPA.

In order to calculate EB-Ratio, we must estimate the overall physical activity level (PAL) of the individual. The PAL represents a single index of total daily physical activity, whether in work or leisure-time pursuits, and is defined as the ratio of total daily caloric expenditure to basal expenditure or BMR. Guidelines for determining PAL values based on survey data related to physical activities (such as those contained in NHANES) are provided in NHANES documentation as well as by the World Health Organization (FAO/WHO/UNU 2001). All individuals in our regression sample responded to the "daily activities" question and some also provided information on leisure-time physical activities. For all individuals, we create a baseline PAL value equal to the NHANES-recommended MET value for the individual's response to the "daily activities" question–for example, an individual who "mostly sits" is assigned a baseline PAL of 1.4. For individuals with non-missing data on leisure-time physical activities, the PAL value is subject to an adjustment which depends on the total amount of LTPA, in line with WHO guidelines. As a result, individuals with missing data for LTPA have lower PAL values, on average, than those with non-missing LTPA, consistent with evidence that missing-LTPA people are less active. People with non-missing LTPA but with only light activity do not receive an upward adjustment and therefore have PAL values similar to those of people with missing LTPA. As a robustness check, we run models in which PAL values are held at their baseline values for all individuals. These results involve larger coefficients on kcal than our published results and are better able to explain racial gaps in BMI and obesity risk. Therefore, our published results represent conservative estimates in addition to making fuller use of the information that is available.

C.2 Dietary intake and smoking

In the NHANES data from 1999–2006, a subset of survey participants reported extensive information on food consumption using the 24-hour recall method, in which individuals are asked to describe every food and beverage item that they consumed in the previous 24-hour period. Based on these reports, the survey uses standardized nutrition information to compute total kilocalories consumed per day. All individuals in our regression samples completed an in-person 24-hour recall for one day's worth of food consumption. Some subjects (a subset of observations from years 2003–2006) also completed a second recall, conducted by phone, pertaining to a different day's consumption. To maintain consistency across subjects and maximize sample size, the variable "total kcal" used in our empirical analysis always refers to the single day's calories computed on the basis of the in-person recall.

The NHANES surveys contain self-reported information on both past and present smoking activity. Based on this information, we construct a smoking variable with three categories: "non-smoker," for those individuals who report having smoked fewer than 100 cigarettes in their lifetime; "current smoker," for those who smoked at least 100 cigarettes in their lifetime and also reported smoking regularly at the time of the interview; and "former smoker," for those who smoked at least 100 cigarettes in their lifetime but were not still smoking regularly at the time of the interview.

C.3 Demographic variables

NHANES 1999–2006 contains five racial/ethnic categories: non-Hispanic white, non-Hispanic black, Mexican, other Hispanic, and "other," which embeds Asian-Americans and all other identities. We use the race/ethnicity variable named "ridreth1" in NHANES terminology. In the regression analysis, we include dummy variables for each racial/ethnic category, letting whites be the omitted group, such that our reported contrasts pertain explicitly to blacks versus whites. Effects for other racial/ethnic groups are suppressed in the results tables.

The NHANES data indicate whether or not each participant was born in the United States. One's country of origin (United States or other) is an exogenous factor that may have a significant impact on an individual's BMI. Since we want to assess racial differences in BMI that are not driven by an individual's country of origin, a dummy variable for "not born in the United States" is included as a control in all empirical models.

NHANES 1999–2006 reports age in years for all interviewees. Within the sample of adults aged 20-65 years, we construct four age groups: 20–29 years, 30–39 years, 40–49 years, and 50-65 years. We include the age category as a control in all regression models to control for racial differences (by sex) in age composition. While the results are not shown, for robustness we test alternative models that are linear and quadratic in age.