DISCUSSION PAPER SERIES

IZA DP No. 5841

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July 2011

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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IZA Discussion Paper No. 5841
July 2011

ABSTRACT

Explaining the Female Black-White Obesity Gap: A Decomposition Analysis of Proximal Causes*

There exists remarkably large differences in body weights and obesity prevalence between black and white women in the US, and crucially these differences are a significant contributor to black-white inequalities in health. In this paper, we investigate the most proximal explanations for the weight gap, namely differences in diet and exercise. More specifically, we decompose black-white differences in body mass index and waist-to-height ratio into components reflecting black-white differences in energy intake and energy expenditure. The analysis indicates that over consumption is much more important than a lack of exercise in explaining the weight gap, which suggests that diet interventions will have to play a fundamental role if the weight gap between black and white women is to decline.

JEL Classification: I1, J11

Keywords: obesity, decomposition

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* We thank Richard Burkhauser and Deborah Cobb-Clark for valuable comments and discussions, as well as two anonymous referees for their comments and suggestions. All errors are our own.

1. INTRODUCTION

The proportion of Americans who are overweight or obese has reached alarming levels; approximately 66% of American adults are now overweight and 32% are obese (Ogden et al., 2006).[1] This has significant consequences, because the overweight and obese have much higher rates of cardiovascular disease, diabetes, hypertension, cancer and premature death than normal weight individuals (Mokdad et al., 2001; Fontaine et al., 2003; Flegal et al., 2005). Furthermore, the excess medical expenditures that result from the diagnosis, treatment and hospitalizations of obesity-related diseases are enormous: obesity-related medical expenditures are estimated to cost the US $75 billion each year (in 2003 dollars) and to be responsible for between 4.3% and 7% of total health care expenditure (Colditz and Wang, 2008).

Worse still, the prevalence and consequences of obesity are not spread evenly across the population. Obesity rates are much higher among some racial and ethnic minorities, and these differences are particularly apparent for women: approximately 54% of African-American (hereafter ‘black’) women are obese and 15% are extremely obese (BMI $\geq$ 40), compared with 30% and 6% of non-Hispanic white (hereafter ‘white’) women (Ogden et al., 2006). Moreover, the female black-white ‘weight gap’ has increased by around five percentage points since the late 1970’s, despite the considerable narrowing of other racial gaps during this period and the considerable gains in the general health of Americans.

The female weight gap is a significant problem because it is causing black-white disparities in rates of illness. For example, Brancati et al. (2000) report that black women are more than twice as likely to develop type-2 diabetes than white women, and that the black-white differences in modifiable risk factors, particularly adiposity, accounts for almost 50 percent of the excess risk. In addition, the weight gap will be contributing to existing black-white disparities in socioeconomic status if obese persons are discriminated against in the labor market, as suggested by Baum and Ford (2004), Cawley (2004) and Morris (2006). With regards to the weight gap, Penn (2007, p. 183) states that “[w]hile we focus on many of the challenges of the black community such as improving education and creating new opportunities for young people, this clear and statistically significant problem remains essentially unaddressed, effectively swept under the rug, despite high human and social cost.”

[1] The Centers for Disease Control (CDC) and the World Health Organization (WHO) define overweight and obesity as a body mass index (BMI) value of over 25 and over 30, respectively, where BMI is the ratio of weight, measured in kilograms, to squared height, measured in meters.

The most often considered explanation for the weight gap concerns black-white differences in socioeconomic status (SES). The SES explanation has been tested, implicitly or explicitly, in a number of studies that regress body mass index (BMI) on measures of race and individual SES (e.g. Lakdawalla and Philipson, 2002; Chou et al., 2004; Burke and Heiland, 2008). The studies find that blacks exhibit significantly higher BMI than whites, even after controlling for individual differences in SES. For example, Burke and Heiland (2008) find that controlling for educational attainment, income, occupation, location of residence and marital status reduces the female weight gap by only 0.71 BMI units, from 4.04 to 3.33. Further evidence against the SES explanation is that the income-obesity gap has narrowed quite dramatically since the 1970's, but the race-obesity gap has not.

Another explanation that has received some attention, predominantly in the medical and epidemiology literatures, is that there are important genetic differences between races. In particular, some studies have shown that the basal metabolic rate (energy expended in maintaining basic body functions at rest) is lower for blacks than whites (e.g. Carpenter et al., 1998; Weyer et al., 1999; Sharp et al., 2002).[2] However, if a black-white difference in basal metabolic rate is the principal cause, we would also expect to observe a weight gap for men, which we do not: approximately 34 percent of black men are obese, compared to 31 percent of white men (Ogden et al., 2006).

The absence of conclusive SES and genetic explanations for the female weight gap highlights the need for further research. In this paper, we investigate the most proximal explanations for the gap, namely differences in diet (i.e. energy intake), exercise (i.e. energy expenditure) and age. Uncovering whether black-white differences in energy intake or energy expenditure are causing the weight gap is important, because before effective policy can be enacted to reduce the gap, we must ascertain whether unhealthy eating practices or sedentary lifestyles are mostly responsible.

Our methodological approach involves decomposing black-white differences in adiposity (i.e. fat) distributions with the Blinder-Oaxaca and the DiNardo-Fortin-Lemieux decomposition procedures. An important issue in performing the decompositions is that adiposity, energy intake and energy expenditure are often measured with considerable error. We respond to the measurement error issue by using a number of adiposity measures, adjusted energy intake and objectively measured energy expenditure. The main result from the analysis is that over consumption is much more important than a lack of exercise in

[2] Other studies argue that a racial difference in the basal metabolic rate may not exist (e.g. Cruichshank, 1999; Luke et al., 2000).

explaining the female weight gap. For example, using our preferred specification the proportion of the gap explained by differences in energy intake is over three times larger than the proportion explained by differences in energy expenditure for each measure of adiposity. The finding suggests that if the remarkably large weight gap between black women and white women is to decline, diet interventions will have to play a fundamental role.

2. DECOMPOSITION PROOCEDURES

Our aim is to determine the proportions of the female weight gap that can be attributed to black-white differences in diet and exercise. In addition, we determine the proportion of the gap that is due to differences in the age distributions of the black and white populations. Age differences are also examined because age affects adiposity independently of energy intake and expenditure levels. We do not control for other individual-level characteristics, such as socioeconomic or marital status, because they should affect adiposity only through their effect on intake and expenditure.

Our empirical methodology consists of two decomposition procedures: the Blinder-Oaxaca decomposition and the DiNardo-Fortin-Lemieux decomposition. The Blinder-Oaxaca (BO) decomposition (Blinder 1973; Oaxaca 1973) involves first specifying and estimating for each group a linear regression model of an outcome (e.g. BMI) on observable characteristics (e.g. intake, expenditure and age). Next, the difference in mean outcomes across groups is partitioned into differences in observable characteristics and differences in coefficients, as shown in equation (1):

$$\bar{y}^B - \bar{y}^W = \left[\left(\bar{X}^B - \bar{X}^W\right)\hat{\beta}^B\right] + \left[\bar{X}^W\left(\hat{\beta}^B - \hat{\beta}^W\right)\right] \tag{1}$$

where $\bar{X}^k$ is a vector of average values of the independent variables and $\hat{\beta}^k$ is a vector of coefficient estimates for race *k*.[3] The first term on the right hand side of equation (1) represents the proportions of the mean BMI gap that can be explained by differences in each observable characteristic, and the second term represents the proportion that is unexplained. An alternative and equally valid formulation of Equation (1) multiplies differences in mean observable characteristics by differences in white OLS coefficient estimates and multiplies differences in coefficient estimates by black mean observable characteristics. We follow Jann

[3] See Jann (2008) for a detailed discussion of the BO decomposition procedure.

(2008) and perform the decomposition using coefficients from a pooled model over both groups as the reference coefficients, with race included in the pooled model as an additional covariate.

The main advantages of the BO decomposition procedure are that it's well-known, based on standard statistical methods (i.e. linear regression) and provides easily interpretable results. It is for these three reasons that we use the procedure in this paper. An important limitation, however, is that it requires the researcher to specify a parametric model of the relationship between outcomes and observable characteristics. The parametric nature of the BO decomposition is particularly problematic for our application, because the relationship between adiposity and the variables representing energy intake and energy expenditure are highly non-linear (Burke and Heiland, 2007). The nonlinearity implies that empirical models that assume adiposity is linearly separable in intake and expenditure, such as that used in the BO decomposition, are misspecified.

To overcome this potential misspecification, we also use the DiNardo-Fortin-Lemieux (DFL) decomposition (DiNardo et al., 1996).[4] The DFL procedure does not require a parametric model of the relationship between adiposity and the variables representing energy intake and energy expenditure. Another advantage of the DFL procedure is that it allows us to consider changes across the entire distribution. For example, we are able to decompose changes at multiple points of the distribution (e.g. 25th and 75th percentiles) and decompose changes in the proportion of people who are overweight and obese. This is an important advantage, because differences in average BMI or obesity rates may not fully reflect important differences in adiposity, especially if the distributions have different shapes.

The DFL decomposition involves re-weighting the black sample of women to have the same distributions of intake, expenditure and age as the white sample.[5] The opposite counterfactual of re-weighting white women is not examined because there are few whites in our data with high energy intake levels (the maximum white caloric intake is 4597 and the maximum black caloric intake is 5129; the maximum white sugar intake is 392 grams compared to the maximum black sugar intake of 614 grams) and so it is not possible to

[4] Studies using the DFL decomposition include Bell and Pitt (1998), DiNardo and Butcher (2002), Hyslop and Mare (2005), Daly and Valletta (2006), Cobb-Clark and Hildebrand (2006), and Altonji et al. (2008).

[5] The BO decomposition also involves a re-weighting but of a very different nature. In a basic BO decomposition, group differences in the independent variables are weighted by regression coefficients in order to determine the part that is explained by the independent variables. When one uses coefficients from the pooled model over both groups as the reference coefficients, we can express the pooled coefficients as: $b = Wb^W + (1-W)b^B$, where W is a weighting matrix given by $W = \mathrm{diag}(b-b^B)\ \mathrm{diag}(b^W-b^B)^{-1}$. b, b^B and b^W denote the coefficients from a pooled model, white model and black model, respectively.

speculate about the BMI-intake relationship at high energy intake levels without making a functional form assumption and extrapolating out of the observed energy intake range for whites.[6] The difference between the actual BMI distributions of whites and blacks and a series of counterfactual BMI distributions form the basis of the decompositions underlying our empirical results. More specific details of this procedure are outlined in the below subsection.

2.1 DiNardo-Fortin-Lemieux Decomposition Procedure

This subsection outlines the DFL decomposition procedure used to determine how much of the change in the BMI distribution can be explained by observed determinants of BMI, and how much remains unexplained.[7] Let *b* be a continuous variable denoting BMI, *x* be a vector of BMI determinants (e.g. grams of sugar, duration of moderate activity etc.) and *r* be a binary variable denoting the persons racial background, with *r* = 1 denoting whites and *r* = 2 denoting blacks. The marginal distribution of BMI for white women can be expressed as:

$$f(b \mid r=1) = \int f(b,x \mid r=1)dx = \int f(b \mid x, r=1) f(x \mid r=1)dx \qquad (2)$$

This equation expresses the marginal BMI distribution as the product of two conditional distributions: the distribution of BMI conditional on BMI determinants and race, and the distribution of BMI determinants conditional on race.

In this representation, all BMI determinants are grouped together in the vector *x*. However, the aim of the paper is to determine which particular set of determinants have the largest impact on the weight gap and so we partition this vector into three groups: intake (*i*); expenditure (*e*); and age (*a*). Thus, *x* = (*i*, *e*, *a*). Given this partitioning, we can expand the term $f(x \mid r=1)$ in equation (2) into three sequential components:

$$f(b \mid r=1) = \int_i \int_e \int_a f(b \mid i,e,a,r=1) \cdot f(i \mid e,a,r=1) \cdot f(e \mid a,r=1) \cdot f(a \mid r=1) dideda \qquad (3)$$

[6] See Barsky et al. (2002) for a more detailed discussion of this issue.
[7] This presentation draws on Cobb-Clark and Hildebrand (2006).

The first term in equation (3) denotes the conditional BMI distribution given all BMI determinants and race. The second term is the conditional distribution of energy intake given energy expenditure, age and race. The third term is the conditional distribution of energy expenditure given age and race. Finally, the fourth term is the distribution of age conditional on race only.

Using this framework we can construct interesting counterfactual distributions. Suppose, for example, we are interested in the BMI distribution that would prevail if white women retained their own conditional distribution of energy intake ($f_{i|e,a}$), but had the same conditional distributions of BMI, energy expenditure, and age as black women. This distribution can be expressed as:

$$f^{A}(b) = \int_{i}\int_{e}\int_{a} f(b \mid i,e,a,r=2)\cdot f_{i|e,a}(i \mid e,a,r=1)\cdot f_{e|a}(e \mid a,r=2)\cdot f(a \mid r=2)dideda \qquad (4)$$

Similarly, we can write another BMI distribution $f^{B}(w)$ that would result if white women retained their own conditional distributions of energy intake ($f_{i|e,a}$) and energy expenditures ($f_{e|a}$), but had the same conditional distributions of BMI and age as black women:

$$f^{B}(b) = \int_{i}\int_{e}\int_{a} f(b \mid i,e,a,r=2)\cdot f_{i|e,a}(i \mid e,a,r=1)\cdot f_{e|a}(e \mid a,r=1)\cdot f(a \mid r=2)dideda \qquad (5)$$

Repeating this procedure we can also define a counterfactual BMI distribution $f^{C}(b)$ that would result if white women retained their own conditional distributions of energy intake, energy expenditures and age, but had the same conditional BMI distribution of black women.

Using the counterfactual distributions $f^{A}(b)$, $f^{B}(b)$, and $f^{C}(b)$, and defining $f^{1}(b)$ as the distribution of BMI for white women, and $f^{2}(b)$ as the distribution of BMI for black women, the racial differences in the distributions of BMI between black and white females can be expressed as:

$$f^{2}(b) - f^{1}(b) = [f^{2}(b) - f^{A}(b)] + [f^{A}(b) - f^{B}(b)] + [f^{B}(b) - f^{C}(b)] + [f^{C}(b) - f^{1}(b)] \qquad (6)$$

In this equation, the first right-hand-side term captures the effect of differences in energy intake on the differences in BMI, the second captures the effect of energy expenditures differences, and the third captures the effect of age differences. The last term captures the unexplained portion of differences in BMI.

DiNardo et al.'s (1996) procedure for estimating the counterfactual distributions involves propensity score re-weighting the observed BMI distributions. Consider, for example, the counterfactual distribution $f^A(b)$ given by equation (4). It can alternatively be written as a re-weighted BMI distribution for black women :

$$f^A(b) = \int_i \int_e \int_a \omega_{i|e,a} f(b \mid i,e,a,r=2) \cdot f_{i|e,a}(i \mid e,a,r=2) \cdot f_{e|a}(e \mid a,r=2) \cdot f(a \mid r=2) dideda \quad (7)$$

where the weighting factor $\omega_{i|e,a}$ is given by:

$$\omega_{i|e,a} = \frac{f_{i|e,a}(i \mid e,a,r=1)}{f_{i|e,a}(i \mid e,a,r=2)} = \frac{p(r=1 \mid i,e,a)p(r=2 \mid e,a)}{p(r=2 \mid i,e,a)p(r=1 \mid e,a)} \quad (8)$$

Similarly, re-weighting the observed BMI distribution for $r=2$ with suitable constructed weights provides the counterfactual distributions $f^B(b)$ and $f^C(b)$, respectively. In the literature applying the DFL decomposition there is no clear consensus regarding how best to estimate the probabilities (or propensity scores) that are used to create the weights. In our paper, we follow Bell and Pitt (1998) and Cobb-Clark and Hildebrand (2006) in using a logit model with independent variables entered additively and linearly.[8] In contrast, for example, DiNardo et al. (1996) and Butcher and DiNardo (2002) choose to include some interaction terms in their binary choice model. Recently, Millimet and Tchernis (2009) suggest that there might be some benefits to over-specifying the propensity score model by including higher-order or interaction terms. Based on Monte Carlo evidence, they found little penalty for over-fitting propensity scores, and in fact found numerous cases in which over-specifying the model proved beneficial.

In our case, if we are to include interaction terms in our propensity score model, it would make sense only to do so within each category and not across categories. Doing the

[8] To account for unequal probabilities of selection resulting from the complex survey design in NHANES, relevant sampling weights provided by NHANES were also used in our estimation.

latter is problematic because it is not clear, for example, whether one should place an interaction term involving an intake and expenditure variable in the intake or expenditure category. When we experimented with using a logit model with all possible interaction terms the results are qualitatively very similar. Hence, we chose only to present results for the simpler model in this paper.[9]

Note that our framework, which partitions BMI determinants into 3 components, allows a total of 7 (or $2^n - 1$) counterfactual distributions and weights for black women to be computed. Equation (6) represents just one of many possible decompositions. Using all the alternative counterfactual distributions allows a total of 6 (or $3! - 1$) decomposition sequences. Given that we have no *a priori* preference for one weighted counterfactual distribution over another, we follow the approach used in Cobb-Clark and Hildebrand (2006) and calculate each possible decomposition in turn and then present the simple average across all possible decompositions.

In addition, an important issue that arises when allowing several factors in the decomposition is the order in which these factors enter the decomposition, i.e. intake first, expenditures second, and age third. Importantly, the proportion of the BMI growth that is attributable to each factor varies depending upon the sequence. Some authors choose a pre-determined order and then use the reverse order as a robustness check (e.g. DiNardo et al., 1996). Our approach is based upon using an order in which the most endogenous term will be represented by the first term in the conditional distribution, and the most exogenous term the last. In our context, the factors are considered in the primary sequence: (1) intake; (2) expenditures; and (3) age and a second candidate sequence: (1) expenditures; (2) intake; and (3) age. We focus on these two sequences as it is likely that either energy intake or energy expenditure play the leading role in explaining black-white BMI differences. As employing either of these sequences makes little qualitative difference to our results, we focus on presenting results based on using the primary sequence.

3. MEASUREMENT ERROR ISSUES IN INTAKE, EXPENDITURE AND FATNESS

An important issue that arises when investigating the role of energy intake is that it is often measured with considerable error. For example, energy intake is usually under-reported and the extent of under-reporting is associated with individual-level characteristics, such as weight, obesity, and sex (Lichtman et al., 1993; Schoeller, 1995; Macdiarmid, 1998; Nielsen,

[9] DFL decomposition results based on the over-specified model are available upon request.

2007). In a decomposition framework the measurement error will bias the estimated importance of a factor towards zero. We overcome the issue in two ways. First, we use high-quality data from the National Health and Nutrition Examination Surveys (NHANES) that contains detailed dietary interviews and objectively measured energy expenditure. Second, we provide decomposition results based on samples that are adjusted for the underreporting of energy intake.

To adjust the sample for underreporting we follow the most common approach in the public health and medical literatures and classify an individual's self-reported food intake values as implausible if the individual's total energy intake (EI) is considerably smaller or larger than that individual's estimated energy expenditure (EE) (see Goldberg et al., 1991). More specifically, we classify an observation implausible if the EI:BMR ratio (called the intake ratio) is over two standard deviations smaller or larger than the average EE:BMR ratio (referred to as the physical activity level or the average daily metabolic rate), where BMR denotes an individual's estimated basal metabolic rate. We use estimated age- and gender-specific values of average physical activity levels that are based on a summary of 74 medical studies (see Table 1 in Black, 2000).[10] These values are considered conservative (lower bound) estimates because most of the studies oversampled white collar workers relative to workers in manual occupations (Black, 2000). We estimate the intake ratio by using the total energy intake values calculated by NHANES and by estimating BMR for each individual using the formula in Miffin et al. (1990).[11]

Figure 1 presents a scatter plot of BMI versus self-reported energy intake, with plausible observations represented by a circle and implausible observations represented by a cross. Also shown is the estimated linear relationship between BMI and energy intake using all observations and using plausible observations only. The figure demonstrates that most of the implausible observations are those with low reported energy intake values: average caloric intake of implausibly low observations equals just 1357 kcal and the average BMI of the women with these low observations is 31.24. To help put this figure in perspective, the average female in our analysis sample – 45 years old, 1.64m tall and weighing 76.8 kg (BMI = 28.6) doing little or no exercise – would require approximately 1800 calories per day to

[10] For example, a female aged 30-39 would be considered to be reporting plausible caloric intake information if she reports consuming daily calories that are between 1.18 to 2.18 times her BMR.

[11] The BMR formula is: BMR = 9.99*(weight in kg) + 6.25*(height in meters*100) – 4.92*age + 166*male – 161.

maintain her current weight.[12] Figure 1 also demonstrates that the correlation between BMI and energy intake using all observations is approximately zero and is significantly positive when using eligible observations only.

Measurement error is also an issue when examining the role of energy expenditure. Measurement of physical activity is typically self-reported, and centered on leisure-time physical activities such as walking, cycling or other sport-related activities. However, these standard self-reported measures of leisure-time activities do not cover many day-to-day domestic-based activities (e.g. household chores, gardening or yard work) that involve substantial energy expenditures. As a result, prevalence estimates of physical activity may be underestimated (Weller and Corey, 1998). Even if measures of both leisure-time and non-leisure-time activities are available, they rely on perfect recall and comprehension by the survey participants. Recently, the National Institute of Health (NIH) has supported improvements in data collection by including an objective measure of physical activity, which involves requiring survey respondents to wear physical activity monitors for several consecutive days. We employ such objective measures of physical activity in our paper.

Finally, although adiposity has almost universally been measured in the social science literature using body mass index, a limitation of using BMI as a measure of adiposity is that it cannot distinguish fat from muscle mass. As a result, health risks tend to be overstated in muscular persons and understated in older persons. Burkhauser and Cawley (2008) show that the limitation leads to an overestimation of the black-white weight gap. Therefore, in addition to the decomposition of BMI, we decompose differences in the black and white distributions of the waist-to-height ratio (WHR). WHR is chosen as an ancillary measure because a number of studies find that WHR is an exceptional tool for quantifying adiposity. For example, Lee et al. (2008) conduct a meta-analysis to determine which of the prominent indices of overweight and obesity is the best discriminator, and find that WHR was the best discriminator for hypertension, diabetes, and elevated cholesterol in both sexes.

4. DATA, DEFINITIONS AND DESCRIPTIVE STATISTICS

Data in this paper come from the 2003-2004 and 2005-2006 National Health and Nutrition Examination Surveys (NHANES). NHANES is a nationally representative cross-sectional survey that has been used repeatedly in the analysis of U.S. obesity. The surveys

[12] This was based on the calorie counter on the Mayo Clinic website (http://www.mayoclinic.com/health/calorie-calculator/NU00598) assuming an inactive lifestyle. It is essentially based on a BMR equation with an allowance for different levels of physical activity.

consist of interview, examination and laboratory components, and collect information on individual's demographics (e.g. age and gender), socioeconomic status (e.g. labor income and government program participation), health, and most importantly for this paper: physical measurements, food consumption and energy expenditure.[13] The survey over-samples Mexican Americans, African Americans, adolescents 12–19 years, pregnant women, and persons 60 years of age and older to assure adequate representation, and includes weights to make the sample nationally representative.

The unique feature of NHANES is its use of mobile examination centers (MEC) to obtain objective body measurements from all survey participants, in addition to medical examinations, and laboratory tests. In the 2003-2004 and 2005-2006 versions, trained technicians obtained measurements of individual's: weight; height; leg and arm length; arm, waist, thigh and calf circumference; and triceps and scapular skin fold. We use this body measurement information to compute our two measures of adiposity, namely BMI and waist-to-height (WHR) ratio.[14] Bioelectrical impedance analysis (BIA) readings are also available in NHANES 2003-2004 and enable one to construct measures of fat-free mass and body fat using conversion equations (Burkhauser and Cawley, 2008); but they are not available in NHANES 2005-2006. Using observations solely from NHANES 2003-2004 results in a sample size too small for our analysis to be reliably undertaken, and so we do not analyze the BIA readings.

For our main analysis, we focus exclusively on non-Hispanic white and black female NHANES participants aged 20-74 years, who had valid weight, height and waist measurements, and who had valid information regarding energy intake and energy expenditure. The original sample size in NHANES 2003-2004 and NHANES 2005-2006 is a combined total of 20,470 individuals, of which 10,420 are female. When restricted to black and whites, the sample drops to 6,791. When we also impose the age restriction the sample is reduced to 3,164. Further restricting it to those with valid physical activity recordings and energy input measurements leaves us with a sample size of 1,768, the sample we use for analysis in our paper.

[13] NHANES questionnaires and a comprehensive listing of laboratory and examination components are posted on the NHANES website: http://www.cdc.gov/nchs/nhanes.htm.

[14] As NHANES in nationally representative data that uses actual height and weight measurements, rather than self-reported data, it is often referred to as the "gold standard" for studies that focus on obesity in the US.

4.1 Measuring Energy Intake and Energy Expenditure

Energy intake and energy expenditure are notoriously difficult to measure on either an individual or a population level. A benefit of using the NHANES survey, however, is that it has been at the forefront of using new survey methodologies and technology to obtain accurate estimates of these items. In 2002, NHANES began using a new automated dietary interview system developed by the United States Department of Agriculture (USDA). Dietary information is first collected from NHANES respondents in mobile examination centers (MEC), where a trained dietary interviewer records all food eaten by the respondent in the prior 24-hour period (midnight to midnight) with a computer assisted multiple-pass dietary interview. The type and amount of foods consumed are recalled with help from aids such as abstract food models, special charts, measuring cups, and rulers, which help in quantifying the amounts consumed. Special probes were also used to help recall commonly forgotten items such as condiments, accompaniments, fast foods, and alcoholic beverages, etc. All participants are also asked to complete a second 24-hour dietary recall (Day 2) interview. The NHANES Day 2 dietary recalls are collected by telephone approximately 3 to 10 days after the MEC exam. The information obtained from both dietary interviews is converted using the Food and Nutrient Database for Dietary Studies into variables representing the weight in grams of each food type. It is these variables that we use to represent energy intake in the decomposition analysis. More specifically, we use eight variables representing the average number of grams consumed of: protein, starch, sugar, fiber, saturated fat, mono-unsaturated fat, poly-unsaturated fat, and alcohol.[15]

Physical activity measurement is characterized by the synthesis of information on the type, frequency, intensity and duration of activity over a specified period. The NIH has recently supported improvements in the methods for assessing physical activity by including an objective measure of physical activity in NHANES, beginning with NHANES 2003-2004. Energy expenditure is objectively measured using physical activity monitors called Actigraph accelerometers (ACC), which detect all locomotion-type activities such as walking or jogging. The monitors were attached to an elastic belt and worn at the right hip by people

[15] NHANES reports the total number of calories consumed, as well as the total number of grams of protein, carbohydrates, fats, and alcohol consumed. In order to make the analysis of inputs more informative, in addition to total protein and alcohol consumption, we use in our decomposition analysis the three components of carbohydrates (starch, sugar and fiber) and the three components of fat (saturated fat, mono-unsaturated fat, poly-unsaturated fat) instead of the aggregate measures of carbohydrates and fat. Note that NHANES reports total fat consumption (in grams) as well as consumption of saturated fat, mono-unsaturated fat, and poly-unsaturated fat. However, NHANES only reports total carbohydrates consumed (in grams) as well as consumption of total sugar and total dietary fiber. Our total consumption of starch measure is therefore computed using total carbohydrates – (total sugar + total fiber).

aged over six years who did not have impairments to walking or wearing the monitor. The benefit of the monitors is that they provide a means of capturing non-structured activities that are often difficult for survey respondents to self-report. We use data from the monitors that according to the NHANES data quality procedures is reliable.[16] Furthermore, data is only used if the participant wore the monitor for at least 4 days and for at least 600 minutes per day – although participants were asked to wear the monitor for seven consecutive days, some participants did not wear the monitor for the whole week. Comparing objective and subjective measures of physical activity in NHANES 2003-2004, Troiano et al. (2008) find that accelerometer-measured activity is substantially lower than levels according to self-report. They suggest that caution be taken when interpreting self-reported physical activity in guiding the design of intervention efforts.

We follow the approach used in Ness at al. (2007) and code one minute of ACC data as one minute of either moderate physical activity or vigorous physical activity, depending upon the value of the ACC count within that minute. From these definitions, we then construct three variables to represent energy expenditure: mean duration (minutes) of moderate activity bouts; mean duration (minutes) of vigorous activity bouts; and mean intensity count per minute, where a bout is defined as a continual stretch of physical activity.[17]

4.2 Descriptive Analysis

Table 1 reports for white and black females summary statistics for our BMI and WHR adiposity measures. As expected, the statistics reveal that black women have significantly higher levels of adiposity than white women. The figures for black women and white women for each adiposity measure are: 31.7 and 28.1 for mean BMI; 0.61 and 0.57 for mean WHR; and 0.55 and 0.32 for proportion obese (BMI > 30).[18] To better illustrate the different locations and shapes of the white and black BMI and WHR distributions we plot kernel

[16] SAS code is available from the NIH for analyzing Actigraph 7164 Physical Activity Monitor (PAM) data from the 2003-2004 NHANES. These programs are written to import and analyze accelerometer data downloaded from the National Center for Health Statistics. For this paper, we adapt this code to similarly analyze PAM data from the 2005-2006 NHANES.

[17] The ActiGraph AM-7164 device was programmed to detect and record the magnitude of acceleration or "intensity" of movement; acceleration data in NHANES were stored in memory according to a one minute time interval. The intensity count is the intensity value recorded by the device and each minute has an intensity value. The intensity files were reviewed for outliers and unreasonable values. The criteria used for reasonable ranges of activity count data were based on published literature and expert judgment.

[18] The averages and propensities reported in Table 1 for the analysis sample with non-missing values of energy input and expenditure variables are very similar to those for the entire sample: This suggests that our analysis sample does not constitute an unusual group of respondents.

density estimates of BMI and WHR in Figures 2 and 3. The estimates clearly show that the black BMI and WHR distributions lie to the right of the white distributions, and also that the black distributions have substantially more density at higher values: values where health risks are particularly high. The black and white distributions are also differently shaped. For example, the skewness of the black BMI distribution equals 0.60, whereas the skewness of the white BMI distribution equals 1.29 - it is the difference in skewness that is partially responsible for the dramatic differences in the proportion of the populations that are obese. The difference in shapes supports the use of the DFL decomposition, which is able to decompose differences at any point in the distribution, rather than only at mean values.

The energy intake and energy expenditure descriptive statistics in Table 1 also reveal some significant differences. Black women consume less fiber and alcohol, and significantly more sugar than white women. Also, average duration of moderate physical activity is significantly less for black women. There are, however, no significant differences in protein, starch and fat consumption, and no significant difference in mean duration of vigorous physical activity and mean physical activity per minute. Thus, descriptive statistics based on mean differences do not indicate which of energy intake and energy expenditure is most to blame for the weight gap. For this, we must rely on our decomposition analysis.

Finally, the sample averages suggest that black females in the NHANES sample are on average younger than white females. The significant age difference likely has a negative impact on the weight gap: adiposity tends to increase with age because of the strong influence age has on metabolism and body composition. In estimating the propensity score, we use a set of age dummies (five year intervals) rather than continuous age to allow for non-linear effects.

5. DECOMPOSITION RESULTS

The female weight gap is decomposed using three measures of adiposity (average BMI, average WHR and proportion obese), two estimation samples (total sample and sample with plausible intake values), and two decomposition procedures (BO and DFL), with each combination presented in Table 2. A comparison across combinations provides an indication of which factor is most important in explaining the gap. Unfortunately, it is not possible to confidently declare that one combination is superior to all others, because there is no consensus in the literature on what are the best measures of adiposity and energy intake; however, our preferred combinations are those using the DFL decomposition, chiefly because it's semi-parametric, and those using plausible energy intake values, because substantial measurement error in self-reported intake is well established.

Decompositions of average BMI are presented in panel 1, decompositions of average WHR are presented in panel 2, and decompositions of proportion obese are presented in panel 3. The first row in each panel shows the total difference in the adiposity measure between black and white women for each combination of estimation sample and decomposition procedure. These values differ across columns within each panel because the BO procedure decomposes mean BMI and WHR, and the DLF procedure decomposes median BMI and WHR. Total difference values will also differ because the DFL procedure restricts the sample to those that are in the region of common support.[19] The additional rows in each panel show the portion of the total difference that can be attributed to differences in energy intake, energy expenditure, age and unobserved factors. We emphasize that differences in adiposity between blacks and whites can only be caused by systematic differences in intake, expenditure, and biology/genetics. This relationship might be viewed as almost being an accounting identity. Of course, individual-level characteristics such as education, marital status and region of residence can affect obesity, but these are mediating variables and they are not expected to affect adiposity directly and independently except through their effects on intake and expenditure decisions. Adding these variables to the decomposition would likely reduce the size of the unobservable category because of measurement error, but we deliberately choose not to do so in order to focus on the role that intake and expenditure play in explaining the obesity gap.

A comparison across rows in each panel shows that the most important observed factor is energy intake. In each of the 12 decompositions, energy intake is estimated to explain more of the weight gap than both energy expenditure and age. For example, using our preferred specification of plausible intake values and DFL decomposition procedure, differences in energy intake are estimated to explain around 48% of the gap in average BMI, 44% of the gap in average WHR and 38% of the gap in proportion obese. In comparison, differences in energy expenditure are estimated to explain around 13% of the gap in average BMI, 16% of the gap in average WHR and 11% of the gap in proportion obese; though none

[19] Common support is imposed in our analysis by dropping all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group. Implementing the common support condition ensures that any combination of characteristics observed for blacks can also be observed among whites, and that we are not comparing the incomparable.

of the energy expenditure effects are statistically different from zero.[20] Age differences are estimated to explain little of the difference in adiposity; though, what little it does explain is in-fact negative. Negative estimates indicate that the younger average ages of black women work to make the observed weight gap smaller rather than larger. Figure 4 graphically displays these results.

Table 2 also shows that unobservables play an important role in explaining the weight gap. Large unobservable effects are not uncommon in decomposition analyses. For example, unobservables are the largest factor in the DFL analyses of Hyslop and Mare (2005), Daly and Valletta (2006), and Cobb-Clark and Hildebrand (2006). To a large extent this is unavoidable if some factors have a negative impact on the gap and other factors have a positive impact on the gap, as we observe in our analysis. It is still important, however, to consider possible explanations for the unobservable effects. One likely explanation is measurement error. The unobservables category captures any differences in adiposity, diet and exercise not captured by observed differences. Therefore if BMI, for example, poorly represents adiposity then the unobservable effect will be large. Another explanation is genetic differences between white and black women. Genetic differences, for example in basal metabolic rates, could create weight differences even if there exists no differences in energy intake and expenditure. In a review of 15 studies, Gannon et al. (2000) provide support for this explanation. They conclude that black women living in the U.S. may be particularly vulnerable to obesity due to a relatively lower energy expenditure for their metabolic size. We lack measured data on basal metabolic rates and so cannot examine this issue in detail; however, it is unlikely that genetic differences are the main cause of the female weight gap given that no gap exists for men.

A comparison across columns in each panel show that the contributions of energy intake and energy expenditure to the weight gap are generally larger in the DFL procedure than in the BO procedure. For example, between columns (1) and (3) the proportions explained by differences in energy intake increase from 6.1% to 25.5% for average BMI, 13.3% to 26.4% for average WHR, and 9.8% to 25.5% for proportion obese. The equivalent numbers for differences in energy expenditure are: 3.3% to 8.2%, 4.0% to 9.5% and 3.0% to 7.8%. One simple explanation for the different results is that the BO procedure compares

[20] An alternative interpretation of our results is that there exists substantially more measurement error in energy expenditure than energy intake, and that this error is making it falsely appear that intake is more important. However, given that our intake measures are self-reported and the expenditure measures are based on objective measurements of movement, this conclusion seems unlikely.

mean adiposity and the DFL procedure compares median adiposity. Given the dramatic differences in the shape of the black and white adiposity distributions (e.g. mean BMI gap equals 3.56 and median BMI gap equals 4.33), this could substantially impact the estimated effects. Another explanation is that the BO procedure relies upon a simple linear approximation of the relationship between adiposity and intake, expenditure and age. While it is true that one can add higher-order terms to attempt to capture the curvature of the true function, unless the chosen non-linear specification is correct, the effects will be over- or under-estimated in different segments of the adiposity distribution.[21] On the other hand the semi-parametric DFL approach avoids the issue of making functional form assumptions of inputs, expenditure and age by the use of a re-weighting scheme. A third difference between the procedures is that the DFL procedure imposes a common support requirement, ensuring that any combination of characteristics observed for blacks can also be observed among whites. This explains why the sample sizes differ for BO decomposition (N=1768) and DFL decomposition (N=1748). Finally, even with well-specified regression models and similarly shaped distributions, the BO and DFL decomposition procedures are not numerically equivalent (Dinardo, 2002).

Another clear difference between columns is that the proportion of the weight gap explained by energy intake is much higher for the sample that omits implausible intake values, with most of the increase coming at the expense of unobserved factors. For example, the proportion of average BMI differences explained by energy intake increases from 25.5% to 47.9% and the proportion explained by unobservables decreases from 71.3% to 38.7%. The pattern supports our hypothesis that the unobserved factors component largely reflects the existence of measurement error.

An advantage of the DFL procedure is that it allows decompositions at any point in the distributions, not only at the mean. In Table 3 we exploit this advantage and decompose the weight gap in the 25th and 75th percentiles of the BMI and WHR distributions.[22] Results from these decomposition are consistent with those from the results in Table 2. In general, the effects of energy intake differences are again much larger than the effects of energy expenditure differences, although few of the differences are statistically significant due to smaller sample sizes as we move away from the median.

[21] We also performed the BO procedure using an equation that included interaction terms in the intake category and expenditure category and found that the results were very similar to the results presented in Table 2.

[22] It is common to also decompose differences at the extremes of the distribution, e.g. at the 10th and 90th percentiles. We do not follow this approach here because of a low density of observations at the extremes of the distribution, which will result in estimates that are too imprecise.

Interestingly, our results contrast starkly with those contained in Burke and Heiland (2008). They estimate regression models containing variables representing exercise, intake and smoking history and find that these variables account for 0.25 BMI units or 6.4% of the gap in mean BMI. In addition, they conclude from their regression results that "black women's lower exercise levels figure most prominently among the behavioral factors that contribute to their having higher BMI" (p.21). The differences in the proportion explained and the prominence of energy expenditure are likely a consequence of the different measures used for physical activity. Instead of using Actigraph accelerometer data for measuring physical activity, Burke and Heiland (2008) construct a discrete variable with three categories based on responses to "yes" or "no" questions concerning whether the individual participated in a given type of activity for at least 10 minutes during the previous month. In addition, it may also be because they use an OLS regression approach and implausible intake values. In column 1 of panel 1, we also find that the observed factors explain little of the difference in average BMI; though, even in this specification we find that intake explains more than expenditure.

There are a number of factors that may be contributing to black women's higher energy intake. One candidate is that predominantly black neighborhoods are different to predominantly white neighborhoods. For example, Baker et al. (2006) find black-white differences in the availability of healthy food retailers: black areas, regardless of income, were less likely than predominantly white higher-income communities to have access to foods that enable individuals to make healthy choices. It's also possible that cultural factors contribute to higher intake. For example, a number of studies find black-white differences in conceptions of ideal body size, with black women tending to select larger images of ideal size (Flynn and Fitzgibbon, 1998; Lovejoy, 2001; Fitzgibbon et al., 2000). These studies also find black-white differences in attitudes towards dieting and exercise, with black women tending to be more satisfied with their own size and less likely to be attempting to lose weight.

6. CONCLUSION

There exists dramatic differences in body weights and obesity prevalence between black and white women in the U.S., and crucially, these differences are a significant contributor to black-white inequalities in health. In this paper, we provide one of the few empirical investigations of the female weight gap by assessing the relative culpability of energy intake and energy expenditure. Uncovering whether energy intake or energy expenditure dominates is important, because before effective policy can be enacted to reduce the weight gap, we must ascertain whether unhealthy eating practices or sedentary lifestyles are mostly responsible. Furthermore, understanding which factor dominates helps to highlight the social and environmental differences that are indirectly causing the weight gap.

Our empirical approach is based on decomposing black-white differences in BMI and waist-to-height ratio into four components: energy intake, energy expenditure, age and unobservables. Importantly, we use objectively measured energy expenditure data based on physical activity monitors, and self-reported food intake adjusted for measurement error. The results from our decomposition analyses suggest that increased energy intake is the driving force behind the weight gap.

There are few existing studies that consider the roles of energy intake and energy expenditure in explaining black-white BMI differences; however, there exists a large literature that investigates their roles in explaining the considerable growth in BMI over time. The relative culpability of 'gluttony versus sloth' is in fact the subject of some dispute, with a number of studies suggesting that increased physical inactivity is the major cause (Prentice and Jebb, 1995; Heini and Weinsier, 1997; Weinsier et al., 1998; Philipson, 2001) and a number suggesting that over consumption is largely to blame (McCrory et al., 2002; Cutler et al., 2003; Nielsen and Popkin, 2003; Bleich et al., 2008). Though we don't investigate changes in obesity rates over time, the results from this paper provide some new evidence to this on-going debate.

The main implication of our results is that policies aimed at helping black women to reduce their food intake may be more successful in reducing the weight gap than policies aimed at increasing physical activity; though, improving physical activity levels must clearly be part of the solution. Common policy suggestions include improving access to healthy food options, using pricing strategies to promote purchase of healthy foods, and increasing media promotion of healthy eating (French et al., 2001; Bleich et al., 2008). The specific targeting of black female eating practices, however, likely requires more specialized policies, and for such policies to be developed more research is needed to improve our understanding of the factors driving the black-white differences in energy intake.

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Table 1: Summary Statistics of Main Variables by Race

Variable	White		Black		Test of Mean Difference
	Mean	Std. Dev.	Mean	Std. Dev.	(p-values)
Adiposity Measures					
BMI	28.12	7.17	31.68	7.70	0.000
Proportion obese (BMI > 30)	0.32	0.47	0.55	0.50	0.000
Waist-to-height ratio × 100	57.17	9.88	61.29	10.55	0.000
Energy Intake					
Protein (grams)	71.69	25.69	70.76	30.08	0.591
Starch (grams)	106.05	41.87	102.60	45.90	0.206
Sugar (grams)	101.91	54.51	121.25	68.17	0.000
Fiber (grams)	15.05	7.29	12.07	5.64	0.000
Saturated fats (grams)	23.91	11.18	24.02	12.11	0.871
Monounsaturated fats (grams)	26.40	11.74	27.59	13.32	0.115
Polyunsaturated fats (grams)	15.68	8.24	16.36	9.24	0.204
Alcohol (grams)	5.87	13.47	3.66	12.47	0.006
Energy Expenditure					
Mean intensity count per minute	327.95	635.91	304.32	531.26	0.386
Mean duration (minutes) of moderate activity bouts	18.67	22.50	16.49	16.96	0.046
Mean duration (minutes) of vigorous activity bouts	1.80	22.47	1.11	15.65	0.441
Age	45.60	14.48	42.09	14.11	0.000
Sample Size	1280		488		

Notes: Descriptive statistics are weighted using NHANES sampling weights.

Table 2: Decompositions of Black-White Differences in Adiposity

	BO		DFL	
	All values	Plausible intake values	All values	Plausible intake values
	(1)	(2)	(3)	(4)
		Average Body Mass Index		
Total Difference	3.564**	3.473**	4.350**	4.000**
	(0.454)	(0.594)	(0.474)	(0.843)
Energy Intake	0.219	1.236**	1.108**	1.917*
	(0.191)	(0.336)	(0.418)	(0.795)
	[6.1%]	[35.6%]	[25.5%]	[47.9%]
Energy Expenditure	0.117	0.052	0.358+	0.517
	(0.079)	(0.043)	(0.203)	(0.471)
	[3.3%]	[1.5%]	[8.2%]	[12.9%]
Age	-0.169+	-0.639**	-0.217	0.017
	(0.092)	(0.177)	(0.164)	(0.403)
	[-4.7%]	[-18.4%]	[-5.0%]	[0.4%]
Unobserved Factors	3.397**	2.825**	3.100**	1.550
	(0.459)	(0.543)	(0.612)	(0.973)
	[95.3%]	[81.3%]	[71.3%]	[38.7%]
Sample size	1768	967	1748	903
		Average Waist-to-Height Ratio (×100)		
Total Difference	4.119**	3.988**	4.875**	4.800**
	(0.636)	(0.863)	(0.658)	(1.004)
Energy Intake	0.548*	2.127**	1.287**	2.100+
	(0.257)	(0.474)	(0.588)	(1.102)
	[13.3%]	[53.3%]	[26.4%]	[43.8%]
Energy Expenditure	0.166	0.104	0.462	0.788
	(0.118)	(0.083)	(0.286)	(0.831)
	[4.0%]	[2.6%]	[9.5%]	[16.4%]
Age	-0.482**	-1.176**	-0.475**	-0.263
	(0.15)	(0.298)	(0.225)	(0.495)
	[-11.7%]	[-29.5%]	[-9.7%]	[-5.5%]
Unobserved Factors	3.887**	2.933**	3.600**	2.175
	(0.635)	(0.806)	(0.841)	(1.342)
	[94.4%]	[73.5%]	[73.8%]	[45.3%]
Sample size	1752	959	1732	895
		Proportion Obese (BMI > 30)		
Total Difference	0.234**	0.241**	0.222**	0.230**
	(0.029)	(0.042)	(0.024)	(0.040)
Energy Intake	0.023*	0.082**	0.057**	0.087*
	(0.011)	(0.020)	(0.020)	(0.035)
	[9.8%]	[34.0%]	[25.5%]	[38.0%]
Energy Expenditure	0.007	0.005	0.017+	0.026
	(0.005)	(0.004)	(0.010)	(0.017)
	[3.0%]	[2.1%]	[7.8%]	[11.4%]
Age	-0.007	-0.028*	-0.011	-0.004
	(0.006)	(0.011)	(0.008)	(0.020)
	[-3.0%]	[-11.6%]	[-4.9%]	[-1.6%]
Unobserved Factors	0.211**	0.183**	0.159**	0.120*
	(0.030)	(0.041)	(0.031)	(0.048)
	[90.2%]	[75.9%]	[71.5%]	[52.2%]
Sample size	1768	967	1748	903

Note: The BO procedure decomposes differences in mean BMI and WHR. The DFL procedure decomposes differences in median BMI and WHR. Variables representing each category are shown in Table 1, apart from age which is modeled using 11 discrete categories. Standard errors are reported in parentheses. For the DFL procedure bootstrapped standard errors are calculated using 200 repetitions. Percent of total difference explained in brackets. +, * and ** denote significance at .10, .05 and .01 levels.

Table 3: DFL Decomposition of Black-White Difference in the BMI and WHR Distribution at Alternative Percentiles

	BMI		WHR	
	All values	Plausible intake values	All values	Plausible intake values
	(1)	(2)	(3)	(4)
		25th Percentile		
Total Difference	2.800**	2.450**	4.050**	3.300**
	(0.414)	(0.631)	(0.751)	(1.217)
Energy Intake	0.575	0.883	1.162	2.038
	(0.359)	(0.554)	(0.764)	(1.258)
	[20.5%]	[36.1%]	[28.7%]	[61.7%]
Energy Expenditure	0.175	0.433	0.187	0.837
	(0.189)	(0.549)	(0.403)	(0.960)
	[6.3%]	[17.7%]	[4.6%]	[25.4%]
Age	-0.250+	-0.167	-0.600*	-0.925+
	(0.149)	(0.286)	(0.288)	(0.528)
	[-8.9%]	[-6.8%]	[-14.8%]	[-28.0%]
Unobserved Factors	2.300**	1.300*	3.300**	1.350
	(0.506)	(0.606)	(0.989)	(1.524)
	[82.1%]	[53.1%]	[81.5%]	[40.9%]
		75th Percentile		
Total Difference	4.750**	4.950**	5.250**	5.850**
	(0.702)	(0.782)	(0.893)	(1.318)
Energy Intake	0.842	1.400	0.713	1.625
	(0.537)	(0.900)	(0.661)	(1.407)
	[17.7%]	[28.3%]	[13.6%]	[27.8%]
Energy Expenditure	0.367+	0.450	0.488+	0.800
	(0.216)	(0.348)	(0.294)	(0.673)
	[7.7%]	[9.1%]	[9.3%]	[13.7%]
Age	-0.258	-0.450	-0.225	-0.325
	(0.194)	(0.473)	(0.258)	(0.816)
	[-5.4%]	[-9.1%]	[-4.3%]	[-5.6%]
Unobserved Factors	3.800**	3.550**	4.275**	3.750+
	(0.836)	(1.261)	(0.993)	(2.117)
	[80.0%]	[71.7%]	[81.4%]	[64.1%]

Note: Variables representing each category are shown in Table 1, apart from age which is modeled using 11 discrete categories. Standard errors are reported in parentheses. Bootstrapped standard errors are calculated using 200 repetitions. Percent of total difference explained in brackets. +, * and ** denote significance at .10, .05 and .01 levels.

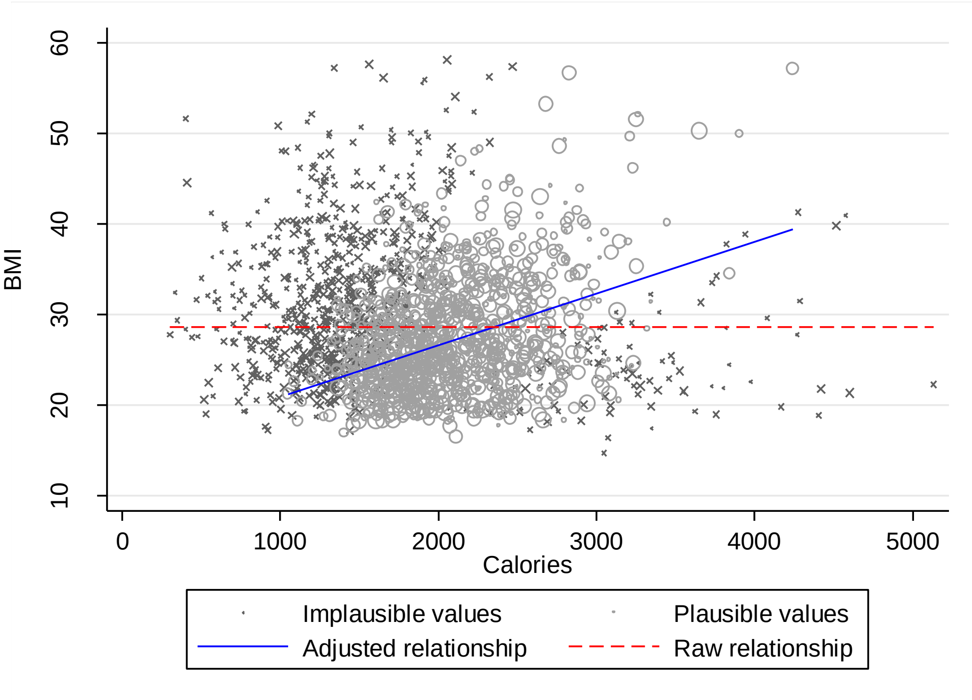

Figure 1: Adjusted and Raw Relationships Between Reported Energy Intake and BMI

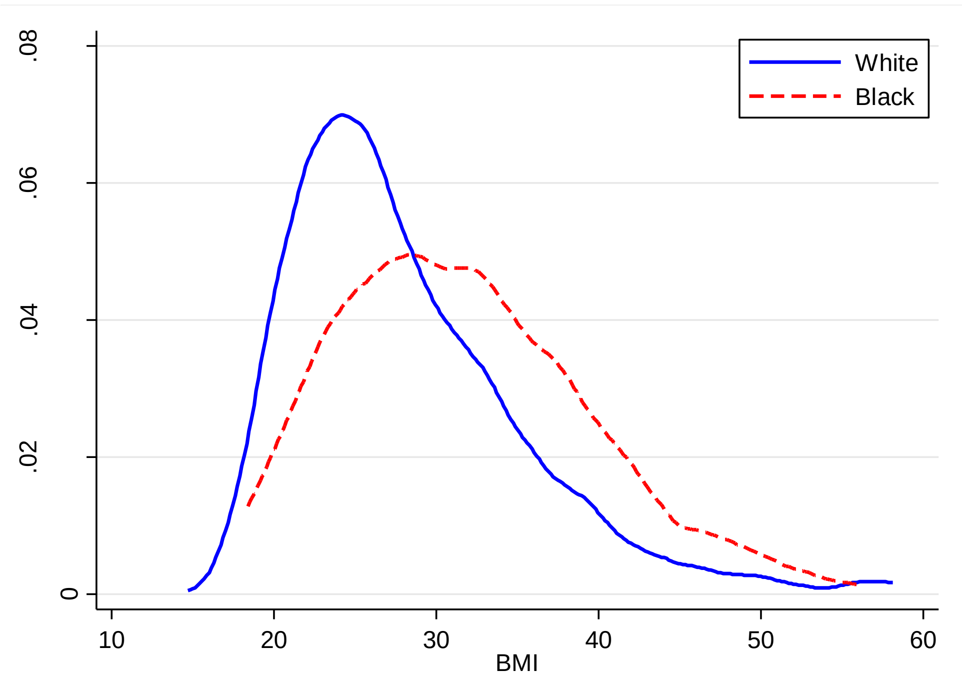

Figure 2: Estimated BMI Densities for White and Black Females

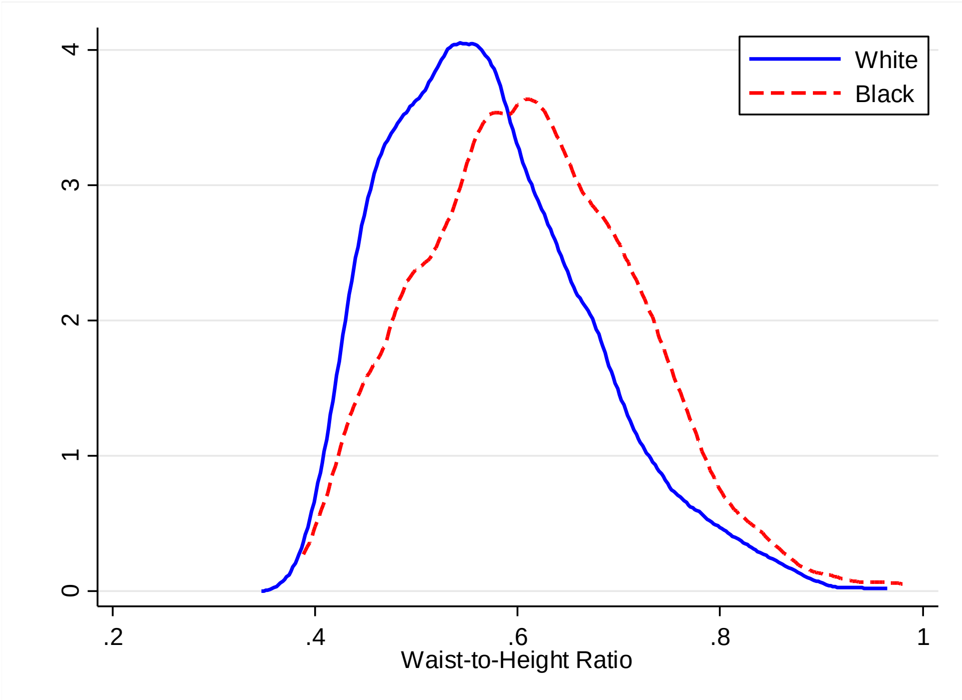

Figure 3: Estimated Waist-to-Height Ratio Densities for White and Black Females

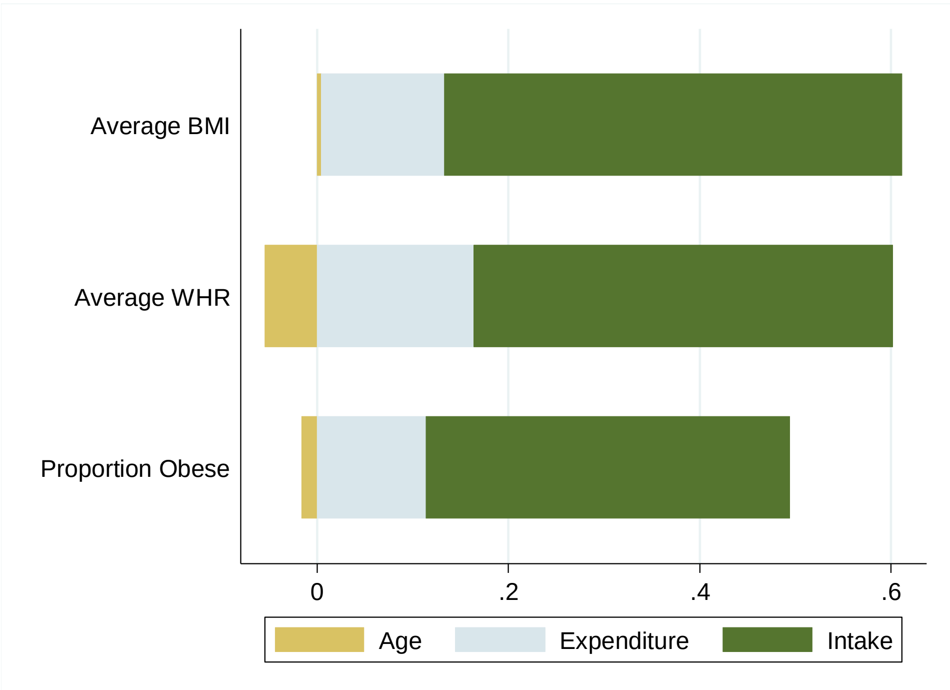

Figure 4: Proportions of Black-White Weight Gap Explained by Observable Factors in DFL Decomposition with Plausible Intake Values