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BODY COMPOSITION AND WAGES

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ABSTRACT

This paper examines the effect of body composition on wages. We develop measures of body composition – body fat (BF) and fat-free mass (FFM) – using data on bioelectrical impedance analysis (BIA) that are available in the National Health and Nutrition Examination Survey III and estimate wage models for white respondents in the National Longitudinal Survey of Youth 1979. Previous research used body size or BMI for measuring obesity despite the growing concern in the medical literature that BMI-based measures do not distinguish between body fat and fat-free body mass and that BMI does not adequately control for non-homogeneity inside human body. Therefore, measures used in this paper represent a useful alternative to BMI-based proxies of obesity. This paper also contributes to the growing literature on the role of non-cognitive skills on wage determination. Our results indicate that calculated BF is unambiguously associated with decreased wages for both males and females among whites We also present evidence indicating that FFM is consistently associated with increased wages. We show that these results are not the artifacts of unobserved heterogeneity. Finally, our findings are robust to numerous specification checks and to a large number of alternative BIA prediction equations from which the body composition measures are derived.

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I. Introduction

Obesity is defined as the presence of excessive body fat (Bjorntorp 2002, World Health Organization 1998). Therefore, it is the excessive levels of body fat that makes someone classified as obese and is responsible for the well-documented obesity-related health problems.[2] If it is the levels of body fat that define someone as obese, then it is important to use a measure of body fat in order to develop a better understanding of the potentially harmful effects of obesity on an array of economic and social outcomes ranging from labor market outcomes to self-esteem, discrimination, and marriage problems. Body fat, however, is not directly observed by researchers. In fact, most individuals are unaware of exactly how much body fat they possess. While it can be measured with the aid of clinical instruments, opportunities for such measurements are rare. It would be an expensive and difficult undertaking to collect them in a survey. For this reason most social surveys have relied on a variety of proxies for indicating the presence of excessive body fat. The most commonly used of these proxies for body fat is body mass index (BMI), which is calculated as weight in kilograms divided by height in meters squared (World Health Organization, 1995). An advantage of BMI is that it is easily calculated from height and weight, which are readily obtainable.

Unfortunately, BMI is an imperfect surrogate for body fat (Smalley et al., 1990; Gallagher et al., 1996; Romero et al., 2006). BMI alone explains only 26% of the variations in body fat (Gallager et al., 1996). A wide a range of conditions exist in which BMI provides misleading information about the levels of body fat (Prentice and Jebb, 2001). In a recent review of the medical literature on the association between BMI-based

[2] Obesity-related diseases include coronary heart disease, type 2 diabetes, hypertensions, stroke, cancers, and liver and gallbladder diseases (Centers for Disease Control and Prevention, 2007).

measures of obesity and total mortality for patients with coronary artery disease, Romero-Corral et al. (2006) found that overweight patients actually have a *better* survival rate and *lower* cardiovascular events than underweight or obese patients. Also referred to as obesity paradox, this lack of association (or an inverse association) between obesity and mortality has puzzled many medical researchers.[3] Economists who recently studied the effect of obesity on the labor market outcomes using BMI have also obtained mixed findings.[4]

While BMI is widely used by social scientists, a number of researchers have recently suggested that the inconsistent effects of BMI may be due to its inability to properly distinguish body fat from lean body mass (i.e. Allison et al., 2002; Romero-Corral et al., 2006, Wada, 2007; Cawley, 2008). A consensus report by World Health Organization (1995) warned researchers that BMI must be interpreted carefully to avoid confusing muscularity with obesity. Then, BMI might be less sensitive to male obesity due to the higher levels of lean body mass in males (Wada, 2005).[5] Gallager et al. (1996) and De Lorenzo et al. (2001) suggested that the reliability of BMI for measuring body fat

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[3] Similar findings are also reported by several other studies that examine the association between BMI and mortality in patients without evidence of cardiovascular disease (Flegal et al., 2005; McGee, 2005).

[4] There is some consensus on a negative association between obesity and wages for white females, but no clear evidence of a wage penalty exists for males or other female population groups and some studies even report a positive association between obesity and wages of black males .Averett and Korenman (1996), Baum and Ford (2004), and Cawley (2004) have all found a negative association between BMI and wages for white females but not for males or non-white females. For white males, the effect of BMI on wages was found to be non-linear with overweight workers earning more than underweight or obese workers. Cawley (2004) finds that BMI is positively and significantly associated with the wages of Black males. Baum and Ford (2004) report a weak penalty for male obesity, but the result becomes mixed when the sample is further divided by ethnicity, as reported by Averett and Korenman (1999) and Cawley (2004).

[5] A higher portion of women's body consists of body fat due to demands of childbearing and other hormonal functions.

is questionable, and that direct measurements of body fat would provide a significant improvement towards the detection and diagnosis of obesity.[6]

Direct measurement of body fat is available as a part of body composition analysis conducted by clinical investigators. In body composition analysis, body is analytically broken down to its various components (Heyward and Wagner, 2004). A popular model for studying obesity is the two-compartment model of body fat (BF) and fat-free mass (FFM).[7] In this model, BF is the smaller component consisting mostly of fat tissues, while FFM is the larger component that includes everything else, including muscles and skeletons. One advantage of two-compartment model is that body fat, which is characteristically unhealthy and the basis for classifying someone as obese, can now be tracked independently from the rest of a person's body. Indeed, using body composition, it has been clinically shown that BF is responsible for the ill effects of obesity, while FFM is associated with health and physical fitness (e.g., Heitmann et al., 2000; Allison et al., 2002). Thus, the marginal effects of BF can be interpreted as the incremental effect of obesity, while the marginal effects of FFM can be considered as that of healthy body growth. In other words, BF and FFM can exert a complex influence on the economic and social outcomes that cannot necessarily be captured by a single measure that fails to distinguish one from the other. Because the expected effects of BF and FFM are opposite

[6] For more on the shortcomings of BMI as a measure of obesity, see Wada (2005, 2007) and Cawley and Burkhauser (2006).

[7] The two-compartment modes were first proposed by Siri (1961) and Brozek et al. (1963). FFM is sometimes referred to as lean body mass (Heyward and Wagner, 2004). Technically, lean body mass contains a small amount of lipids, while FFM does not any lipids at all. In males, about 97 percent of lean body mass is FFM, while it is about 92 percent in females (Lohman, 1992).

to each other, a single index such as BMI may actually result in a situation where the opposing effects cancel each other out.[8]

In this paper, we combine data from the National Health and Nutrition Examination Survey 1988-94 (the NHANES III) and the National Longitudinal Survey of Youth 1979 (NLSY) to estimate the effect of body composition on the wages of white males and white females. Our paper makes four main contributions to the literature. First, we develop and propose using body composition measures as an alternative to the BMI-based proxies of obesity. Second, we empirically demonstrate that the calculated body fat is unambiguously associated with decreased wages for white males and females. This result is in contrast to the mixed results obtained by using BMI. Our results lend further support to the notion that that obesity is associated with a wage penalty. Third, we find that calculated fat-free mass is associated with increased wages for both white males and females. This is important evidence in favor of the nutrition hypothesis regarding worker productivity. In his Nobel address, Fogel (1994) hypothesized that increased body size should be associated with increased worker productivity.[9] This assumption of "bigger-is-better" has been questioned in light of the obesity epidemic.[10] Our result using the fat-free mass is important because it points to the beneficial effect of healthy body growth on wages. Since health is the conduit through which body size is

[8] Many attempts were made to eliminate bias due to omitted variables and potential simultaneity, but they were aimed at BMI instead of body fat itself. These include instrumental variables (Pagan and Davila, 1997; Behrman and Rozensweig, 2001; Cawley, 2004), individual, sibling, or twin fixed effects (Averett and Korenman, 1996; Behrman and Rosenzweig, 2001; Baum and Ford, 2004; Cawley, 2004), and using lagged values of obesity or weight (Sargent and Blanchflower, 1994; Gortmaker et al., 1993; Averett and Korenman, 1996; Cawley, 2004).

[9] See Fogel (1994) and Steckel (1995) for a summary of the nutrition hypothesis.

[10] Behrman and Rozensweig (2001) explore the possibility that the negative effect of obesity is due to unobserved heterogeneity and not necessarily due to increased body size. Fogel (1994) presents his theory that the beneficial effect of body size is not properly captured by the observed relationship between BMI and mortality, which is U-shaped.

thought to influence worker productivity, it should be the healthy body component or the fat-free mass that should be associated with worker productivity. Fourth, our paper contributes to the growing literature on role of non-cognitive factors in wage determination by providing insights into the effects body fat and fat-free mass on wages.[11]

II. Body Composition and Empirical Strategy

Body composition has been used for almost hundred years by nutritionists and physiologists for the purpose of studying nutrition, physical growth, and physical performance (Forbes, 1999). Improvements in clinical measurements and the rising tide of obesity have led to a renewed interest in body composition. In multivariate analyses, body composition has been shown to be significantly better at explaining individual variations in strength, health, and physical performance than body size (Bjorntorp, 2002; Institute of Medicine, 2005). Furthemore, it has been demonstrated that fat-free mass (FFM) has a positive effect on health and physical performance, while body fat (BF) has a negative effect (e.g., Heitmann et al., 2000; Allison et al., 2002).

A drawback of body composition is that it is considerably more difficult to obtain than BMI. To overcome this difficulty, clinical investigators have developed the bioelectrical impedance analysis (BIA) for measuring body composition (Kushner et al.,

[11] Given that a large body of research in the human capital literature has concluded that most of the variation in wages across individuals remains unexplained even after extensive controls of human capital investment (Keane, 1993; Bowles, Gintis, and Osborne, 2001), have led many economists to focus on the potential role of non-cognitive factors on wage determination (e.g., Hamermesh and Biddle, 1994; Mocan and Tekin, forthcoming - a; Mobius, and Rosenblat, 2006; Kuhn and Weinberger, 2005; and Persico, Postlewaite and Silverman, 2004).

1990; Roubenoff et al., 1995; Sun et al., 2003; Chumlea et al., 2002).[12] In the BIA, the electrical resistance of an individual's body is measured, which is then converted into BF and FFM with the use of a predetermined prediction equation (National Institutes of Health, 1994).[13] At the 1994 National Institutes of Health (NIH) conference on BIA, it was concluded that BIA is a useful technique for determining body composition in healthy individuals (National Institutes of Health, 1994).[14]

The construction of body composition from BIA has recently caught the attention of several economists. For example, Wada (2005, 2007) takes a departure from the other economic studies of obesity by using BIA information from the National Health and Nutrition Examination Survey (the NHANES IIII) to estimate the effect of body composition on labor market outcomes. Cawley and Burkhauser (2006) also used the BIA and body composition information from the NHANES III to study the effect of body composition on employment disability for respondents in the Panel Study of Income Dynamics (PSID). Johansson et al. (2009) used a Finnish data set containing information on body composition to ascertain the relationship between obesity and wages.

In this paper, we also use BIA information the NHANES III, which is a nationally representative cross-sectional survey conducted between 1988 and 1994. In the NHANES III, trained technicians in mobile laboratories obtained the necessary information from respondents over the age of 12 who were not known to be physically handicapped or

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[12] Some of the other alternative methods of measuring body composition include skinfold thickness, underwater weighting, dual x-ray absorptiometry, magnetic resonance imaging (Caterson, 2002; Heshka, Buhl, and Heymsfield, 1994; Heymsfield et al., 1998). However, compared to BIA, these methods are prohibitively expensive or unreasonably intrusive (Caterson, 2002; Heshka, Buhl, and Heymsfield, 1994; Heymsfield et al., 1998) for use in large-scale epidemiological studies.

[13] FFM registers a lower electrical resistance due to its high water content, whereas BF does not conduct electricity very well.

[14] The conference also stressed that the National Health and Nutrition Examination Survey (NHANES IIII), which contain measurements of BIA for a nationally representative population, is promising for examining the relationship between body composition and clinical risk factors.

pregnant at the time.[15] The BIA information from the NHANES III can be converted into body composition using the predictive equations developed by a number of clinical researchers. We start our analysis by using those developed by Sun et al. (2003) for mainly illustrative purposes, but also for the following reasons. First, these equations were published in anticipation of use with the NHANES III. Second, this is one of the most recently published studies on the subject. Third, other studies on the topic (Wada, 2005, 2007; Cawley and Burkhauser, 2006) also relied on this study. [16] However, we recognize that relying only on a single set of prediction equations raises the legitimate question as to whether our results are driven by the choice of this particular set of prediction equations. To address this concern, we gathered a comprehensive set of prediction equations from published sources developed by other clinical researcher. We will present results from these equations as a robustness analysis.

Sun et al. (2003) developed their equation using a sample containing 1,474 whites and 355 blacks aged 12-94. Because many of the predictive equations are developed using mostly white samples and the sample sizes are often too small when minority groups are included, they are not expected to work for minority groups (see National

[15] For more information on the sample design of NHANES III, see U.S. Department of Health and Human Services (1996).

[16] Sun et al. (2003) used data from five research centers to establish the models that predict fat-free mass as a function of electrical resistance as well as height and weight. They obtain their measure of body fat by subtracting fat-free mass from total bodyweight. Fat-free mass is calculated from a deterministic formula based on bone mineral content, total body water, body volume, and bodyweight using a multicomponent molecular model derived particularly for body composition analysis (Heymsfield et al., 1996). This multicomponent molecular model is developed using superior clinical measurements by densitometry, isotope dilution or dual-energy X-ray absorptiometry (Heymsfield et al., 1996).

Institutes of Health, 1994; Segal et al., 1987). Therefore, we will restrict our analysis to white men and white women only.[17]

The predictive equation provided by Sun et al. (2003) takes the following forms for males,

$$\mathrm{FFM} = -10.678 + 0.262\ \text{weight} + 0.652\,\frac{\text{stature}^2}{\text{resistance}} + 0.015\ \text{resistance}\,, \qquad (1)$$

and for females,

$$\mathrm{FFM} = -9.529 + 0.168\ \text{weight} + 0.696\,\frac{\text{stature}^2}{\text{resistance}} + 0.016\,\text{resistance}, \qquad (2)$$

where weight is clinically measured weight in kilograms and stature is is clinically measured height in centimeters. The resistance is a measure of electrical resistance measured in ohms. The predictive power of these equations is excellent with the R-squared values of 0.90 for males and 0.83 for females (Sun et al., 2003). Once the FFM is obtained from above equations, BF can easily be calculated as the difference between total weight and FFM.[18] Once the FFM is obtained from above equations, BF can easily be calculated as the difference between total weight and FFM.

Unfortunately, the NHANES III does not contain information on hourly wages. To overcome this problem, we use the information on body composition found in the NHANES III to impute measures of body composition for respondents in the National Longitudinal Survey of Youths 1979 (NLSY). The imputed body composition is then used to estimate the wage equation for the respondents in NLSY. The parameters

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[17] While there are a few predictive equations designed specifically for blacks or Hispanics, they are not necessary for the main purpose of this paper, which is to demonstrate the usefulness of body composition in research related to economics of obesity.
[18] They mentioned that their final equations tended to over-predict the FFM for white males by 0.4 kilogram and the FFM for white females by 0.3 kilogram. Our observations have been adjusted accordingly by adding or subtracting the average errors from each gender group.

necessary to predict body composition was extracted from the NHANES by separately regressing FFM and BF on self-reported characteristics found in both datasets. These characteristics include the following self-reported variables: age, age^2, age^3, weight, $weight^2$, $weight^3$, height, $height^2$, $height^3$, and height x weight.[19]

The results from the prediction equations for FFM and BF are presented in Appendix Tables 1A and 1B. To help account for differences across gender, they are estimated separately for males and females. Age, weight, and height as well as their polynomials and interactions between height and weight appear to be important determinants of FFM for most males and females. The adjusted R-squared values for FFM are quite high at 0.82 for both males and females. They are also high for BF at about 0.76 and 0.90. These high R-squared values imply that a very large proportion of the variation in the FFM and BF can be explained by the variations in the covariates included in these regressions. Taken together, results in Appendix Tables 1A and 1B suggest that these models accurately predict the FFM and BF in the NHANES III and that the estimated coefficients can reliably be used to construct FFM and BF in other data sets such as the NLSY.

Using the parameter estimates from these prediction equations, we imputed levels of FFM and BF for respondents in NLSY. The imputed values, $\hat{FFM}_{it}$ and $\hat{BF}_{it}$, are then used to included in the hourly wage equation estimated in NLSY.[20] The wage equation has the following form,

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[19] We only use self-reported characteristics in this regression using NHANES III because similar variables are self-reported in NLSY Note that Cawley and Burkhauser (2006) used a similarly parsimonious specification to predict BF and FFM in NHANES III.

[20] In a way, the logic used here is contextually similar to approximating years of experience as age minus years spent in school minus 6, which is commonly used in estimating the Mincer's equation since years of experience is usually unobserved in the data.

$$\ln(\mathrm{w}_{it}) = \beta\ X_{it} + \alpha_1\ \widehat{\mathrm{FFM}}_{it} + \alpha_2\ \widehat{\mathrm{BF}}_{it} + \varepsilon_{it} \quad , \tag{5}$$

where $\ln(\mathrm{w}_{it})$ is the logarithm of the hourly wage rate for individual *i* in year *t*, X_{it} is a vector of the observed determinants of wages; β and α's are the parameters and ε_{it} is the disturbance term.

We will exclude both height and weight from the wage equations, since they are already contained in $\widehat{\mathrm{FFM}}_{it}$ and $\widehat{\mathrm{BF}}_{it}$. This is similar to the estimation strategy using BMI, where height and weight enters the wage equation only through BMI. Here we basically allow the data to determine how height and weight interact with other characteristics of individuals to define someone as obese. However, height can also influence earnings due to higher social capital accumulated through participation in social and sport clubs during high school years as well as possibly more favorable treatment by their peers (Persico, Postlewaite and Silverman, 2004). To account for the possibility that height can have an independent effect on wages, we will control for a set of variables that would serve as a proxy for the sociability of individuals, such as participation in high school sports and clubs, as measured in the NLSY. Alternatively, we will use height during adolescence (prior to age 18) as an additional specification check. We also include in our wage models variables like education, AFQT test scores, and parents' education, that can also help further control for the individual's social skills. We will also estimate all of our models with individual fixed effects that will account for all the time-invariant unobserved heterogeneity, including social skills developed during high school as well as height during adolescence. Finally, we will present the results using the same-sex sibling differencing that will control for family-specific unobservable factors.

III. Data

The NHANES III, which is described in the previous section, is an ideal dataset for studying body composition because it provides information on both self-reported and measured height and weight, and more importantly the BIA readings. The availability of BIA readings in the NHANES III is critical for the purpose of this paper because it enables us to construct measures of FFM and BF, which we later use in the wage regressions.

Our main data set is NLSY, which is a nationally representative survey of the U.S. population. It started in 1979 with a cohort of males and females between ages 14 and 21. These individuals have been followed annually until 1993 and biannually thereafter. The NLSY provides detailed information on the labor market outcomes of respondents along with a rich set of personal and family characteristics. Although the NLSY does not provide a direct measure of body composition, it is one of the few economic surveys with longitudinal information on the body measurements, such as height and weight. We pooled all the NLSY between years 1981-2004 to create our analysis sample because self-reported weight information is available in this period. Our NLSY sample for the wage models is between ages 18 and 49. To avoid changes in body composition during pregnancy, females who were determined to be pregnant at the time of an interview are dropped from our sample.[21] We also omit respondents who are in the armed forces (Baum and Ford, 2004) and omit the supplemental poor white sample. Finally, we restrict our sample to whites because the BIA prediction formulas

[21] Reports of current pregnancies and past pregnancies were not collected at every interview. To overcome this problem, a dataset was constructed from the birth dates of women's biological children and the interview dates. Women were identified as pregnant if the interview occurred between 9 months before or after the birth of a biological child.

were developed mostly using white samples. After applying these exclusion criteria, we have a pooled-sample of 22,833 white males and 19,468 white females with required observations for variables of interest.

The NLSY asks about the hourly wage of respondents at their primary jobs. We deflated the hourly wages to 1991 dollars using the Consumer Price Index.[22] The other variables included in the analyses are age, years of education, years of job tenure, an indicator for marital status, an indicator for urban residence, region indicators, the highest grade completed by the mother, the highest grade completed by the father, the score from Armed Forces Qualification Test (AFQT) as a proxy measure of intelligence, years of employment experience, and year dummies. We also include county unemployment rate as a control for labor demand conditions. A dummy variable indicating whether the individual has any health problems limiting the kind or amount of work one can perform is also included. Finally, we also constructed a binary indicator indicating blue-collar workers.

The height and weight information provided in the NLSY is self-reported. Previous studies show evidence of reporting error in self-reports of weight and height (Rowland, 1989; Gorber et al., 2007).[23] In order to avoid bias in their estimates, several studies utilized the NHANES, which contains both measured and self-reported height and weight, to correct for reporting bias in the NLSY (Cawley, 2004, 2006; Lakdawalla and Philipson, 2002; and Chou, Grossman, and Saffer, 2004). Following the approach in

[22] Following Cawley (2004), hourly wages were top- and bottom-coded to be between 1 and 500 in 1991 dollars.

[23] Gorber et al. (2007) conducted a review of existing empirical evidence to determine the degree of agreement between measured and self-reported measures of height, weight, and BMI. Their review of 64 studies suggested evidence for under-reporting for weight and BMI and over-reporting for height that varies between men and women.

these studies, we regressed measured weight on self-reported weight, its square and cube, age, age-squared, and age-cubed, separately by race and sex. We then repeated this process for height. Finally, we used the coefficient estimates from the NHANES weight and height regressions to construct measures of weight and height in the NLSY that are corrected for reporting error. However, our results are not sensitive to this implementation.

Table 1 presents the descriptive statistics for the NLSY sample along with the definitions of the variables, including the predicted FFM and BF. The descriptive statistics is presented by the gender. As illustrated in Table 1, white males are taller and heavier than white females, but this is due to their higher levels of FFM. White females, in fact, possess a higher level of BF. White males and females earn about 13.59 dollars and 10.39 dollars per hour, respectively. The proportion of sample having a health problem limiting work and other activities is slightly higher for females. As expected, there is little difference between the genders regarding the mother's and father's education. Similarly, the AFQT test scores are almost the same. Finally, white males are much more likely to work in blue-collar occupations than white females.

IV. Results

Studies using conventional measures of obesity (BMI, weight, binary indicators of overweight and obese) typically implement the empirical analyses in a numbers of steps. First, they usually estimate models using contemporaneous measures of obesity. Second, they repeat their analysis using lagged measures of obesity to guard against the possibility of reverse causality from wages to obesity. Third, they estimate models controlling for fixed effects to control for time-invariant unobserved heterogeneity that would potentially bias the results.[24] We follow the same pattern in our analysis of the effect of body composition on wages. Note that we also estimated our models using these conventional measures to confirm the findings of the previous studies. Our results are largely consistent with those of previous studies, but they are not discussed here to economize on space.[25]

Table 2A presents the results from the wage models with two contemporaneous measures of body composition – FFM in kilograms and BF in kilograms. Table 2B and 2C display the results from the models with the lagged measures and the fixed effects, respectively. Differently from the previous studies, we also estimate models with same-sex sibling fixed effects, whose results are displayed in Table 2D.[26]

As we discussed in Section II, in order to account for the possibility that current height may serve as a proxy of the degree of the individual's social skills and that this may have an independent impact on wages, we also control for variables that would serve as a proxy for the sociability of the individual in some specifications. Specifically, the sociability variables that we include in the models are nine binary indicators for the most active high school club participation, such as athletics or marching band.[27] To better

[24] See Cawley (2004) for a more detailed discussion of the empirical specifications used in studies with conventional measures.

[25] These results are available in a longer version of this paper and are available from the authors upon request.

[26] Note that, since these models use measures of body composition constructed from the regressions coefficients that are transferred from NHANES III to the NLSY, the standard errors will be underestimated. Therefore, we present bootstrapped standard errors in all these tables. We implemented bootstrapping with 399 replications. The implications of the results remained the same when we repeated higher values of replications.

[27] There are ten clubs minus one for the excluded category. It is likely that the contemporaneous sociability variables are endogenous to wages because higher wages are likely to raise sociability. In order to avoid bias due to potential reverse causality from wages to sociability, we use sociability indicators from high school years rather than current indicators of sociability. Nevertheless, models that also included current

assess the effect of these variables on the impact of body composition measures, we present results in Tables 2A and 2B with and without these indicators. Note that the sociability variables are not included in Table 2C because their effects are captured by the individual fixed effects.

In Table 2A, we find that the coefficients on the measures of body composition have the signs consistent with our expectations for both genders. That is, the FFM and the BF are associated with an increase and a decrease in wages, respectively, regardless of the gender. The results with social indicators remain very similar to those without them. Including nine variables for high school clubs that capture the social skills of the individual do not cause appreciable changes to the coefficient estimates. Looking at the coefficients in the results with social indicators in Table 2A, a one kilogram increase in the BF reduces wages by about one percent for both white males and females. When the FFM is raised by one kilogram, the wages increase by about 0.8 percent for white males and about 1.3 percent for white females. [28] These results indicate that, while an increase in body size due to BF will hurt wages, an increase due to FFM is actually beneficial.

Table 2B presents the result for lagged values of FFM and BF. We chose to lag FFM and BF by seven years because larger lags will considerably reduce the number of available observations, while smaller lags may not be sufficiently different from the contemporaneous values.[29] Sample size is reduced by approximately half as a result of using 7-year lags. The results from the lagged estimations are largely similar to the

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indicators of sociability such as measures of self-assessed "shyness" did not change the results. These results are available from the authors upon request.

[28] Note that a one kilogram increase in BF is equivalent to about 5 percent increase in the body fat of white males and about 4 percent increase in the body fat of white females. Similarly, a one kilogram increase in the FFM is equivalent to about 2 percent increase in the fat-free mass of white males and white females.

[29] Seven lags were also used by Averett and Korenman (1996) and Cawley (2004) for their studies using BMI. Note that our lags are for seven-year lags instead of seven-observation lags, given that NLSY became biannual after 1994.

results using contemporaneous FFM and BF in Table 2A. Both the coefficients for FFM and BF are significant for white males and females. The estimated magnitudes are also similar to the contemporaneous results but slightly larger (away from zero).

Table 2C presents the coefficients of FFM and BF from regressions with individual fixed effects. These models account for all of the time-invariant unobserved factors, including sociability from high school. Despite controlling for time-invariant heterogeneity, the results from Table 2C indicate that the effects of BF and FFM are still significant for white males and white females. More interestingly, the magnitudes of the FFM and BF effects for white males and white females approximately double between Tables 2A and 2C after controlling for fixed effects.

The persistent and significant effects of body composition even after controlling for individual fixed effects suggest that an increase in BF is indeed bad for the wages of not only white females but also for white males. We also find that individuals earn a wage premium for having an increase in their FFM. These findings are a departure from the previous studies based on BMI that consistently find an obesity penalty for white females but not always for males.

Finally, we present the results from the models with the same-sex sibling fixed effects in Table 2D. The number of available observations was significantly reduced by this operation, 3,597 for males and 2,666 for females, which represent about 1/3 of the original sample. We present the results with and without social indicators. The estimated coefficients are remarkably similar to the earlier results in magnitude, although controlling for high school sociability appears to slightly reduce the estimated effect. Also the effects for white males are not estimated with much precision possibly due to reduced sample size and the fact that the identification in these model comes from discordant measures between siblings. The results from the same-sex fixed effects further support the notion that our results for FFM and BF are not generated by unobserved heterogeneity in household or environmental characteristics.

Alternative BIA Conversion Equations for FFM and BF

It is possible that the findings that are discussed above are driven by the choice of a particular set of BIA conversion equations. In order to address this question, we gathered a comprehensive set of predictive equations estimated by other clinical researchers. This set includes 47 BIA separate equations derived and published by various researchers at various times.[30] We believe that this set includes most of the well-known BIA prediction equations that exist in published sources. These equations are presented in Appendix Table 4. We estimated our models using each of these alternative equations. Note that we use the same set of regressors in these models and also include individual fixed effects. Remarkably, as discussed below, these estimations produced FFM and BF coefficients that are extremely consistent with those presented in this paper.

In Table 3, we present the coefficients on the FFM and BF for each gender for each of these 47 prediction equations. It is a very interesting that, in all 47 equations, all four FFM and BF coefficients – a total of 188 regression coefficients (47 x 2 x 2) – have

[30] This is the same list identified in a recent study by Willet et al. (2006), minus one redundant equation due to replication. We combine four equations in that list because they were body-fat specific equations of Segal et al. (1988) that were originally meant to be combined (see Heyward and Wagner, 2004) and should have been combined by Willet et al. (2006). All 4 equations based on percentage body fat (as opposed to level measures of FFM or bodyweight) are dropped from the list due to high degree of prediction errors stemming from a linear model being fitted to truncated values between 0 and 100. Many of the remaining prediction equations are actually less suitable for the purpose of this paper because they are derived for populations of different ages like children and older adults. Nevertheless, they are retained in our analysis to show that the final result is largely robust to such built-in errors. To this list, we further add four equations from other published resources.

the expected sign, that is, the effect of FFM is positive and the effect of BF is negative. In our opinion, it is a remarkable finding that not a single coefficient has a sign that contradicts with our expectations. As summarized in Table 4, the FFM coefficients are statistically significant in 47 out of 47 models and the BF coefficients are statistically significant in all 47 models for white males. This is consistent with our results presented in Table 2C. For white females, the FFM coefficients are significant in 41 models and the BF coefficients are significant in 43 models.

In order to summarize the information in Table 3, Table 4 also presents the medians of the 47 BF and 47 FFM coefficients for each group. The medians for females are generally larger in magnitude (about 70%) than the estimated coefficients using the prediction equations of Sun et al. (2003). For males, they are similar for FFM, but the median for BF is about 20% smaller. The fact that most of the median values move away from zero give support to our claim that our main result was not driven by the choice of a particular prediction equation. We believe that this analysis provides strong and clear evidence that the results presented in Table 3 are not driven by the choice of a particular set of prediction equations.

In summary, the persistent and significant effects of body composition even after controlling for individual fixed effects suggest that an increase in BF is indeed bad for the wages of not only white females as usually found in the studies using BMI but also for white males. Also FFM is consistently associated with increased hourly wages.

Discussion and Robustness

Several potential explanations can be offered for the negative effect of body fat on wages. One of these explanations is that body fat lowers an individual's productivity through adversely affecting health. Fixed effects would capture any time-invariant health problems or limitations that would be correlated with body fat. However, this explanation is still plausible if the health limitations or problems are time-variant. Note that all of our wage models include a binary variable indicating any health limitation in the kind or amount of work one can perform while on the job. This variable is also included in the fixed effects models since it is available in every year, and thus can be time-variant. The effect of this variable is negative in every model and it remains mostly statistically significant even in the fixed effects models. Furthermore, the coefficients on body composition variables remain essentially the same when the health limitation variable is excluded from the models.[31]

Customer discrimination may be another explanation for the negative effect of body fat if customers in certain occupations have negative preferences against employees with higher levels of body fat. Note that we include a binary indicator for the individual's blue-collar occupation in our models. The exclusion of the blue-collar occupation indicator did not cause any appreciable chance in the coefficients of body composition variables in Table 2C. As a further test of customer discrimination explanation, we also constructed ten binary occupational indicators and included them in the fixed effects models instead of a single indicator for blue-collar occupation. The fixed effects results with occupation dummies are presented in Appendix Table 2. As illustrated in the table, the estimates remained almost identical when we controlled for

[31] Another possible explanation is that health limitations due to high levels of body fat adversely affecting the ability of individuals to work rather than their wages (Baum and Ford, 2004).

occupation indicators in the models. These results suggest that the opposing effects of body fat and fat-free mass are independent of customer discrimination.[32]

Another explanation would be that individuals with excess body fat may be less concerned about their future and thus invest less in accumulating human capital (Baum and Ford, 2004). Note that our models include education, tenure, experience, and current school attendance, which should control for investments in human capital. Thus, this hypothesis is unlikely to explain why body fat lowers wages in our analysis.

Another possibility is the likely negative correlation between self-esteem and obesity. Mocan and Tekin (forthcoming – b) show that wages of individuals are affected directly by obesity and indirectly through the impact of obesity on self-esteem. Cawley (2004) also offers self-esteem channel as an explanation as to why obesity has a negative effect on the wages of white females. In order to support his argument, he cites evidence indicating that obesity has a more adverse effect on the self-esteem of white females than it does on the self-esteem of black and Hispanic females. Averett and Korenman (1999) find that obesity is associated with low self-esteem among white females, but not among black females. If increased body fat is indeed negatively correlated with self-esteem, this may be an explanation for the negative effects of BF that we find in this paper. Note that we control for a large number of variables that proxy sociability of the individual. For example, we control in some of our models participation in high school clubs and sports as well as self-assessed indicators of shyness. If these variables capture the self-esteem of the individuals, then this explanation is unlikely to be responsible for the effects obtained in this paper. Of course, we acknowledge the possibility that these controls are imperfect proxies for self-esteem.

[32] Note that we cannot rule out the possibility of employer discrimination.

The sociability indicators, which are included in the models to control for any direct effect that height can have on wages through impacting an individual's social capital, do not cause any appreciable change to the coefficients. In order to guard against the possibility that sociability indicators do not fully capture this channel, we experimented with models controlling for height during adolescence. Specifically, we estimated models with earliest available height before age 18 in addition to the sociability indicators. In order to implement this, we had to restrict our sample such that earliest available height of an individual is from a point in life before age 18. As a result of this, our sample sizes went down to less than 1/4th of the original sizes. These results are presented in Appendix Table 3. Despite dramatic reductions in the sample sizes, all of the FFM and BF coefficients are in the expected sign and the effects are largely consistent with those in previous tables. Note that sociability indicators are also controlled for in these models. Results remained very similar when we controlled only for height before age 18.

V. Conclusion

In this paper, we examine the effect of body composition on wages of white males and white females. Previous studies on this subject exclusively relied on BMI and bodyweight to measure obesity. However, there is ample evidence to suggest that these are not the best surrogates of obesity because of their inability to distinguish between fat body mass and fat-free mass. Since it is the body fat that classifies an individual as obese, the effects obtained in previous studies may be confounded by the impact of fat-free component of body composition.

We measure body composition by body fat (BF) and fat-free mass (FFM). In order to do this we utilize the information on the Bioelectrical Impedance Analysis that is available in NHANES III and develop a method for directly calculating body composition for use in regression analysis. By using measures of BF and FFM, we are also able to distinguish between the effects of health physical growth (represented by an increase in FFM) and an unhealthy physical growth (represented by an increase in BF) on wages. The analysis of body composition also allows us to study the effect of FFM on wages for the first time in the literature. Because FFM consists mostly of muscles and skeletons, it presents a plausible way to estimate the effect of physical health on worker earnings.

Our results suggest that a rise in BF is associated with decreases in the wages of both white males and white females, while a rise in the FFM is associated with an increase in the wages of both groups. These findings are in contrast to the previous studies that found strong evidence of a negative effect on white females but not always for white males. Given that a higher proportion of women's body consists of fat than men due to demands for childbearing and other hormonal functions, BMI may serve as a better measure of excessive fatness for women than men. Such gender-dependent correlation could particularly explain the previously mixed and unstable findings for men.

Our results indicate that individuals with high levels of FFM or lean body mass earn a wage premium. In other words, it is the healthy growth in body size that is beneficial for wages. To the extent that FFM can be seen as a measure of healthy growth, our results provide evidence in favor of the nutrition hypothesis expounded by Fogel (1994). It has been long hypothesized that increased body size should be associated with increased worker productivity. Our result using fat-free mass demonstrates that it is the healthy growth of FFM that is beneficial. We also present evidence that these results are not artifacts of other characteristics of the individuals that are correlated with obesity.

Finally, we show evidence that our findings are robust to the choice of prediction equation based on which the body composition measures are derived. Researchers have recently found that non-cognitive characteristics such as beauty, leadership, and tallness are positively related to earnings. By studying the effects of BF and FFM on wages, this study also contributes to the growing literature on the role of non-cognitive factors on wage determination.

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Table 1
Descriptive Statistics (Mean and Standard Error) of NLSY 1979

Variables	**Definitions**	**White Males**	**White Females**
Hourly Wage	Hourly wage rate in 1991 dollars (adjusted by CPI)	13.59 (18.00)	10.39 (16.49)
FFM	Estimated Fat-free Mass in kilograms	63.15 (8.657)	43.74 (5.651)
BF	Estimated Body Fat in kilograms	20.56 (7.550)	23.02 (9.960)
BMI	Weight/Height^2	26.23 (4.497)	24.71 (5.442)
Underweight	Dummy variable = 1 if BMI<18.5	0.00631 (0.0792)	0.0311 (0.174)
Healthy	Dummy variable = 1 if 18.5≤BMI<25	0.441 (0.496)	0.617 (0.486)
Overweight	Dummy variable = 1 if 25≤BMI<30	0.383 (0.486)	0.208 (0.406)
Obese	Dummy variable = 1 if 30≤BMI	0.169 (0.375)	0.143 (0.350)
Weight [b]	Kilograms	83.70 (15.94)	67.02 (15.34)
Height [b]	Meters	1.785 (0.0625)	1.646 (0.0565)
Health Limitation	Dummy variable = 1 if Health limits kind or amount of work	0.0343 (0.182)	0.0484 (0.215)
AFQT 1980	Armed Forces Qualification Test from 1980-1981	54.88 (27.94)	54.94 (25.36)
Mother's Education	Years of education completed by mother	12.07 (2.346)	11.97 (2.363)
Father's Education	Years of education completed by father	12.33 (3.322)	12.23 (3.164)
Children	# of biological/step/adopted children in the household	0.823 (1.119)	0.974 (1.130)
Attend	Dummy variable =1 if currently attending school	0.0824 (0.275)	0.101 (0.302)
Married	Dummy variable =1 if married	0.541 (0.498)	0.550 (0.498)
Education	Years of education	13.37 (2.413)	13.50 (2.198)
Age	Age in years (to the closest month)	31.31 (6.836)	31.65 (7.107)
Tenure	Years of tenure (50 weeks/year)	4.705 (5.100)	4.059 (4.630)
Experience	Years of work experience (50 weeks/year)	12.15 (6.760)	11.28 (6.587)
Low unemployment [a]	Dummy variable =1 if unemployment rate is less than 5.9%	0.462 (0.499)	0.467 (0.499)
Medium unemployment	Dummy variable =1 if unemployment rate is between 6% and 8.9%	0.356 (0.479)	0.352 (0.478)

High unemployment	Dummy variable =1 if unemployment rate is between 9% and 11.9%	0.118 (0.323)	0.117 (0.322)
Very high unemployment	Dummy variable =1 if unemployment rate is higher than 12%	0.0640 (0.245)	0.0632 (0.243)
Urban	Dummy variable =1 if urban	0.728 (0.445)	0.724 (0.447)
Northeast	Dummy variable =1 if Northeast region	0.188 (0.390)	0.186 (0.389)
West	Dummy variable =1 if West region	0.165 (0.371)	0.168 (0.374)
Midwest	Dummy variable =1 if Midwest region	0.360 (0.480)	0.325 (0.468)
South [a]	Dummy variable =1 if South region	0.287 (0.453)	0.322 (0.467)
Blue-collar	Dummy variable =1 if blue-collar occupation [b]	0.554 (0.497)	0.297 (0.457)
Year 1981	Dummy variable =1 if year=1981	0.0443 (0.206)	0.0480 (0.214)
Year 1982	Dummy variable =1 if year=1982	0.0693 (0.254)	0.0716 (0.258)
Year 1985	Dummy variable =1 if year=1985	0.0685 (0.253)	0.0678 (0.251)
Year 1986	Dummy variable =1 if year=1986	0.0671 (0.250)	0.0671 (0.250)
Year 1988	Dummy variable =1 if year=1988	0.0724 (0.259)	0.0682 (0.252)
Year 1989	Dummy variable =1 if year=1989	0.0733 (0.261)	0.0685 (0.253)
Year 1990	Dummy variable =1 if year=1990	0.0705 (0.256)	0.0649 (0.246)
Year 1992	Dummy variable =1 if year=1992	0.0703 (0.256)	0.0669 (0.250)
Year 1993	Dummy variable =1 if year=1993	0.0718 (0.258)	0.0675 (0.251)
Year 1994	Dummy variable =1 if year=1994	0.0692 (0.254)	0.0655 (0.247)
Year 1996	Dummy variable =1 if year=1996	0.0709 (0.257)	0.0713 (0.257)
Year 1998	Dummy variable =1 if year=1998	0.0685 (0.253)	0.0700 (0.255)
Year 2000 [a]	Dummy variable =1 if year=2000	0.0603 (0.238)	0.0668 (0.250)
Year 2002	Dummy variable =1 if year=2002	0.0590 (0.236)	0.0653 (0.247)
Year 2004	Dummy variable =1 if year=2004	0.0646 (0.246)	0.0706 (0.256)
Observations		22,833	19,468

Notes: Standard deviations are in parentheses. [a] Omitted category. [b] Adjusted height and weight. (See the text for explanations).

Table 2A
OLS Results from the Models using Contemporaneous Fat-Free Mass and Body-Fat

Variable	White Males		White Females	
Fat-Free Mass	0.00789***	0.00740***	0.0130***	0.0127***
	(0.00221)	(0.00223)	(0.00334)	(0.00337)
Body Fat	-0.00947***	-0.00937***	-0.0113***	-0.0109***
	(0.00259)	(0.00259)	(0.00195)	(0.00196)
Sociability indicators	No	Yes	No	Yes
Observations	22,833	22,833	19,468	19,468

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2B
OLS Results from the Models using Lagged Fat-Free Mass and Body-Fat

Variable	White Males		White Females	
Fat-Free Mass	0.00818***	0.00771***	0.0160***	0.0160***
	(0.00272)	(0.00276)	(0.00433)	(0.00432)
Body Fat	-0.0106***	-0.0107***	-0.0132***	-0.0135***
	(0.00348)	(0.00352)	(0.00252)	(0.00253)
Sociability indicators	No	Yes	Yes	No
Observations	9,466	9,466	7,896	7,896

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2C
Fixed Effects Results from the Models using Fat-Free Mass and Body-Fat

Variable	White Males	White Females
Fat-Free Mass	0.0172***	0.0355**
	(0.00581)	(0.0155)
Body Fat	-0.0180***	-0.0196**
	(0.00575)	(0.00789)
Observations	22,833	19,468

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2D
Same-Sex Sibling Results from the Models
using Contemporaneous Fat-Free Mass and Body-Fat

Variable	White Males	White Males	White Females	White Females
Fat-Free Mass	0.0138**	0.0128**	0.00938	0.0123
	(0.00636)	(0.00649)	(0.0104)	(0.0104)
Body Fat	-0.0149**	-0.0132*	-0.00920	-0.0103*
	(0.00728)	(0.00751)	(0.00597)	(0.00585)
Sociability indicators	No	Yes	Yes	No
Observations	3,597	3,597	2,666	2,666

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Fixed-Effects Estimation with Supplementary BIA Equations with FFM and BF

	White Males				White Females			
Prediction Equation	**FFM**		**BF**		**FFM**		**BF**	
Boulier	0.00962***	(0.00320)	-0.0427***	(0.0131)	0.0338***	(0.0124)	-0.116***	(0.0408)
Cordain	0.0166***	(0.00534)	-0.00922***	(0.00278)	0.0541***	(0.0195)	-0.0202***	(0.00679)
Danford1	0.0143***	(0.00463)	-0.00922***	(0.00278)	0.0474***	(0.0171)	-0.0202***	(0.00679)
Danford2	0.0196***	(0.00627)	-0.0143***	(0.00434)	0.0625***	(0.0225)	-0.0348***	(0.0120)
Davies	0.0163***	(0.00523)	-0.00922***	(0.00278)	0.0530***	(0.0191)	-0.0202***	(0.00679)
Deurenberg1	0.0183***	(0.00584)	-0.00922***	(0.00278)	0.0588***	(0.0211)	-0.0202***	(0.00679)
Deurenberg2	0.0219***	(0.00698)	-0.00922***	(0.00278)	0.0694***	(0.0249)	-0.0202***	(0.00679)
Deurenberg3	0.0193***	(0.00657)	-0.0228***	(0.00741)	0.0474**	(0.0186)	-0.0475***	(0.0177)
Deurenberg4	0.0184**	(0.00725)	-0.0142***	(0.00523)	0.0339**	(0.0155)	-0.0226**	(0.00953)
Deurenberg5	0.0229***	(0.00727)	-0.00922***	(0.00278)	0.0721***	(0.0258)	-0.0202***	(0.00679)
Eston1	0.0198***	(0.00631)	-0.0205***	(0.00623)	0.0629***	(0.0227)	-0.0525***	(0.0182)
Fjeld1	0.0136***	(0.00441)	-0.00922***	(0.00278)	0.0454***	(0.0164)	-0.0202***	(0.00679)
Fjeld2	0.0303***	(0.00957)	-0.0546***	(0.0168)	0.0932***	(0.0334)	-0.150***	(0.0528)
Gray1	0.0123**	(0.00581)	-0.00467**	(0.00196)	0.0135	(0.00962)	-0.00617*	(0.00336)
Gray2	0.00848**	(0.00342)	-0.00676***	(0.00242)	0.00392	(0.00483)	-0.00544	(0.00415)
Heitmann1	0.0166**	(0.00754)	-0.0100**	(0.00419)	0.0324**	(0.0165)	-0.0121**	(0.00544)
Heitmann3	0.0139**	(0.00606)	-0.0116**	(0.00463)	0.0261**	(0.0130)	-0.0150**	(0.00666)
Houtkooper1	0.0182***	(0.00583)	-0.0179***	(0.00543)	0.0585***	(0.0211)	-0.0450***	(0.0156)
Houtkooper2	0.0165***	(0.00531)	-0.0178***	(0.00540)	0.0536***	(0.0194)	-0.0447***	(0.0155)
Jebb	0.0407***	(0.0128)	-0.0194***	(0.00588)	0.123***	(0.0439)	-0.0492***	(0.0171)
Kushner_Schoeller1	0.0147***	(0.00474)	-0.0128***	(0.00387)	0.0483***	(0.0175)	-0.0305***	(0.0104)
Kushner_Schoeller2	0.0250***	(0.00793)	-0.0150***	(0.00453)	0.0780***	(0.0280)	-0.0366***	(0.0126)
Kushner_Schoeller3	0.0218***	(0.00694)	-0.0168***	(0.00509)	0.0688***	(0.0248)	-0.0418***	(0.0144)
Kushner1	0.0143***	(0.00462)	-0.0115***	(0.00348)	0.0471***	(0.0171)	-0.0267***	(0.00911)
Kyle	0.0278***	(0.00697)	-0.0197***	(0.00479)	0.102***	(0.0229)	-0.0554***	(0.0121)
Lohman1	0.0219***	(0.00695)	-0.0222***	(0.00676)	0.0689***	(0.0248)	-0.0574***	(0.0200)
Lohman2	0.0194***	(0.00618)	-0.0238***	(0.00725)	0.0617***	(0.0223)	-0.0620***	(0.0216)
Lohman3	0.0211***	(0.00567)	-0.0171***	(0.00441)	0.0803***	(0.0200)	-0.0485***	(0.0117)
Lukaski_Bolonchukl	0.0239***	(0.00758)	-0.0172***	(0.00522)	0.0747***	(0.0268)	-0.0431***	(0.0149)
Lukaski_Bolonchuk2	0.0232***	(0.00737)	-0.0177***	(0.00536)	0.0727***	(0.0262)	-0.0444***	(0.0153)
Lukaski1	0.0163***	(0.00524)	-0.00922***	(0.00278)	0.0531***	(0.0191)	-0.0202***	(0.00679)
Lukaski2	0.0161***	(0.00518)	-0.00922***	(0.00278)	0.0526***	(0.0189)	-0.0202***	(0.00679)
Lukaski3	0.0184***	(0.00506)	-0.0125***	(0.00329)	0.0708***	(0.0182)	-0.0332***	(0.00817)
Lukaski4	0.0188***	(0.00522)	-0.0128***	(0.00339)	0.0719***	(0.0188)	-0.0342***	(0.00856)
Macias	0.0174***	(0.00470)	-0.0147***	(0.00380)	0.0678***	(0.0169)	-0.0406***	(0.00971)
Rising	0.0320***	(0.0101)	-0.0295***	(0.00902)	0.0981***	(0.0351)	-0.0784***	(0.0274)
Roubenoff	0.0188***	(0.00522)	-0.0128***	(0.00339)	0.0719***	(0.0188)	-0.0342***	(0.00856)
Segal1	0.0164**	(0.00806)	-0.00738**	(0.00329)	0.0216	(0.0145)	-0.00989*	(0.00559)
Segal2	0.0112**	(0.00478)	-0.00895***	(0.00347)	0.0102	(0.00839)	-0.00931	(0.00604)
Segal3	0.0128**	(0.00549)	-0.0274**	(0.0110)	0.0132	(0.0104)	-0.0270	(0.0187)
Stolarczyk	0.0177***	(0.00565)	-0.00650***	(0.00198)	0.0152*	(0.00877)	-0.00712**	(0.00326)
VanLoan_Maychn	0.0148**	(0.00682)	-0.0122**	(0.00517)	0.0175	(0.0124)	-0.0145	(0.00889)
VanLoan1	0.0172***	(0.00551)	-0.0247***	(0.00753)	0.0554***	(0.0200)	-0.0645***	(0.0225)
VanLoan2	0.0183***	(0.00585)	-0.0228***	(0.00693)	0.0587***	(0.0212)	-0.0590***	(0.0205)
VanLoan3	0.0188***	(0.00602)	-0.0207***	(0.00628)	0.0602***	(0.0217)	-0.0530***	(0.0184)
Wattanapenpaiboonl	0.0191***	(0.00611)	-0.0233***	(0.00709)	0.0610***	(0.0220)	-0.0605***	(0.0211)

Wattanapenpaiboon2	0.0176***	(0.00564)	-0.0147***	(0.00445)	0.0567***	(0.0205)	-0.0359***	(0.0123)

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Summary Statistics for Supplemental BIA Equations with FFM and BF

Statistics	Variable	White Males	White Females
# of equations with	FFM	47	41
significant coefficients	BF	47	43
Median coefficient	FFM	0.0183	0.0585
	BF	-0.0143	-0.0342

Appendix Table 1A
Determinants of Fat-free Mass (FFM) from NHANES III

Variable	White Males	White Females
Age	0.0296	0.121***
	(0.0631)	(0.0366)
Age^2 (/100)	-0.0986	-0.316***
	(0.135)	(0.0800)
Age^3 (/100)	0.000340	0.00194***
	(0.000881)	(0.000531)
Height	301.9	-181.3
	(250.4)	(115.2)
$Height^2$ (/100)	-175.8	108.8
	(147.3)	(76.45)
$Height^3$ (/100)	33.71	-18.86
	(28.98)	(16.92)
Weight	0.259*	0.262***
	(0.152)	(0.0889)
$Weigh^2$ (/100)	-0.168	0.187**
	(0.113)	(0.0784)
$Weight^3$ (/100)	0.000265	-0.000757***
	(0.000347)	(0.000288)
Height*Weight	0.276***	-0.0359
	(0.0870)	(0.0539)
Constant	-160.6	111.2*
	(142.3)	(57.97)
Observations	3201	3539
R-squared	0.824	0.816

Notes: Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 1B
Determinants of Body Fat (BF) from the NHANES III

Variable	White Males	White Females
Age	-0.0653	-0.158***
	(0.0628)	(0.0456)
Age^2 (/100)	0.241*	0.350***
	(0.134)	(0.0995)
Age^3 (/100)	-0.00166*	-0.00222***
	(0.000877)	(0.000660)
Height	-258.2	545.6***
	(249.2)	(143.3)
$Height^2$ (/100)	147.9	-373.9***
	(146.6)	(95.14)
$Height^3$ (/100)	-29.30	80.59***
	(28.84)	(21.06)
Weight	0.327**	0.685***
	(0.151)	(0.111)
$Weigh^2$ (/100)	0.402***	-0.165*
	(0.112)	(0.0976)
$Weight^3$ (/100)	-0.000964***	0.000343
	(0.000345)	(0.000359)
Height*Weight	-0.162*	0.122*
	(0.0866)	(0.0671)
Constant	151.1	-270.8***
	(141.6)	(72.15)
Observations	3201	3539
R-squared	0.763	0.897

Notes: Robust standard errors are in parentheses.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 2

Fixed Effects Results from the Models using Fat-Free Mass and Body-Fat with Occupational Dummies

Variable	White Males	White Females
Fat-Free Mass	0.0163***	0.0341**
	(0.00580)	(0.0153)
Body Fat	-0.0177***	-0.0184**
	(0.00572)	(0.00780)
Observations	22,833	9,509

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 3

OLS Results from the Models using Contemporaneous Fat-Free Mass and Body-Fat (Restricted to Earliest Available Height at Age before 18)

Variable	White Males	White Females
Fat-Free Mass	0.0144**	0.0388**
	(0.00566)	(0.0187)
Body Fat	-0.0113*	-0.0212**
	(0.00583)	(0.00966)
Sociability indicators	Yes	Yes
Earliest available Height	Yes	Yes
Observations	5,110	3,870

Notes: Bootstrapped, robust standard errors clustered around individuals are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table 4
BIA Prediction Equations

For Lean Body Mass [a]	
Heitmann1	$0.279Ht^2/R + 0.181Wt + 0.231Ht + 0.064(Sex + Wt) - 0.077Age - 14.94$; M = 1, F = 0
Segal 1	$0.00108Ht^2 - 0.02090R + 0.23199Wt - 0.06777Age + 14.59453$
Segal 2	$0.00132Ht^2 - 0.04394R + 0.30520Wt - 0.16760Age + 22.66827$
Segal 3	Segal 3a-3d combined together. See Heyward and Wagner (2004, p.140)
Segal 3a	$0.00066360Ht^2 - 0.02117R + 0.62854Wt - 0.12380Age + 9.33285$
Segal 3b	$0.00088580Ht^2 - 0.02999R + 0.42688Wt - 0.07002Age + 14.52435$
Segal 3c	$0.00064602Ht^2 - 0.01397R + 0.42087Wt + 10.43485$
Segal 3d	$0.00091186Ht^2 - 0.01466R + 0.29990Wt - 0.07012Age + 9.37938$
Van Loan and Mayclin	$0.000985Ht^2 + 0.3736Wt - 0.0238R - 4.2921Sex - 0.1531Age + 17.7868$; M = 0, F = 1
For FFM	
Boulier	$0.40Ht^2/R + 0.64Wt - 0.16Age + 6.37 - 2.71Sex$; M = 1, F = 2
Cordain	$0.81Ht^2/R + 6.86$
Chumlea	$-10.678 + 0.262Wt + 0.652Ht^2/R + 0.015R$ (M) and $-9.529 + 0.168Wt + 0.696Ht^2/R + 0.016R$ (F)
Deurenberg1	$0.762Ht^2/R + 4.20$
Deurenberg2	$0.672 \times Ht^2/R + 3.1Sex + 3.9$; M = 1, F = 0
Deurenberg3	$0.406 \times Ht^2/R + 0.360Wt + 5.58Ht + 0.56Sex - 6.48$
Deurenberg4	$0.340 \times Ht^2/R + 15.34Ht + 0.273Wt - 0.127Age + 4.56Sex - 12.44$
Deurenberg5	$0.652 \text{ x } Ht^2/R + 3.8Sex+10.9$
Eston1	$0.52Ht^2/R + 0.28Wt + 3.25$
Gray1	$0.00151Ht^2 - 0.0344R + 0.140Wt - 0.158Age + 20.387$
Gray2	$0.00139Ht^2 - 0.0801R + 0.187Wt + 39.830$
Houtkooper1	$0.58Ht^2/R + 0.24Wt + 2.69$
Houtkooper2	$0.61Ht^2/R + 0.25Wt + 1.31$
Jebb	$0.348613Ht^2/R + 0.168998Wt + 13.96674$
Lohman1	$0.475Ht^2/R + 0.295Wt + 5.49$
Lohman2	$0.485Ht^2/R + 0.338Wt + 5.32$
Lohman3	$0.62Ht^2/R + 0.21Wt + 0.10X_c + 4.2$
Lukaski1	$0.821Ht^2/R + 4.917$
Lukaski2	$0.827Ht^2/R + 5.21$
Lukaski3	$0.756Ht^2/R + 0.110Wt + 0.107X_c - 5.463$
Lukaski4	$0.734 Ht^2/R + 0.096Xc + 0.116Wt + 0.878Sex - 4.033$
Macias	$0.7374Ht^2/R + 0.1763Wt - 0.1773Age + 0.1198*Xc - 2.4658$
Rising	$0.34Ht^2/R + 0.33Wt - 0.14Age + 6.18Sex + 13.74$
Roubenoff	$0.734Ht^2/R + 0.116Wt + 0.096X_c + 0.984Sex - 4.03$; M = 1, F = 0
Stolarczyk	$0.001254Ht^2 - 0.04904R + 0.1555Wt + 0.1417X_c - 0.0833Age + 20.05$
Van Loan1	$0.50Ht^2/R + 0.37Wt + 1.93Sex + 3.12$; M = 1, F = −1
Van Loan2	$0.51Ht^2/R + 0.33Wt + 1.69Sex + 3.66$; M = 1, F = −1
Van Loan3	$0.53Ht^2/R + 0.29Wt + 1.38Sex + 4.40$; M = 1, F = −1
Wattanapenpaiboon1	$0.4936Ht^2/R + 0.332Wt + 6.493$
Wattanapenpaiboon2	$0.6483Ht^2/R + 0.1699Wt + 5.091$

For Total Bodyweight [a]	
Danford1	$0.65Ht^2/R + 0.71$
Danford2	$0.45Ht^2/R + 0.11Wt + 1.84$
Davies	$0.60Ht^2/R + 0.50$
Fjeld1	$0.67Ht^2/R + 0.48$
Fjeld2	$0.18Ht^2/R + 0.39Wt + 0.76$
Heitmann3	$0.240Ht^2/R + 0.172Wt + 0.040(Sex \times Wt) + 0.165Ht - 17.58$
Kushner1	$0.593Ht^2/R + 0.065Wt + 0.04$
Kushner and Schoeller1	$0.5561Ht^2/R + 0.0955Wt + 1.726$
Kushner and Schoeller2	$0.382Ht^2/R + 0.105Wt + 8.315$
Kushner and Schoeller3	$0.396Ht^2/R + 0.143Wt + 8.399$
Lukaski and Bolonchuk1	$0.372Ht^2/R + 3.05Sex + 0.142Wt - 0.069Age + 4.98$; M = 1, F = 0
Lukaski and Bolonchuk2	$0.374Ht^2/R + 0.151Wt - 0.083Age + 2.94Sex + 4.65$; M = 1, F = 0

Ht is height in centimeters, Wt is weight in kilograms, R is resistance in ohms, Xc is reactance in ohms (reactance is a different type of resistance sometimes used in BIA). Source: Willett et al. (2006), supplemented by Heyward and Wagner (2004), Deurenberg et al (1989), Kyle, et al (2001), Lukaski (1985), and Macias (2007).[a] Lean body mass (LBM) is converted to FFM by the equation FFM = 0.97*LBM for males and FFM = 0.92*LBM for females (Willett, 2006; Lohman, 1992). Total bodyweight (TBW) is converted to FFM by FFM = TBW/0.73 (Willett, 2006; Houtkooper et al., 1996).