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ABSTRACT

Is the BMI a Relic of the Past?*

The most widely used measure of adiposity is to express weight adjusted for height using the body mass index (BMI). However, its limitations such as its inability to distinguish muscle weight from fat weight are well known, leading public health authorities in the UK and US to recommend measuring waist circumference as a complementary diagnostic tool for obesity. Recent attention placed on the syndrome referred to as 'normal weight obesity' – individuals with normal BMI but high body fat content – emphasizes the need for a more comprehensive diagnostic tool for obesity. Based on the NHANES III data, we utilize a semi-parametric spline approach to depict graphically the relationship between BMI, waist circumference and percent body fat. In this note, we propose that percent body fat charts that incorporate information from three anthropometric dimensions supersede the one-size-fits-all obesity diagnostic approach based on power-type indices such as the BMI.

JEL Classification: I10

Keywords: BMI, waist circumference, body fat, semi-parametric, P-spline

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1. Introduction

The body mass index (BMI) is the standard measure of fatness in social science research. The popularity of BMI as a measure of adiposity stems from the fact that it is easy to measure, that there are several studies supporting its use. (e.g., Keys et al., 1972; Micozzi et al., 1986; Welborn et al., 2000) and that it is available in many social science datasets. Its widespread use continues despite its well-known flaw of being unable to distinguish fat from fat-free mass such as muscle and bone. Burkhauser and Cawley (2008) highlight that obesity defined using percent body fat (PBF) provides a different picture of who is obese in the U.S. compared to traditional statistics based on BMI. Additionally, when one uses skinfold thickness rather than BMI to define obesity, Burkhauser, Cawley and Schmeiser (2009) find that the rise in the prevalence of obesity in the U.S. is detectable 10–20 years earlier. A more precise and complete measure of fatness may therefore enable clearer public understanding of this important public health issue.

Given issues of using BMI as a measure of adiposity, several variations based on the BMI have been suggested. Suppose we are interested in restricting our search to power-type indices of the form (weight)/(height)^p where p is some constant. One way to proceed is to use a different exponent for height, a suggestion first made by Benn (1971) who showed how a power-type index would be approximately equivalent to a form of relative weight, the ratio of actual body weight to some standard weight-for-height such as those used in actuarial life tables. Assuming that weight is a linear function of height, Benn (1971) proposed that p could be obtained by a regression of log weight on log height in a sample, with the value of p given by the coefficient on log height.

More recently, in a short letter published in the *Economist* magazine on 5 January 2013, Nick Trefethen, a professor of numerical analysis at Oxford University made a simple critique of the current BMI formula:

> "The body-mass index that you (and the National Health Service) count on to assess obesity is a bizarre measure. We live in a three-dimensional world, yet the BMI is defined as weight divided by height squared. It was invented in the 1840s, before calculators, when a formula had to be very simple to be usable. As a consequence of this ill-founded definition, millions of short people think they are thinner than they are, and millions of tall people think they are fatter."

Instead, he proposed a "new BMI" formula that is based on a value of p = 2.5. This simple suggestion received widespread media attention in early 2013.[1]

Other values for p have also been suggested in the literature. Having dual-energy X-ray absorptiometry (DXA) measures of body fat at their disposal, Larsson et al. (2006) systematically measure the correlation between PBF with power-type indices as well as the correlation between total body fat (TBF) with power-type indices over different values of p. Using Swedish data, they found that the optimal weight-for-height index for the prediction of TBF was close to weight/height^1 in both men (p = 1.1) and women (p = 0.9). Similarly, Heo et al. (2013) find using the NHANES 1999-2004 data that the optimal scaling powers are p = 1.0 for men and p = 0.8 for women.

In contrast, Larsson et al. (2006) found that PBF was better predicted by weight-for-height indexes close to BMI – (weight)/(height)$^{1.8}$ for men and (weight)/(height)$^{1.9}$ for women. Another possibility is to keep the formula for BMI in its current form but to use different cutoffs

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[1] It is worth noting that if we let y = weight and x = height, then the obesity cutoff defined as BMI = weight/height^2 = 30 is simply the graph of $y = 30x^2$ for relevant values of height and weight. Its simplicity is part of its appeal.

for BMI. For example, it has been suggested that a better cutpoint for obesity based on the BMI is 24 for females and 28 for males instead of using a cutpoint of 30 for both males and females (Shah and Braverman, 2012).

Other medical researchers have concluded that BMI and other commonly used weight–height indices are inaccurate predictors of PBF. For example, Smalley et al. (1990) conclude that it appears that an index based on weight and height alone will not be sufficient to diagnose obesity accurately, at least at the individual level. This suggests that additional body measurements will be necessary for the individual evaluation of fatness focused on preventive medicine.

As an alternative to the BMI for measuring obesity in large populations, it has also been proposed that a person's waist circumference (WC) be used due to its similar ease of measurement and its utility for assessing health risk (e.g., Lean et al., 1995; Janssen et al., 2002; Koster et al., 2008).[2] Recognizing the limitations of the BMI as a measure of obesity, both the National Institutes of Health (NIH, 2000) in the US and the National Institute for Health and Clinical Excellence (NICE, 2006) in the UK suggest the combined use of BMI and WC in predicting obesity related health risk (see Table 1). Their guidelines indicate that the health risk increases when moving from the normal-weight through obese BMI categories, and that within each BMI category, men and women with high WC values are at a greater health risk than those with normal WC values. In other words, it is assumed that BMI and WC have independent effects on obesity related comorbidity.

In this paper, we build on the UK and US public health guidelines and propose to use both BMI and WC in a non-linear fashion to estimate fatness. If a power-type index based on

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[2] Clinical guidelines for accurate waist measurements suggest wrapping the tape measure around the waist at a point that is midway between the top of one's hip bone and the bottom of one's ribs.

weight and height alone does not contain enough information to accurately measure adiposity, adding an additional piece of information could therefore be helpful. We accomplish this by estimating the relationship between fatness, BMI and WC using a semi-parametric spline approach in which no specific functional forms for BMI and WC are assumed. Using nationally representative data of the US population, we provide separately by gender and race easy to read charts that help determine a person's level of fatness simply by having measurements of a person's body weight, height and WC.

2. Data

The NHANES III is a nationally representative cross-sectional survey conducted from 1988 to 1994. The survey is unique in that it combines interviews and physical examinations. The NHANES III interview includes demographic, socioeconomic, dietary, and health-related questions. The examination component consists of medical, dental, and physiological measurements. The oversampled groups included children aged 2 months to 5 years, persons over 60 years, Mexican-American persons, and non-Hispanic black persons.

The NHANES III includes many measures of fatness: weight and height (both measured and self-reported), triceps skinfold thickness, WC, waist-to-hip ratio, and bioelectrical impedance analysis (BIA) readings that can be used to calculate TBF and PBF. Following Burkhauser and Cawley (2008), we use the NHANES III data for our analysis because of the availability of published prediction equations for TBF and PBF.[3] We use a person's PBF as our primary measure of adiposity when we examine more closely the relationship between BMI, WC and adiposity. It is arguable that PBF calculated based on BIA measurements should not be considered to be the gold-standard as there are superior and more precise ways of measuring

[3] Sun et al. (2003) predict fat-free mass using BIA resistance measurements from the NHANES III data.

body fat (e.g., DXA and hydrostatic underwater weighing).[4] We follow Burkhauser and Cawley (2008) in using PBF in the NHANES III data as the benchmark measure of fatness.

The examination data file for NHANES III contains data for 31,311 persons. In this paper we focus on adults aged 18–65, the same age restrictions that Burkhauser and Cawley (2008) impose for their empirical analysis. We compute PBF as described in their paper and also provide estimates separately for white males, white females, black males and black females as they do. The non-missing data we have on BMI, WC and PBF are for 2170 white females, 1902 African American females, 1905 white males, and 1635 African American males. Descriptive statistics of the variables used in the paper are presented in Table 2.

There are several reasons why PBF is a very relevant outcome measure for the general population. For example, a key reason why many individuals might abandon a newly embarked on exercise program is because of the lack of immediate results. As Tim Ferriss (2010), author of the New York Times Bestseller 'The 4-Hour Body' writes:

> "People often conclude they're not making progress when, in fact, they are making tremendous progress. This leads to a musical chairs of fad diets and demoralizing last-ditch efforts that do more harm than good. To hit your target 20-pound recomposition, you'll need to track the right numbers." (Ferriss, 2010: 46)

As muscle mass is denser than fat mass, weight loss and a corresponding reduction in BMI does not occur in the short term. Better immediate feedback can be provided by examining one's body fat levels and Ferriss (2010) suggests eyeballing images of individuals with different levels of PBF to help one set one's target PBF levels.

[4] The charts we ultimately create require PBF as a key input. The more precise the measurement of PBF, the more precise our charts will be. One advantage of BIA is that it is relatively cheap to implement for large populations, an important consideration if our proposed approach is to be implemented for many different ethnicities. The use of BIA in this analysis is not suggestive that it is preferable to all other methods of measuring body fat.

There currently exists no consensus on PBF criteria to define obesity or excess percentage of body fat. The American Association of Clinical Endocrinology/American College of Endocrinology suggests 25% and 35% of body fat as cutoffs for obesity in men and women, respectively. The National Institutes of Health's (NIH) recommended cutoffs of PBF for obesity are 25% for men and 30% for women. The American Council on Exercise, a leading non-profit fitness certification, education and training provider in the US, also provides their own PBF guidelines (Bryant and Green, 2009). Finally, the US Army and Navy also strictly enforce PBF standards for new recruits in addition to weight-given-height guidelines.[5]

At present, it is not clear whether PBF is the most relevant variable in terms of the relationship of body composition with health outcomes, and whether BMI, or some other aspect of body composition, might be equally or more important. Studies have found that high PBF is an independent risk factor for coronary events (e.g., Calling et al., 2006), cardiovascular disease (e.g., Marques-Vidal et al., 2009) and mortality (e.g., Lahmann et al., 2002). However, not all studies find an advantage of using body composition measures over BMI. For example, Bosy-Westphal et al. (2006) found that BMI, WC, and PBF all predicted metabolic risk factors equally well. Similarly, Dolan et al. (2007) demonstrated no obvious advantage of predicting mortality in women aged 65 years and older using PBF compared with BMI and WC.

Although the relation of mortality and comorbidities with BMI is well recognized as U- or J-shaped (e.g., Berrington de Gonzalez et al., 2010), Allison et al. (1997) suggest that differential health consequences of fat mass and fat-free mass can be masked by the use of BMI. They show that if fat mass and fat free mass had opposite effects on mortality, a U- or J-shaped relation between BMI and mortality rate could occur even if the probability of death increases linearly with fat mass and decreases linearly with fat-free mass.

[5] For example, see http://www.military.com/join-armed-forces/navy-weight-rules.html.

Several recent studies discuss the concept of ‘normal weight obesity’ (NWO), which describes an individual with normal BMI but high body fat content. This literature highlights the importance of incorporating PBF measurement in the regular physical exam. In particular, this syndrome stresses that under prediction of obesity might be considered a greater error than an equal-magnitude over prediction would be. Classifying an individual as lean, when in fact the individual is truly obese, may put this individual at risk for diseases associated with obesity and potentially delay possible beneficial therapy. For example, Romero-Corral et al. (2010) find that NWO is associated with significant cardiometabolic dysregulation, including metabolic syndrome and cardiovascular risk factors when compared with normal weight subjects with low body fat content. Madeira et al. (2013) find associations between NWO and metabolic syndrome and insulin resistance early in life in young adults with BMI within the normal range.

There also appears to be a strong link between PBF and physical attractiveness. Such a link can be important in establishing the practical importance of knowing one’s PBF. For example, Rantala et al. (2013) find that male body fat levels are more important than having a masculine looking face when it comes to attractiveness. They find that body fat is related to attractiveness in a curvilinear fashion, with attractiveness peaking at 12% body fat. Similarly, Faries and Bartholomew (2012) provide empirical support for PBF’s impact on female attractiveness.

Despite the recognition of PBF as a useful and important measure of adiposity and one which provides additional information beyond that provided by the BMI, relatively few people actually know their level of PBF. The next section describes an approach that will help make it easier for individuals to ascertain their PBF using easily available anthropometric measurements.

3. Methodology

The main approach we use in this paper is to estimate the following equation for PBF:

$$PBF_i = f(Z_i) + X_i\beta + \varepsilon_i \tag{1}$$

where PBF_i is the percent body fat of individual *i*, Z_i is an individual's BMI and waist circumference, X_i is a person's age, and ε_i is a residual term. In equation (1), the function $f(.)$ is a continuous but unspecified function of BMI and WC that is estimated from the data.

In the economics literature, equation (1) is referred to as a partially linear regression model or a semi-parametric model because part of the model contains a parametric functional form but another part does not make any parametric assumptions. As the model is additively separable and includes a non-parametric component, it is sometimes also referred to as a generalized additive model (GAM) in the statistical literature. This is because it extends a generalized linear model by replacing the linear functional form with an unknown functional form determined by the data. Complicated non-linear problems can be easily accommodated, even for models with many explanatory variables. GAMs are able to accommodate the interaction of two or more predictors in a way that is conceptually comparable to interactions in a linear regression model. The joint smooth function of the predictors can be specified using tensor product smooths which is optimal for variables measured on different scales (Wood, 2006a). We use this interaction to map out the BMI and waist circumference combinations that are related to different levels of PBF.

In this paper, we focus on using a P-splines for performing our empirical analysis (Eilers and Marx, 1996). Marx and Eilers (1998) further introduce P-splines to the GAM setting. The asymptotic behavior of P-spline estimation has been explored in detail recently. Hall and Opsomer (2005) use a white-noise process representation of P-splines to provide insights into its asymptotic properties. Li and Ruppert (2008) provide theoretical asymptotic results where they derive equivalence between kernel smoothing and penalized splines in the univariate case with a large number of knots. Claeskens et al. (2009) relate the asymptotic properties of P-splines to known asymptotic results for regression splines and smoothing splines.

P-spline smoothing models are fit using penalized likelihood maximization in which the model likelihood is modified by the addition of a penalty for each smooth function, penalizing its 'wiggliness'. As discussed by Eilers and Marx (1996), when a large number of equally spaced knots and a large number of splines are used, the primary role of the basis function is to serve as a convenient smooth interpolation device.

Specifically, Eilers and Marx (1996) propose adding the following penalty to the objective function to be minimized:

$$P_{\lambda}(f) = \lambda \sum_{i=d+1}^{k} (\Delta^{d} \beta_i)^2 \tag{2}$$

The penalty can be written as a linear combination of some basis functions, where Δ^d is the difference operator of order *d*. To control for the tradeoff between penalizing wiggliness and penalizing badness of fit, each penalty is multiplied by an associated smoothing parameter.

The choice of the smoothing parameter λ or the amount of smoothing that is applied to the data can strongly affect the fit of the model. The smoothness of $f(.)$ is calculated with the aim of optimal balance between the fit to the data versus a penalty for excessive "wiggliness" of the functions. In this paper, we estimate the smoothing parameter using a restricted maximum likelihood (REML) approach (Ruppert et al., 2003; Wand, 2003).

Related recent applications of P-splines in health include Clark and Etilé (2011) and Liu and Tu (2012). In our GAM application, we use cubic splines as the basis with a second order difference penalty. We use a basis dimension of 5 for both BMI and WC. The mgcv library (Wood, 2006b) in R version 3.0.2 is used to estimate the models.

4. Results

The shortcomings of using BMI on its own to measure adiposity is illustrated in Figure 1. The top left hand panel of Figure 1 plots the relationship between PBF and BMI for white males, with reference lines indicating the NIH recommended cutoffs of BMI for obesity (BMI >30) and PBF for obesity (25% for men and 30% for women).

From Figure 1, it is apparent that for white males (top left hand panel of Figure 1), a high fraction of the observations fall in the upper left quadrant, indicating that the false negative rate is very high. These are men who would not conventionally be labeled as being obese using BMI but who actually have a high percentage of body fat. For white and black females in particular, it can be seen that there is a significant proportion of the sample who have BMI in the 18-25 range but have high PBF, and who would therefore be identified as NWO. Finally, quite a large fraction of black males have high BMI values but correspondingly low values for PBF, suggesting that these black men have substantial amounts of muscle mass.

The results of estimating equation (1) using P-splines are depicted in Figure 2, where the focus is on examining the non-linear relationship between BMI, WC and PBF. For men, it can be seen that BMI is largely inconsequential and WC plays a primary role in determining PBF levels.

For the case of black males, the iso-contour lines are almost horizontal, implying that black men with certain WC measurements have the same body fat percentage regardless of their BMI. For example, looking at black males who have a waist circumference of 100 cm, it can be seen that moving to the right in the graph (which represents an increase in BMI holding WC constant) keeps one at a constant level of percent body fat (PBF = 25).

For women, the interaction between BMI and WC is more complex. This tradeoff between BMI and WC allows for some flexibility in catering for different body shapes. It is well known that while men tend to accumulate fat in the abdominal area, women are more likely to have fat accumulate in the pelvis, buttocks and thigh areas (e.g., Power and Schulkin, 2008). Based on our analysis, for both black and white females to remain under 30% in body fat, they would need to watch both their BMI and WC measurements carefully. An increase in BMI requires a corresponding decrease in WC in order to keep PBF constant.

In the literature, there currently are several PBF prediction equations for adults based on linear regression models. For example, a highly cited paper by Deurenberg et al. (1991) suggest using the following conversion equation to obtain predicted PBF:

$$PBF = (1.20 \times bmi) - (10.8 \times male) + (0.23 \times age) - 5.4 \tag{3}$$

In order to compare the performance of the semi-parametric P-spline approach with OLS models that are typically used in the literature, we compare the out-of-sample predictive performance of several alternative models for predicting PBF:

$$PBF_i = \beta_0 + \beta_1 BMI_i + \beta_2 age_i + \beta_3 Male_i + \varepsilon_i \tag{4}$$

$$PBF_i = \beta_0 + \beta_1 BMI_i + \beta_2 WC_i + \beta_3 age_i + \beta_4 Male_i + \beta_5 White_i + \varepsilon_i \tag{5}$$

$$PBF_i = \beta_0 + \beta_1 BMI_i + \beta_2 WC_i + \delta(BMI_i \times WC_i) + \beta_3 age_i + \beta_4 Male_i + \beta_5 White_i + \varepsilon_i \tag{6}$$

$$PBF_i = f(BMI_i, WC_i) + f(age_i) + \gamma_1 Male_i + \gamma_2 White_i + \nu_i \tag{7}$$

Equation (4) is Deurenberg et al.'s (1991) model, whereas equations (5) and (6) are augmented versions of the model where WC and ethnicity have been added as extra explanatory variables. Finally, equation (7) is a P-spline model based on the same covariates.

We divide our analysis data from the NHANES III into a training sample of 5000 to estimate the coefficients that are applied to an evaluation sample of 2250. The latter is used to compare the out-of-sample forecast ability of the semi-parametric P-spline approach. Based on 5000 simulations, the boxplot in Figure 3 shows that the semi-parametric spline model outperforms the various linear models in the holdout sample in terms of having lower predicted mean-squared error (MSE). Pairwise *t*-tests of the mean differences of the MSE of the semi-parametric model with each of the respective OLS models finds that the differences are all statistically significant at the 1% level.

5. Conclusion

Despite not being originally intended to serve as a measure of obesity, the power index first suggested by Quetelet (1842) has emerged as the most widely used approach for measuring adiposity. Public health authorities such as the World Health Organization support its use despite its limitations. However, recognizing the inherent limitations of a two-dimensional measure such as the BMI, public health authorities in the UK and US have decided to complement it with additional WC guidelines within BMI categories.

In primary care clinical health practice, indirect assessments of body fat are often limited to anthropometric measures such as BMI or skinfold thickness. This is because more accurate measures of adiposity used in research settings such as DXA and hydrostatic underwater weighing are too costly to implement. The question we pose in this paper is whether it makes sense to continue to use a one-size-fits-all BMI chart for males and females and for different ethnicities. It can be viewed as a response to Burkhauser's and Cawley's (2008) call to social scientists to consider more accurate measures of fatness. Tables such as those released by the National Institutes of Health in the US and the National Institute for Health and Clinical Excellence in the UK lack the appeal of a simple BMI chart that has height on the y-axis and weight on the x-axis. Measures of fatness based on two dimensions such as power indices based on weight and height might not be able to fully capture the nature of obesity. We propose the use of easy-to-use PBF charts that incorporate information from three dimensions, yet are as simple to read as a BMI chart. For measuring PBF, the striking results are that BMI appears to matter for white and black women but not for white and black men.

With increasing research emphasis being placed on the health of normal weight individuals with high body fat content, PBF is emerging as an important public health issue. As reflected in the millions of dollars spent each year in the fitness and weight-loss industry, a PBF chart based on easily available anthropometric measurements could also have great public appeal because of its links with physical fitness and physical appearance. To the best of our knowledge, although some progress has been made (e.g., Cameron et al., 2010), recommended waist measurements are yet to be determined for all ethnic groups. Consequently, it will be interesting to see how BMI, WC and PBF are associated for other ethnic groups beyond those examined in this paper.

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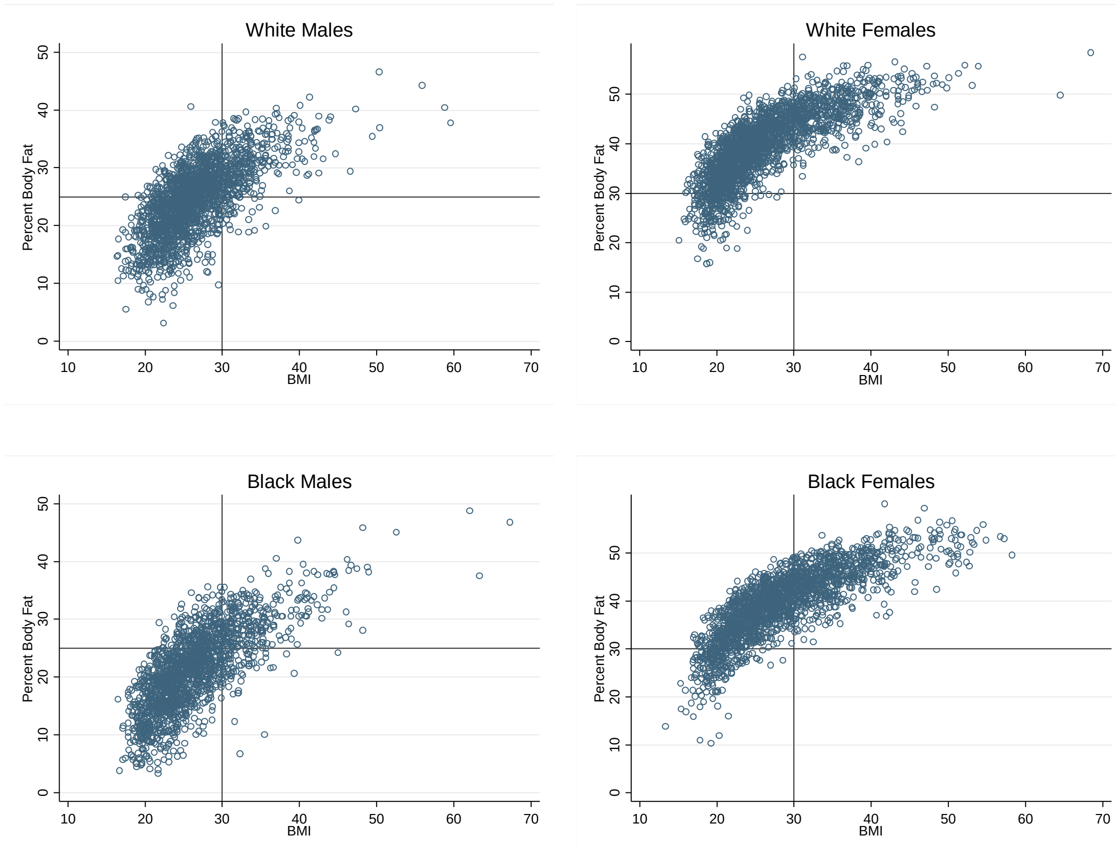
Figure 1: Scatter Plot of Body Mass Index vs Percent Body Fat, By Gender and Race



Notes: y-axis reference lines denote PBF cutoffs for obesity from NIH guidelines (PBF = 25 for men, PBF = 30 for women); x-axis reference lines denote BMI cutoffs for obesity (BMI = 30).

Figure 2: Percent Body Fat Contour Plots, By Gender and Race

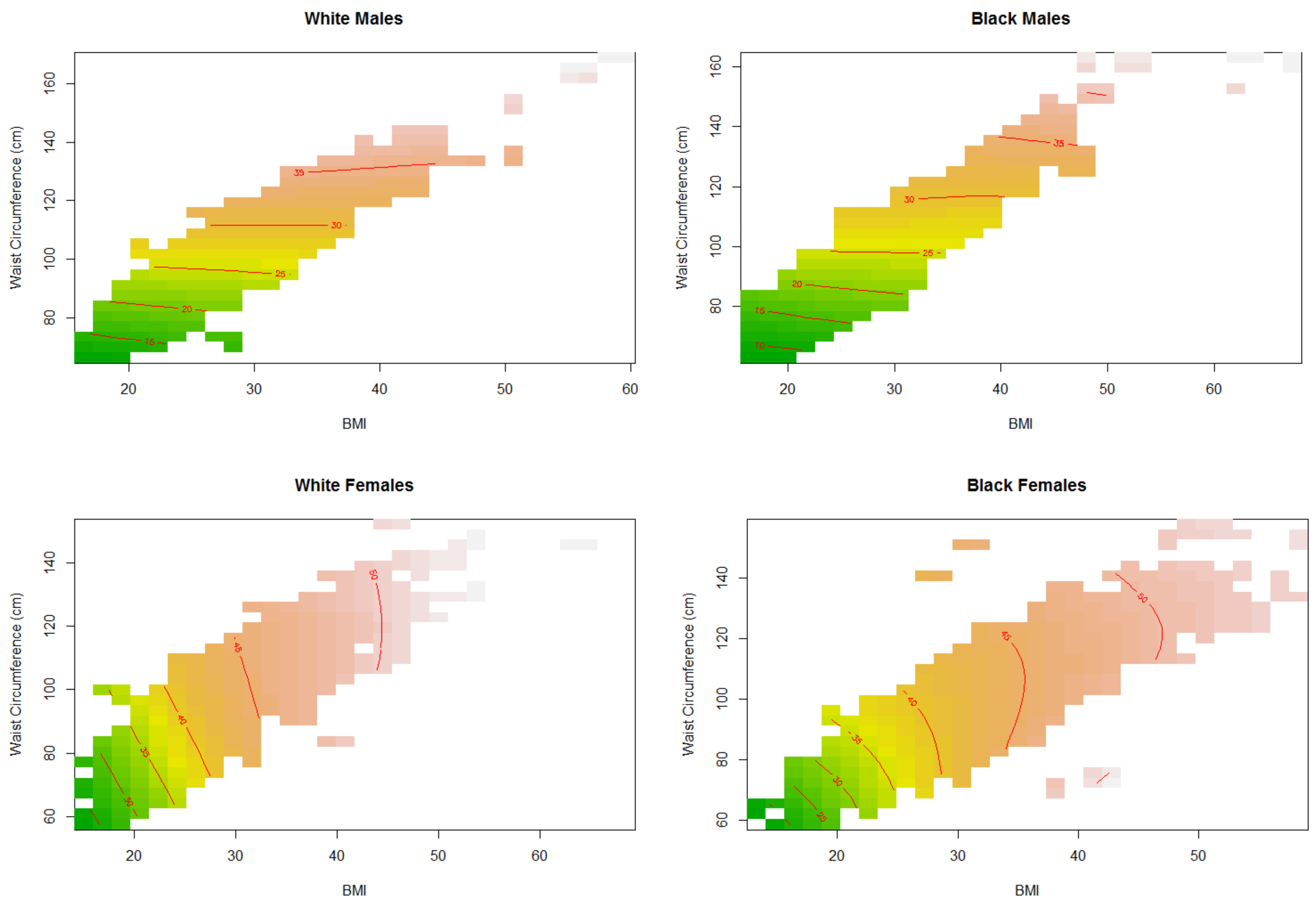
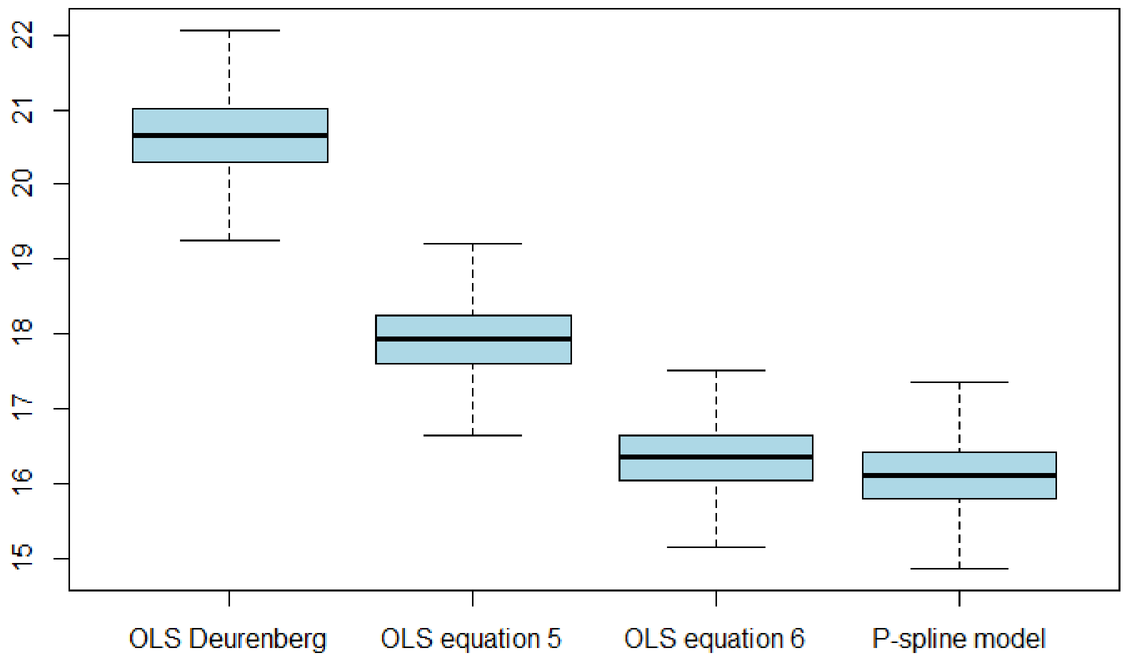


Figure 3: Predicted Mean Squared Error of the Linear and Semi-Parametric Models



Notes: Based on 5000 Monte Carlo Simulations.

Table 1: UK and US Obesity Guidelines

US National Institutes of Health (2000, p. 10)

Classification of Overweight and Obesity by Body Mass Index (BMI), Waist Circumference, and Associated Disease Risks

	BMI (kg/m²)	Obesity class	Disease risk* relative to normal weight and waist circumference: Men ≤102 cm (≤40 in) Women ≤88 cm (≤35 in)	Men >102 cm (>40 in) Women >88 cm (>35 in)
Underweight	<18.5		-	-
Normal**	18.5-24.9		-	-
Overweight	25.0-29.9		Increased	High
Obesity	30.0-34.9	I	High	Very High
	35.0-39.9	II	Very High	Very High
Extreme Obesity	≥40.0	III	Extremely High	Extremely High

*Disease risk for type 2 diabetes, hypertension, and coronary heart disease.
**Increased waist circumference can also be a marker for increased risk even in persons of normal weight
Reprinted from National Institutes of Health and National Heart, Lung, and Blood Institute, 1998.

UK National Institute for Health and Clinical Excellence (2006, p. 37)

BMI classification	Waist circumference: Low	High	Very high	Comorbidities present
Overweight				
Obesity I				
Obesity II				
Obesity III				

- General advice on healthy weight and lifestyle
- Diet and physical activity
- Diet and physical activity; consider drugs
- Diet and physical activity; consider drugs; consider surgery

Notes: For men, waist circumference of less than 94 cm is low, 94–102 cm is high and more than 102 cm is very high. For women, waist circumference of less than 80 cm is low, 80–88 cm is high and more than 88 cm is very high.

Table 2: Descriptive Statistics (NHANES III data)

	Mean	Std. Dev.	Min	Max
		White Males (n = 1905)		
Height (m)	1.77	0.07	1.55	2.07
Weight (kg)	83.16	16.29	44.10	202.47
BMI	26.50	4.71	16.40	58.80
Waist circumference (cm)	95.70	13.12	66.30	168.80
Percent body fat	24.56	6.02	3.16	46.59
		Black Males (n = 1635)		
Height (m)	1.76	0.07	1.53	2.02
Weight (kg)	82.52	18.95	42.95	218.90
BMI	26.45	5.52	16.50	67.30
Waist circumference (cm)	90.75	14.86	62.80	163.00
Percent body fat	21.29	6.94	3.31	48.74
		White Females (n = 2170)		
Height (m)	1.63	0.06	1.37	1.83
Weight (kg)	69.77	17.04	37.45	158.60
BMI	26.18	6.32	15.10	64.50
Waist circumference (cm)	87.65	15.48	57.50	152.10
Percent body fat	39.51	6.92	15.61	57.49
		Black Females (n = 1902)		
Height (m)	1.63	0.06	1.36	1.83
Weight (kg)	76.40	19.84	37.30	166.25
BMI	28.58	7.19	13.30	58.30
Waist circumference (cm)	92.01	16.90	58.60	157.80
Percent body fat	39.36	7.19	10.22	60.31