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Apostolos Davillas[a], Victor Hugo de Oliveira[b], and Andrew M Jones[c]

A Model of Errors in BMI Based on Self-reported and Measured Anthropometrics with Evidence from Brazilian Data*

Abstract

The economics of obesity literature implicitly assumes that measured anthropometrics are error-free and they are often treated as a gold standard when compared to self-reported data. We use factor mixture models to analyse and characterize measurement error in both self-reported and measured anthropometrics with national representative data from the 2013 National Health Survey in Brazil. Indeed, a small but statistically significant fraction of measured anthropometrics are attributed to data-recording errors. The estimated mean body weight (height) for those cases that are subject to error is 10% higher (2.9% lower) than the estimated mean of latent true body weight (height). As they are imprecisely measured and due to individual's reporting behaviour, only between 10% and 24% of our self-reported anthropometrics are free from any measurement error. Postestimation analysis allows us to calculate hybrid anthropometric predictions that best approximate the true body weight and height distribution. BMI distributions based on the hybrid measures are close to those based on measured data, while BMI based on self-reported data under-estimates the true BMI distribution. Analysis of regression models for health care utilization shows little differences between the relationship with BMI when it is based on measured data or on our hybrid BMI measure, however some differences are observed when both are compared to BMI based on self-reported data.

Keywords: *Body mass index; Measurement error; Mixture models; Obesity.*

JEL classification: *C18; C81; I10.*

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1. Introduction

Obesity is a strong predictor of overall mortality (Li et al., 2021; Prospective Studies Collaboration et al., 2009) and an important risk factor for several noncommunicable diseases such as cardiovascular diseases, diabetes, musculoskeletal disorder, and some cancers (Lin et al. 2020). A large literature has explored the economic and social ramifications of obesity, such as poorer labour market outcomes, increased health care utilization and associated public health costs (e.g., Cawley, 2004; Cawley, 2015; Rooth, 2009). Moreover, studies have investigated and measured socioeconomic inequalities in obesity (e.g., Bilger et al., 2017; Davillas and Benzeval, 2016; Zhang and Wang, 2004).

Many studies in the economics of obesity literature and beyond are based on self-reported body weight and height, that are used to calculate the Body Mass Index (BMI). Given recent advances in data collection for large scale social science surveys, there are some studies that allow for measured anthropometrics instead (e.g., Cawley, 2015; Cawley et al., 2015; Davillas and Jones, 2021; Gil and Mora, 2011). Studies that analyse measurement error in anthropometric data typically compare self-reports and measured anthropometric data (e.g., Davillas and Jones, 2021; Gil and Mora, 2011; O'Neill and Sweetman, 2013). These raise concerns regarding measurement error in self-reported anthropometric data and its potential implications for research when BMI is based on self-reported data as opposed to measured anthropometrics. These studies argue that measurement error in BMI based on self-reports is non-classical and is associated with individual's socioeconomic characteristics (Cawley et al., 2015; Gil and Mora, 2011) as well as with within-household peers' true BMI (Davillas and Jones, 2021).

Self-reported anthropometric data is a likely source of measurement error, but an assumption of this literature is often that measured anthropometric data is error-free. However, the accuracy of measured anthropometrics may be affected by other sources of non-sampling errors. For instance, recent evidence has documented the influence of interviewers on reliability of measured and self-reported body height data in different surveys (e.g., Finn and Ranchhod, 2017; Olbrich et al., 2021). Potential sources of measurement error in measured anthropometric data are relevant to both unintentional (such as accidental recording errors) and intentional (i.e., fabricating parts of the measurement or even conducting measurements without the intended respondent) recording errors that may affect the measurement of anthropometrics (e.g., Finn and Ranchhod, 2017; Groves, 2005; Olbrich et al., 2022). It has been argued that often interviewers have an incentive to shorten interviews to increase their hourly wage (more so in the case of skipping/fabricating time consuming measurements). This behaviour may not be easy to detect if they visited the household and conducted (part) of the interview (Olbrich et al., 2022). More broadly, the literature has discussed the presence of measurement error in more objectively measured nurse-collected and blood-based health data (Davillas and Pudney, 2020a, 2020b). These studies use latent variable models to account for measurement error, but they do not aim to explicitly model measurement error or to explore its potential implications for econometric models. Overall, there is limited analysis and modelling of the extent of measurement error in measured anthropometrics in existing research.

Our paper contributes to the literature in various ways. We model potential measurement error in both self-reported and measured anthropometrics (i.e., body weight and body height). We use data from the 2013 National Health Survey (Pesquisa Nacional de Saúde – 2013 PNS) of Brazil, which is a nationally representative dataset that allows for measured and self-reported data on body weight and height to be collected from the same individuals within the span of a household interview. In Brazil, obesity has systematically increased since the 2010s, with one in every five adults experiencing obesity (Trianca et al., 2020). Projections of the obesity-related costs in Brazil show that the annual health care costs may double from 2010 ($5.8 billion) to 2050 ($10.1 billion) — a total health care cost of $330 billion over 40 years (Rtveladze et al., 2013). As such, obesity is an important public health concern for Brazil.

To analyse measurement error in the Brazilian data we use a factor mixture model, initially proposed by Kapteyn and Ypma (2007); this Kapteyn and Ypma (KY) factor mixture model is applied and extended by Jenkins and Rios-Avila (2020) and Jenkins and Rios-Avila (2021a, 2021b) to analyse measurement error in self-reported and administrative income data. To the best of our knowledge, the KY factor mixture model has not been used to analyse measurement error in both self-reported and measured anthropometric data. Unlike the existing literature, that assumes no measurement error in measured body weight and height data, our analysis allows us to model different types of errors in both self-reported and measured anthropometrics. Specifically, we test the hypothesis that measured anthropometrics encompass data-recording errors. Moreover, the self-reported anthropometric data are assumed to be subject to a wider set of measurement errors. These include the precision of the scale for the self-reported data, which are only recorded as whole numbers (in cm or Kg), non-classical mean-reverting errors, and any other type of remaining errors.

Our analysis also allows us to estimate the probability of the occurrence of each type of measurement error in both self-reported and measured data. Of particular interest, given that measured anthropometric data are often implicitly considered as error-free (e.g., Cawley, 2015; Davillas and Jones, 2021; Gil and Mora, 2011), our results suggest that a small but systematic fraction of measured anthropometrics contain data recording errors. Turning to self-reported weight and height, the estimated probability that the self-reported anthropometrics equal the true body weight and height (i.e., they are free from any measurement error) are relatively low at about 10% and 24%, respectively.

Post-estimation analysis allows us to generate a set of predictions of the distribution of the true latent weight and height data that combine information from both self-reported and measured anthropometrics. Based on reliability and mean square errors estimated using simulated out of the sample predictions, we select the best performing prediction of true latent weight and height distributions. After choosing our preferred prediction, our sample data are used to compute body weight and height measures that approximate the true values; these are then used to calculate our proxy of the true BMI distribution.

Finally, we compare the distributions of BMI using self-reported, measured and our proxy of true BMI; the latter is very close to the distribution of BMI based on measured anthropometrics, while the BMI based on self-reported data under-estimates the true BMI distribution. In addition, we provide evidence to explore the potential implications of the measurement error in both self-reported and measured anthropometrics for economics research; we compare results when each of the self-reported, measured and hybrid BMI measures are used as explanatory variables in linear regression models for the frequency of hospital admissions in the past 12 months. We find little difference in the results between the hybrid BMI measure and the one based on measured anthropometrics.

The rest of the paper is organized as follows. Section 2 present the methods used in our study to analyse measurement error in both self-reported and measured anthropometric data. Our data source and descriptive statistics are presented in Section 3. The results of our analysis, post-estimation predictions and a preliminary analysis of the potential implications on measurement error in both self-reported and measured anthropometrics for economic research are presented in Section 4. Section 5 concludes and provides a summary of our findings.

2. Methods

To model the relationship between measured and self-reported anthropometrics we adapt the factor mixture model initially proposed by Kapteyn and Ypma (2007). This model has been applied and extended by Jenkins and Rios-Avila (2020) and Jenkins and Rios-Avila (2021a, 2021b) to analyse measurement error in income data. For the needs of this study, we employ the KY model to model measurement error in both self-reported and measured anthropometric data, on weight and height, using the 2013 National Health Survey of Brazil.

We assume that the true values of each anthropometric measure (weight and height) for an individual i (ξ_i) are unobserved, but we can observe both measured (r_i) and self-reported (s_i) anthropometrics. In the case of measured anthropometrics, we assume that the distribution of each anthropometric measure is a mixture of two types of observation:

$$r_i = \begin{cases} \xi_i & \text{with probability } \pi_r \\ \zeta_i & \text{with probability } (1 - \pi_r) \end{cases} \tag{1}$$

where, measured anthropometrics (r_i) equals the true value with probability π_r (case R1)[1]. However, measured anthropometrics may be not equal to the true value for certain respondents with probability $1 - \pi_r$ (case R2); thus, an error-ridden measure (ζ_i) is observed in this case. Recording errors (either unintentional or intentional) are assumed to be the source of measurement error here. Intentional errors by interviewers (i.e., fabricating parts of the interview) may be a source of error here which is hard to separate from unintentional interviewer errors. It has been argued that there are significant incentives for interviewers to skip parts of interviews that may be more time consuming (as with the measurement of anthropometrics) or even fabricate the measurement of anthropometrics (Finn and Ranchhod, 2017; Olbrich et al., 2022). In the spirit of the KY factor mixture model, this erroneous anthropometric measure, which is incorrectly attributed to individual i, is denoted by ζ_i. The true values and those with recording errors are both assumed to be independently and identically normally distributed:

[1] An implicit assumption here is that the true values have the same precision as the measured values; in our case, this implies an accuracy of one decimal point as measured anthropometric data (in cm for height and Kg for weight) are recorded to the first decimal point. In contrast the self-reported measures are reported as whole numbers.

$\xi_i \sim N(\mu_\xi, \sigma_\xi^2)$, $\zeta_i \sim N(\mu_\zeta, \sigma_\zeta^2)$; this implies that the marginal distribution of r_i is a mixture of two normals. Given the type of errors that are captured by ζ_i, as described above, we assume that there is no correlation between ξ_i and ζ_i[2]. The assumption that the erroneous measurements are uncorrelated with the true values contributes to the identification of the full model as it implies that these measurements are also uncorrelated with the self-reported anthropometrics.

Each of our self-reported anthropometrics (i.e., weight and height) are assumed to be a mixture of three types of observation:

$$s_i = \begin{cases} \xi_i & \text{with probability } \pi_s \\ \xi_i + \eta_i + \rho(\xi_i - \mu_\xi) & \text{with probability } (1-\pi_s)(1-\pi_\omega) \\ \xi_i + \eta_i + \rho(\xi_i - \mu_\xi) + \omega_i & \text{with probability } (1-\pi_s)\pi_\omega \end{cases} \quad (2)$$

Specifically, we assume that each of our self-reported anthropometrics (s_i) equals the true latent value (ξ_i) with probability π_s (case S1). The self-reported values are recorded as integer values so this case only applies when the true value is a whole number[3]. Otherwise (cases S2 and S3), there must be some imprecision in s_i due the scale of measurement. This imprecision, reflecting the different ways in which respondents may round their responses to whole numbers along with random noise in the self-reports, is captured by the error term η_i. This error is independent of the true value (ξ_i). In addition, as in the KY factor model, we allow for the possibility of non-classical mean-reverting (or mean-diverging) error (survey measurement error, which is captured by term $\rho(\xi_i - \mu_\xi)$.[4] The second case (S2), which allows for both of these sources of error, occurs with probability $(1-\pi_s)(1-\pi_\omega)$. The third case (S3), which occurs with probability $(1-\pi_s)\pi_w$, adds a third source of measurement error (ω_i) to allow for additional random noise that may occur in some observations who make additional errors in their self-assessments of height

[2] Even in the case of fabricated interviews or when anthropometric measurement are not conducted for the intended respondent (as described above), this may be a strong assumption in the case that quality control takes place, where the self-reported values are compared to the measured values (or other quality control checks took place) to define excess measurement error cases in the measured anthropometric data. However, there is no such quality control undertaken in the dataset used in our analysis (as well as in many other multipurpose social science datasets that collect anthropometrics).

[3] Self-reported anthropometrics are collected as integer values (cm for height and Kg for weight), while the corresponding measured values are measured to one decimal point. In those cases where the respondent provided a non-integer value of their self-reported body weight and/or height (for example 61.5Kg), the interviewer recorded an integer value (such as 61Kg or 62Kg).

[4] Mean reversion ($\rho < 0$) means that respondents with high (low) values of true anthropometric measures, relative to the true mean, tend to under-report (over-report) their body weight and height in self-reports; the opposite is the case for mean divergence ($\rho > 0$).

or weight. The measurement errors are both assumed to be independently and identically normally distributed: $\eta_i \sim N(\mu_\eta, \sigma_\eta^2)$, and $\omega_i \sim N(\mu_\omega, \sigma_\omega^2)$.

The full KY model defines a mixture of six latent classes that correspond to the combination of cases R1 or R2 with S1, S2 or S3. Table 1 describes all the potential latent classes. For instance, the class 1 (R1, S1) consists of error-free self-reported (S1) and measured (R1) data and occurs with probability $\pi_r \pi_s$. The full model is a mixture of the six bivariate normal distributions for the observed outcome pairs (r_i, s_i), each with different means and covariance matrices (see Jenkins and Rios-Avila,2020,2021a and Kapteyn and Ypma,2007 for full details).

The parameter estimates (for Eqs. 1 and 2.) are obtained by maximizing the model log-likelihood (see Kapteyn and Ypma, 2007, Appendix B), with identification relying on the existence of the "completely labelled" group that contains observations with error-free anthropometrics (class 1: R1-S1). Parameters μ_ξ and σ_ξ^2 are identified from these "completely labelled" observations and this contributes to identification of the other unknown parameters from the mixture of normals implied by the model specification (see Kapteyn and Ypma (2007) for further details on identification). Kapteyn and Ypma (2007) provide the expressions for the probability density functions and the associated log-likelihood function. Employing Jenkins and Rios-Avila's (2021c) user-written Stata command, we fit the full Kapteyn and Ypma (2007) model by maximum likelihood, assuming that the sample likelihood function is a finite mixture of latent class distributions. Our analysis is done separately for each of our anthropometric measures, i.e., for weight and height.[5]

As a post-estimation exercise, we generate predictions of the distribution of the true latent weight and height (e.g., Meijer et al., 2012). In line with Jenkins and Rios-Avila (2021b), we employ the most reliable prediction among all the potential hybrid measures of weight and height and then calculate BMI as weight (in Kg) over the square of height (in metres). We compare the distributions of hybrid, self-reported, and measured BMI. In addition, we provide some evidence to explore the implications of the measurement error in both self-reported and measured anthropometrics for empirical research; we compare results when each of the self-reported, measured and hybrid BMI

[5] As we have no information about interviewer characteristics to parameterise measurement error in measured anthropometrics and given the existing evidence that interviewer characteristics may not only affect measurement error in measured but also in self-reported anthropometrics (see Olbrich et al., 2022), we decided not to include covariates in our analysis. This is in line with the existing literature that uses KY models to model measurement error in self-reported and administrative income data (Jenkins and Rios-Avila, 2020; 2021a).

measures are used as explanatory variables. If measurement error is non-classical, i.e., systematically associated with the measured values, it may cause bias in regression models that use anthropometrics as a regressor, even in the case where instrumental variable analysis is employed to deal with endogeneity or errors-in-variables (Cawley et al., 2015; O'Neill and Sweetman, 2013).

Table 1: Groups (latent classes) in mixture model of self-reported and measured anthropometrics.

Groups (i)	Types	Probability (π_j)
1	R1,S1	$\pi_r\pi_s$
2	R1,S2	$\pi_r(1-\pi_s)(1-\pi_w)$
3	R1,S3	$\pi_r(1-\pi_s)\pi_\omega$
4	R2,S1	$(1-\pi_r)\pi_s$
5	R2,S2	$(1-\pi_r)(1-\pi_s)(1-\pi_\omega)$
6	R2,S3	$(1-\pi_r)(1-\pi_s)\pi_\omega$

3. Data

Data on self-reported and measured anthropometrics are extracted from the 2013 National Health Survey of Brazil (Pesquisa Nacional de Saúde – 2013 PNS).[6] This is a cross-sectional, nationally representative dataset for all Brazilian states and geographic regions. The survey focuses on access and use of health care services, population health conditions, and surveillance of chronic non-communicable diseases and their associated risk factors. The 2013 PNS collects demographics and socioeconomic characteristics of all household members. For each household, a randomly selected household member aged 18 or older is chosen for their body weight and height to be measured along with self-reports of the same anthropometrics. This results in a working sample of 37,335 PNS respondents, men and non-pregnant women aged 20 or older, with valid self-reported and measured weight and height data. We focus on adults (aged 20+) to avoid any puberty-related changes in body-size.

[6] The 2013 National Health Survey of Brazil is publicly available online: https://www.ibge.gov.br/estatisticas/sociais/saude/9160-pesquisa-nacional-de-saude.html?=&t=microdados.

3.1 Self-reported and measured body weight and height data

Self-reported body weight and height data are collected as part of the survey questionnaire. Measured weight and height are collected twice by a trained survey team member at the end of the questionnaire. Weight is measured by a portable digital scale, following standard measurement protocols which require that the respondents remove their shoes, heavy clothes, accessories, and objects from their pockets (PNS, 2013). Following common practice in the literature, when measured health data are used, we take the second measurement for weight and height for our base case analysis (e.g., Johnston et al., 2009; Davillas and Pudney, 2017). A sensitivity analysis is done using the average of the two measures.

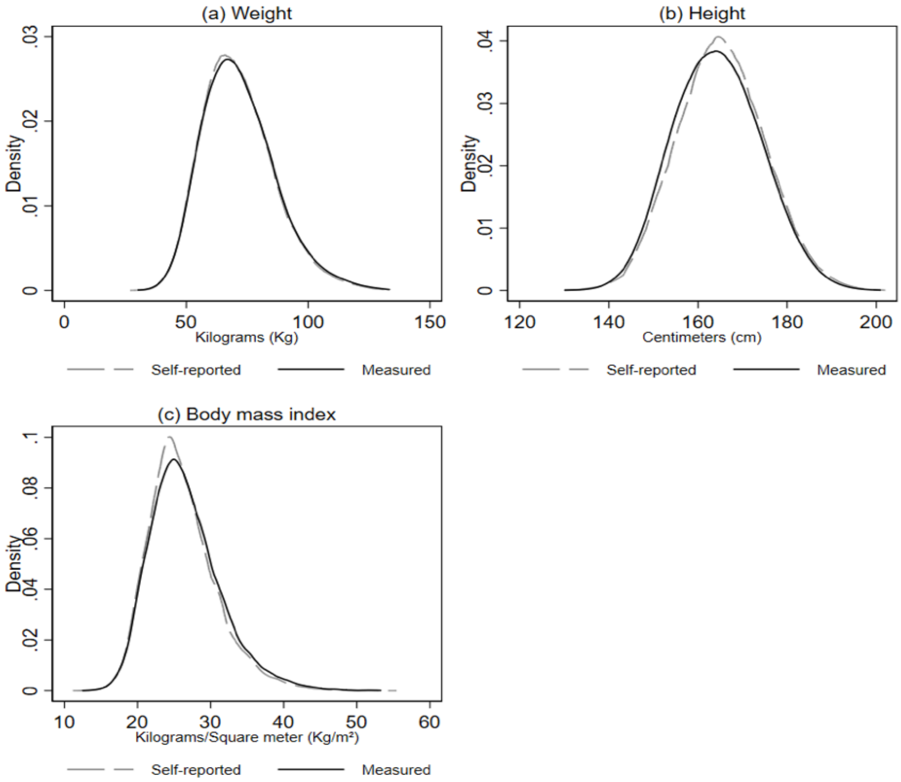
For height, a portable stadiometer is used to measure stature (PNS, 2013). Measurement protocols for body height require that the respondent must remove their shoes and other accessories, if possible, and keep at least three points of the body on the posterior surface of the stadiometer (PNS, 2013).

Although the standard measurement protocols for weight and height facilitate measurement of anthropometric data with limited errors, we cannot rule out the possibility of both intentional and unintentional data recording errors relevant to potentially fabricated anthropometric measurements. For example, even the methodological notes of our dataset acknowledge and acknowledge the role of the interviewer and their competence as a potential source of error in the measured anthropometric data (PNS, 2016). It also well documented in the literature that self-reported data on anthropometrics suffer from potential measurement error (e.g., Cawley et al., 2015; Davillas and Jones, 2021). Our analysis allows for modelling of all these sources of non-sampling errors in the measured anthropometrics along with measurement errors in the self-reported anthropometric data.

3.2 Descriptive statistics

Figure 1 displays the kernel density function for self-reported and measured body weight and height, as well as for BMI created from the measured and self-reported anthropometrics; they show a high degree of congruence between the measured and self-reported outcomes. Body height data have approximately normally shaped distributions, although right skewed distributions are observed for the case of body weight and BMI. This is important as our model assumes normality for the factor distributions and identification of the components of the mixture of normals stems from non-normality in the (joint) distribution of observed outcomes.

Figure 1. Kernel densities: body weight, height, and BMI



Descriptive statistics of the self-reported and measured weight and height data as well as for BMI measures are presented in Table 2. The mean self-reported weight (71.5Kg) is slightly smaller than the mean measured weight (72Kg). Mean self-reported height is 0.8cm higher than measured height. Table 2 also shows that the mean absolute difference between the self-reported and measured data (expressed in terms of % of the measured values) is about 3% for body weight, 1% for height and 4.5% for the derived BMI measure.

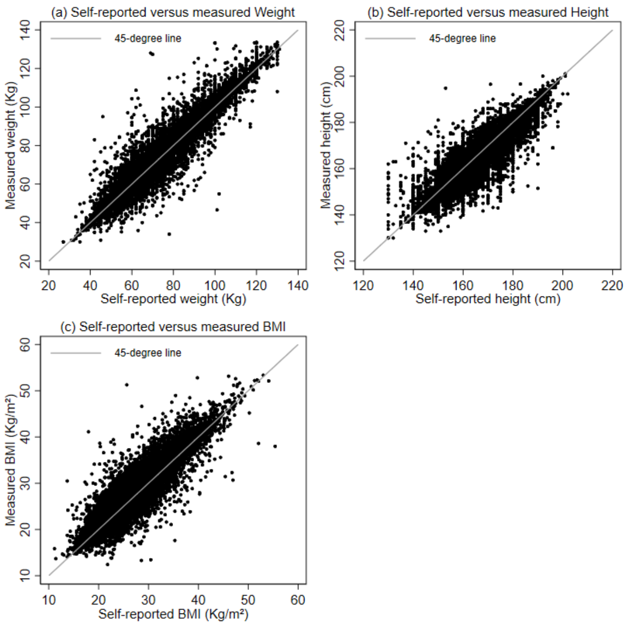
Table 2. Descriptive statistics and difference between measured and self-reported data.

	Weight (Kg)		Height (cm)		BMI (Kg/m²)	
Measure	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Self-reported	71.5	14.6	165.2	9.5	26.2	4.7
Measured	72.0	15.0	164.4	9.5	26.6	4.9
Raw difference† (measured–self-reported)	0.4	3.8	-0.8	3.7	0.4	1.8
Absolute difference	2.2	3.1	2.2	3.1	1.2	1.5
Absolute difference (% measured)	3.1	4.4	1.4	1.9	4.5	5.3

† The raw difference is calculated as the difference of measured from self-reported data. The absolute difference takes the absolute value of this difference.

In line with Figure 1, scatter plots of measured versus self-reported data (Figure 2) show that there is a positive and high correlation between the self-reported and measured anthropometrics. However, there is a far from perfect match given the large dispersion of individual observations around the 45-degree line. The greater number of observations above the reference line for body weight supports the evidence that people tend to under-report their weight in self-reports as opposed to measured body weight data (Figure 2a). The reverse is observed for height (Figure 2b). Consequently, our results for the derived BMI shows that, for the Brazilian population, BMI is in more cases lower when computed from self-reported weight and height data as opposed to measured data (Figure 2c).[7]

Figure 2. Scatter plots: self-reported and measured body weight, height, and BMI.



[7] Specifically, the fraction of respondents that under-report (over-report) their body weight, versus the relevant measured data, is 52% (38%). However, 45% (32%) of respondents' over-report (under-report) their height in self-reports as opposed to measured data.

4. Results

4.1 Estimates of structural parameters

Table 3 presents the estimates for the KY model. Following Jenkins and Rios-Avila (2020), the completely labelled observations are defined as those observations with $|r_i - s_i| \leq \delta$. Our baseline model (Table 3) assumes $\delta = 0$, i.e., the completely labelled observations are only those with no differences between self-reported and measured values. Under this demanding requirement, given the differences in precision of the scales used for measured and the self-reported outcomes, the completely labelled cases represent just 10% and 23% of our observations for weight and height respectively. Sensitivity analysis is also conducted to test the robustness of our results when this requirement is relaxed.

Table 3 shows that the mean of latent true body weight (μ_ξ) is 71.9Kg (with a standard deviation $\sigma_\xi = 14.9$). The distribution of the latent true weight has a higher mean (by about 0.4Kg) than the mean of self-reported body weight (Table 2); the p-value for the difference in means < 0.01. The estimated mean of true body height is 164.5 cm (with a standard deviation $\sigma_\xi = 9.4$). This value is lower (by -0.7 cm) than the mean of the self-reported height (Table 2).

The probability (π_r) that measured weight and height reflect the corresponding true values is high: 98.6% for weight and 96.7% for height. This indicates that data-recording-related errors in measured body weight and height data occur with a low, but systematically different from zero, probability $(1 - \pi_r)$ of about 1.4% (p-value < 0.01) and 3.3% (p-value < 0.01), respectively. Error-prone measurement of body weight (due to data recording errors) leads to an estimated mean (μ_ζ) of 78.9Kg for these erroneous observations, which is 7Kg (or almost 10%) higher than the estimated mean of true weight; data recording error in measured weight is also associated with a higher standard deviation $(\sigma_\zeta = 19.4)$ compared to the estimated true weight distribution $(\sigma_\xi = 14.9)$. Measured body height that is subject to potential data recording error has an estimated mean (μ_ζ) for the erroneous observations of 159.8cm, which is lower than the estimated mean of the true height (by about 4.7cm, i.e., 2.9% of the mean of the true height), as well as having a lower estimated standard deviation compared to the true height distribution ($\sigma_\zeta = 8.9$ compared to $\sigma_\xi = 9.4$).

Turning to self-reported weight and height, the estimated probability (π_s) that the self-reported anthropometrics equal the true body weight and height (i.e., they are free from any measurement error) are, as expected given the difference in precision of the two measures, relatively low at about 10% and 24%, respectively. Table 3 shows that mean reversion (ρ) in case of both self-reported body weight and height data is small in magnitude (close to zero) although statistically significant at the 1% level. Error due to the reporting precision (collected as integer values only) in self-reported body weight and height data have mean values (μ_η); of -0.33Kg and 0.4cm for weight and height, respectively. The estimated probability of the Case S2 type of observations, $(1-\pi_s)(1-\pi_\omega)$, is about 62% and 44% for weight and height, respectively. Moreover, Table 3 shows that the probability $(1-\pi_s)\pi_\omega$ that self-reported anthropometric data contains additional measurement error, Case S3, is about 28% for self-reported weight and 31% for self-reported height.

Table 3 (Panel B) presents estimates of the membership probabilities for the six latent classes (as described in Table 1). The first latent class consists of error-free self-reported (S1) and measured (R1) anthropometric data with a probability of 10% for body weight and 23% for height. These correspond to cases where the measured and the self-reported values equal the same whole number (i.e., cm for height and Kg for weight). The probability that there are error-free measured anthropometrics and survey reporting error in self-reported anthropometrics is about 61% for weight and 43% for height $\left(Pr(R=1,S=2)\right)$. The probability of error free measured anthropometrics and additional reporting error, corresponding to the third latent class, is 27% for weight and 30% for height. Regarding the remaining latent classes, where there are data recording errors in measured anthropometrics, we find small probabilities. For instance, the probability that weight and height observations contain error in the self-reported data and data recording errors in the measured anthropometrics, corresponding to the fifth latent class $\left(Pr(R=2,S=2)\right)$, is 0.9% and 1.5% for weight and height, respectively. Overall, these results indicate that, although there are non-negligible data recording errors in measured body weight and height data (about 7kg and 4.7cm difference on average as compared to true body weight and height, respectively), their probability of occurrence is small.

We conducted a sensitivity analysis, where measured body weight and height data are rounded to the nearest integer (Table A1, Appendix); this allows us to have the same scale in measured and reported data, but it masks the part of measurement error that is attributable to lack of precision in the recording of the self-reported data. There are differences in the six latent classes probabilities, reflecting the difference in the proportion of completely labelled cases $\left(Pr(R=1,S=1)\right)$. For instance, the increase in the probability of completely labelled cases as opposed to the case of our base case results (from 10% in the base case to 26.3% for the sensitivity analysis for weight; and, from 23.3% to 32.4% for height), is reflected in the reduction in the latent class probabilities for classes two and three (Table 3 vs Table A1).

Finally, we conducted a sensitivity analysis to explore whether our base-case results presented in Table 3 are sensitive to using the average of the two weight and height measurements to define measured anthropometrics (for the mixture models). The corresponding parameter estimates, and latent class probabilities (Table A2, Appendix) are practically identical to those presented in Table 3.

Table 3: Estimates of our factor mixture model for body weight and height.

	Weight (Kg)	Height (cm)
Panel A: Parameters		
μ_ξ	71.911***	164.518***
	(0.077)	(0.050)
σ_ξ	14.853***	9.448***
	(0.055)	(0.035)
μ_ζ	78.892***	159.767***
	(1.099)	(0.395)
σ_ζ	19.395***	8.895***
	(0.728)	(0.261)
μ_η	-0.328***	0.400***
	(0.014)	(0.024)
σ_η	1.636***	1.837***
	(0.018)	(0.027)
μ_ω	-0.333***	1.185***
	(0.067)	(0.070)
σ_ω	5.127***	4.469***
	(0.085)	(0.074)
π_r	0.986***	0.967***
	(0.001)	(0.002)
π_s	0.101***	0.241***
	(0.002)	(0.002)
π_ω	0.306***	0.414***
	(0.007)	(0.011)
ρ	-0.024***	-0.037***
	(0.001)	(0.002)
Panel B: Class probabilities		
$Pr(R=1, S=1)$	0.100***	0.233***
	(0.002)	(0.002)
$Pr(R=1, S=2)$	0.615***	0.430***
	(0.007)	(0.009)
$Pr(R=1, S=3)$	0.271***	0.304***
	(0.007)	(0.008)
$Pr(R=2, S=1)$	0.001***	0.008***
	(0.000)	(0.001)
$Pr(R=2, S=2)$	0.009***	0.015***
	(0.001)	(0.001)
$Pr(R=2, S=3)$	0.004***	0.011***
	(0.000)	(0.001)
Log-likelihood	-251,431	-234,482
Observations	37,335	37,335

Note. The fraction of completely labelled observations (i.e., $|r_i - s_i| = 0$) is 10.0% for body weight, and 23.3% for body height.
*** p<0.01

4.2 Post-estimation analysis

Our analysis so far has focused on estimating our structural parameters and distinguishing the different types of measurement errors. Following Meijer et al. (2012), we take those estimated parameters, presented in Table 3, to create "hybrid" anthropometric predictions that combine information from both self-reported and measured anthropometrics.[8] Specifically, seven "hybrid" measures to approximate the true body weight and height are generated (see Meijer et al., 2012). Predictions 1 to 6 use two within-class predictors for ξ. The first set $\hat{\xi}_i^j$, used for predictors 1, 3, and 5 minimize the mean square error (MSE), $E\left[\left(\xi_i - \xi_i^j\right)^2 | \xi_i, i \in J\right]$. The second of set predictors,$\hat{\xi}_i^{Uj}$, used for predictors 2, 4 and 6 minimize the MSE conditional on $E\left(\xi_i - \xi_i^{Uj} | \, i \in J\right) = 0$. Predictors 1 and 2 provide weighted predictions using the unconditional within-class probabilities π_j. Predictors 3 and 4 provide weighted predictions using conditional or posterior within-class probabilities $\pi_j(r_i, s_i)$. Predictors 5 and 6 use a two-step Bayesian classification. Finally, the seventh predictor (ξ_{7i}) is the system-wide predictor that minimizes MSE under the assumption of linearity and imposing the condition of unbiasedness. To assess the precision of those predictions, we estimate reliability statistics and the MSE.[9] These reliability statistics and the MSE with respect the seven "hybrid" measures come from out of the sample simulations for body weight and body height data based on estimated parameters from Table 3.[10]

Table 4 shows the precision of the seven types of "hybrid" predictions (as described above) for body weight using simulations with 1,000 replications; the corresponding results for height are shown in Table 5. Our first measure of reliability is analogous to the slope coefficient from a (hypothetical) regression of true earnings on the observed earnings measure; higher value corresponds to greater reliability and a value greater than one indicates mean reversion. Reliability 2 represents the squared correlation between true earnings and observed earnings measure. These reliability measures should only be used

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[8] The user written Stata command "ky_fit" allows for predicting the seven "hybrid" measures proposed by Meijer et al. (2012). Table 6 in Jenkins and Rios-Avila (2021c) provides the descriptions of the predictors ("hybrid" outcomes), with the corresponding derivation of the formulae presented in their appendix.

[9] The mean square error is computed as $E(predictor - \xi)^2 = Bias^2 + Variance$. Reliability measures are computed as follows: $Rel1(r) = cov(\xi, r)/var(r)$, $Rel1(s) = cov(\xi, s)/var(s)$, $Rel2(r) = cov(\xi, r)^2/[var(\xi) \cdot var(r)]$ and $Rel2(s) = cov(\xi, s)^2/[var(\xi) \cdot var(s)]$. Further details can be found in Jenkins and Rios-Avila (2021b).

[10] Simulations are done using the user-written Stata command "ky_sim". Further details can be found in Jenkins and Rios-Avila (2021c).

to assess how close a given measure is to the relevant true value and should not be compared across model specifications. For the case of both body weight and height "hybrid" predictions, all hybrid measures provide very large reliability coefficients. A closer look at Tables 4 and 5 shows that the smallest MSE is found for the weighted (conditional) prediction for both anthropometric measures; this indicates that these predictors perform better, as shown by the MSE using out of the sample simulations, and, thus, the weighted (conditional) prediction is our preferred "hybrid" prediction for both weight and height.

Table 4: Precision of "hybrid" body weight predictions.

	Rel1	Rel2	MSE
Measured body weight (r)	0.973	0.959	9.242
Self-reported body weight (s)	0.977	0.956	9.973
Hybrid body weight predictors			
1. Weighted (unconditional)	0.978	0.964	8.142
2. Weighted (unconditional) unbiased	0.978	0.964	8.139
3. Weighted (conditional)	1.000	0.997	0.697
4. Weighted (conditional) unbiased	1.000	0.997	0.701
5. Two-stage	0.998	0.996	0.867
6. Two-stage, unbiased	0.998	0.996	0.869
7. System-wide linear	1.000	0.978	4.791

Table 5: Precision of "hybrid" body height predictions.

	Rel1	Rel2	MSE
Measured body height (r)	0.962	0.930	6.442
Self-reported body height (s)	0.927	0.901	9.804
Hybrid body height predictors			
1. Weighted (unconditional)	0.980	0.946	4.881
2. Weighted (unconditional) unbiased	0.977	0.946	4.872
3. Weighted (conditional)	1.000	0.985	1.338
4. Weighted (conditional) unbiased	0.997	0.985	1.355
5. Two-stage	0.991	0.980	1.828
6. Two-stage, unbiased	0.989	0.980	1.839
7. System-wide linear	1.000	0.957	3.838

As mentioned above, simulation analysis helps us to identify our preferred predictors for the latent true body weight and height. After choosing our preferred prediction, our sample data are used to compute the true latent anthropometric measures in order to calculate a BMI measure that aims to approximate the true BMI distribution. Table 6 provides descriptive statistics of this preferred "hybrid" BMI measure and those based on self-reported and measured anthropometrics. Overall, the "hybrid" BMI measure and the BMI based on measured data are very close both at the mean and across their distribution. It seems however that at the right tails, the q75 and q90 are slightly lower for the "hybrid" measure as opposed to the BMI based on measured data; the later reflected at the inter-quantiles ranges differences (q90-q10) between the "hybrid" and measured BMI. On the other hand, BMI values that are based on self-reported data are always lower at the mean level and across quantiles of the distribution as well as with a lower dispersion compared to both the "hybrid" and the BMI based on measured data. These results suggest that the "hybrid" measure approximating the true BMI is very close to the BMI measure based on the measured weight/height data, while BMI measured based on self-reported data underestimate the "true" values. This indicates that the estimated data recording error in measured anthropometrics does not translate into major differences between the "hybrid" and the measured anthropometrics as a result of their small likelihood of occurrence in our sample.

Table 6. Distributions of BMI based on our preferred "hybrid" anthropometric predictions and BMI based on self-reported and measured body weight/height data.

	Self-reported BMI	Measured BMI	"Hybrid" BMI
Statistics			
Mean	26.158	26.580	26.526
q10	20.776	20.911	20.936
q25	22.942	23.147	23.131
q50	25.510	25.960	25.914
q75	28.720	29.320	29.237
q90	32.242	32.941	32.829
Inter-quantile ranges			
q75 - q25	5.778	6.173	6.106
q50 - q10	4.735	5.049	4.977
q90 - q50	6.732	6.981	6.916
q90 - q10	11.466	12.030	11.893

4.3 Implications for empirical research using BMI

In this sub-section, we provide evidence to test the sensitivity of econometric analyses where BMI is used as an explanatory variable. We compare results in the case that our hybrid BMI measure, estimated to proxy the true BMI distribution, with results based on self-reported and measured anthropometrics.

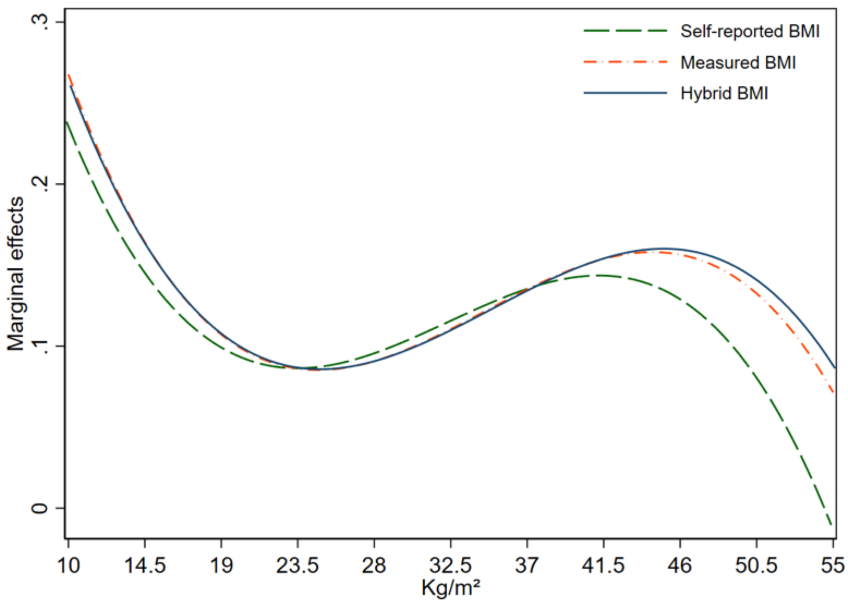
We estimate linear regression models to measure the association between BMI and the frequency of hospital admissions in the last 12 months (Table 7). To facilitate interpretation of polynomials in BMI, Figure 3 presents the adjusted predictions at representative values (APRs), i.e., the predicted health care use across selected BMI values with all the other variables kept at their mean values (based on the models presented in Table 7). As shown in Figure 3, APRs for health care use are close for the measured and the "hybrid" BMI across their distribution, while they differ from the results for the BMI based on self-reported data, especially at the lower (BMI values below 23.5 kg/m^2) and higher tails (BMI values above 37 kg/m^2) of the BMI distribution.

Table 7: Linear regression models of healthcare utilization in the last 12 months on BMI measures.

	Self-reported	Measured	Hybrid
BMI†	-5.994***	-6.281***	-5.991**
	(2.165)	(2.378)	(2.374)
BMI squared†	19.951***	19.791**	18.796**
	(7.375)	(8.096)	(8.101)
BMI cubed†	-20.484**	-19.101**	-17.997**
	(8.137)	(8.929)	(8.967)
Observations	**37,335**	**37,335**	**37,335**

† BMI is divided by 100.
Notes: Standard errors robust to heteroscedasticity in parentheses. Our models account for age, gender, ethnicity and geographic region fixed effects.
** p<0.05, *** p<0.01

Figure 3: Predicted health care use across selected BMI values (based on OLS models in Table 7)



4. Conclusion

Comparing self-reported and measured anthropometric data, existing research in the economics of obesity literature shows that self-reported data are subject to measurement error, which can lead to potential biased estimates in empirical research that relies on self-reported anthropometrics (e.g., Cawley, 2015; Cawley et al., 2015; Davillas and Jones, 2021; Gil and Mora, 2011; O'Neill and Sweetman, 2013). These analyses, however, implicitly assume that measured anthropometrics are error-free as they are treated as gold standards when compared to self-reported data; therefore, this growing literature provides little discussion about the potential measurement errors that the measured anthropometrics may entail. The latter is of particular relevance given developments in the large-scale social surveys that involve the integration of physical health measurements, in addition to traditional self-reported measures, in hope that these measures may improve survey measurement of health and eliminate measurement errors. To fill this gap in the literature, we use the KY factor mixture model (Kapteyn and Ypma, 2007) to analyse and characterize measurement error in both self-reported and measured anthropometrics with national representative data from the 2013 National Health Survey in Brazil.

We find that a small but statistically significant fraction of measured anthropometrics contain data-recording errors. Turning to self-reported weight and height, the estimated probability that the self-reported anthropometrics are free from any measurement error are, as expected, relatively low at about 10% and 24% for body weight and height data. This highlights that people's reporting behaviour in combination with the lack of precision of the self-reported questionnaires, when it comes to the collection of the self-reported data on anthropometrics, may be sources of the observed measurement error. For example, it has been argued that enhancing people's knowledge of their exact anthropometric values (by monitoring interventions) may indeed improve their ability to accurately report their anthropometric values (Sherry et al., 2007).

Post-estimation analysis and out of the sample simulations allow us to estimate hybrid anthropometric predictions that best approximate the true body weight and height distribution. Comparisons of the distribution of BMI using self-reported, measured and our proxy of true BMI distribution show that the latter is very close to the distribution of BMI based on measured anthropometrics; BMI based on self-reported data seems to under-estimate the true BMI distribution. We also explore the potential implications of the measurement error when BMI based on self-reported or measured anthropometrics is used as explanatory variable in econometric models on health care utilization. We find limited differences in our results between BMI based on measured data and our hybrid BMI measures, however some differences are observed when both are compared to the BMI based on self-reported data. These results are in line with the observed differences in the distribution of the different BMI measures and further confirm existing evidence suggesting that BMI based on self-reported data may bias econometric results when BMI is used as an explanatory variable (e.g., Cawley et al., 2015).

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Appendix

Table A1: Estimation of our factor mixture model for body weight and height – measured weight/height data are rounded at the nearest integer.

Parameter	Weight (kg)	Height (cm)
μ_ξ	71.571***	164.338***
	(0.077)	(0.050)
σ_ξ	14.883***	9.459***
	(0.055)	(0.035)
μ_ζ	79.543***	158.978***
	(1.457)	(0.450)
σ_ζ	20.207***	8.591***
	(0.949)	(0.307)
μ_η	0.080***	1.065***
	(0.021)	(0.029)
σ_η	2.287***	2.306***
	(0.023)	(0.037)
μ_ω	-0.511***	0.544***
	(0.101)	(0.094)
σ_ω	5.936***	4.757***
	(0.127)	(0.101)
π_r	0.990***	0.970***
	(0.001)	(0.002)
π_s	0.265***	0.334***
	(0.002)	(0.003)
π_ω	0.252***	0.379***
	(0.009)	(0.016)
ρ	-0.041***	-0.056***
	(0.001)	(0.002)
Class probabilities		
$Pr(R = 1, S = 1)$	0.263***	0.324***
	(0.002)	(0.002)
$Pr(R = 1, S = 2)$	0.544***	0.401***
	(0.007)	(0.011)
$Pr(R = 1, S = 3)$	0.183***	0.245***
	(0.006)	(0.011)
$Pr(R = 2, S = 1)$	0.003***	0.010***
	(0.000)	(0.001)
$Pr(R = 2, S = 2)$	0.005***	0.012***
	(0.001)	(0.001)
$Pr(R = 2, S = 3)$	0.002***	0.008***
	(0.000)	(0.001)
Log-likelihood	-249,954.7	-230,849.5
Observations	37,335	37,335

Notes: The fraction of labelled observations (i.e., $|r_i - s_i| = 0$) is 26.3% for weight, and 32.4% relative to height.
*** p<0.01

Table A2: Estimation of our factor mixture model for body weight and height (measured data: average between 1st and 2nd measurement).

Parameter	Weight (kg)	Height (cm)
μ_ξ	71.936***	164.519***
	(0.077)	(0.050)
σ_ξ	14.848***	9.443***
	(0.055)	(0.035)
μ_ζ	79.557***	159.380***
	(1.208)	(0.391)
σ_ζ	19.751***	8.716***
	(0.793)	(0.260)
μ_η	-0.342***	0.333***
	(0.014)	(0.022)
σ_η	1.600***	1.695***
	(0.017)	(0.026)
μ_ω	-0.351***	1.216***
	(0.065)	(0.064)
σ_ω	5.097***	4.320***
	(0.082)	(0.066)
π_r	0.988***	0.967***
	(0.001)	(0.002)
π_s	0.088***	0.217***
	(0.001)	(0.002)
π_ω	0.309***	0.437***
	(0.007)	(0.011)
ρ	-0.023***	-0.032***
	(0.001)	(0.002)
Class probabilities		
$Pr(R=1,S=1)$	0.087***	0.210***
	(0.001)	(0.002)
$Pr(R=1,S=2)$	0.622***	0.426***
	(0.007)	(0.009)
$Pr(R=1,S=3)$	0.278***	0.331***
	(0.007)	(0.008)
$Pr(R=2,S=1)$	0.001***	0.007***
	(0.000)	(0.000)
$Pr(R=2,S=2)$	0.008***	0.015***
	(0.001)	(0.001)
$Pr(R=2,S=3)$	0.004***	0.011***
	(0.000)	(0.001)
Log-likelihood	-250,889.2	-234,764.3
Observations	37,335	37,335

Notes: Robust standard errors to heteroscedasticity in parentheses. The fraction of labelled observations (i.e., $|r_i - s_i| = 0$) is 8.7% for weight, and 21.0% relative to height.
*** p<0.01

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