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The changing relationship between bodyweight and longevity in high- and low-income countries☆

Joanna Kopinska[a], Vincenzo Atella[b,*], Jay Bhattacharya[c,d], Grant Miller[c,d]

[a] *DiSSE, Sapienza University of Rome, Italy*
[b] *Department of Economics and Finance, University of Rome Tor Vergata, Italy*
[c] *School of Medicine - Stanford University, Stanford, United States of America*
[d] *NBER, United States of America*

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ABSTRACT

Standard measures of bodyweight (overweight and obese, for example) fail to reflect differences across populations and technological progress over time. This paper builds on the pioneering work of Hans Waaler (1984) and Robert Fogel (1994) to empirically estimate how the relationship between body mass index (BMI) and longevity varies across high-, middle-, and low-income countries. Importantly, we show that these differences are so profound that the share of national populations above mortality-minimizing bodyweight is not clearly greater in countries with higher overweight and obesity rates (as traditionally defined)–and in fact, relative to current standards, a larger share of low-income countries' populations can be unhealthily heavy.

1. Introduction

Bodyweight has been rising around the world for centuries. Historically, innovation in agriculture has fueled increases in human stature through a process termed "techno-physio evolution" (Fogel, 1994; Fogel and Costa, 1997; Floud et al., 2011). Between the mid-17th and 19th centuries, advances in crop rotation, ploughing technology, and farming methods increased crop and livestock yields (a process that continued with the advent of mechanically-powered farming during the 20th century), leading to substantial reductions in the real price of calories (Ankli, 1980). The resulting increases in bodyweight reduced chronic malnutrition, promoting immune resilience and greater ability to survive prevalent infectious diseases, leading to dramatic gains in life expectancy in Western countries (Fogel and Costa, 1997; Sen, 1982; Drèze and Sen, 2013). Improvement in public health measures played a key role as well.[1]

However, the continued rise in bodyweight, and obesity in particular, has more recently been treated with alarm because of accompanying chronic disease morbidity and mortality (Fontaine et al., 2003; Yach et al., 2006; Popkin and Gordon-Larsen, 2004; Ebbeling et al., 2002). In lower-income countries today, which confront a simultaneous "double burden" (that is, the simultaneous existence of both undernutrition and obesity), rising bodyweight is a mixed blessing, helping some and harming others (Shrimpton and Rokx, 2012; Strauss and Thomas, 1998; Biswas et al., 2020). In higher-income countries, metabolic syndrome (characterized by abdominal obesity, insulin resistance, hypertension, and hyperlipidemia) is a leading source of non-communicable disease (Saklayen, 2018; Ezzati and Riboli, 2012; Gaziano and Pagidipati, 2013; Bennett et al., 2018; Templin et al., 2019). Taken together, approximately two billion people globally are overweight or obese, a number projected to continue rising (Roberto et al., 2015).

Clinically, whether or not a particular bodyweight is healthy for an individual is a complex question determined by more than just weight and height. For example, body mass index (BMI, or the ratio of weight in kilograms to height in meters squared) does not discriminate well between fat and muscle mass (Heitmann et al., 2000; Ortega et al., 2016; Burkhauser and Cawley, 2008).[2] Nonetheless, at the population level, BMI is a widely used summary statistic and proxy measure for body fat. According to the World Health Organization (WHO), for adults, a BMI less than 18.5 indicates underweight, between 18.5 and 25 indicates healthy bodyweight, between 25 and 30 indicates overweight, and 30

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* Corresponding author.
E-mail address: atella@uniroma2.it (V. Atella).

[1] For a review of the contribution made by various factors to increases in longevity, see Cutler et al. (2006).

[2] By contrast, Woolcott and Bergman (2018) have recently developed a Relative Fat Mass (RFM) measure, which is easier to implement than other more direct body fat estimation methods.

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or above indicates obesity (WHO, 1995; Onis et al., 2007). Population increases in BMI above 25 or 30 are therefore generally considered markers of deteriorating health (Di Angelantonio et al., 2016).

However, there are several important problems with this approach. First, these BMI thresholds are somewhat arbitrarily defined (Henderson, 2005). Second, they do not reflect genotypic differences across ethnic groups (relative to Caucasians, Patel et al. (2022) shows that Asians have health risks at lower BMI levels, for example) (WHO, 2000; Mehta et al., 2013; Nakagami et al., 2003; Bodicoat et al., 2014). Third, and importantly, health technology is changing in response to population anthropometrics in ways that promote longevity among those considered overweight or obese.[3] In fact, several studies now find that BMI in the overweight range is not associated with increased mortality risk (Flegal et al., 2013; Chen et al., 2019; Gu et al., 2006), particularly among the elderly (Winter et al., 2014; Berraho et al., 2010).

A potentially superior approach to relying on fixed BMI thresholds across countries and over time is to use iso-mortality curves. Pioneered by Waaler (1984) and used prominently by Robert Fogel and Dora Costa (Fogel, 1994; Fogel and Costa, 1997), Waaler surfaces (iso-mortality curves) provide a simple tool for understanding differences in the health consequences of anthropometric status across populations, and how these relationships are changing over time. Estimated using detailed data containing information on both anthropometric status and mortality risk, these curves relate mortality to height and weight in a way that circumvents many of the problems associated with using traditional fixed BMI thresholds as markers of poor health. They do not impose bright-line thresholds on the joint distribution of height and weight. Moreover, they can be estimated separately for different populations at different points in time, and importantly, changes in their shape and location within a population capture changes in health technology, broadly defined.[4]

Building on pioneering data collection efforts in recent years, this paper estimates new iso-mortality Waaler surfaces for three different contemporary environments, relating height and weight to longevity in the United States (a high-income country), Mexico (a middle-income country), and Indonesia (a lower-income country) using detailed individual-level longitudinal data. These countries vary in many ways, and they also represent different technological regimes, broadly defined, for longevity at different heights and weights. We also conduct complementary analyses (focusing on the U.S. because of its substantially larger number of survey waves) which document shifts in iso-mortality curves over time as well as heterogeneity consistent with known patterns of health inequality, providing suggestive evidence on the important role of technological progress over time and face validity for our analysis generally.

Overall, our findings show that differences across national populations are so profound that the share of people above mortality-minimizing bodyweight is not clearly greater in countries with higher overweight and obesity rates (as traditionally defined). In fact, relative to current standards, a larger share of low-income countries' populations may be unhealthily heavy. Accounting for these differences is critical for understanding the population health implications of evolving anthropometric status around the world.

2. Data

The data requirements for estimating Waaler surfaces are stringent. Few representative surveys measure individual anthropometric characteristics and follow the same individuals over time, recording subsequent deaths. We use data from the Health and Retirement Study (HRS) in the U.S., the Mexican Health and Aging Study (MHAS) in Mexico, and the Indonesian Family Life Survey (IFLS) in Indonesia. Focusing on anthropometric measures, demographic characteristics, and deaths (including dates of death), we exploit the longitudinal nature of each survey to track individual respondents over time, constructing separate samples by country and gender. We standardize the construction of these samples between years 2000 to 2016, focusing on adult populations at ages in which chronic diseases commonly emerge (ages 50–79).[5]

We pool all available waves of each survey conducted between 2000 and 2016 (separately by country and gender, yielding 6 subsamples). The timing of the HRS, the MHAS, and the IFLS waves differ, as Table 1 shows. The HRS waves are conducted every other year, so we use a total of 9 waves between 2000/01 and 2016/17. Specifically, we use HRS waves conducted in 2000/01, 2002/03, 2004/05, 2006/07, 2008/09, 2010/11, 2012/13, and 2014/15, yielding a sample of about 44,000 individuals. MHAS waves were conducted less regularly, with a substantial interval between the second and third wave, yielding 4 waves in total (fielded in 2000/01, 2002/03, 2012/13, and 2014/15, a combined sample of about 15,000 individuals). Three IFLS waves were conducted between 2000 and 2016 (in 2000, 2007/2008, and 2014/15, a combined sample of roughly 33,000 individuals).

Our samples are necessarily unbalanced for two reasons: (1) each survey year, new 50-year-old individuals enter the sample due to exit/death of previously sampled individuals, and (2) different surveys were fielded at different times (and with different intervals). For these reasons, we had to apply a "rectangularization" procedure to each individual/survey. For every survey participant who has at least one recorded height and weight measurement, we use nearest-neighbor imputation for otherwise missing values. The "nearest neighbor" in our case is constrained to be the same individual observed in a different year.[6] Unlike height and weight measurements, we do not need to interpolate mortality data because this data is available for all years, not just survey years (death dates are recorded for all individuals who exit the surveys due to death).

Finally, to remove the undue influence of outliers (which may in part also reflect measurement error), we trim the bottom and top percentile of the BMI distribution from each of our six subsamples (each of the three country surveys, stratified by sex). In the MHAS and the IFLS data, we also top-code the top and bottom percentile

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[3] Henderson (2005) shows that men in the United States during the nineteenth century had higher mortality risk at given BMI levels then do men in the United States today.

[4] In this paper, we consider the technological environment to broadly encompass any non-genotypic moderator of the relationship between height/weight and longevity – including knowledge about biological processes, public health and social welfare programs, social norms, health behaviors, basic health care services and pharmacological therapies – and importantly, the social, political, and economic processes that determine access to them (Cutler and Miller, 2005; Cutler et al., 2006; Preston, 1975).

[5] The HRS and MHAS do not sample individuals younger than 50, and there are few individuals in any of our data sources ages 80 years and above. Our age range differs from Fogel (1994), who focuses on individuals ages 50 to 64 years old using data collected by Waaler (1984).

[6] We only impute height and weight data for individuals who reported this information at least once, and we exclude individuals without any height and weight data from our sample. Without imputation, our results are qualitatively similar, but noisier. Differences across countries by health status and by level of economic development could also lead to differences in frequency of health care visits, which could in turn lead to differences in opportunities to have anthropometric status measured (and hence be known accurately by respondents). To consider this possibility, we also regress an indicator for the absence of height or weight data in wave w on various health conditions (separately) recorded in wave w-1, controlling for age (and using survey weights). In the HRS and MHAS, we have data on diabetes, high blood pressure, heart disease, and hospitalizations; in the IFLS, we have data on diabetes and high blood pressure. Appendix B Fig. B.1 presents these results, generally showing no meaningful relationship between missingness and these measures of health status.

Table 1
Data sources.

	USA HRS	Mexico MHAS	Indonesia IFLS
Waves	2000/01, 2002/03, 2004/05, 2006/07, 2008/09, 2010/11, 2012/13, 2014/15, 2016/17	2000/01, 2002/03, 2012/13, 2014/15	2000, 2007/2008, 2014/15
Survey type	Household level, Longitudinal, Self-reported	Household level, Longitudinal, Self-reported	Household level, Longitudinal, Self-reported
Target population	Age 50+	Age 50+	All ages (26+)
Sample size and other characteristics	Around 44,000 individuals	Around 15,000 individuals	Around 33,000 individuals, with above 90% re-contact rate each year, the survey sample represented about 83% of the Indonesian population, and as the population aged, it turned comparable to HRS style data collections

Notes: The data come from Health and Retirement Study (HRS) in the U.S., the Mexican Health and Aging Study (MHAS) in Mexico, and the Indonesian Family Life Survey (IFLS) in Indonesia, waves between 2000 and 2016. We use harmonized versions of the HRS and MHAS available through the Gateway to Global Aging platform (https://g2aging.org/). Bodyweight and height are physically measured in the IFLS, and are self-reported in the HRS and MHAS (HRS introduced physical measurement of height and weight in 2006 for a subsample of the individuals, to maintain comparability across waves we use self-reported measures throughout the entire analysis period.)

Table 2
Descriptive statistics.

	HRS - USA		MHAS - Mexico		IFLS - Indonesia	
	Men	Women	Men	Women	Men	Women
Raw data						
	2000–2016		2000–2015		2000–2014	
Age (years)	62	63	61	61	60	61
Weight (kg)	90	75	74	66	56	51
Height (cm)	177	163	166	156	160	149
BMI	28	28	27	27	22	23
Disease	.62	.58	.42	.57	.05	.07
Death	0.013	0.010	0.008	0.006	0.013	0.001
N	76.254	96,719	25,133	30,004	9,509	11,490
Rectangularized data						
	2000–2016		2000–2015		2000–2016	
Age (years)	62	63	61	61	60	61
Weight (kg)	90	75	74	66	55	49
Height (cm)	177	163	166	156	160	148
BMI	28	28	27	27	22	23
Disease	.61	.57	.43	.61	.02	.02
Death	0.013	0.010	0.010	0.007	0.023	0.017
N	97,857	121,399	57,706	66,141	28,603	35,484

Notes: The data come from Health and Retirement Study (HRS) in the U.S., the Mexican Health and Aging Study (MHAS) in Mexico, and the Indonesian Family Life Survey (IFLS) in Indonesia. Each dataset is rectangularized by filling in the data between two subsequent waves, the missing information on weight and height at the individual level is interpolated with the nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death). The top and bottom percentile of the BMI distribution are trimmed from the MHAS and IFLS samples because the top and bottom percentiles of height and weight are top-/bottom-coded. The statistics in the first panel refer to raw data relative to the waves carried out, while the second panel refers to rectangularized data constructed by filling in the missing information for the periods where the data collection was not carried out.

of the weight and height distributions. Tables A.1, A.2 and A.3 in Appendix A show the descriptive statistics for both samples (raw data and rectangularized/imputed data).

Descriptive statistics for our final samples are shown in Table 2.[7] Average respondent ages for men and women in the HRS samples are 62 and 63 (respectively), 61 for both men and women in the MHAS, and 60 and 61 in the IFLS (respectively). Average weights and heights are highest in the HRS (90 kg and 177 cm for men, 75 kg and 163 cm for women), followed by the MHAS (74 kg and 166 cm for men, 66 kg and 156 cm for women) and then the IFLS (56 kg and 160 cm for men, 51 kg and 149 cm for women).

3. Methods

Developed by Hans Waaler in a study of Norwegian men, Waaler surfaces provide a flexible graphical representation of the relationship

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[7] Our statistics are based on samples restricted to individuals ages 50–79 years. The HRS and the MHAS do not sample individuals younger than 50, and there are few individuals in any of our data sources ages 80 years and above. To contextualize our results within the existing literature, we note that the age range of our samples differs from Fogel (1994), who focuses on individuals ages 50 to 64 years using data collected by Waaler (1984) who combined information on height and weight obtained from the State Mass Miniature X-ray Examination carried out between 1963 and 1975 in Norway with the death register data for the years 1963–1979 from the Norwegian Central Bureau of Statistics.

between height, weight, and mortality risk in a population (Waaler, 1984). Since Waaler's pioneering work, this tool has been widely used in epidemiology and population health research (Fogel, 1993; Allison and Faith, 1996; Allebeck and Bergh, 1992; Engeland et al., 2003; Song et al., 2003; Strandberg, 1997; Palloni et al., 2006).

To generate new Waaler surfaces using our samples, we first estimate probit models relating probability of death at a given point in time to past weight and height, controlling for age. Following Waaler (1984) and Fogel (1994), we do not otherwise condition our estimates on moderators of the relationship between height/weight and mortality risk. Unlike Waaler and Fogel, however, our longitudinal data allows us to standardize the time lag between the measurement of height/weight and the measurement of death. This is important because, in addition to chronological age, time to death is also associated with the onset and subsequent rate of weight loss (Alley et al., 2010). We therefore exclude height and weight measurements within the preceding 3 years, producing consistent 4-year time lags between anthropometric measurement and the time at which we assess survival (or death). This choice of a 4-year lag is empirically supported by our data: conditional on age, weight loss prior to death occurs within three years of death (or less).

Specifically, for each country and gender sub-sample, we estimate probit models for mortality as a function of height and weight using the following general specification:

$$\begin{aligned} Death_{it} &= \alpha + \beta_1 H_{it-4} + \beta_2 H_{it-4}^2 + \gamma_1 W_{it-4} + \gamma_2 W_{it-4}^2 \\ &\quad + \delta W_{it-4} * H_{it-4} + \lambda Age_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

where $Death_{it}$ is the death of individual i in period t, H_{it-4} and W_{it-4} are height in centimeters and weight in kilograms measured four years prior to period t (we include squared terms of each and interaction between them as well), Age_{it} is age in years, and ϵ_{it} is an idiosyncratic error term clustered at the individual level. All estimates are generated using sampling weights.

We use these estimates by country and gender to predict individual mortality risk on a smooth grid of height/weight combinations in intervals of whole centimeters/kilograms, holding age constant at 60. With these predictions, we plot the three-dimensional surfaces with colors corresponding to different level-sets of mortality risk. We also use these predictions to generate minimum risk curves defined by the locus of (height, weight) pairs that minimize mortality risk at each height (or weight). Mortality risk increases at bodyweights both to the left and right of this minimum risk curve. We compute standard errors as well for these minimum risk curves using a block bootstrap procedure with 1000 replications.

4. Results

4.1. Changes in bodyweight over time

To set the stage, Fig. 1 first shows how average combinations of weight and height at middle and older ages (50–79) in the U.S., Mexico, and Indonesia have changed in recent decades (from 1995 to 2014) relative to the original minimum risk curves estimated by Waaler (1984) and Fogel (1994). In the United States, average height has generally remained constant over time, while average bodyweight has increased, reflecting the well-known increase in obesity in the U.S. Thus, the U.S. was already to the right of Fogel's minimum risk curve in 1995, rising to a point further above it in 2014. By contrast, Mexico's and Indonesia's average height and bodyweight have both risen steadily over the same period, moving Mexico above Fogel's minimum risk curve by 2014 and Indonesia toward it (but still below it). These national averages mask underlying heterogeneity in their distribution, which we consider below as well.

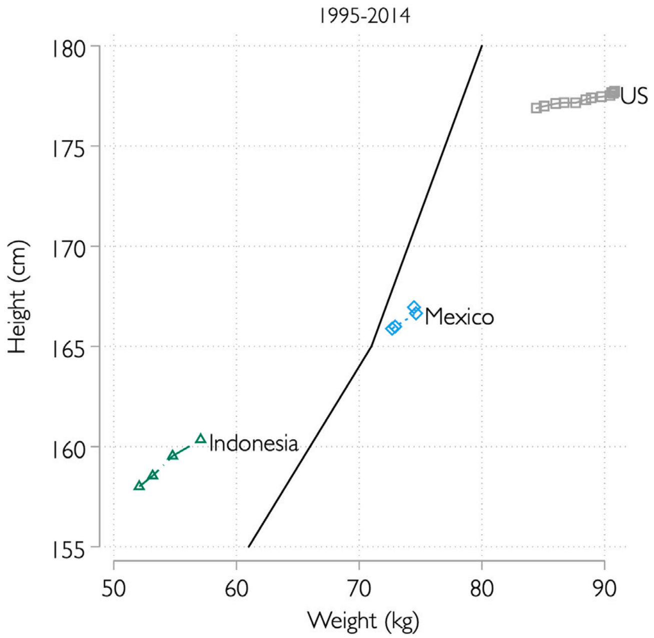

Fig. 1. Population average heights and weights trend and Waaler's minimum mortality risk curve for elderly males (ages: 50–79). *Notes*: The data come from Health and Retirement Study (HRS) in the U.S., the Mexican Health and Aging Study (MHAS) in Mexico, and the Indonesian Family Life Survey (IFLS) in Indonesia, all available waves between 1995 and 2014 for men aged 50–79. The black line is the Fogel (1994) minimum mortality risk curve based on the Norwegian data on individuals ages 50 to 64 years collected by Waaler (1984). Waaler (1984) combined information on height and weight obtained from the State Mass Miniature X-ray Examination carried out between 1963 and 1975 in Norway with the death register data for years 1963–1979 from the Norwegian Central Bureau of Statistics.
Source: HRS, MHAS and IFLS data.

4.2. Waaler surfaces

Fig. 2 presents our age-adjusted Waaler surfaces for the United States, Mexico, and Indonesia, estimated separately for men and women in each country (generated using marginal probabilities calculated with estimates from Eq. (1)).[8] The colored curves represent level sets of mortality risk, spaced in equal increments/decrements of absolute risk. Each panel also shows a corresponding minimum risk curve (the red-dashed curve) across the joint distribution of height and weight (i.e., the weights that minimize mortality risk at each height, and vice versa).[9]

To facilitate comparisons across each country's Waaler surfaces (and corresponding differences in the relationship between BMI and mortality risk), Fig. 3 shows the minimum risk curves corresponding to the Waaler surfaces in Fig. 2 together with Fogel's original minimum risk curve (obtained from Norwegian male data). Additionally, it also shows a line denoting the current WHO threshold for overweight (BMI ≥ 25). For a given height, the weight that minimizes mortality risk is lowest in Indonesia for both men and women. The corresponding values are substantially higher in Mexico, and even more so in the U.S. For example, for a 1.83 m (approximately 6 ft) tall male, the corresponding

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[8] The focus of our paper is on Waaler surfaces based on Eq. (1), and differences in their corresponding minimum mortality curves are our primary focus for inference. However, Appendix A Table A.4 also reports marginal probabilities evaluated at the mean of each independent variable for purposes of interpretation. We include standard errors clustered at the individual level for completeness but do not advocate hypothesis tests with them to avoid problems associated with testing multiple irrelevant hypotheses.

[9] Fig. A.1 in Appendix A shows these three-dimensional minimum risk curves with accompanying standard errors.

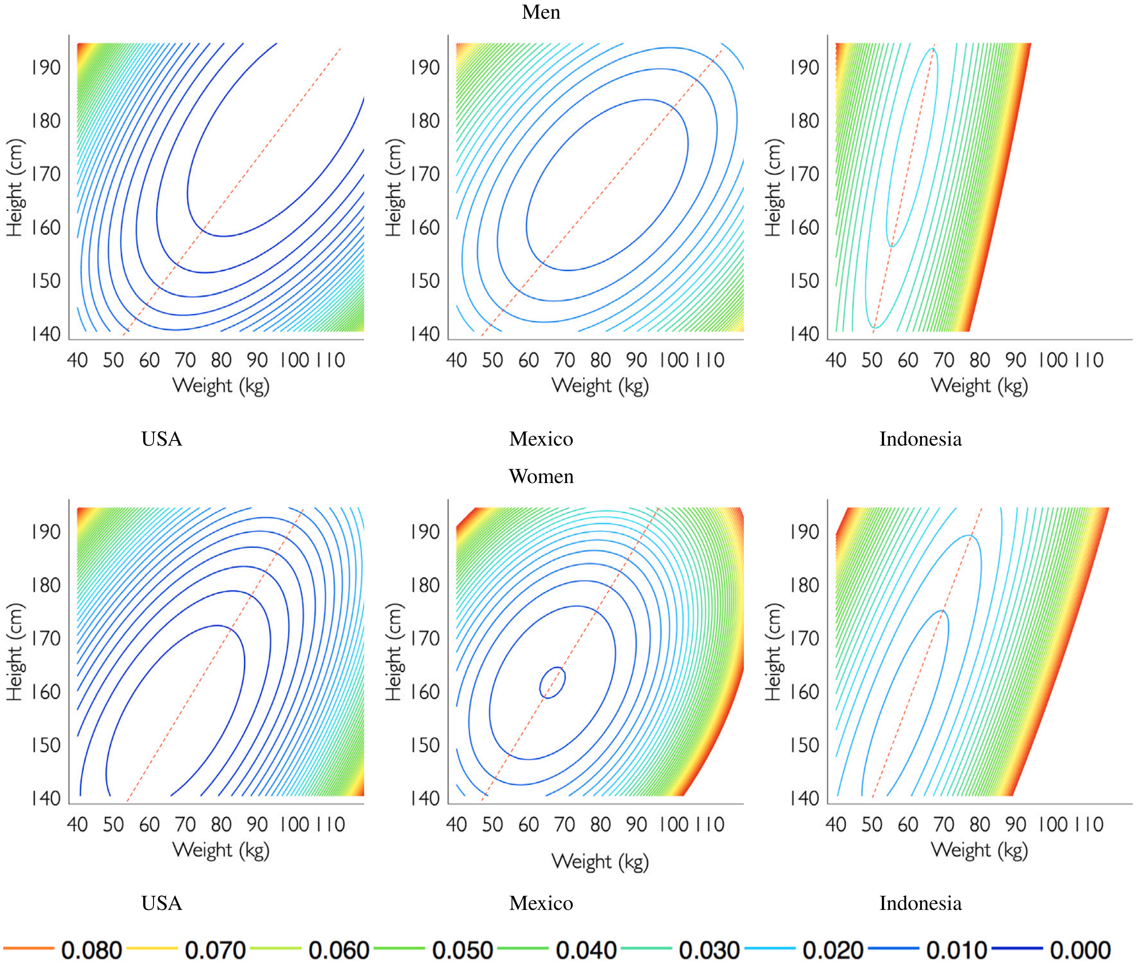

Fig. 2. Waaler iso-mortality curves by gender and country. *Notes*: We use HRS data in the U.S., MHAS in Mexico and IFLS in Indonesia, all available waves between 2000 and 2016 for individuals aged 50–79. Each dataset is rectangularized between waves, with missing information on individual weight and height interpolated using nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death). Each panel is produced using estimates of probit response surfaces together with sampling weights, described in detail in Appendix A, and shows model predictions on a regular height/weight grid. The red dashed lines in each panel represent minimum mortality risk curves. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

minimum mortality bodyweights are 64 kg (in Indonesia), 89 kg (in Mexico), and 96 kg (in the U.S.), corresponding to BMIs of 19.1, 26.6, and 28.7, respectively. These differences across countries are present, but less pronounced, for women. For example, for a 1.73 m (approximately 5 ft 7 inch) tall female, minimum mortality weights are 69 kg, 76 kg, and 80 kg, with corresponding BMIs of 23.1, 25.4, and 26.7, respectively. Notably, relative to a BMI of 25 (the WHO threshold for overweight), these minimum mortality risk bodyweights are consistently lower in Indonesia and higher in Mexico and the U.S.

4.3. Implied mortality reductions

Although informative, Figs. 2 and 3 do not consider the actual distribution of anthropometric status in these three populations. We therefore next analyze how the joint distributions of height and weight in each country relate to our contemporary minimum risk curves estimates. Specifically, Fig. 4 shows a heat map of these joint distributions of height and weight, by country and gender, using 5 × 5 unit cells (in cm of height and kg of weight) together with the corresponding minimum risk curves. The color gradient ranges from light blue to magenta, reflecting lowest to highest relative frequencies/density, respectively, in the most recent survey year.

As the figure shows, national populations are distributed both above and below their minimum risk curves—and notably, the share of the population above the minimum risk curve is not clearly greater in a country with a higher obesity rate like the U.S. than in countries with relatively lower obesity rates like Mexico or even Indonesia. An important share of men in the U.S. and Mexico (and of shorter men in Indonesia) would need to weigh more to reach the minimum risk curve, while the opposite is often true for women. To formalize this point, Fig. 4 also shows the implied number of averted deaths over a 4-year horizon if all individuals in each population were to move to her/his minimum risk bodyweight (holding height constant). These averted deaths, weighted to obtain implied national totals, are shown to the left of the minimum risk curve for those gaining weight and to the right of the curve for those losing weight.[10] It is important to note that Fig. 4 does not answer the medical question of what would happen,

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[10] We obtain these implied number of averted deaths using our probit equations to generate predictions at observed weights and at risk-minimizing weights (given height), taking the difference between the two. We then compute the implied mortality reduction implied by our estimates under the assumption that all individuals were to move to her/his mortality-minimizing weight (holding height constant). All estimates are obtained using

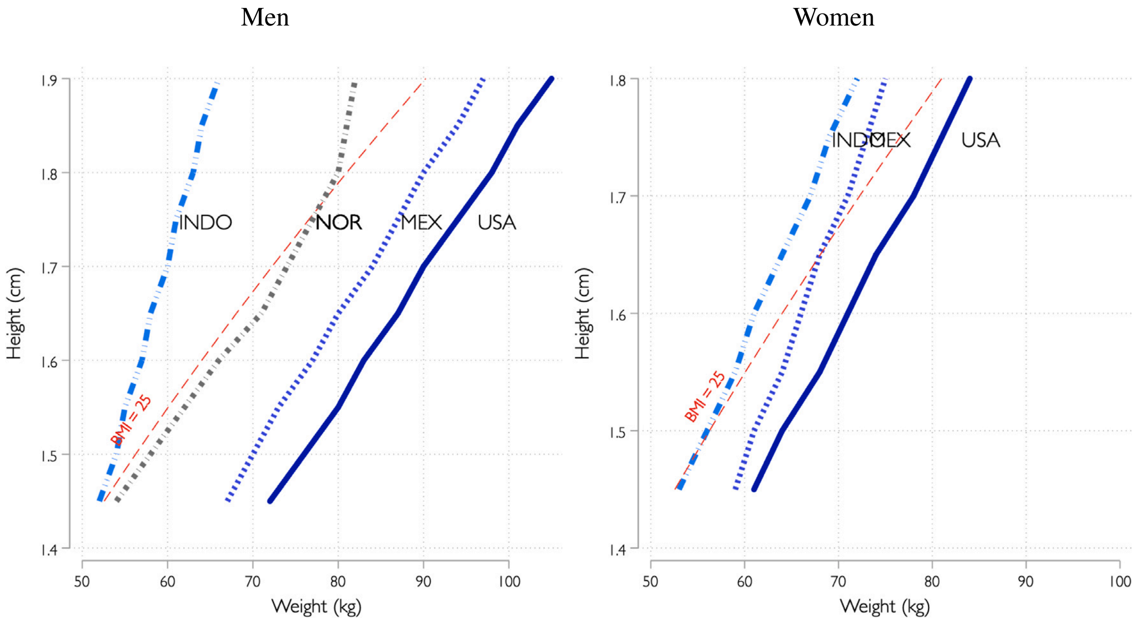

Fig. 3. Waaler minimum mortality risk curve by gender and country. *Notes*: Our data sources are waves, conducted between 2000 and 2016, of the Health and Retirement Study (HRS) for the U.S., the Mexican Health and Aging Study (MHAS) for Mexico, and the Indonesian Family Life Survey (IFLS) for Indonesia. Each dataset is rectangularized between waves, with missing information on individual weight and height interpolated using nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death). Each panel shows minimum mortality risk curves from Fig. 1 together with Fogel's (1994) minimum mortality risk curve (shown in black) and a line indicating the conventional overweight threshold (BMI = 25, shown in dotted red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

causally, to the mortality risk of any individual patient gaining or losing weight, which depends on many clinical and other factors, including the means used to modify weight, the presence of chronic conditions, etc.

Finally, for each country, we compute ratios of the share of each national population above mortality-minimizing bodyweight to the share of each national population considered overweight by contemporary WHO standards (BMI > 25).[11] If contemporary standards defining unhealthily high bodyweights matched bodyweights above mortality-minimizing levels, these ratios would be 100% for each country. Instead, we find them to be 52.6% in the United States, 56.8% in Mexico, and 151.4% in Indonesia.[12] These results imply that contemporary standards for assessing overweight and obesity do not accurately capture mortality risk associated with bodyweight. Although not conclusive, they could also potentially suggest that access to health technology promoting longevity at higher bodyweights varies so profoundly across countries that, relative to current international standards, unhealthily high adult bodyweight is *underestimated* in Indonesia (a country with relatively low overweight/obesity rates: 17% and 4%) and *overestimated* in the U.S. and Mexico (countries with relatively high overweight/obesity rates: 41%/29% and 43%/21%, respectively).

4.4. Heterogeneity

In this section, we consider heterogeneity in our minimum risk curve estimates for three reasons. First, demonstrating shifts in the minimum risk curves within populations over time (heterogeneity across time periods) may provide some insight into the role that technological progress, and access to technology, play in explaining our main results. Second, heterogeneity in minimum risk curves across socio-economic subgroups should generally conform to other known socioeconomic differences in access to health technologies. And third, as an extension of our main analysis, we consider how minimum risk curve estimates for mortality compare with risk curve estimates for other non-fatal measures of illness.

In doing so, we limit our analysis to the U.S., where the Health and Retirement Survey (HRS) allows us to have a larger sample collected over a longer time and containing more detail about individual respondents than the Mexican and Indonesian surveys.

4.4.1. Shifts in the minimum risk curve over time

We first study how the minimum mortality risk curves shown in Fig. 5 have changed over time. If market forces have focused innovation disproportionately on longevity at higher bodyweights (Lichtenberg, 2009), this would be evident as shifts to the right in the minimum risk curve over time.[13] Specifically, we pool HRS waves into two groups, one containing waves conducted between 1992 and 2001 and the other containing waves fielded between 2002 and 2017.

Fig. 5 Panel A shows that the minimum risk curve has in fact shifted substantially to the right from the first period to the second.[14]

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sampling weights to recover the implied number of individuals in each country-age-gender population.

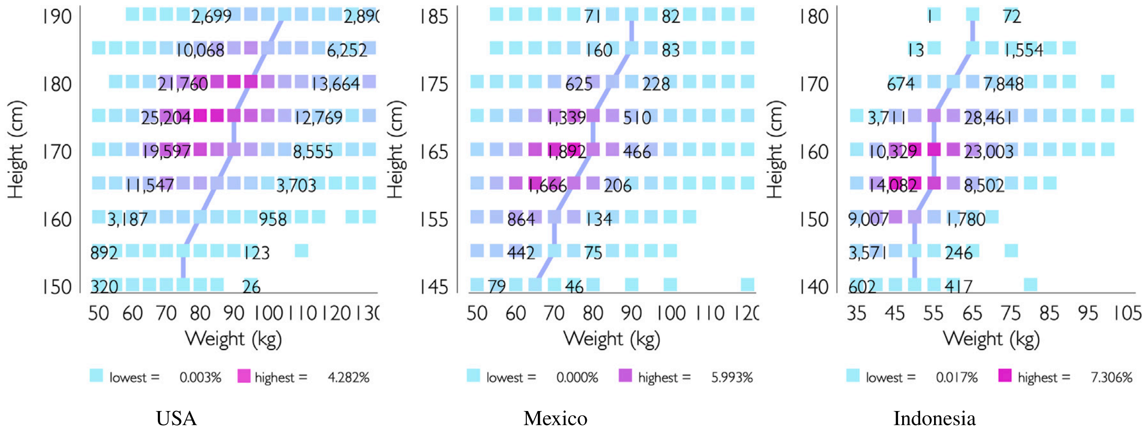
[11] The population totals are of 44 million men and 48 million women ages 50–79 in the US in 2016; 9.5 million men and 9.9 million women in Mexico ages 50–79 in 2014; and 19.6 million men and 20.1 million in Indonesia in 2014.

[12] The shares are computed as ratios of the total number of individuals (men and women aged 50–79) whose weight is greater than the optimum for their height as indicated by our Waaler minimum mortality curve (33,608,854 individuals for the U.S., 7,356,378 for Mexico, and 12,361,973 for Indonesia) over the total number of individuals who are overweight or obese (63,850,227 for the U.S., 12,951,129 for Mexico, and 8,186,011 for Indonesia).

[13] For example, high BMI is associated with elevated cardiovascular disease mortality risk, and new pharmacological therapies have reduced the age-adjusted cardiovascular disease mortality rate in the U.S., thus reducing the riskiness of obesity (Lichtenberg, 2009).

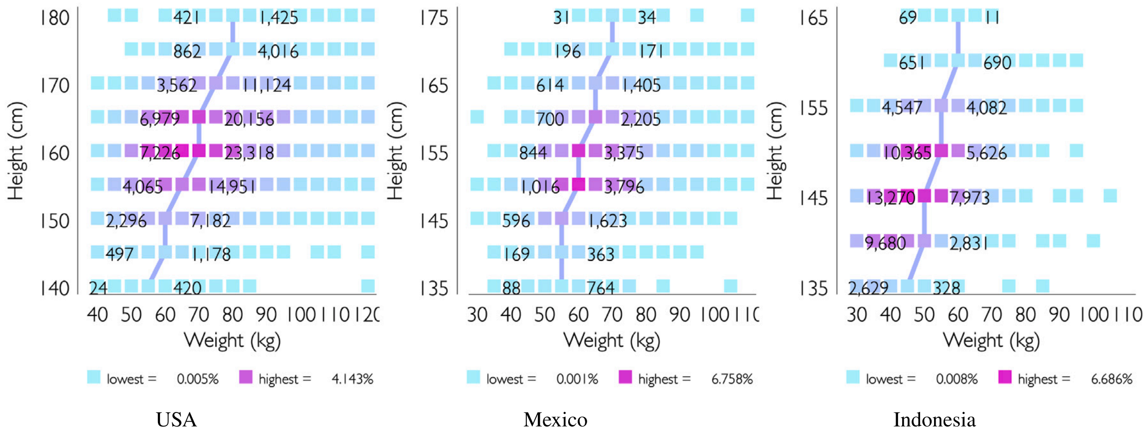
[14] In all cases, we also include a constant BMI = 25 line as a reference given that it is currently the threshold for unhealthily high bodyweight.

Men



USA Mexico Indonesia

Women



USA Mexico Indonesia

Fig. 4. Number of lives saved by moving to optimum weight. *Notes*: We use HRS data in the U.S., MHAS in Mexico, and IFLS in Indonesia, all available waves between 2000 and 2016 for individuals aged 50–79. Each panel shows minimum mortality risk curves from Fig. 2 together with the two-dimensional distribution of each sample's height and weight. The histograms are constructed using 5 cm *x* 5 kg bins of height and weight and are displayed as square fields with a color gradient, ranging from light blue to dark purple, representing lowest to highest relative frequencies, respectively. The predicted averted deaths if every individual moved to her/his mortality-minimizing weight, are calculated using sampling weights in 2012 for the U.S., and 2014 for Mexico and Indonesia. They report the difference between expected mortality associated with actual weights, given height, and mortality risk associated with mortality-minimizing weights, given height. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Interestingly, this shift to the right over time is also somewhat larger at lower heights as well. Because height is a common marker for early life health investments (Floud et al., 2011; Komlos and Baten, 2004; Marco-Gracia and González-Esteban, 2021; Steckel, 2008), this differential shift by height over time could potentially suggest that technological progress has benefited those with lower levels of early life health investments relatively more.

4.4.2. *Heterogeneity across socio-economic subgroups*

We then examine heterogeneity in minimum mortality risk curves across socio-economic subgroups, focusing specifically on differences by place of birth (U.S. vs. foreign-born), ethnicity (Hispanic vs. white non-Hispanic), and educational attainment.[15] In all three cases, there is substantial evidence of overall health disparities (Akresh, 2008; Min et al., 2021; Ljungdahl and Bremberg, 2015; Hamad et al., 2018; Cutler et al., 2006; Cutler and Lleras-Muney, 2006; Cohen et al., 2013; Devaux et al., 2011; Bollyky et al., 2017; Baker et al., 2017; Templin et al., 2019). Fig. 5 Panel B shows that the minimum risk curve for foreign-born and Hispanic respondents is to the left of those born in the U.S., consistent with other documented differences in access to health technology. Fig. 5 Panel C then considers differences by level of educational attainment, comparing those completing 12 years of schooling or less with those completing 15 or more years of schooling.[16] Similarly, the panel shows that mortality risk is minimized at higher bodyweights among those with more education, a result also consistent with other documented differences in access to health technology.[17]

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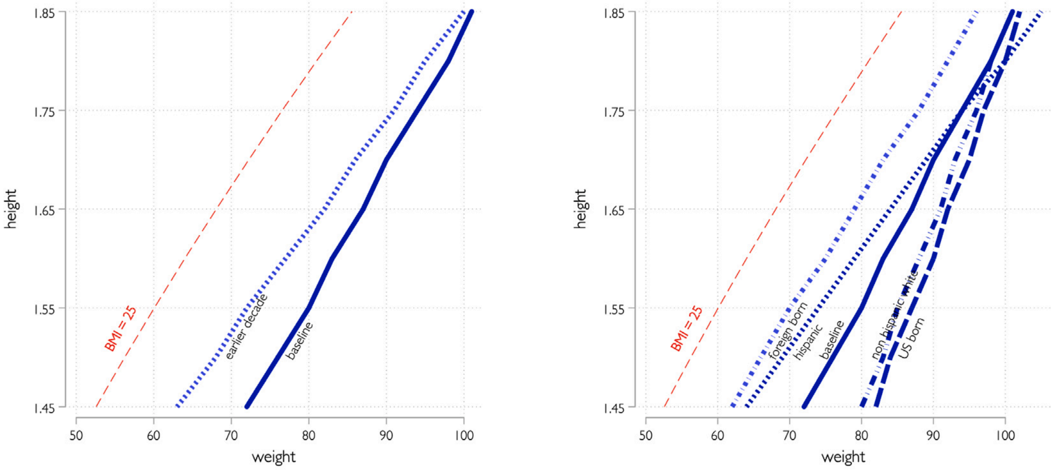
[15] Small sample sizes prevent us from exploring heterogeneity among other racial and ethnic minorities.

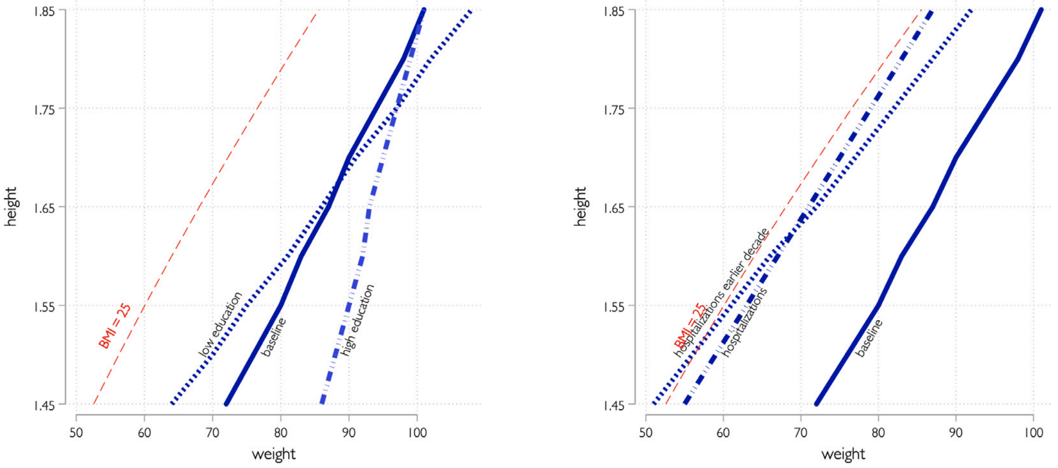
[16] The compulsory number of years of schooling is generally 12 (ISCED 1-3), and 15 years of schooling generally corresponds to completion of tertiary education (ISCED 6-8).

[17] We conduct the additional by education level also for Mexico and Indonesia, despite the smaller sample. The MHAS provides information on educational attainment in number of years, while the IFLS provides information by level of schooling. To ensure consistency in our analysis, we standardize the levels of schooling by converting them into the number of years, relying on information about the Indonesian schooling system. Subsequently, for both Mexico and Indonesia, we classify individuals into low and high education categories based on the average number of years of schooling. Fig. A.2 in the Appendix A shows these results. Heterogeneity by educational attainment



(a) Past vs Present

(b) US vs Foreign born



(c) High vs Low Education

(d) Hospitalizations vs Mortality

Fig. 5. Heterogeneity in Waaler minimum mortality risk curve in the USA. *Notes*: We use HRS data for men in the U.S. for all available waves between 2000 and 2016 for individuals aged 50–79. Each panel presents the minimum mortality risk curve based on the baseline estimates against alternative data subsamples or outcomes. In Panel (a) we additionally plot the curve based on estimates obtained for 1992–2001. We plot the curves based on estimates obtained for subsamples of US vs Foreign born individuals in Panel (b), and for individuals with High vs Low education in Panel (c). In Panel (d) we plot the minimum mortality risk curve against the minimum hospitalization risk curve. Each dataset is rectangularized between waves, with missing information on individual weight and height interpolated using nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death). The red dashed line indicates the conventional overweight threshold (BMI = 25).

4.4.3. Minimum hospitalization risk curves

Finally, we consider how bodyweights that minimize morbidity risk (proxied by hospitalization risk) compare to bodyweights that minimize mortality risk. Relative to the minimum mortality risk curve, Fig. 5 Panel D shows that hospitalization risk is minimized at markedly lower bodyweights – and in fact, bodyweights much closer to the standard reference case of $BMI = 25$. Notably, and in contrast to the shift of the minimum mortality risk curve over time, the minimum hospitalization risk curves have essentially not moved over the same period of time. Hence, while similar bodyweights for each level of height are associated with the lowest risk of hospitalization over twenty years of our analysis, the same does not hold for the risk of mortality. Although not conclusive, these results could potentially suggest that health-specific technological progress has focused relatively more on longevity at higher bodyweights than on functional status and quality of life, a result consistent with evidence that metabolic syndrome and associated co-morbidities are increasing among the elderly–and are a key driver of functional disability (Denys et al., 2009; Liaw et al., 2016; Froehlich-Grobe et al., 2013).

4.5. Measurement and robustness

4.5.1. Physical vs. Self-reported height and weight data

In this subsection, we consider the potential role of physical and self-reported anthropometric measurement in explaining our results (due to data limitations, we use self-reported height and weight data in

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in Mexico resembles what we observe in the U.S., while in Indonesia, more educated individuals differ from less educated only at higher levels of height.

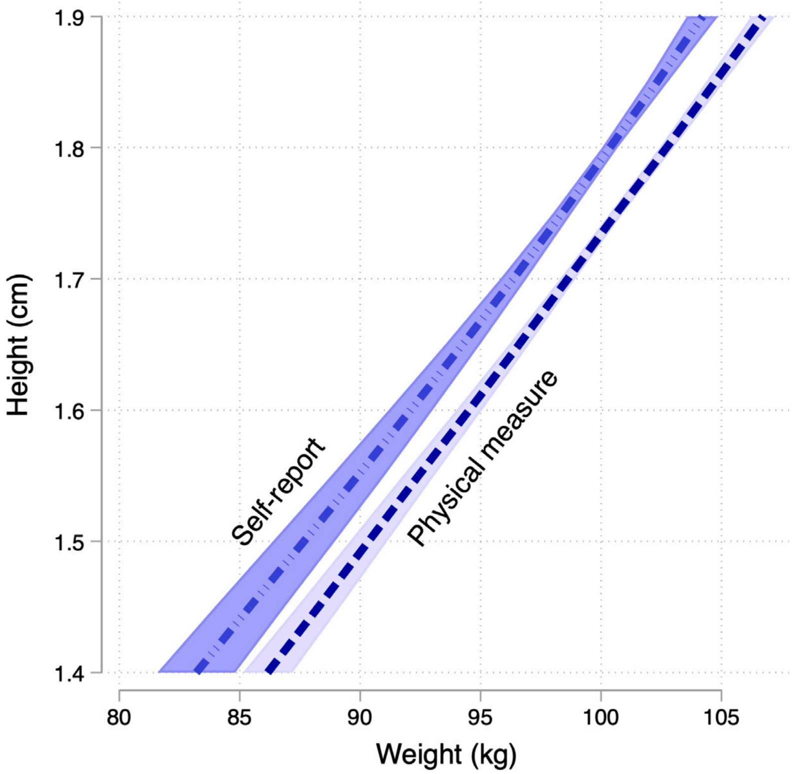

Fig. 6. Minimum mortality risk curve comparison between physically-measured and self-reported height and weight in the HRS data - (2008–2016). *Notes*: We use HRS data for men for all available waves between 2008 and 2016, when physically-measured weight, height waist circumference were collected for a subsample of the baseline individuals. We focus on individuals aged 50–79. Each line presents the minimum mortality risk curve obtained based on the baseline estimates against alternative data, subsamples or outcomes. Each dataset is rectangularized between waves, with missing information on individual weight and height interpolated using nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death).

the HRS and MHAS and physical measurements of height and weight in the IFLS). Relatedly, Cawley (2004) considers measurement error in self-reported height and weight data, showing that on average, women under-report their weight (but not their height). Sanz de Galdeano (2007) also compares obesity rates using physical measures from the WHO Global Body Mass Index Database and self-reported measures from the European Community Household Panel (ECHP), finding a correlations of 0.76 for men and 0.96 for women.

Our ability to examine the role of measurement modality is limited. Only 11% of the MHAS sample has both physical and self-reported measures, and the IFLS does not include self-reported measures. We therefore focus on the HRS, for which 63.5% of our sample has both physical and self-reported measurements of height and weight. Fig. 6 shows separate minimum mortality risk curves estimated using physical and self-reported measures of height and weight (along with standard errors). In general, the minimum risk curve produced using physical measurements lies somewhat to the right of the curve produced using self-reported data–suggesting that if anything, our main results may understate mortality-minimizing bodyweights and BMI values.[18]

4.5.2. Body fat and waist circumference

Although BMI is the most widely used measure of obesity, it does not account for body fat or body composition. Waist circumference (WC) can be a more accurate measure of body fat (Cornier et al., 2011) and can better predict adiposity-related conditions and mortality (Gaynor et al., 2018; Klein et al., 2007; Seidell, 2010). However, we do not focus our analysis on waist circumference because it is inconsistent with our Waaler surface approach (and would not allow direct comparison with earlier work) and because data on waist circumference is less readily available than data on height and weight. In our datasets, information on waist circumference is available only for a small subset of respondents (20% of the Indonesian sample, 11% of the Mexican sample, and 63% in the U.S. sample, but only after 2006).

Nonetheless, we consider how our results vary when we condition on waist circumference (accounting to some extent for variation in body fat distributions at given height and weight combinations). Specifically, we re-estimate Eq. (1) using physical measures of weight and height, conditioning on waist circumferences in the subsamples in which this is feasible, and generate minimum risk curves using the resulting estimates. Fig. 7 shows the resulting minimum risk curves compared to our baseline obtained using subjective measures. Relative to the minimum risk curve that does not control for waist circumference, the minimum risk curve that does is parallel but shifted to the right (albeit with more noise given to the smaller sample sizes). These results again suggest that, if anything, our results may understate the BMI-mortality relationship.

4.6. Limitations

Our study has at least four limitations. First, our estimates rely on the correlation between anthropometric status and mortality risk over the subsequent four years. Chronic diseases at the end of life are often associated with weight loss, which could contribute to a positive correlation between low bodyweight and mortality (Banack and Stokes, 2017; Kalantar-Zadeh et al., 2014). However, this phenomenon was

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[18] An additional implication is that our results may understate differences between the United States/Mexico and Indonesia.

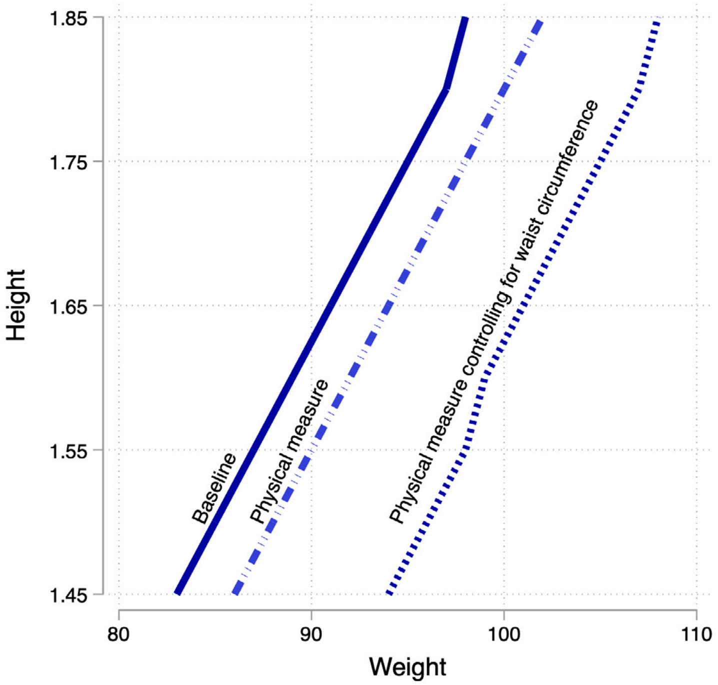


Fig. 7. Minimum mortality risk curve based on physical measures of BMI with and without controlfor waist circumference in the HRS data (2008–2016). *Notes*: The data come from the Health and Retirement Study (HRS) in the U.S. for all available waves between 2008–2016 for men aged 50–79.

present in the work of Waaler (1984) and Fogel (1994), and our use of a long lag between measured anthropometric status and mortality mitigates this limitation to some extent. Moreover, conditional on age, weight loss prior to death in our samples only begins within three years of death. Second, our approach requires imputation of bodyweight for some individuals when there are long intervals between data collection. The longitudinal datasets that we use to track obesity – the Health and Retirement Study and its sister studies around the world – are the gold standard for individual-level panel data tracking health. In Indonesia and Mexico, however, there are longer intervals between waves than in the U.S., where data is collected every two years. To address this issue, we use standard interpolation methods to impute information between waves. Without imputation, our results are qualitatively similar but noisier. Third, data limitations prevent us from systematically examining important dimensions of morbidity correlated with anthropometric status. Finally, our methodology does not permit us to identify the specific mechanisms through which minimum mortality curves differ and have shifted. Our primary hypothesis is that advances in medical technology, and access to them, have made it possible for people with chronic diseases associated with obesity (such as diabetes and heart disease) to live longer. If this hypothesis were correct, then the welfare consequences of reductions in mortality must be weighed against the morbidity of living with those chronic conditions. These are important issues which we are unable to study directly.

5. Conclusions

Health-specific technological change, encompassing changes in knowledge, social norms, health behaviors, and health care services, has been dramatic over time. In the past half-century, it has focused particularly on the emerging population health needs of wealthy countries, fundamentally transforming the relationship between bodyweight and longevity. Moreover, access to it varies greatly across higher- and lower-income countries, leading to substantial cross-country differences in the bodyweights that minimize mortality risk (or maximize health).

Although our paper does not formally evaluate the role of technological progress, and access to it, we produce new iso-mortality Waaler surfaces for three distinct contemporary technological environments, building on innovative data collection initiatives in recent years. We use comprehensive individual-level longitudinal data to link height and weight to longevity in the United States (a high-income country), Mexico (a middle-income country), and Indonesia (a lower-income country)–nations reflecting various technical regimes for longevity at various heights and weights. Doing so, we show that the share of national populations above mortality-minimizing bodyweight is not obviously greater in countries with higher overweight and obesity rates (as traditionally defined), and that, relative to current standards, a larger share of low-income countries' populations can be unhealthily heavy.

Current bodyweight classification standards such as “overweight” (BMI 25–30) and “obese” (BMI 30+) do not reflect important differences across populations and differences in access to health technology. Our results in this paper demonstrate that BMI thresholds corresponding to unhealthy bodyweight or mortality risk are not universal. Understanding these differences is critical, in turn, for understanding the population health implications of evolving anthropometric status around the world. Rising bodyweights, even conditional on height, may not unambiguously indicate a decline in population health status.

Funding

None

Ethics approval

The study did not require ethics approval.

Consent to participate

The study did not require consent to participate.

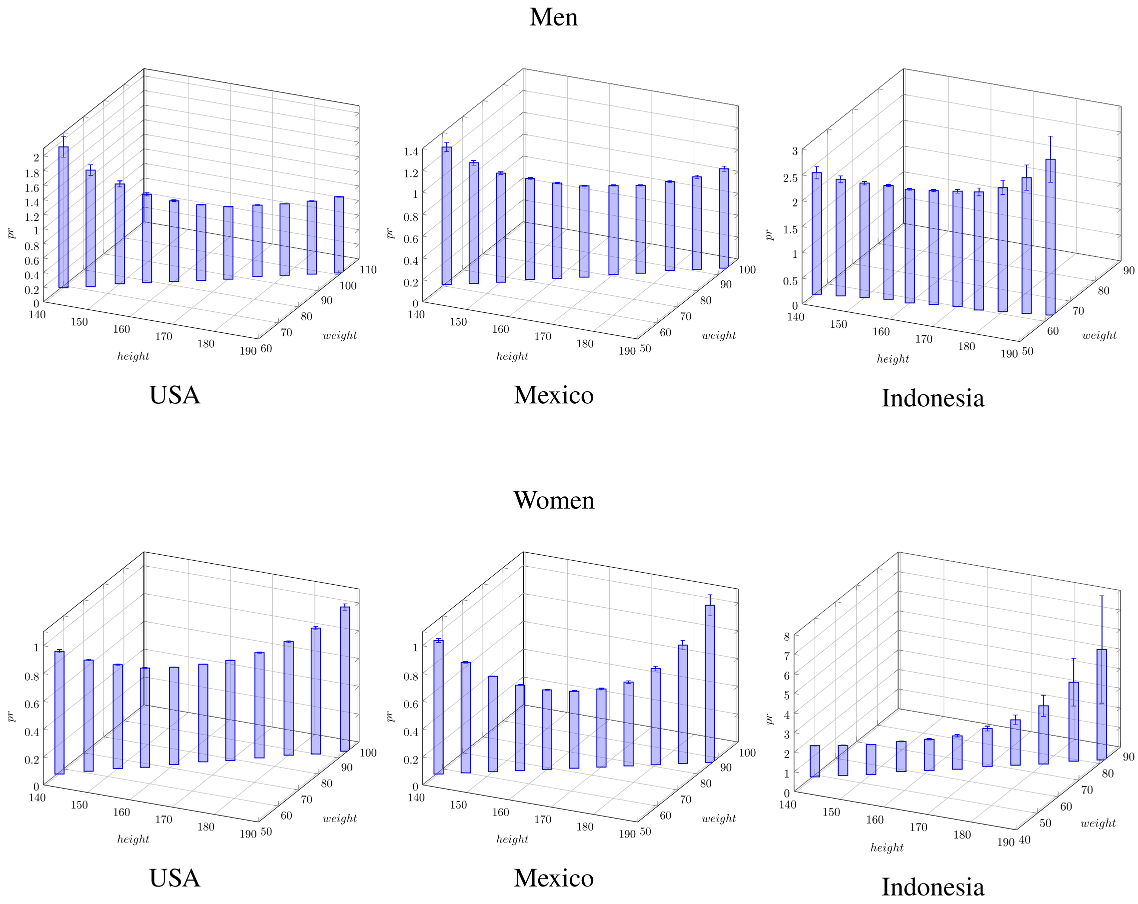


Fig. A.1. Minimum mortality probabilities with standard errors based on block bootstrap procedure. *Notes*: The data come from Health and Retirement Study (HRS) in the U.S., the Mexican Health and Aging Study (MHAS) in Mexico, and the Indonesian Family Life Survey (IFLS) in Indonesia, waves between 2000 and 2016. Each dataset is rectangularized by filling in the data between two subsequent waves, the missing information on individual weight and height is interpolated with nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death). The top and bottom percentile of the BMI distribution are trimmed from the MHAS and IFLS samples because the top and bottom percentiles of height and weight are top-/bottom-coded. Each panel pictures minimum probabilities defined by the locus of (height, weight) pairs that minimize mortality risk and their standard errors computed using block bootstrap procedure with 1000 replications, using estimates of probit response surfaces together with sampling weights, described in Supplement C.

CRediT authorship contribution statement

Joanna Kopinska: Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Vincenzo Atella:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Jay Bhattacharya:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Grant Miller:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

Acknowledgments

All authors approved the version of the manuscript to be published.

Declaration of competing interest

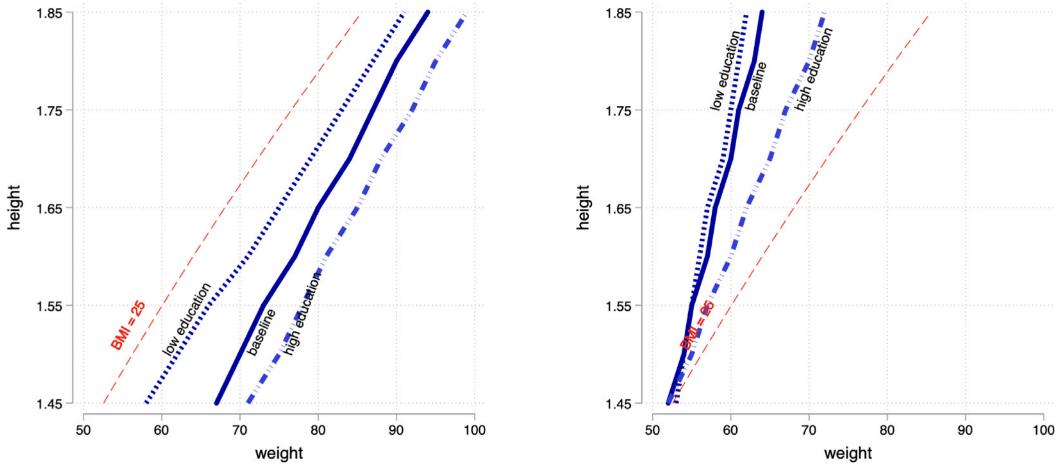
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See Figs. A.1, A.2 and Tables A.1–A.4

Appendix B

Concerning the role of health status in determining the missingness of height and weight measures we have conducted balance tests for the three surveys. The dependent variable in these tests is the absence of weight or height data in a specific survey wave (w). The independent variables are the health conditions reported in the preceding wave (w-1), with each condition considered separately. For HRS and MHAS, we have data on four health conditions: diabetes, high blood pressure, heart disease, and hospitalization episodes. However, the IFLS survey only includes the first two conditions. Furthermore, the models for HRS and MHAS control for gender and wave, in addition to incorporating individual fixed effects and survey weights. In the case of IFLS, the health data are only available between two consecutive



(a) High vs Low Education Mexico

(b) High vs Low Education Indonesia

Fig. A.2. Heterogeneity by education levels in Waaler minimum mortality risk curve for men in Mexico and Indonesia. *Notes*: We use MHAS and IFLS data for men for all available waves between 2000 and 2016 for individuals aged 50–79. Each panel presents the minimum mortality risk curve based on physically-measured (IFLS) and self-reported (MHAS) weight and height. Each dataset is rectangularized between waves, with missing information on individual weight and height interpolated using nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death).

Table A.1
Imputed and raw descriptive statistics - USA.

	Mortality		Weight		Height	
	Imputed	Raw	Imputed	Raw	Imputed	Raw
Men						
2001	0.0154	0.0154	87.64	87.64	177.16	177.16
2002	0.0165		88.05		177.24	
2003	0.0143	0.0143	88.47	88.47	177.31	177.31
2004	0.0138		88.60		177.39	
2005	0.0137	0.0137	88.91	88.91	177.41	177.41
2006	0.0153		89.27		177.45	
2007	0.0121	0.0121	89.75	89.75	177.46	177.46
2008	0.0111		90.04		177.47	
2009	0.0099	0.0099	90.43	90.43	177.52	177.52
2010	0.0118		90.56		177.55	
2011	0.0126	0.0126	90.72	90.72	177.63	177.63
2012	0.0121		90.67		177.65	
2013	0.0132	0.0132	90.58	90.58	177.66	177.66
2014	0.0170		90.70		177.70	
2015	0.0125	0.0125	90.79	90.79	177.70	177.70
2016	0.0129		90.80		177.72	
Women						
2001	0.0103	0.0103	72.64	72.64	162.36	162.36
2002	0.0118		73.01		162.37	
2003	0.0087	0.0087	73.47	73.47	162.43	162.43
2004	0.0116		73.78		162.46	
2005	0.0093	0.0093	74.30	74.30	162.56	162.56
2006	0.0090		74.68		162.60	
2007	0.0089	0.0089	75.13	75.13	162.66	162.66
2008	0.0091		75.32		162.69	
2009	0.0104	0.0104	75.60	75.60	162.75	162.75
2010	0.0096		75.79		162.80	
2011	0.0095	0.0095	75.59	75.59	162.93	162.93
2012	0.0092		75.62		162.97	
2013	0.0099	0.0099	75.60	75.60	163.00	163.00
2014	0.0118		75.66		163.03	
2015	0.0108	0.0108	75.76	75.76	163.03	163.03
2016	0.0093		75.73		163.04	

Notes: The data come from the HRS, we use waves 2000/01, 2002/03, 2004/05, 2006/07, 2008/09, 2010/11, 2012/13, 2014/15, 2016/17. The raw dataset is rectangularized by filling in the data between two subsequent waves, the missing information on weight and height at the individual level is interpolated with the nearest neighborhood imputation. Individuals are followed until death or attrition from the sample.

waves (2007 and 2014), making it impossible to identify individual and wave fixed effects. Therefore, we have restricted our analysis to models that only control for age and use survey weights. As we can see from Fig. B.1, across all model specifications, we found no correlation between missingness and any of the health status measures we controlled for.

Table A.2
Imputed and raw descriptive statistics - Mexico.

	Mortality		Weight		Height	
	Imputed	Raw	Imputed	Raw	Imputed	Raw
Men						
2001	0.0130	0.0030	72.68	72.68	165.88	165.88
2002	0.0134		72.93		165.95	
2003	0.0167	0.0167	72.93	72.93	165.99	165.99
2004	0.0147		73.19		166.00	
2005	0.0133		73.61		166.14	
2006	0.0114		73.83		166.23	
2007	0.0117		74.21		166.40	
2008	0.0108		73.89		166.50	
2009	0.0110		74.09		166.64	
2010	0.0116		74.27		166.71	
2011	0.0101		74.40		166.74	
2012	0.0097	0.0097	74.63	74.63	166.65	166.65
2013	0.0092		74.89		166.71	
2014	0.0119		74.24		166.76	
2015	0.0161	0.0160	74.47	74.22	166.95	166.75
Women						
2001	0.0035	0.0035	65.28	65.28	156.16	156.16
2002	0.0043		65.30		156.39	
2003	0.0039	0.0039	65.55	65.55	156.31	156.31
2004	0.0080		65.79		156.36	
2005	0.0098		66.09		156.45	
2006	0.0072		66.18		156.43	
2007	0.0070		66.47		156.53	
2008	0.0081		65.67		156.58	
2009	0.0061		65.80		156.68	
2010	0.0074		66.06		156.79	
2011	0.0058		66.23		156.81	
2012	0.0092	0.0092	66.40	66.40	156.87	156.87
2013	0.0090		66.47		156.94	
2014	0.0082		66.18		157.12	
2015	0.0089	0.0089	66.33	66.22	157.21	157.26

Notes: The data come from the Mexican MHAS, we use waves 2000/01, 2002/03, 2012/13, 2014/15. The raw dataset is rectangularized by filling in the data between two subsequent waves, the missing information on weight and height at the individual level is interpolated with the nearest neighborhood imputation. Individuals are followed until death or attrition from the sample.

Table A.3
Imputed and raw descriptive statistics - Indonesia.

	Mortality		Weight		Height	
	Imputed	Raw	Imputed	Raw	Imputed	Raw
Men						
2000	0.0217	0.0225	53.18	53.17	158.53	158.54
2001	0.0217		53.58		158.68	
2002	0.0251		53.99		158.85	
2003	0.0257		54.33		159.01	
2004	0.0261		54.69		159.19	
2005	0.0236		55.15		159.40	
2006	0.0225		55.49		159.49	
2007	0.0271	0.0263	54.96	54.79	159.63	159.53
2008	0.0257		55.31		159.79	
2009	0.0209		55.62		159.91	
2010	0.0207		55.93		160.03	
2011	0.0247		56.10		160.12	
2012	0.0239		56.42		160.25	
2013	0.0227		56.81		160.43	
2014	0.0209	0.0213	57.13	56.98	160.39	160.30
Women						
2000	0.0176	0.0181	46.92	46.97	146.99	147.04
2001	0.0182		47.31		147.18	
2002	0.0165		47.73		147.38	
2003	0.0164		48.20		147.60	
2004	0.0183		48.49		147.70	
2005	0.0192		48.93		147.85	
2006	0.0187		49.33		148.00	
2007	0.0194	0.0191	49.51	49.37	148.20	148.12
2008	0.0176		49.94		148.35	
2009	0.0173		50.34		148.51	
2010	0.0173		50.80		148.73	
2011	0.0191		51.14		148.81	
2012	0.0193		51.61		148.99	
2013	0.0199		52.18		149.14	
2014	0.0196	0.0192	52.63	52.73	149.22	149.19

Notes: The data come from the Indonesian Family Life Survey (IFLS) in Indonesia, we use waves 2000, 2007/2008, 2014/15. The raw dataset is rectangularized by filling in the data between two subsequent waves, the missing information on weight and height at the individual level is interpolated with the nearest neighborhood imputation. Individuals are followed until death or attrition from the sample.

Table A.4
Probit estimates - marginal effects.

	HRS - USA		MHAS - Mexico		IFLS - Indonesia	
	Men	Women	Men	Women	Men	Women
Weight	0.000837	0.000464	0.000359	0.000155	−0.000779	0.001133
	(0.0008384)	(0.0005374)	(0.0011393)	(0.0011464)	(0.0049129)	(0.0020382)
Weight ∗ weight	0.000011***	0.000006***	0.000006	0.000009***	0.000047**	0.000023***
	(0.0000015)	(0.0000010)	(0.0000035)	(0.0000029)	(0.0000229)	(0.0000055)
Height	−0.004418	−0.001869	−0.003053	−0.003791	−0.000660	−0.001540
	(0.0027340)	(0.0021817)	(0.0023268)	(0.0033482)	(0.0069614)	(0.0055753)
Height ∗ height	0.000017**	0.000008	0.000011	0.000014	0.000007	0.000010
	(0.0000085)	(0.0000070)	(0.0000078)	(0.0000122)	(0.0000270)	(0.0000200)
Weight ∗ height	−0.000016***	−0.000009**	−0.000008	−0.000009	−0.000028	−0.000025*
	(0.0000055)	(0.0000036)	(0.0000087)	(0.0000086)	(0.0000424)	(0.0000151)
Age	0.001301***	0.001043***	0.001238***	0.000838***	0.001704***	0.001382***
	(0.0000408)	(0.0000341)	(0.0000813)	(0.0000659)	(0.0001171)	(0.0000891)
N	97,857	121,399	57,706	66,141	28,603	35,484

Notes: The data come from Health and Retirement Study (HRS) in the U.S., the Mexican Health and Aging Study (MHAS) in Mexico, and the Indonesian Family Life Survey (IFLS) in Indonesia, waves between 2000 and 2016. Each dataset is rectangularized by filling in the data between two subsequent waves, the missing information on individual weight and height is interpolated with nearest neighborhood imputation. Individuals are followed until death or attrition from the sample. Weight and height data from the four years prior to when survival or death is observed are excluded (to account, in part, for weight loss approaching the time of death). The top and bottom percentile of the BMI distribution are trimmed from the MHAS and IFLS samples because the top and bottom percentiles of height and weight are top-/bottom-coded. The estimates are based on a probit response surface, with weights and heights products of maximum 2nd order for each dataset and gender separately. The controls include age in years. The coefficients reported in the table represent marginal effects of each covariate calculated at the means of the variables. Standard errors are clustered at the individual level. The estimates are computed using sampling weights.

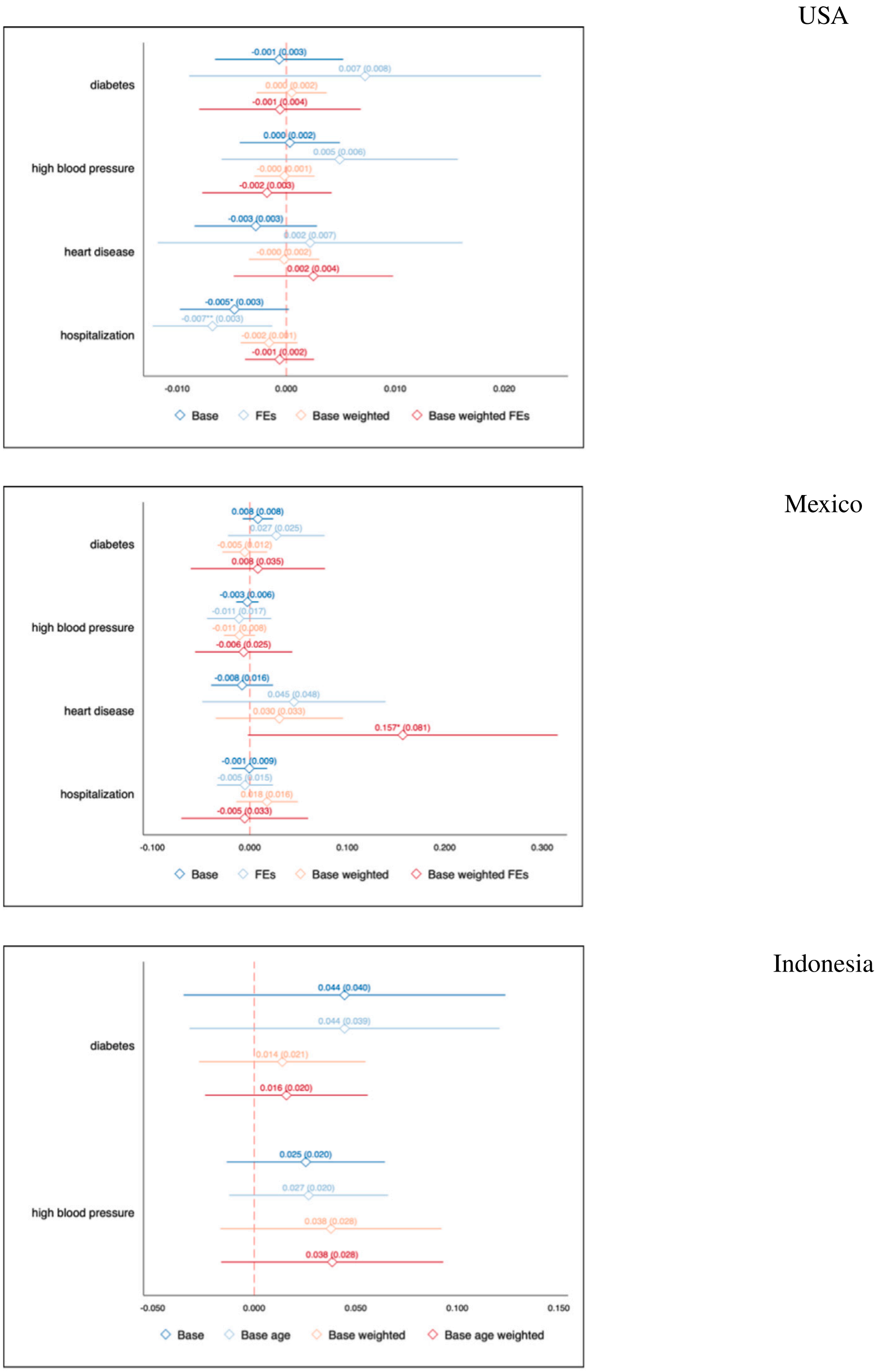


Fig. B.1. Determinants of missingness in reporting height and weight. *Notes*: add some note.

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