Contribution of socioeconomic factors to the variation in body-mass index in 58 low-income and middle-income countries: an econometric analysis of multilevel data

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Contribution of socioeconomic factors to the variation in body-mass index in 58 low-income and middle-income countries: an econometric analysis of multilevel data

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Summary

Background Most epidemiological studies have not simultaneously quantified variance in health within and between populations. We aimed to estimate the extent to which basic socioeconomic factors contribute to variation in body-mass index (BMI) across different populations.

Methods We pooled data from the cross-sectional Demographic and Health Surveys (2005–16) for 15–49 year old women with complete data for anthropometric measures in 58 low-income and middle-income countries (LMICs). We compared estimates from multilevel variance component models for BMI before and after adjusting for age and socioeconomic factors (place of residence, education, household wealth, and marital status). The hierarchical structure of the sample included three levels with women at level 1, communities at level 2, and countries at level 3. The primary outcome was BMI. We did a sensitivity analysis using the 2002–03 World Health Surveys.

Findings Of 1 212 758 women nested within 64 764 communities and 58 countries, we found that most unexplained variation for BMI was attributed to between-individual differences (80%) and the remaining was between-population differences (14% for countries and 6% for communities). Socioeconomic factors explained a large proportion of between-population variance in BMI (14·8% for countries and 47·1% for communities), but only about 2% of interindividual variance. In country-specific models, we found substantial variation in the magnitude of between-individual differences (variance estimates ranging from 7·6 to 31·4, or 86·0–98·6% of the total variation) and the proportion explained by socioeconomic factors (0·1–6·4%). The disproportionately large unexplained between-individual variance in BMI was consistently found in additional analyses including more comprehensive set of predictor variables, both men and women, and populations from low-income and high-income countries.

Interpretation Our findings on variance decomposition in BMI and explanation by socioeconomic factors at population and individual levels indicate that inferential questions that target within and between populations are importantly inter-related and should be considered simultaneously.

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Introduction

The determinants of population average differences (ie, between-population variance) might be fundamentally different from those causing individual cases (ie, between-individual within-population variance),[1,2] and a distinct set of unmeasured social, cultural, physiological, or genetic factors might contribute to variation in health for these two targets of inference.[3–5] However, most epidemiological studies[6,7] have not evaluated and quantified the amount of variance in health within and between populations. Moreover, although much health inequalities research has focused on the effect of social conditions on either promotion or hindrance of diverse health outcomes,[8] almost none have attempted to systematically quantify the extent to which mean differences in socioeconomic factors explain variability within and between populations.

A study[9] on 39 populations from WHO's Multinational Monitoring of Trends and Determinants in Cardiovascular Disease project, which used multilevel analyses, found only about 7–8% of all differences for systolic blood pressure between individuals to be attributed to the population level. A study[10] on global child anthropometric failures identified that most variations attributable to within-population differences, of which very little (1%) was explained by established maternal and socioeconomic correlates. Understanding both within-population and between-population variation in health is important to target the right inferential unit and achieve optimal health outcomes and reduce health inequalities.[11] To build on this research, we aimed to investigate the extent to which basic socioeconomic factors contribute to variation in body-mass index (BMI) in the context of low-income and middle-income countries (LMICs) where a large variance in BMI reflects the coexistence of continued under-nutrition and rise in overweight and obesity.[12]

By use of the latest nationally representative surveys on women of reproductive age (15–49 years) across

Research in context

Evidence before this study

We searched PubMed database for articles published from Jan 1, 1980, to July 15, 2017, in English, that estimated variance in body-mass index (BMI) using the search terms: "body mass index", "obesity", "weight", "overweight", "global", "geography", "variation", "distribution", "multilevel", "population", "individual", "trend", "dispersion", "inequality", "socioeconomic", and "disparity". Most epidemiological studies have not been able to quantify variance in health measures, including BMI, within and between populations.

Added value of this study

To our knowledge, this is the first comprehensive and systematic examination of variation in BMI across 58 low-income and middle-income countries and the contribution of basic socioeconomic factors. Across various analyses, we consistently find disproportionately large variation in BMI attributed to between-individual differences (80%). We also provide the first quantification of an extremely small (2%) contribution of socioeconomic factors in explaining between-individual variance in BMI. Although socioeconomic factors explain a modest amount of between-population variance, population level accounts for only a small fraction of the total variance in BMI.

Implications of all the available evidence

The pattern in variance decomposition in BMI and explanation by socioeconomic factors at individual and population levels indicate that understanding the magnitude and patterning of between-individual differences are necessary to meaningfully assess variation in any health outcome. The inferential questions on determinants of within populations versus between populations are very inter-related because population health cannot improve without changes in individuals.

58 LMICs, we aimed to decompose the total variation in BMI by differences within-population (ie, individuals) and differences between populations (ie, defined as countries and subnational communities) and compare estimates from multilevel variance components models for BMI before and after accounting for the individual-level socioeconomic factors. Our a-priori hypotheses were that most variance in BMI is attributable to differences between individuals, of which only a small fraction can be explained by socioeconomic factors. By contrast, we expected to find much smaller variance in BMI attributable to differences between populations, of which a larger proportion can be explained by socio-economic factors. We also aimed to summarise the range of variation in BMI and proportion explained by socio-economic factors by country-specific stratified analysis. Heterogeneity in the estimates across 58 LMICs might indicate that a different set of factors are driving variation in BMI within populations.

Methods

Data source and sampling plan

We pooled the data for this study from the cross-sectional Demographic and Health Surveys (DHS) done in 58 LMICs between 2005, and 2016 (rounds V, VI, or VII). DHS are known for standardised and representative sampling of participants, objective measurement of anthropometric measures, and high response.[13] Individual observations were collected after a probability-based cluster sampling procedure, which was then adapted to specific contexts within each country. Sampling frames were first developed on the basis of non-overlapping units of geography (identified as the primary sampling units [PSUs]) that cover the entire country and a fixed proportion of households were selected with systematic sampling within each PSU.[13] For a sensitivity analysis, we used the 2002–03 World Health Surveys (WHS) implemented by WHO for 65 countries of diverse economic development.[14] The study was reviewed by Harvard T H Chan School of Public Health Institutional Review Board and was considered exempt from full review because the study was based on an anonymous public use dataset with no identifiable information on the study participants.

Study population and sample size

Women from LMICs who were 15–49 years of age, not pregnant at the time of the survey, and were included in the study protocol for anthropometry measures met the eligibility criteria for our analysis. We excluded participants with missing anthropometric measures (not present, refused, or other reasons) or biologically implausible height (<100 cm or >200 cm) or weight (<20 kg or >200 kg) measures. We also excluded women with missing information for any of the covariates.

Defining population

Population, as a unit of analysis and inference, can be defined in many ways.[15] In our main analysis, individuals were modelled as nested within populations that were conceptualised in two units. The most conventional practice of defining population is perhaps by membership in a country.[1] Country serves an important macro unit because national economic development, technological advancement, and demographic, epidemiological, and nutritional transitions are known to be consistently associated with obesity prevalence among its population.[16] Another operationalisation of population within a country is community, which was defined as area-based PSUs in DHS that often correspond to villages that relate to meaningful social and administrative divisions.[13] In India-specific analysis and as a sensitivity analysis for the pooled data, we also illustrated additional conceptualisations of population with subnational administrative divisions where policy and health service administration were typically implemented (ie, states or regions, and districts).[17]

Outcome

The primary outcome of interest was BMI (kg/m^2), calculated as weight (kg) divided by the square of height (m^2). Trained investigators weighed each woman by using a solar-powered scale with an accuracy of 100 grams and measured height by using an adjustable board calibrated in millimetres.[18]

Explanatory variables

We adjusted all models for women's age (years 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, and 45–49). We considered four socioeconomic variables: household wealth, women's education, place of residence, and marital status. In DHS, household wealth was captured through a composite index of relative standard of living derived from country-specific indicators of asset ownership, housing characteristics, and water and sanitation facilities, and then divided into quintiles for each country.[19] Education was coded in four categories indicating no formal schooling, and completion of primary, secondary, or higher schooling. A binary variable for place of residence (census-based urban *vs* rural) and a categorical variable for marital status (never married; married or living together; divorced, separated, or widowed) were used. Socioeconomic factors, such as wealth index and education level, were shown to be valid when collected through population-based surveys.[20]

Statistical analysis

We pooled individual level data from the nationally representative DHS to create a global sample that followed a three-level hierarchical structure with women at level 1 (i), nested within communities at level 2 (j), and countries at level 3 (k). To account for the complex survey design and describe individual and population components of variance in BMI, we specified a series of three-level random intercept linear regression models. In model 1, we adjusted for fixed effects of survey year only to provide a baseline for comparing the changes in BMI variations in subsequent models:

$$BMI_{ijk} = \beta_0 + \beta\, Year_k + (e_{0ijk} + u_{0jk} + v_{0k})$$

For interpretation, β_0 represents the average BMI across all countries in baseline year 2005, and bracketed terms represent random effects associated with individuals, communities, and countries. The term v_{ok} is a country-specific residual that represents a departure of each country from the global average BMI; u_{ojk} is a community-specific residual conditional on country; and e_{oijk} is an individual-specific residual. Assuming a normal distribution of these residuals with a mean of 0, this model estimates variation in BMI between individuals, ie

$$e_{0ijk} \sim N(0,\, \sigma^2_{e0})$$

between communities ie,

$$u_{0jk} \sim N(0,\, \sigma^2_{u0})$$

and between countries ie,

$$v_{0k} \sim N(0,\, \sigma^2_{v0})$$

We evaluated the assumption of independently and identically distributed residuals at each level using normal score plots (appendix).

See Online for appendix

We calculated the proportion of variation in BMI attributable to each level, also known as variance partitioning coefficient (VPC), on the basis of variance estimates of random effects. For instance, the proportion of total variation in BMI attributable to countries was calculated by dividing between-country variance by total variance:

$$\left(\frac{\sigma^2_{v0}}{\sigma^2_{v0} + \sigma^2_{u0} + \sigma^2_{e0}}\right) \times 100$$

VPC measures the extent to which individuals in a study population resemble each other more than they resemble those from other study populations in terms of the outcome. A simple random sample of individuals (ie, no correlation in BMI among individuals) will result in 100% VPC at the individual level and 0% at population levels.

In subsequent models, we adjusted for age-related differences in BMI (model 2):

$$BMI_{ijk} = \beta_0 + \beta\, Year_k + \beta\, age_{ijk} + (e_{0ijk} + u_{0jk} + v_{0k})$$

and further adjusted for all socioeconomic variables, including type of residence, education, wealth, and marital status (model 3):

$$BMI_{ijk} = \beta_0 + \beta\, Year_k + \beta\, age_{ijk} + \beta\, SES_{ijk} + (e_{0ijk} + u_{0jk} + v_{0k})$$

The proportion of variance in BMI explained by socioeconomic factors at each level was computed by subtracting the variance of model 3 from the variance of model 2, and converting to a percentage:

$$\left(\frac{\sigma^2_{\text{age adjusted}} - \sigma^2_{\text{age + SES}}}{\sigma^2_{\text{age adjusted}}}\right) \times 100$$

We did two types of country-specific analyses. For each of the 58 LMICs, two-level random effects models (individuals at level 1 and communities at level 2) were estimated to assess the range in BMI variance and proportion explained by socioeconomic factors. For India, we specified four-level random effects models (individuals at level 1, communities at level 2, districts at level 3, and states at level 4) with a larger set of predictor variables, including birth history, religion, health behaviours, current illnesses, dietary intake, and women's empowerment to assess their contribution to variation in BMI within and between populations (appendix).

We additionally did three sensitivity analyses. First, to assess the extent to which our main findings hold consistent across more heterogeneous populations, we replicated our analysis with data from the WHS pooled across 65 low-income and high-income countries.[14] We considered the same set of socioeconomic variables, except for marital status. Second, because the relative household wealth index does not take into account the differences in country wealth (ie, treats the poorest 20% in country A and country B the same even though their living conditions might differ), we re-estimated our main model (model 3) using predicted absolute income for households.[21] Predicted absolute income constructed on the basis of algorithm proposed by Harttgen and Vollmer[22] used asset information and nationally available data for average amounts and overall inequality in income distribution. Finally, to evaluate the importance of considering different conceptualisations of population, we ran the following model specifications for BMI before and after adjusting for socioeconomic factors: individuals within communities only, individuals within countries only, and individuals within communities, states or regions, and countries.

We did all multilevel modelling using MLwiN 3.00, and estimated parameters using iterative generalised least squares.

Role of the funding source

There was no funding source for this study.

Results

We included 1 212 758 (98·2%) women nested within 64 764 communities and 58 countries in the final analytic sample (figure 1). Of the total eligible women, we excluded 22 657 (1·8%) with missing anthropometric measures or biologically implausible height or weight measures (figure 1). Additionally, 98 (<0·1%) women were excluded for missing information on education level (figure 1). Regarding the distribution of sample size and BMI within each country, the overall average BMI was 22·7 kg/m² (SD 4·7), and it varied from 20·2 kg/m² in Ethiopia to 29·8 kg/m² in Egypt (table). A positive BMI gradient by age and socioeconomic indicators was apparent in the full adjusted model, although the association between education and BMI was heterogeneous across countries (appendix). The association between household wealth and BMI was more consistent across countries: on average, women in the wealthiest quintile had 2·3 kg/m² higher BMI than those from the poorest quintile (appendix).

For the pooled analysis, the total variance in BMI was 20·4 in the age-adjusted model (appendix). Of the total age-adjusted variance, 74·6% was attributed to between-individual differences and 25·4% was attributed to between-population differences (ie, 15·1% for countries and 10·3% for communities; figure 2A). Despite the large within-population variation, only 2·3% was explained by socioeconomic factors (ie, individual level variance estimate reduced from 15·2 [95% CI 15·1–15·2] to 14·8 [14·8–14·9]). By contrast, 14·8% of between-country variances and 47·1% of between-community variances were explained by socioeconomic factors, corresponding to changes in variance estimates from 3·1 (2·0–4·2) to 2·6 (1·7–3·6) for countries and from 2·1 (2·1–2·1) to 1·1 (1·1–1·1) for communities. The pattern in variance decomposition remained consistent in the fully adjusted model: 79·9% of the unexplained variation in BMI was attributed to between-individual differences, 14·1% to between-country differences, and 6·0% to between-community differences (figure 2A).

The poor ability to explain between-individual variance for BMI was further supported from India-specific analysis considering a larger set of predictor variables and additional conceptualisations of population (figure 2B, appendix). In India, 655 071 women (accounting for 54% of the pooled sample) were nested within 28 512 communities, 640 districts, and 36 states. Of the total age-adjusted variance in BMI in India (15·8), 84·2% was attributed to between-individual differences and 15·8% was attributed to between-population differences (ie, 5·8% for states, 2·8% districts, and 7·1% communities). Adjusting for socioeconomic factors explained 3·8% of the between-individual variance in BMI and further adjustment for women's religion, birth history, health behaviours, current illnesses, and dietary intake explained an additional 1·1%. At the population levels, 56·8–66·1% of variance was explained by socioeconomic factors, and further adjustment for additional factors explained 4·4–13·7% more variance in BMI. Indicators of women's empowerment were available for a subsample of 114 380 women in India and explained less than 1% of variance in BMI over and above adjustment for socioeconomic factors both within and between populations (appendix).

In the country-specific analysis, we consistently found a disproportionately large variation in BMI between individuals compared with between communities (figure 3). The fully adjusted between-individual variance estimates ranged from 7·6 (95% CI 7·4–7·9) in Madagascar to 31·4 (30·2–32·5) in Jordan, and between-community variance estimates ranged from 0·3 (0·1–0·4) in Zimbabwe to 2·5 (2·2–2·9) in Egypt (figure 3). In terms of VPC, between-individual differences accounted for 86·0–98·6% of the total variance in BMI across countries (figure 3, appendix). The proportion of BMI variance explained by socioeconomic factors was also heterogeneous across countries, but poor explanation at the individual level was uniformly observed (figure 4). At the individual level, socioeconomic factors explained less than 1% of the differences in BMI within 11 countries, including Chad, Egypt, Colombia, and Pakistan, and just over 5% in Lesotho and Bangladesh (figure 4). At the community level, the same factors explained less than 10% of the differences in BMI within seven countries, including Guyana, Jordan, Egypt, and Kyrgyzstan, and up to 85% in Togo (figure 4).

In the first sensitivity analysis, which considered a more heterogeneous population (185 449 men and women aged from 15 years to older than 70 years) from countries of all ranges of economic development, we found a consistent pattern in variance decomposition with larger total unexplained variance in BMI (appendix). The total age-adjusted variance in BMI among 99 356 women nested within 10 732 communities in 63 diverse countries was 30·0, of which 11·3% was attributed to between-country differences and 10·4% to between-community differences, and the remaining 78·4% to between-individual differences (appendix). Of the respective variances, socioeconomic factors explained roughly 2% for between-country differences, 5% for between-community differences, and <0·1% for between-individual differences (appendix). Among 86 093 men within 10 898 communities from the same countries, the total age-adjusted variance in BMI was 23·7 (appendix). Variance partitioning remained the same for men and socioeconomic factors explained slightly larger proportions (roughly 3% for between-country differences, 8% for between-community differences, and 0·4% for between-individual differences; appendix).

The results from the second sensitivity analysis suggested that our findings were robust when predicted absolute income was used instead of relative wealth (appendix). Compared with the original wealth index, the predicted household income quintiles explained more variation in BMI between countries (about 32%) but the same amount of variance between communities (about 41%) and between individuals (about 1%; appendix).

Finally, variance estimates at each level were sensitive to the choice of model specification, but the overall pattern remained consistent (appendix). When country was the only population unit considered, 85% of the total age-adjusted variance in BMI (20·2) was attributed to between-individuals, of which roughly 8% was explained by socioeconomic factors (appendix). Modelling states or regions as an additional population unit within each country (ie, four-level model) resulted in about 15% of the total age-adjusted variance in BMI (20·4) attributed to differences between countries, 4% between states or regions, 7% between communities, and 74% between individuals (appendix). Socioeconomic factors explained up to roughly 12–50% of the variance at population levels, but only about 2% at the individual level (appendix).

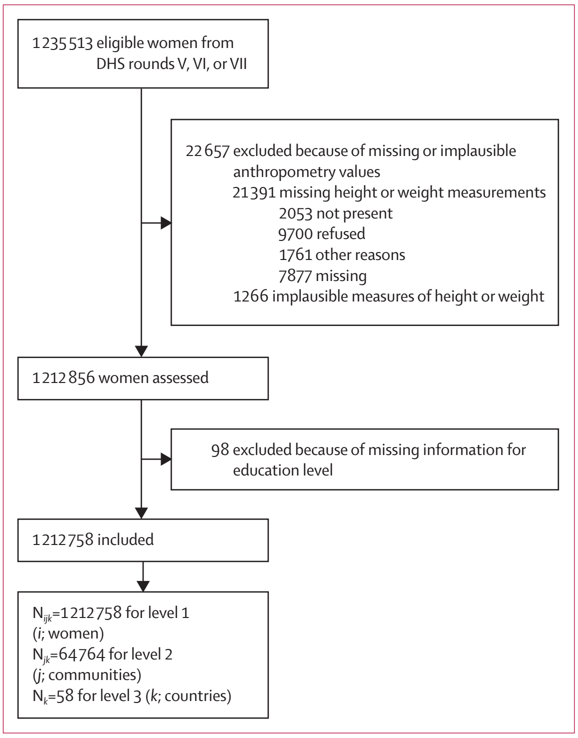

Figure 1: **Study overview**
DHS=Demographic Health Surveys.

Discussion

In this study, we observed three salient findings that had implications for population health. First, most unexplained variation in BMI among reproductive age women across 58 LMICs was attributed to between-individual within-population differences. Second, despite the overwhelmingly large interindividual variation in BMI, only around 2% was explained by socioeconomic variables. Although a smaller fraction of variation in BMI was attributed to between-population differences, a much larger proportion was explained by socioeconomic factors. This pattern was consistently found after adjusting for a more comprehensive set of predictor variables in India and across heterogeneous samples of men and women from diverse low-income and high-income countries. Finally, substantial variation was found across countries in respect to the magnitude of between-individual differences and the proportion explained by socioeconomic factors.

Our study had potential data limitations and we did additional analyses to partially address them. First, our main analysis was restricted to few socioeconomic variables that were comprehensively collected across all countries. Measures of race and ethnicity, occupation, socioeconomic measures at different stages of the life course, and other relevant behavioural factors were not consistently available. However, many of the relevant behavioural factors are likely to be mediators in between socioeconomic conditions and BMI, and hence

	Year	Survey round	Communities (n)	Women (n)	Mean BMI (kg/m²)	BMI percentiles (kg/m²)		
						5th	50th	95th
Albania	2008–09	DHS V	450	7386	24·4 (4·0)	19·1	23·8	31·8
Armenia	2015–16	DHS VII	313	5730	25·4 (5·1)	18·9	24·5	34·8
Azerbaijan	2006	DHS V	318	7862	25·2 (5·2)	18·5	24·3	34·8
Bangladesh	2014	DHS VII	600	16 624	22·3 (4·2)	16·5	21·9	29·7
Benin	2011–12	DHS VI	750	14 563	23·4 (4·3)	18·2	22·6	31·0
Bolivia	2008	DHS V	999	15 539	25·8 (4·8)	19·6	24·9	34·9
Burkina Faso	2010	DHS VI	573	7625	21·4 (3·5)	17·2	20·8	27·7
Burundi	2010–11	DHS VI	376	4103	21·3 (3·5)	17·1	20·8	27·2
Cambodia	2014	DHS VII	611	10 818	22·1 (3·6)	17·2	21·5	28·8
Cameroon	2011	DHS VI	578	7131	23·9 (4·8)	18·1	22·9	33·1
Chad	2014–15	DHS VII	624	9730	21·1 (3·6)	16·5	20·5	27·4
Colombia	2009–10	DHS VI	4951	43 950	25·3 (5·0)	18·6	24·6	34·4
Comoros	2012	DHS VI	252	4828	24·4 (5·0)	18·1	23·5	33·9
Congo (Brazzaville)	2011–12	DHS VI	384	5058	22·3 (4·1)	17·3	21·4	24·0
Côte d'Ivoire	2011–12	DHS VI	351	4312	22·9 (4·0)	18·0	22·1	30·5
Democratic Republic of the Congo	2013–14	DHS VI	536	8159	21·7 (3·6)	17·2	21·2	28·1
Dominican Republic	2013	DHS VI	524	8671	25·9 (5·7)	18·1	25·1	36·4
Egypt	2014	DHS VI	1764	19 345	29·8 (5·4)	22·1	29·2	39·6
Ethiopia	2016	DHS VII	642	13 781	20·2 (3·6)	16·3	20·2	28·0
Gabon	2012	DHS VI	336	4958	24·5 (5·4)	17·9	23·3	35·1
Ghana	2014	DHS VII	427	4393	24·3 (5·1)	18·3	23·2	34·2
Guatemala	2014–15	DHS VII	858	24 193	26·0 (5·1)	19·2	25·2	35·3
Guinea	2012	DHS VI	300	4227	22·3 (4·0)	17·3	21·6	29·7
Guyana	2009	DHS V	325	4515	25·7 (6·0)	17·4	24·8	36·7
Haiti	2012	DHS VI	445	8870	22·6 (4·3)	17·3	21·7	30·9
Honduras	2011–12	DHS VI	1148	21 092	25·8 (5·5)	18·6	24·9	36·0
India	2015–16	DHS VII	28 512	655 071	21·7 (4·2)	16·3	21·0	29·5
Jordan	2012	DHS VI	806	6461	29·1 (6·2)	20·2	28·4	40·1
Kenya	2014	DHS VII	1592	13 455	23·3 (4·7)	17·3	22·4	32·0
Kyrgyzstan	2012	DHS VI	316	7516	24·2 (4·8)	18·1	23·3	32·9
Lesotho	2014	DHS VI	399	3243	25·5 (5·6)	18·6	24·2	36·1
Liberia	2013	DHS VI	322	4180	23·1 (4·2)	18·1	22·2	31·2
Madagascar	2008–09	DHS V	594	7674	20·4 (3·0)	16·4	20·1	25·7
Malawi	2015–16	DHS VII	850	7407	22·9 (4·0)	18·2	22·1	30·6
Maldives	2009	DHS V	270	5153	24·8 (4·7)	17·6	24·4	33·1
Mali	2012–13	DHS VI	413	4643	22·6 (4·4)	17·5	21·7	31·0
Moldova	2005	DHS V	400	7072	25·1 (5·7)	18·3	23·8	36·1
Mozambique	2011	DHS VI	610	12 197	22·7 (4·0)	18·0	21·9	30·5
Namibia	2013	DHS VI	545	4081	23·9 (5·8)	16·9	22·5	34·9
Nepal	2016	DHS VII	383	6164	22·0 (3·9)	16·9	21·3	29·5
Niger	2012	DHS VI	475	4415	22·3 (4·2)	17·0	21·5	30·0
Nigeria	2013	DHS VI	896	33 893	23·0 (4·5)	17·4	22·1	31·6
Pakistan	2012–13	DHS VI	495	4127	24·5 (5·3)	17·4	23·7	34·1
Peru	2012	DHS VI	1426	22 704	26·0 (4·6)	19·7	25·4	34·3
Rwanda	2014–15	DHS VII	492	6217	22·9 (3·5)	18·2	22·4	29·5
São Tomé and Principe	2008–09	DHS V	99	2179	24·3 (5·4)	18·2	23·1	33·8
Senegal	2010–11	DHS VI	391	5258	21·7 (4·4)	16·4	20·8	30·2
Sierra Leone	2013	DHS VI	434	7302	22·6 (4·0)	17·7	21·9	30·0
Swaziland	2006–07	DHS V	274	4591	26·4 (5·8)	19·2	25·0	37·8
Tajikistan	2012	DHS VI	356	8930	23·5 (4·8)	17·5	22·5	32·8

(Table continues on next page)

	Year	Survey round	Communities (n)	Women (n)	Mean BMI (kg/m²)	BMI percentiles (kg/m²)		
						5th	50th	95th
(Continued from previous page)								
Tanzania	2015–16	DHS VII	608	12 027	23·4 (4·8)	17·7	22·4	33·0
The Gambia	2013	DHS VI	281	4176	22·3 (4·7)	16·8	21·3	31·6
Timor-Leste	2009–10	DHS VI	455	11 962	20·2 (2·9)	16·4	19·9	24·9
Togo	2013–14	DHS VI	330	4395	23·4 (4·8)	17·9	22·4	33·2
Uganda	2011	DHS VI	403	2420	22·2 (3·8)	17·6	21·5	29·4
Yemen	2013	DHS VI	781	22 500	22·3 (5·0)	16·2	21·2	31·8
Zambia	2013–14	DHS VI	721	14 824	22·7 (4·1)	17·7	21·9	30·8
Zimbabwe	2015	DHS VII	400	9058	24·5 (5·1)	18·2	23·4	34·4
All countries	..	..	64 764	1 212 758	22·7 (4·7)	16·7	21·8	31·7

Data are n or mean (SD). BMI=body-mass index. DHS=Demographic Health Surveys.

***Table:* Distribution of BMI across 58 low-income and middle-income countries from the DHS, 2005–16**

unlikely to contribute much to the explanation of within-population variation in BMI. In our India-specific analysis, which considered a larger set of variables, only 1% of additional between-individual variance was explained over and above adjustment for basic socioeconomic factors.

Second, our main analysis was restricted to young-aged and middle-aged women in LMICs with complete information on BMI measure and other covariates. An additional analysis with more heterogeneous population resulted in larger variance in BMI and even smaller proportion explained by socioeconomic factors both within and between populations. Moreover, our results were similar with previous studies[23–25] that have explored variance in BMI in different contexts; although, none have attempted to systematically quantify the extent to which mean differences in sociodemographic factors contribute to variation at multiple levels. A study[23] that focused on the USA and Canada found that a 2·5–4·9% variation in BMI attributed to populations (geographically defined sub-national and regional units), and adjusting for age, race, income, educational attainment, and living in an urban environment resulted in almost 27–60% reduction in between-population variance, but only 7% at the individual level for women in the USA.

Finally, estimates in any multilevel variance components analysis are inevitably sensitive to how populations (or units of analysis) are defined. Our sensitivity analyses with different multilevel specifications indicated that both the amount of variation and the proportion explained by socioeconomic factors are different depending on the conceptualisation of populations. For instance, inclusion of state or region as another population unit corresponded to decrease in community effects. However, regardless of how population levels were defined, the largest fraction of unexplained variance in BMI was always attributed to between-individual differences.

Our findings on variance decomposition and explanation by socioeconomic factors at population and individual levels raise the necessity to simultaneously consider two types of inferential questions:[1–3] what

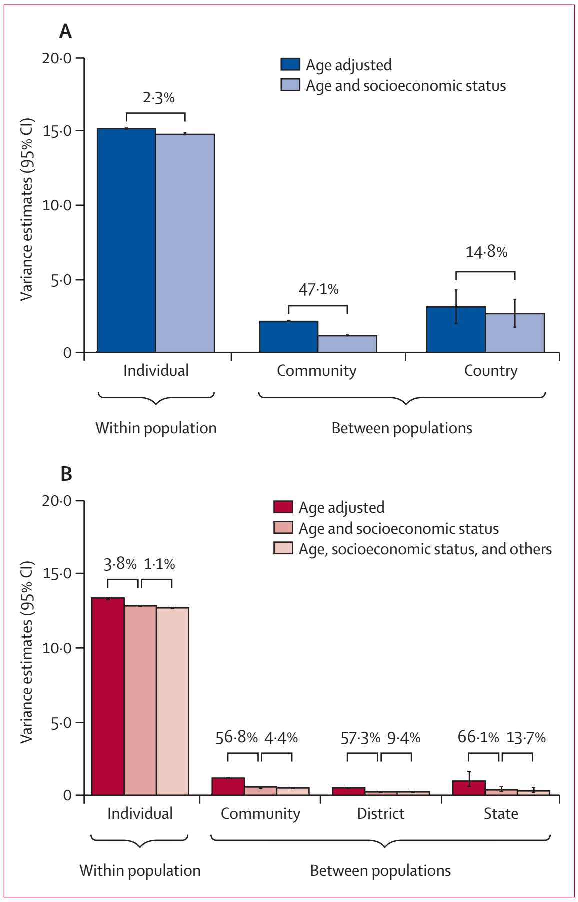

***Figure 2:* Between-population and within-population variance estimates in BMI and proportion explaned by individual-level factors**

(A) Pooled three-level analysis with individual-level socioeconomic factors. (B) India-specific four-level analysis with individual-level socioeconomic status and other factors (religion, birth history, health behaviours, illnesses, and diet). Exact estimates are reported in the appendix. BMI=body-mass index.

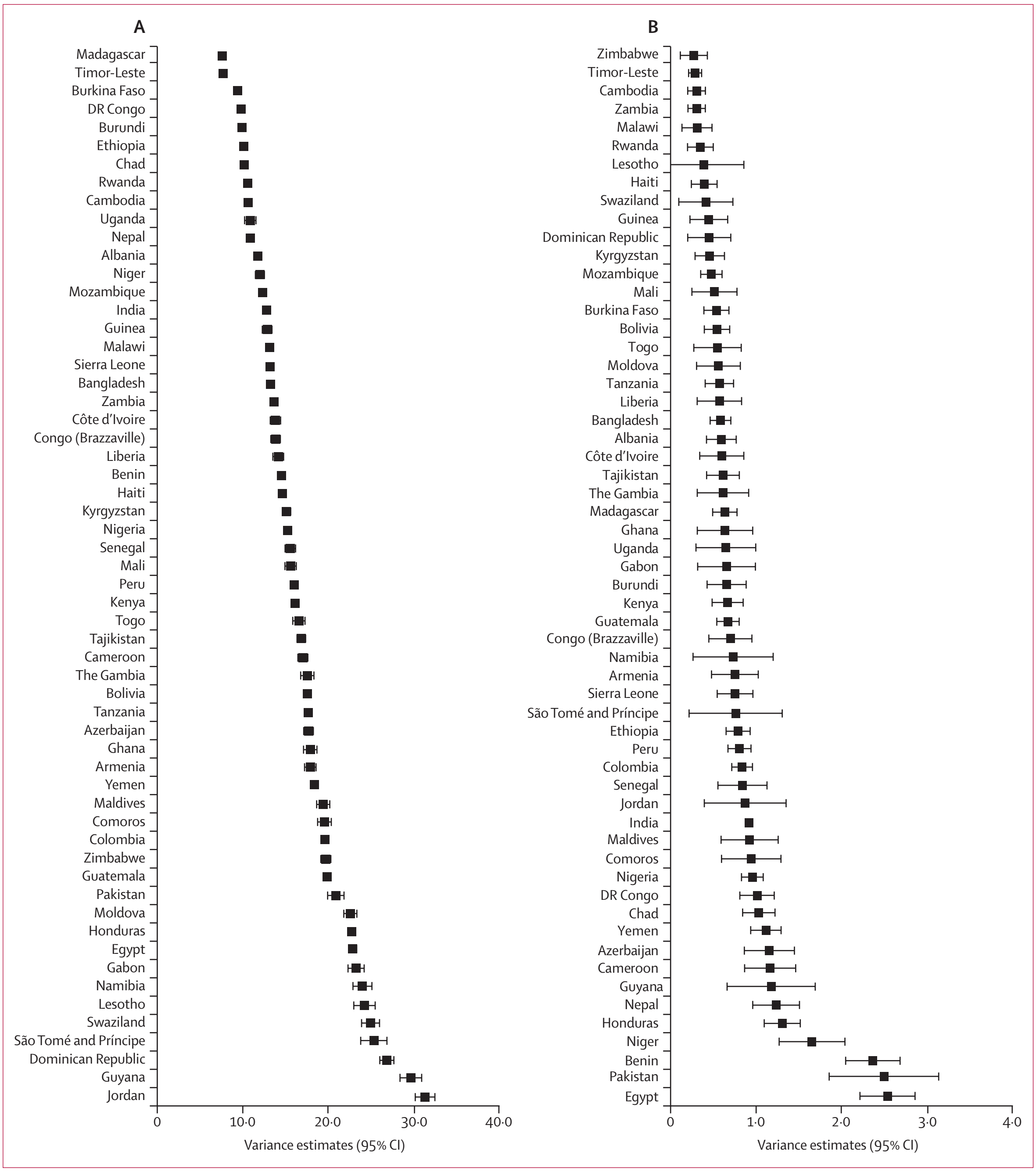

***Figure 3*: Variance estimates from country-specific two-level random intercept models for body-mass index**
Estimates adjusted for age and socioeconomic factors (A) between individuals and (B) between communities. Exact estimates are reported in the appendix.

explains between-individual (within-population) variance in BMI and what explains the mean differences in BMI between populations (ie, differences in the mean values of BMI across populations)? The determinants of within-population versus between-population variance are importantly inter-related. Differences in the mean values of BMI across populations are, by themselves, abstract statistical constructs. For instance, average BMI is a marker of perhaps the nutritional status in a population that is aggregated from individual level measures rather than a measure that is intrinsically meaningful at the population level. Therefore, understanding the magnitude and patterning of between-individual differences is necessary to assess variation in any health outcome. However, too often the focus on population strategies have prioritised between-population differences in isolation from the understanding of within-population processes.[10]

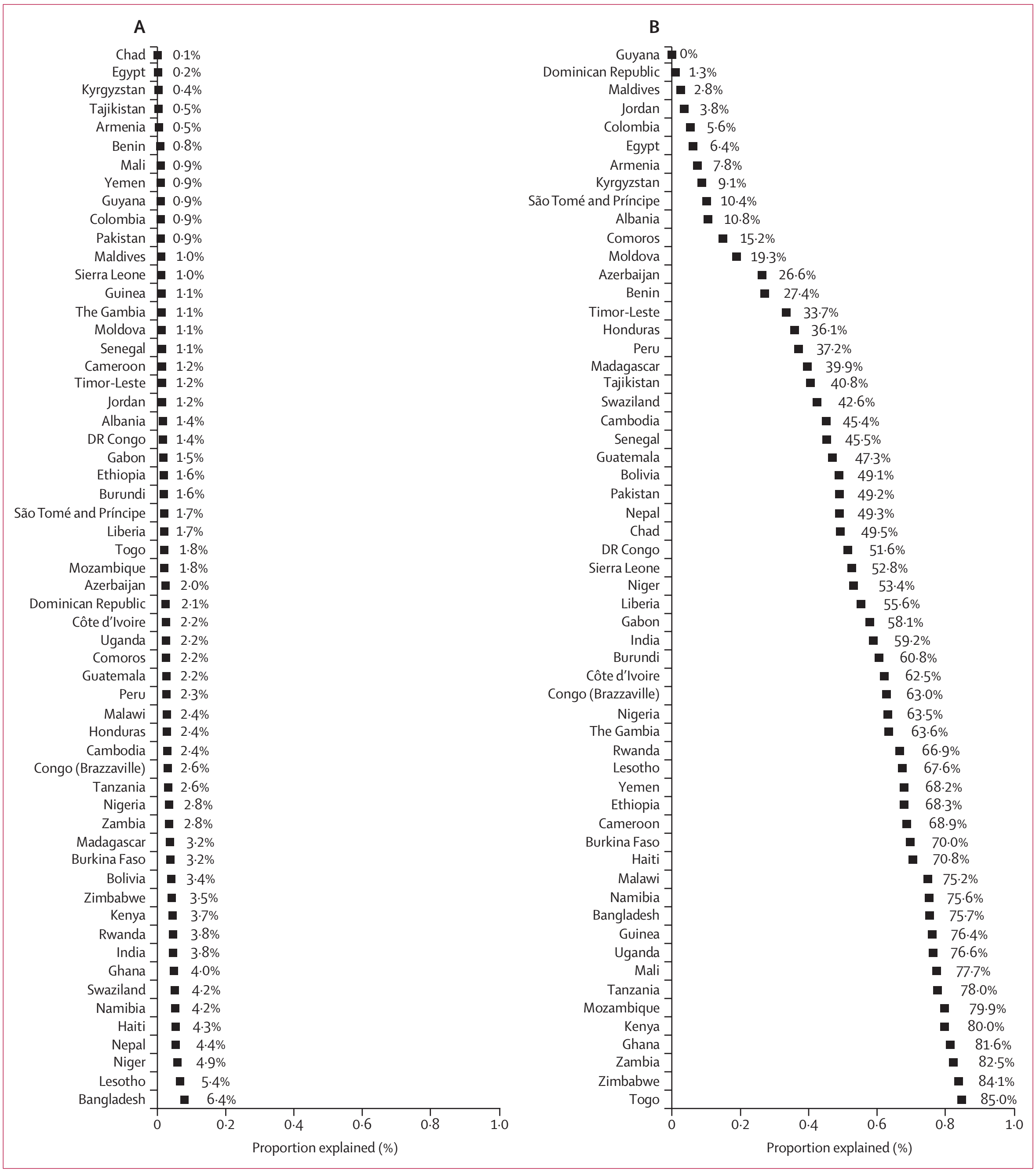

Figure 4: **Proportion of variance for body-mass index explained by basic socioeconomic factors**
Estimates are from country-specific two-level random intercept models (A) between individuals and (B) between communities. Basic socioeconomic factors were type of residence, education, wealth, and marital status. Exact estimates are reported in the appendix.

Income and educational attainment are known to have substantial average associations with BMI across individuals.[26–29] However, our findings indicated that socioeconomic factors have extremely low discriminatory accuracy.[7] To put the 2% variance explained by socio-economic factors in a comparative perspective, the most comprehensive evidence to date on genetic studies for BMI suggests that common genetic variation (all HapMap phase 3 SNPs) can account up to 20% of the phenotypic variance in BMI.[30] If between-individual variation in health is predominantly a stochastic or chance occurrence, then one can expect a relatively constant within-population variance over time and across different populations.[1,5] However, in the context of BMI, studies have found changes in variance accompanied by increase in mean BMI over time[12,31] as well as differential variations within different populations at a given point in time.[32] Furthermore, our country-specific analysis showed substantial heterogeneity in within-population variation in BMI and percentage explained by socioeconomic factors. Taken together, these findings reiterate the importance of considering within-population variance in health outcomes for its intrinsic value and instrumental relevance in helping to interpret population mean and variance.[7,11]

The policy implications based solely on between-population differences are not very straightforward. In our study, between-population variance in BMI was consistently smaller in magnitude but much better explained by socioeconomic factors, indicating their unequal distribution. This outcome might suggest a call for universal strategies affecting overall standards of living and education level to intervene on underlying inequalities at the population level. However, just as mean BMI is a population level marker, so is average socioeconomic condition. Thus ultimately, it is always individuals who have weight gain or loss and have actual changes in education or income level. Therefore, population-level interventions should concurrently address drivers of within-population differences.[11]

In summary, the inferential questions targeting within versus between populations are not independent of one another because population health cannot improve without changes in individuals. Future analyses to understand variance in health should simultaneously consider and quantify individuals and populations as distinct but inter-related units of analysis. Further, better understanding of systematic components in within-population and between-population variances can lead to more focused policy efforts and deliberations to benefit individuals and improve overall population health.

Contributors

RK and SVS conceptualised the study and designed the analyses. RK analysed and interpreted the data and wrote the manuscript. SVS, IK, and BAC contributed to interpretation of the data and writing. All authors have approved the final content presented in the manuscript. SVS provided overall supervision for the study.

Declaration of interests

All authors declare no competing interests.

References

1 Rose G. Sick individuals and sick populations. *Int J Epidemiol* 2001; **30:** 427–32.

2 Rose G. The strategy of preventive medicine. Oxford: Oxford University Press, 1992.

3 Schwartz S, Diez-Roux R. Commentary: causes of incidence and causes of cases—a Durkheimian perspective on Rose. *Int J Epidemiol* 2001; **30:** 435–39.

4 Lewontin R. The analysis of variance and the analysis of causes. *Int J Epidemiol* 2006; **35:** 520–25.

5 Smith GD. Epidemiology, epigenetics and the 'Gloomy Prospect': embracing randomness in population health research and practice. *Int J Epidemiol* 2011; **40:** 537–62.

6 Rockhill B, Kawachi I, Colditz GA. Individual risk prediction and population-wide disease prevention. *Epidemiol Rev* 2000; **22:** 176–80.

7 Merlo J. Invited commentary: multilevel analysis of individual heterogeneity—a fundamental critique of the current probabilistic risk factor epidemiology. *Am J Epidemiol* 2014; **180:** 208–12.

8 Berkman LF, Kawachi I, Glymour MM. Social epidemiology. Oxford: Oxford University Press, 2014.

9 Merlo J, Asplund K, Lynch J, Råstam L, Dobson A. Population effects on individual systolic blood pressure: a multilevel analysis of the World Health Organization MONICA project. *Am J Epidemiol* 2004; **159:** 1168–79.

10 Mejía-Guevara I, Corsi DJ, Perkins JM, Kim R, Subramanian S. Variation in anthropometric status and growth failure in low-and middle-income countries. *Pediatrics* 2018; published online Feb 22. DOI:10.1542/peds.2017-2183.

11 Murray C, Gakidou E, Frenk J. Critical reflection-health inequalities and social group differences: what should we measure? *Bull World Health Organ* 1999; **77:** 537–44.

12 Razak F, Corsi DJ, Subramanian SV. Change in the body mass index distribution for women: analysis of surveys from 37 low- and middle-income countries. *PLoS Med* 2013; **10:** e1001367.

13 Corsi DJ, Neuman M, Finlay JE, Subramanian S. Demographic and health surveys: a profile. *Int J Epidemiol* 2012; **41:** 1602–13.

14 WHO. WHO World Health Survey. http://www.who.int/healthinfo/survey/en/ (accessed Dec 3, 2017).

15 Krieger N. Who and what is a "population"? Historical debates, current controversies, and implications for understanding "population health" and rectifying health inequities. *Milbank Q* 2012; **90:** 634–81.

16 Swinburn BA, Sacks G, Hall KD, et al. The global obesity pandemic: shaped by global drivers and local environments. *Lancet* 2011; **378:** 804–14.

17 Kim R, Mohanty SK, Subramanian S. Multilevel geographies of poverty in India. *World Development* 2016; **87:** 349–59.

18 The Demographic and Health Surveys Program. DHS overview. https://dhsprogram.com/what-we-do/survey-Types/dHs.cfm (accessed Dec 3, 2017).

19 Rutstein SO. The DHS Wealth Index: approaches for rural and urban areas. Calverton, MD: Macro International, 2008.

20 Filmer D, Pritchett LH. Estimating wealth effects without expenditure data—or tears: an application to educational enrollments in states of India. *Demography* 2001; **38:** 115–32.

21 Fink G, Victora CG, Harttgen K, Vollmer S, Vidaletti LP, Barros AJ. Measuring socioeconomic inequalities with predicted absolute incomes rather than wealth quintiles: a comparative assessment using child stunting data from national surveys. *Am J Public Health* 2017; **107:** 550–55.

22 Harttgen K, Vollmer S. Using an asset index to simulate household income. *Econ Lett* 2013; **121:** 257–62.

23 Lebel A, Kestens Y, Clary C, Bisset S, Subramanian S. Geographic variability in the association between socioeconomic status and BMI in the USA and Canada. *PLoS One* 2014; **9:** e99158.

24 Masood M, Reidpath DD. Effect of national wealth on BMI: an analysis of 206,266 individuals in 70 low-, middle- and high-income countries. *PLoS One* 2017; **12:** e0178928.

25 Robert SA, Reither EN. A multilevel analysis of race, community disadvantage, and body mass index among adults in the US. *Soc Sci Med* 2004; **59:** 2421–34.

26 Jones-Smith JC, Gordon-Larsen P, Siddiqi A, Popkin BM. Cross-national comparisons of time trends in overweight inequality by socioeconomic status among women using repeated cross-sectional surveys from 37 developing countries, 1989–2007. *Am J Epidemiol* 2011; **173:** 667–75.

27 Kinge JM, Strand BH, Vollset SE, Skirbekk V. Educational inequalities in obesity and gross domestic product: evidence from 70 countries. *J Epidemiol Community Health* 2015; **69:** 1141–46.

28 McLaren L. Socioeconomic status and obesity. *Epidemiol Rev* 2007; **29:** 29–48.

29 Subramanian SV, Finlay JE, Neuman M. Global trends in body-mass index. *Lancet* 2011; **377:** 1915–16.

30 Locke AE, Kahali B, Berndt SI, et al. Genetic studies of body mass index yield new insights for obesity biology. *Nature* 2015; **518:** 197.

31 Krishna A, Razak F, Lebel A, Smith GD, Subramanian S. Trends in group inequalities and interindividual inequalities in BMI in the United States, 1993–2012. *Am J Clin Nutr* 2015; **101:** 598–605.

32 Kim R, Kawachi I, Coull BA, Subramanian SV. Patterning of individual heterogeneity in body mass index: evidence from 57 low-and middle-income countries. *Eur J Epidemiol* 2018; published online Jan 22. DOI:10.1007/s10654-018-0355-2.