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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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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.

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.11 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.14 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.13 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.15 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.15 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).⁵

Outcome
The primary outcome of interest was BMI (kg/m²), calculated as weight (kg) divided by the square of height (m²). 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.⁶

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.⁷ 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.⁸

Statistical analysis
We pooled individual level data from the nationally representative DHS to create a global sample that followed a three-level hierarchal 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:

\[ BMI_{ijk} = \beta_0 + \beta_{Year} + (\epsilon_{ijk} + u_{ijk} + v_{ijk}) \]

For interpretation, \( \beta_0 \) 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 \( v_{ijk} \) is a country-specific residual that represents a departure of each country from the global average BMI; \( u_{ijk} \) is a community-specific residual conditional on country; and \( \epsilon_{ijk} \) 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

\[ \epsilon_{ijk} \sim N(0, \sigma_{\epsilon}^2) \]

between communities, ie,

\[ u_{ijk} \sim N(0, \sigma_{u}^2) \]

and between countries, ie,

\[ v_{ijk} \sim N(0, \sigma_{v}^2) \]

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

\[ \left( \frac{\sigma_{v}^2}{\sigma_{\epsilon}^2 + \sigma_{u}^2 + \sigma_{v}^2} \right) \times 100 \]

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):

\[ BMI_{ijk} = \beta_0 + \beta_{Year} + (\beta_{Age} + \epsilon_{ijk} + u_{ijk} + v_{ijk}) \]

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

\[ BMI_{ijk} = \beta_0 + \beta_{Year} + (\beta_{Age} + \beta_{SES} \epsilon_{ijk} + u_{ijk} + v_{ijk}) \]

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:

\[ \left( \frac{\sigma_{\epsilon}_{\text{age adjusted}}^2 - \sigma_{\epsilon, \text{age and SES}}^2}{\sigma_{\epsilon, \text{age adjusted}}^2} \right) \times 100 \]

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. 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. Predicted absolute income constructed on the basis of algorithm proposed by Harttgen and Vollmer 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 1212758 (98·2%) women nested within 64764 communities and 58 countries in the final analytic sample (figure 1). Of the total eligible women, we excluded 22657 (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, 655071 women (accounting for 54% of the pooled sample) were nested within 28512 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 114380 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).

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            | 19.1         | 23.8          | 31.8          |
| Armenia      | 2015–16      | DHS VII         | 313       | 5730            | 18.9         | 24.5          | 34.8          |
| Azerbaijan   | 2006         | DHS V           | 318       | 7862            | 18.5         | 24.3          | 34.8          |
| Bangladesh   | 2014         | DHS VII         | 600       | 16.624          | 16.5         | 21.9          | 29.7          |
| Benin        | 2011–12      | DHS VI          | 750       | 14.563          | 18.2         | 22.6          | 31.0          |
| Bolivia      | 2008         | DHS V           | 999       | 15.539          | 19.6         | 24.9          | 34.9          |
| Burkina Faso | 2010         | DHS VI          | 573       | 7625            | 17.2         | 20.8          | 27.7          |
| Burundi      | 2010–11      | DHS VI          | 376       | 4103            | 17.1         | 20.8          | 27.2          |
| Cambodia     | 2014         | DHS VI          | 611       | 10.818          | 17.2         | 21.5          | 28.8          |
| Cameroon     | 2013         | DHS VI          | 578       | 7131            | 18.1         | 22.9          | 33.1          |
| Chad         | 2014–15      | DHS VI          | 624       | 9730            | 16.5         | 20.5          | 27.4          |
| Colombia     | 2009–10      | DHS VI          | 4951      | 43,950          | 18.6         | 24.6          | 34.4          |
| Comoros      | 2012         | DHS VI          | 252       | 4828            | 18.1         | 23.5          | 33.9          |
| Congo        | 2011–12      | DHS VI          | 384       | 5058            | 17.3         | 21.4          | 24.0          |
| Côte d’Ivoire| 2011–12      | DHS VI          | 351       | 4122            | 18.0         | 22.1          | 30.5          |
| Democratic Republic of the Congo | 2013–14 | DHS VI | 536 | 8159 | 17.2 | 21.2 | 28.1 |
| Dominican Republic | 2013 | DHS VI | 524 | 8671 | 18.1 | 25.1 | 36.4 |
| Egypt        | 2014         | DHS VI          | 1764      | 19,345          | 22.1         | 29.2          | 39.6          |
| Ethiopia     | 2016         | DHS VII         | 642       | 13,781          | 16.3         | 20.2          | 28.0          |
| Gabon        | 2012         | DHS VI          | 326       | 4958            | 17.9         | 23.3          | 35.1          |
| Ghana        | 2014         | DHS VII         | 427       | 4393            | 18.3         | 23.2          | 34.2          |
| Guatemala    | 2014–15      | DHS VII         | 858       | 24,193          | 19.2         | 25.2          | 35.3          |
| Guinea       | 2012         | DHS VI          | 300       | 4227            | 17.3         | 21.6          | 29.7          |
| Guyana       | 2009         | DHS V           | 325       | 4515            | 17.4         | 24.4          | 36.7          |
| Haiti        | 2012         | DHS VI          | 445       | 8870            | 17.3         | 21.7          | 30.9          |
| Honduras     | 2011–12      | DHS VI          | 1148      | 21,092          | 18.6         | 24.9          | 36.0          |
| India        | 2015–16      | DHS VII         | 28,512    | 655,071         | 16.3         | 21.0          | 29.5          |
| Jordan       | 2012         | DHS VI          | 806       | 6461            | 20.2         | 28.4          | 40.1          |
| Kenya        | 2014         | DHS VI          | 1592      | 13,455          | 17.3         | 22.4          | 32.0          |
| Kyrgyzstan   | 2012         | DHS VI          | 316       | 7516            | 18.1         | 23.3          | 32.9          |
| Lesotho      | 2014         | DHS VI          | 399       | 3243            | 18.6         | 24.2          | 36.1          |
| Liberia      | 2013         | DHS VI          | 322       | 4180            | 18.1         | 22.2          | 31.2          |
| Madagascar   | 2008–09      | DHS VI          | 594       | 7674            | 16.4         | 20.1          | 25.7          |
| Malawi       | 2015–16      | DHS VII         | 850       | 7407            | 18.2         | 22.1          | 30.6          |
| Maldives     | 2009         | DHS V           | 270       | 5353            | 17.6         | 24.4          | 33.1          |
| Mali         | 2012–13      | DHS VI          | 413       | 4643            | 17.5         | 21.7          | 31.0          |
| Moldova      | 2005         | DHS VI          | 400       | 7072            | 18.3         | 23.8          | 36.1          |
| Mozambique   | 2011         | DHS VI          | 610       | 12,197          | 18.0         | 21.9          | 30.5          |
| Namibia      | 2013         | DHS VI          | 545       | 4081            | 18.6         | 22.5          | 34.9          |
| Nepal        | 2016         | DHS VII         | 383       | 6164            | 16.9         | 21.3          | 29.5          |
| Niger        | 2012         | DHS VI          | 475       | 4415            | 17.0         | 21.5          | 30.0          |
| Nigeria      | 2013         | DHS VI          | 896       | 33,893          | 17.4         | 22.1          | 31.6          |
| Pakistan     | 2012–13      | DHS VI          | 495       | 4127            | 17.4         | 22.7          | 34.1          |
| Peru         | 2012         | DHS VI          | 1426      | 22,704          | 19.7         | 25.4          | 34.3          |
| Rwanda       | 2014–15      | DHS VII         | 492       | 6217            | 18.2         | 22.4          | 29.5          |
| São Tomé and Príncipe | 2008–09 | DHS V | 99 | 2179 | 18.2 | 23.1 | 33.8 |
| Senegal      | 2010–11      | DHS VI          | 391       | 5258            | 16.4         | 20.8          | 30.2          |
| Sierra Leone | 2013         | DHS VI          | 434       | 7302            | 17.7         | 21.9          | 30.0          |
| Swaziland    | 2006-07      | DHS V           | 274       | 4591            | 19.2         | 25.0          | 37.8          |
| Tajikistan   | 2012         | DHS VI          | 356       | 8930            | 17.5         | 22.5          | 32.8          |

(Table continues on next page)
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

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

| Country   | Year       | Survey round | Communities (n) | Women (n) | Mean BMI (kg/m\(^2\)) | BMI percentiles (kg/m\(^2\)) |
|-----------|------------|--------------|-----------------|-----------|------------------------|-----------------------------|
| 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    | 21.2 (4.9)             | 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 | -- | -- | 64764          | 1 212758  | 22.7 (4.7)             | 16.7 21.8 31.7             |

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

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.
Income and educational attainment are known to have substantial average associations with BMI across individuals.\(^\text{26–29}\) However, our findings indicated that socioeconomic factors have extremely low discriminatory accuracy.\(^\text{7}\) 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.\(^\text{30}\) 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.\(^\text{1,5}\) However, in the context of BMI, studies have found changes in variance accompanied by increase in mean BMI over time\(^\text{12,31}\) as well as differential

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.
variations within different populations at a given point in
time. 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.21

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.21

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.

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