Measuring Socioeconomic Inequalities With Predicted Absolute Incomes Rather Than Wealth Quintiles: A Comparative Assessment Using Child Stunting Data From National Surveys

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Objectives. To compare the predictive power of synthetic absolute income measures with that of asset-based wealth quintiles in low- and middle-income countries (LMICs) using child stunting as an outcome.

Methods. We pooled data from 239 nationally representative household surveys from LMICs and computed absolute incomes in US dollars based on households' asset rank as well as data on national consumption and inequality levels. We used multivariable regression models to compare the predictive power of the created income measure with the predictive power of existing asset indicator measures.

Results. In cross-country analysis, log absolute income predicted 54.5% of stunting variation observed, compared with 20% of variation explained by wealth quintiles. For within-survey analysis, we also found absolute income gaps to be predictive of the gaps between stunting in the wealthiest and poorest households ($P < .001$).

Conclusions. Our results suggest that absolute income levels can greatly improve the prediction of stunting levels across and within countries over time, compared with models that rely solely on relative wealth quintiles. (*Am J Public Health.* Published online ahead of print February 16, 2017: e1–e6. doi:10.2105/AJPH.2017.303657)

A large and growing literature has investigated the relationship between household wealth, income, and health in high-income as well as low-income countries. Although direct estimates of incomes and poverty status are widely available in most high-income countries, this is generally not true in low-income settings, where a majority of the rural population engages in subsistence farming, whereas many urban households depend on informal jobs with irregular incomes. Given these limitations, most national household surveys in low- and middle-income countries (LMICs) have focused on collecting information on household infrastructure and asset ownership rather than collecting information on income. Household information typically collected includes household access to clean water and sanitation, household ownership of durable goods like TVs, bicycles, or cars, and household access to electricity. Even though they are not necessarily a reflection of households' income in a given period, these characteristics—loosely referred to as "assets"—do reflect access to resources over longer periods of time, and can therefore be used to classify and rank households with respect to their relative socioeconomic position. Given the complexity of the data collected, most international survey programs use principal component analysis to convert asset information into a single asset score[1]; this asset score is then generally used to divide households into wealth quintiles (first = poorest, fifth = richest) for quantitative analysis.

From an empirical perspective, wealth quintiles are useful for many reasons: they allow comparison of health and well-being measures across equally sized groups within a given population and they can easily be used in regression analyses. When it comes to comparing survey results across countries and time, however, the interpretation of wealth quintiles becomes more challenging: households in any given quintile in Liberia or Tanzania face very different living conditions from households in the same quintile in Brazil or Indonesia. The same difficulty applies when comparing wealth differentials: given the high degree of heterogeneity in income levels and inequality in each country, absolute income differences between households in the first quintile and households in the fifth quintile vary substantially across countries. In countries with high income inequality (like China), the gap between households in the first and third wealth quintiles is enormous; the same is not true for places with relatively low income inequality, such as Albania or Ethiopia.

We used a method recently proposed by Harttgen and Vollmer[2] to compute average household income in LMICs based on their wealth quintile as well as on country- and year- specific consumption and income inequality levels. We then tested the predictive

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power of estimated absolute incomes compared with traditionally used wealth quintile measures using stunting prevalence—an indicator closely related to both children's overall development and poverty[3]—as health outcome in a set of 88 LMICs.

METHODS

Our main objective was to assess the predictive validity of synthetic absolute incomes generated using the Harttgen and Vollmer method[2] relative to asset quintile indicators used in most of the current literature. The study had 3 distinct parts. In the first part, we used data from the United Nations University World Institute for Development Economics Research (UNU-WIDER) World Inequality Database[4] and from the World Bank[5] to predict average household income using the Harttgen and Vollmer method.[2] In the second part, we compared predicted poverty rates with official World Bank poverty estimates to assess the accuracy of the absolute income levels predicted by the model. Last, and most importantly, we compared the predictive power of estimated absolute incomes with that of wealth quintile variables currently used in most household survey analyses.

Data Sources

The primary inputs needed for the method of Harttgen and Vollmer[2] are mean household income and inequality measured by the Gini coefficient. For income and consumption, we downloaded gross domestic product (GDP) per capita data at constant purchasing power parity–adjusted 2011 international dollars from the online World Development Indicator database.[5] We retrieved income inequality data from the UNU-WIDER World Inequality Database, which is the most comprehensive set of income inequality statistics currently available at the global level (https://www.wider.unu.edu/project/wiid-world-income-inequality-database).[4] We extracted poverty estimates for LMICs from the World Development Indicator database.[5]

Data on household size and quintile-specific stunting prevalence was provided by the International Center for Equity in Health's national household survey database (http://www.equidade.org). The database contains 272 Demographic and Health Surveys and Multiple Indicator Cluster Surveys. For this study, we extracted data for a total of 239 surveys with asset quintile and stunting data as well as income and inequality data. We derived wealth quintiles from the first component of a principal components analysis carried out according to the methodology developed by Filmer and Pritchett[1] and described in further detail in the DHS Wealth Index report.[6]

Computing Quintile-Specific Incomes

As outlined in Harttgen and Vollmer,[2] the distribution of incomes in most countries can be approximated by a log-normal distribution with a mean average household income μ and a standard deviation of household income σ. Although most countries do not publish standard deviation estimates for household incomes, Gini inequality measures have become widely available. By construction of the Gini coefficient, the standard deviation σ of any log-normal distribution can be directly computed as

$$(1)\quad \sigma = \sqrt{2}\,\Phi^{-1}\left(\frac{G+1}{2}\right),$$

where G is the Gini coefficient and Φ^{-1} is the inverse of the standard normal cumulative distribution function. The UNU-WIDER World Inequality Database does not publish income inequality estimates for all years; for years not covered in the inequality database, we used a linear interpolation between the closest available data points before and after the survey year of interest, which has been shown to yield relatively accurate estimates with serially correlated data.[7]

Although virtually all countries publish data on total GDP as well as on GDP per capita, data on average household income are not generally available. However, given that total GDP is computed as the sum of private consumption, investment, government consumption, and net exports, average consumption per capita can readily be computed by multiplying GDP per capita with the national consumption share (consumption as percentage of GDP), a statistic that is published by virtually all countries and available in the World Development Indicators database.[5] We computed average household consumption by multiplying average consumption per person by the average number of household members in the country and year. We then computed the mean and standard deviation of the income distribution in the reference country and reference year, and predicted incomes for each income percentile as well as wealth quintile. Figure A (available as a supplement to the online version of this article at http://www.ajph.org) summarizes the main model inputs and logic of the computation.

Linking Predicted Incomes to Household Surveys

Although the main model predicts incomes for all households, data on the relative position (percentile rank) of households are not generally available in household surveys. However, virtually all surveys contain asset-based wealth indices, which rank households with respect to their relative socioeconomic status. To link our predicted incomes to household wealth, we took the household's asset rank as a proxy for its relative position in the income distribution and assigned households in each asset quintile the average income of the same income quintile. In practice, this means that we assigned to all households of the lowest asset quintile in a given survey the average income of the bottom 20% of the estimated income distribution in the respective country and year. The model theoretically allowed us to predict incomes at a much more disaggregated level (i.e., compute incomes for each percentile or smaller population segments); as further discussed in Discussion, we opted to predict at the quintile level rather than the percentile or decile level to reduce the risk of misclassification. Conceptually, it seems relatively likely that households in a given wealth quintile are also in the corresponding income quintile; it seems somewhat less likely that a person exactly at the x^{th} percentile of the asset distribution is also at the x^{th} percentile of the income distribution. In Table A (available as a supplement to the online version of this article at http://www.ajph.org), we compared the predictive power of incomes predicted at the percentile, decile, and quintile level. Given that quintile-based income estimates predicted stunting at least as well as more disaggregated income estimates, we focused on quintile-based estimates. Percentile-specific estimates for all surveys analyzed are available on the corresponding author's Web site (https://www.hsph.harvard.edu/gunther-fink/data).

Health Outcomes

Our primary health outcome was stunting prevalence. Stunting is a key predictor of children's overall developmental status and later life outcomes,[8–11] and has also been strongly and consistently associated with household socioeconomic status.[12,13] We converted length (for children younger than 24 months) and height (for those aged 24–59 months) measures collected in the surveys to age- and sex-specific z-scores using the Anthro software package (World Health Organization [WHO], Geneva, Switzerland), based on the 2006 WHO growth standards. We defined stunting as a height-for-age z-score of –2 or lower.[14]

Statistical Analysis

We started our analysis with summary statistics for predicted incomes. In the second step, we compared poverty estimates based on our predictive models with official poverty estimates published by the World Bank to validate our estimates against existing income and poverty data.

In the third step, we compared the predictive validity of the 2 measures—the absolute income and the relative wealth quintiles—in relation to stunting prevalence. This was done with 2 sets of models. The first was a cross-country analysis in which we analyzed surveys together so that we could compare the explanatory power of both measures at very different levels of income or wealth. The second set of models included an intercept (fixed effects) for each survey (using 1 survey as reference group), so that now the models represented only a within-survey comparison of outcomes across quintiles. We also created figures to track stunting prevalence by quintile across time for selected countries.

We conducted statistical analyses using the Stata version 14 SE statistical software package (StataCorp LP, College Station, TX).

RESULTS

We included in our analysis 239 surveys, conducted between 1993 and 2014 and covering 88 countries (Figure B, available as a supplement to the online version of this article at http://www.ajph.org). Table 1 shows average incomes per decade and wealth quintiles; the overall income differentials across wealth quintiles were rather large, with households in the top wealth quintile on average having annual incomes more than 8 times as large as households in the bottom wealth quintile. The corresponding average daily incomes per capita were low, ranging from an average of $2.4 in the bottom wealth quintile to $21.7 in the top wealth quintile. In terms of the trends over time, we observed the largest improvements in income in the bottom wealth quintile, where average incomes were about 60% higher in the 2010–2014 period compared with the 1990s.

Figure C (available as a supplement to the online version of this article at http://www.ajph.org) provides further details on the distribution of incomes across wealth quintiles. Median annual income increases from $2719 in the first quintile to $24 143 in the top wealth quintile, with substantial overlap in the distributions and increasingly high dispersion of incomes across wealth quintiles. The highest incomes in the bottom wealth quintile were in Iraq (2011), Jordan (2012), Maldives (2009), and Macedonia (2005), all with annual household incomes between $15 000 and $20 000. The lowest incomes in the top wealth quintile were in Malawi (2006) and Ethiopia (2000), with estimated household incomes below $5000.

Figure D (available as a supplement to the online version of this article at http://www.ajph.org) compares poverty rates based on our model predictions with the official poverty estimates in 2012 as a more general test for the predictive power of the model. The pairwise correlation between the actual and predicted poverty rates was 0.89 ($P < .001$); Spearman's rank correlation was 0.91 ($P < .001$).

Figure E (available as a supplement to the online version of this article at http://www.ajph.org) shows the empirical relationships between stunting prevalence and absolute predicted income versus natural logarithm (ln) of predicted income. Both relationships are highly significant and negative, with a somewhat convex shape for absolute income and a mostly linear shape for ln income.

Table 2 shows multivariable regression results. In models 1 through 3, we ran pooled regression models, using wealth quintile indicators (model 1), absolute income (model 2), and ln(income) (model 3) as predictors. The basic model including only indicator

TABLE 1—Estimated Annual Household and Estimated Average Daily per Capita Incomes in 88 Countries

	Surveys Conducted in 1990s (n = 45)		Surveys Conducted 2000–2009 (n = 113)		Surveys Conducted 2010–2015 (n = 81)	
Wealth Quintile	Annual Household Income	Daily per Capita Income	Annual Household Income	Daily per Capita Income	Annual Household Income	Daily per Capita Income
Lowest (WQ1)	3 020	1.6	3 965	2.4	4 539	2.9
Second (WQ2)	5 815	3.2	7 118	4.2	7 951	4.9
Third (WQ3)	8 889	5.0	10 408	6.3	11 469	7.2
Fourth (WQ4)	13 801	8.4	15 604	9.9	16 875	10.8
Top (WQ5)	32 354	20.1	33 287	21.4	34 994	23.0
Relative income, WQ5/WQ1	10.7	12.8	8.4	8.9	7.7	7.8

Note. WQ = wealth quintile. Incomes are in 2011 purchasing power parity–adjusted US dollars.

TABLE 2—Multivariable Regression Results of Stunting Prevalence in 88 Countries: 1993–2014

	Cross-Country Analysis			Within-Country Analysis		
Analysis Level	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Asset quintile 1	(Ref)			(Ref)		(Ref)
Asset quintile 2	−4.391** (0.548)			−4.391** (0.613)		−0.737 (1.586)
Asset quintile 3	−8.372** (1.028)			−8.372** (1.150)		−2.358 (2.502)
Asset quintile 4	−12.97** (1.290)			−12.97** (1.442)		−4.529 (3.491)
Asset quintile 5	−20.70** (1.356)			−20.70** (1.517)		−7.836 (5.528)
Income		−0.580** (0.0461)				
Ln(income)			−10.78** (0.551)		−9.399** (0.732)	−5.851* (2.711)
Survey-specific intercepts	No	No	No	Yes	Yes	Yes
No. of observations	1195	1195	1195	1195	1195	1195
R^2	0.201	0.375	0.545	0.910	0.911	0.914

Note. Coefficients are expressed as percentage points. Robust standard errors (in parentheses) are clustered at the country level. Income is in 2011 purchasing power parity–adjusted US dollars. Model 1 shows an ordinary least squares (OLS) regression model with asset quintiles only. Model 2 shows an OLS regression model with absolute income estimates only. Model 3 shows an OLS regression model with ln(income) only. Models 4 through 6 repeat the same regression models but also include survey-specific intercepts (fixed effects).
*$P<.05$; **$P<.01$.

variables for asset quintiles (model 1) predicts roughly 20% of total variation. An alternative model including absolute incomes predicts 38% of variation in stunting prevalence; a model using log-normalized income explains 55% of total variation.

In models 4 through 6 (Table 2), we compared the performance of the asset and income variables in models including survey-specific intercepts (survey fixed effects). With survey-specific intercepts, total R^2 increases to more than 90%, with income

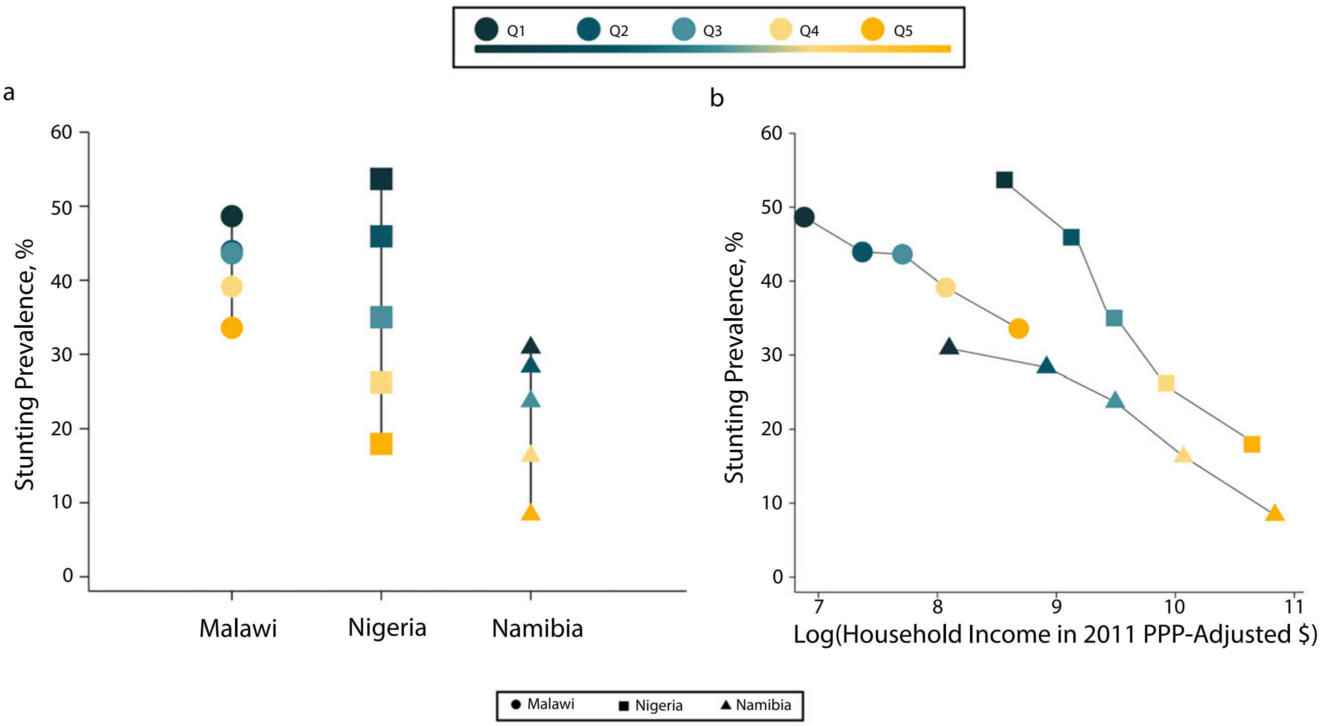

FIGURE 1—Stunting Prevalence in Malawi, Nigeria, and Namibia, by (a) Wealth Quintile and (b) Household Income: 2013

and asset variables explaining a similar share of within-survey variation in stunting. When both variables are included in model 6, only the ln(income) variable has a *P* value less than .05 ($P = .027$).

To further illustrate the relative advantage of the asset versus income variables, we show stunting prevalences for Malawi (poorest), Nigeria (lower middle income) and Namibia (upper middle income) in Figure 1. Figure 1a shows stunting prevalence by wealth quintile for the 3 countries. This type of graph, known as an equiplot (http://www.equidade.org/equiplot), is currently a standard graphic presentation of socioeconomic inequalities in health in LMICs. The figure nicely illustrates the large differentials in stunting outcomes across countries, as well as the generally lower prevalences for Namibia, a more developed country than Malawi, whereas Nigeria remains in an intermediate position with wider inequalities. Figure 1b shows stunting prevalences relative to predicted, absolute incomes. As the figure shows, incomes overlap only partially across the 3 countries, with Malawian households in the top quintile having roughly the same incomes as Nigerian households in the bottom quintile and Namibian households at the low end of the second quintile. For any given income, children in Malawi and Namibia seem to face approximately the same risk of stunting; the same is not true for Nigeria, where stunting prevalences are much higher than what would have been expected on the basis of the overall income levels in the country.

In Figure 2, we plot stunting prevalence as a function of predicted incomes for the first and last survey rounds in Zambia and Zimbabwe. In both countries, the average income of households in the bottom quintile in the last survey round roughly corresponds to the average income of households in the second quintile in the first survey round. In Zimbabwe, the relationship between incomes and stunting seems to have changed very little, whereas Zambia appears to have achieved on average slightly lower stunting prevalence at the lower income levels, with similar outcomes at higher levels.

Figure E shows the country survey–level association between stunting ratios—stunting prevalence in the top quintile divided by the prevalence in the bottom quintile—as a function of the estimated income differentials in the 239 surveys. The correlation between the 2 variables is 0.43 ($P < .001$).

DISCUSSION

We used the algorithm outlined in Harttgen and Vollmer[2] to predict incomes for households in LMICs based on their observed asset information as well as nationally available data on average levels and overall inequality in income distribution. Our results suggest that poverty estimates based on predicted incomes align rather well with country-specific estimates; we also found that absolute income levels greatly increase the degree to which stunting levels across countries can be predicted, compared with models that rely solely on wealth quintiles.

Our analysis has limitations. The first and most obvious limitation is that data on the relative position of households in the income distribution are not available. In the absence of households' relative rank—which would only be available if we had incomes for all households (in which case the entire exercise would be redundant)—we could only assign

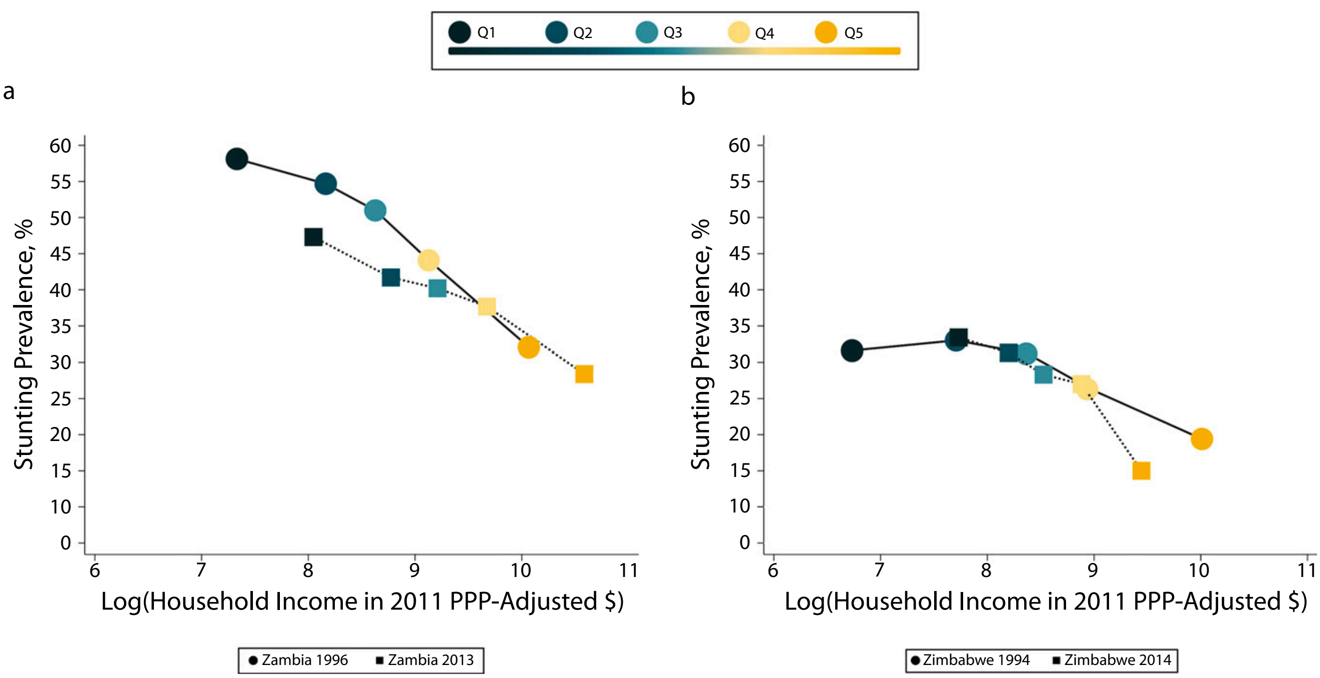

FIGURE 2—Within-Country Variation in Stunting Over Time in (a) Zambia (1996–2013) and (b) Zimbabwe (1994–2014)

incomes based on the assumption that the relative income and asset rankings are the same or at least similar. Empirically, some households with few asset holdings may have relatively high incomes, whereas some households with many assets may not have high current incomes. For the projections used in this study, we grouped households into quintiles, which reduced measurement error to some extent. It is worth highlighting that even with perfect measurement, income and asset rankings would not fully align. As mentioned in the Introduction, household incomes, particularly in low-income settings, tend to be volatile over time. Household asset holdings are generally not the result of current income alone, but rather a reflection of past incomes invested into durable goods. One could in theory get a better idea of short-term incomes by analyzing recent changes in asset holdings; however, such data are rarely available in practice.[15]

A second limitation of our analysis is that data on inequality are not available for all years; we used linear interpolation to compute Gini coefficients for missing years, which will induce some additional measurement error; however, given that Gini coefficients tend to move very slowly, this error is likely to be small. Similarly, data on average household income are not currently available from most LMICs. Although we believe that average incomes can be approximated well through use of available consumption data, the overall quality of the income predictions could clearly be improved with higher-quality measures of mean household incomes across countries and time. It is also worth noting that the officially reported average income and inequality measures are hard to reconcile in some cases. Pakistan is a great example: the latest estimates suggest a purchasing power parity–adjusted income per capita of approximately US $5000 per person, which is very similar to that of Moldova—both countries report low income inequality (Gini = 0.30 for Pakistan and 0.28 for Moldova), and yet Pakistan claims poverty levels almost 15 times as large as those reported for Moldova (Figure D). These numbers are hard to reconcile empirically and suggest a substantial amount of estimation error in either officially published income inequality or poverty estimates (or both). A last and related limitation is the lack of detail on within-household resource allocation. Our model focuses exclusively on average household resources but does not allow analyzing the distribution of resources within a household, which may be highly unequal across different environments.

In spite of these limitations, we show that absolute income is markedly superior to relative wealth in terms of predicting stunting prevalence across countries. The analyses presented in Table 2 and Figures E and F (available as a supplement to the online version of this article at http://www.ajph.org) show that use of absolute income adds new insights when comparing stunting prevalence in different countries, or when interpreting time trends in the same country. Similar analyses may be carried out for the large number of health and nutrition indicators available from surveys in LMICs. Our findings support the use of absolute income estimates for comparisons among countries and for understanding the evolution of nutrition and health trends within any given country. This represents a remarkable advancement compared with the limitation imposed by wealth quintiles, which do not account for differences in levels of wealth observed across countries. Income estimates also allow for more analyses within countries over time, as well as direct assessment of whether changes in incomes may explain the improvement in health indicators, rather than specific health policies or programs.

In 2015, the United Nations adopted the Sustainable Development Goals. Target number 17.18 (http://indicators.report/targets/17-18) states,

> [B]y 2020, enhance capacity building support to developing countries . . . to increase significantly the availability of high-quality, timely and reliable data disaggregated by income, gender, age, race, . . .

We are hopeful that our study will contribute to this worthwhile goal. AJPH

CONTRIBUTORS

G. Fink and C. G. Victora had the original study idea. G. Fink drafted the article and the analytical plan. K. Harttgen, S. Vollmer, L. P. Vidaletti, and A. J. D. Barros supported the data analysis. All of the authors contributed to the final article.

HUMAN PARTICIPANT PROTECTION

No protocol approval was necessary for this study because no human participants were involved.

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